main_new_5_2_0_0

August 28, 2021

1 IMPORTANT LIBRARIES

[1]:
```
# Warning Libraries :
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
# Scientific and Data Manipulation Libraries :
import pandas as pd
import numpy as np
from numpy import percentile
import math
import os
from sklearn.model_selection import train_test_split
```

[3]:
```
# Data Visualization Libraries :
%matplotlib inline
import seaborn as sns
import matplotlib.pyplot as plt
```

[4]:
```
#pip install lasio
```

[5]:
```
#Libraries to convert .las files to .csv and merge

import lasio
from sys import stdout
import glob  ##For merging csv files
```

[6]:
```
#DATA IMPUTATION LIBRARY
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.impute import KNNImputer
from sklearn.linear_model import LinearRegression
```

[7]:
```
#Feature Selection Libraries
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import mutual_info_classif
from sklearn.feature_selection import SelectKBest
```

[8]:
```
#SCALING LIBRARIES
from sklearn.preprocessing import StandardScaler, MinMaxScaler, Normalizer,␣
↪RobustScaler, MaxAbsScaler
```

[9]:
```
#pip install catboost
```

[10]:
```
#MODEL TRAINING LIBRARIES
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from catboost import CatBoostClassifier
from sklearn.svm import OneClassSVM
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import VotingClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import RandomForestClassifier
```

[11]:
```
#MODEL ACCURACY LIBRARIES
from sklearn import metrics
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

[12]:
```
#grid searching key hyperparametres for logistic regression
from sklearn.datasets import make_blobs
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV
```

[13]:
```
path='/media/mr-robot/Local Disk/summer_training/Train'
os.chdir(path)
```

2 LAS TO CSV

[14]:
```
# Converting all las files in csv by iterating using lasio
for file in os.listdir():
    if file.endswith(".las"):
        file_path = f"{path}/{file}"
        las=lasio.read(file_path)
        size=len(file_path)
        filepath1=file_path[:size-3]
        las.to_csv(filepath1+'csv', units=False)
```

[15]:
```
# Adding Well name to easily identify
for file in os.listdir():
    if file.endswith(".csv"):
        s=pd.read_csv(file)
        size=len(file)
        dict=[]
        filename= file[:size-4]
```

```
        t=s.shape[0]
        for i in range(t):
            dict.append(filename)
        s['WELL']=dict
        s.to_csv(filename+'.csv',index=False)
```

[16]:
```
## To avoid furthur merging data and redundancy
if(os.path.isfile('./merged_data.csv') ):
    os.remove("merged_data.csv")

if(os.path.isfile('./FACIES_imputed.csv')):
    os.remove("FACIES_imputed.csv")

if(os.path.isfile('./FACIES_TRAIN.csv')):
    os.remove("FACIES_TRAIN.csv")
```

[17]:
```
# Merging all Well Log using Glob
filenames = glob.glob(path + "/*.csv")
dfs = []
for filename in filenames:
    dfs.append(pd.read_csv(filename))
big_frame = pd.concat(dfs, ignore_index=True)
big_frame.to_csv('merged_data.csv',index=False)
```

3 IMPUTATION

[18]:
```
df = pd.read_csv('merged_data.csv')
df
```

[18]:

	DEPTH	ACOUSTICIMPEDANCE1	AI	AVG_PIGN	CALI	\
0	1275.0552	12875.0811	12875081.0	NaN	9.7141	
1	1275.2076	12854.2256	12854226.0	NaN	9.7848	
2	1275.3600	13024.1377	13024138.0	NaN	9.8300	
3	1275.5124	13093.3428	13093343.0	NaN	9.8587	
4	1275.6648	13169.9307	13169931.0	NaN	9.8756	
…	…	…	…	…	…	
58494	1622.6028	6069.1309	6069130.5	NaN	8.5257	
58495	1622.7552	6067.8120	6067812.0	NaN	8.5282	
58496	1622.9076	6105.7729	6105773.0	NaN	8.5313	
58497	1623.0600	6152.9897	6152977.5	NaN	8.5331	
58498	1623.2124	6157.8291	6157829.5	NaN	8.5338	

	CALI[DERIVED]1	DT	FACIES	FLD1	GR	…	CALI_1	NPHI_1	\
0	9.7141	50.2544	NaN	NaN	50.2128	…	NaN	NaN	
1	9.7848	50.3881	NaN	NaN	49.7509	…	NaN	NaN	
2	9.8300	49.8852	NaN	NaN	48.2513	…	NaN	NaN	
3	9.8587	49.9032	NaN	NaN	46.8212	…	NaN	NaN	

```
4              9.8756   50.0157     NaN   NaN  45.3463  …     NaN     NaN
…               …        …      …    …       …  …      …      …
58494             NaN  123.7404     NaN   NaN       NaN  …     NaN  0.4993
58495             NaN  123.8728     NaN   NaN       NaN  …     NaN  0.5313
58496             NaN  123.3722     NaN   NaN       NaN  …     NaN  0.5448
58497             NaN  122.6038     NaN   NaN       NaN  …     NaN  0.5364
58498             NaN  122.3045     NaN   NaN       NaN  …     NaN  0.5331

       ZCOR  RHOB_1  RXO  SPDH      DTDS    M2R1  TH   U
0       NaN     NaN  NaN   NaN       NaN     NaN NaN NaN
1       NaN     NaN  NaN   NaN       NaN     NaN NaN NaN
2       NaN     NaN  NaN   NaN       NaN     NaN NaN NaN
3       NaN     NaN  NaN   NaN       NaN     NaN NaN NaN
4       NaN     NaN  NaN   NaN       NaN     NaN NaN NaN
…     …      …   …   …       …     …   ..  ..
58494   NaN  2.4639  NaN   NaN  123.7404  1.5970 NaN NaN
58495   NaN  2.4660  NaN   NaN  123.8728  1.6128 NaN NaN
58496   NaN  2.4714  NaN   NaN  123.3722  1.7043 NaN NaN
58497   NaN  2.4750  NaN   NaN  122.6038  1.8375 NaN NaN
58498   NaN  2.4709  NaN   NaN  122.3045  1.9363 NaN NaN

[58499 rows x 67 columns]
```

[19]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58499 entries, 0 to 58498
Data columns (total 67 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   DEPTH                58499 non-null  float64
 1   ACOUSTICIMPEDANCE1   58499 non-null  float64
 2   AI                   55259 non-null  float64
 3   AVG_PIGN             323 non-null    float64
 4   CALI                 54981 non-null  float64
 5   CALI[DERIVED]1       44090 non-null  float64
 6   DT                   58499 non-null  float64
 7   FACIES               52641 non-null  float64
 8   FLD1                 3963 non-null   float64
 9   GR                   58379 non-null  float64
 10  LLD                  44942 non-null  float64
 11  LLS                  27394 non-null  float64
 12  DEPTH_1              50885 non-null  float64
 13  NPHI                 58172 non-null  float64
 14  ONE-WAYTIME1         15713 non-null  float64
 15  PIGN_MODELLING       51101 non-null  float64
 16  PIMP                 55259 non-null  float64
 17  RHOB                 58499 non-null  float64
```

```
18  RT_MODELLING        53629 non-null  float64
19  SP                  55992 non-null  float64
20  SUWI_MODELLING      51099 non-null  float64
21  TDVSS               58437 non-null  float64
22  ZLT                 44562 non-null  float64
23  WELL                58499 non-null  object
24  DFL                 23458 non-null  float64
25  HDRS                26951 non-null  float64
26  HMRS                26951 non-null  float64
27  PERF_INT            1569 non-null   float64
28  PERMEABILITY        28149 non-null  float64
29  PIGN                46949 non-null  float64
30  RT_POWER            51379 non-null  float64
31  SUWI                46947 non-null  float64
32  VCL                 46947 non-null  float64
33  WATER_VOL           43735 non-null  float64
34  LL3                 12373 non-null  float64
35  BS                  6706 non-null   float64
36  CALI1               2389 non-null   float64
37  DEVI                10283 non-null  float64
38  DT1                 6130 non-null   float64
39  PHIT                16532 non-null  float64
40  PIGE                5245 non-null   float64
41  LLD_1               9518 non-null   float64
42  SXWI                27938 non-null  float64
43  PEF                 19419 non-null  float64
44  AZI1                2487 non-null   float64
45  TEMP                14514 non-null  float64
46  DRES                2765 non-null   float64
47  DT2                 2765 non-null   float64
48  DT4P                5854 non-null   float64
49  GR_EDTC             2765 non-null   float64
50  M2R2                8568 non-null   float64
51  LLS_1               238 non-null    float64
52  MSFL                2765 non-null   float64
53  PR                  2757 non-null   float64
54  TENS                2765 non-null   float64
55  VPVS                2757 non-null   float64
56  BIT                 5553 non-null   float64
57  CALI_1              2999 non-null   float64
58  NPHI_1              10811 non-null  float64
59  ZCOR                2998 non-null   float64
60  RHOB_1              10899 non-null  float64
61  RXO                 1552 non-null   float64
62  SPDH                3069 non-null   float64
63  DTDS                2546 non-null   float64
64  M2R1                2546 non-null   float64
65  TH                  2509 non-null   float64
```

```
 66  U                    2509 non-null   float64
dtypes: float64(66), object(1)
memory usage: 29.9+ MB
```

[20]:
```
df.shape[1]
```

[20]: 67

[21]:
```
obj = df.isnull().sum()
for key,value in obj.iteritems():
    print(key,",",value)
```

```
DEPTH , 0
ACOUSTICIMPEDANCE1 , 0
AI , 3240
AVG_PIGN , 58176
CALI , 3518
CALI[DERIVED]1 , 14409
DT , 0
FACIES , 5858
FLD1 , 54536
GR , 120
LLD , 13557
LLS , 31105
DEPTH_1 , 7614
NPHI , 327
ONE-WAYTIME1 , 42786
PIGN_MODELLING , 7398
PIMP , 3240
RHOB , 0
RT_MODELLING , 4870
SP , 2507
SUWI_MODELLING , 7400
TDVSS , 62
ZLT , 13937
WELL , 0
DFL , 35041
HDRS , 31548
HMRS , 31548
PERF_INT , 56930
PERMEABILITY , 30350
PIGN , 11550
RT_POWER , 7120
SUWI , 11552
VCL , 11552
WATER_VOL , 14764
LL3 , 46126
BS , 51793
```

```
CALI1 , 56110
DEVI , 48216
DT1 , 52369
PHIT , 41967
PIGE , 53254
LLD_1 , 48981
SXWI , 30561
PEF , 39080
AZI1 , 56012
TEMP , 43985
DRES , 55734
DT2 , 55734
DT4P , 52645
GR_EDTC , 55734
M2R2 , 49931
LLS_1 , 58261
MSFL , 55734
PR , 55742
TENS , 55734
VPVS , 55742
BIT , 52946
CALI_1 , 55500
NPHI_1 , 47688
ZCOR , 55501
RHOB_1 , 47600
RXO , 56947
SPDH , 55430
DTDS , 55953
M2R1 , 55953
TH , 55990
U , 55990
```

[22]:
```
#Selecting required feature
df=df[["DT","GR","NPHI","RHOB","FACIES"]]
```

[23]:
```
df
```

[23]:

	DT	GR	NPHI	RHOB	FACIES
0	50.2544	50.2128	0.5340	2.1228	NaN
1	50.3881	49.7509	0.5316	2.1250	NaN
2	49.8852	48.2513	0.5126	2.1316	NaN
3	49.9032	46.8212	0.5137	2.1437	NaN
4	50.0157	45.3463	0.5472	2.1611	NaN
…	…	…	…	…	…
58494	123.7404	NaN	0.4993	2.4639	NaN
58495	123.8728	NaN	0.5313	2.4660	NaN
58496	123.3722	NaN	0.5448	2.4714	NaN

```
58497  122.6038      NaN  0.5364  2.4750     NaN
58498  122.3045      NaN  0.5331  2.4709     NaN

[58499 rows x 5 columns]
```

[24]:
```
df.isnull().sum()
```

[24]:
```
DT           0
GR         120
NPHI       327
RHOB         0
FACIES    5858
dtype: int64
```

[25]:
```
#Exporting required features to csv
df.to_csv("FACIES_TRAIN.csv",index=False)
```

[26]:
```
df=pd.read_csv("FACIES_TRAIN.csv")
```

[27]:
```
df.head(20)
```

[27]:

	DT	GR	NPHI	RHOB	FACIES
0	50.2544	50.2128	0.5340	2.1228	NaN
1	50.3881	49.7509	0.5316	2.1250	NaN
2	49.8852	48.2513	0.5126	2.1316	NaN
3	49.9032	46.8212	0.5137	2.1437	NaN
4	50.0157	45.3463	0.5472	2.1611	NaN
5	50.6831	44.0819	0.5550	2.1740	NaN
6	51.4311	43.6654	0.5612	2.1707	NaN
7	52.1678	43.3915	0.5566	2.1595	NaN
8	52.2883	44.1249	0.5390	2.1534	NaN
9	51.5991	46.1805	0.5245	2.1551	NaN
10	50.6185	48.6156	0.5152	2.1542	NaN
11	50.5171	49.6999	0.5152	2.1535	NaN
12	50.1209	49.4600	0.5180	2.1586	NaN
13	50.0558	48.3665	0.5156	2.1662	NaN
14	49.4216	46.8647	0.5070	2.1705	NaN
15	47.9804	45.7345	0.4913	2.1702	NaN
16	46.3324	45.5512	0.4696	2.1657	NaN
17	45.1378	45.9222	0.4570	2.1579	NaN
18	45.2291	46.4844	0.4654	2.1533	NaN
19	45.6106	49.6481	0.4952	2.1526	NaN

[28]:
```
df.shape
```

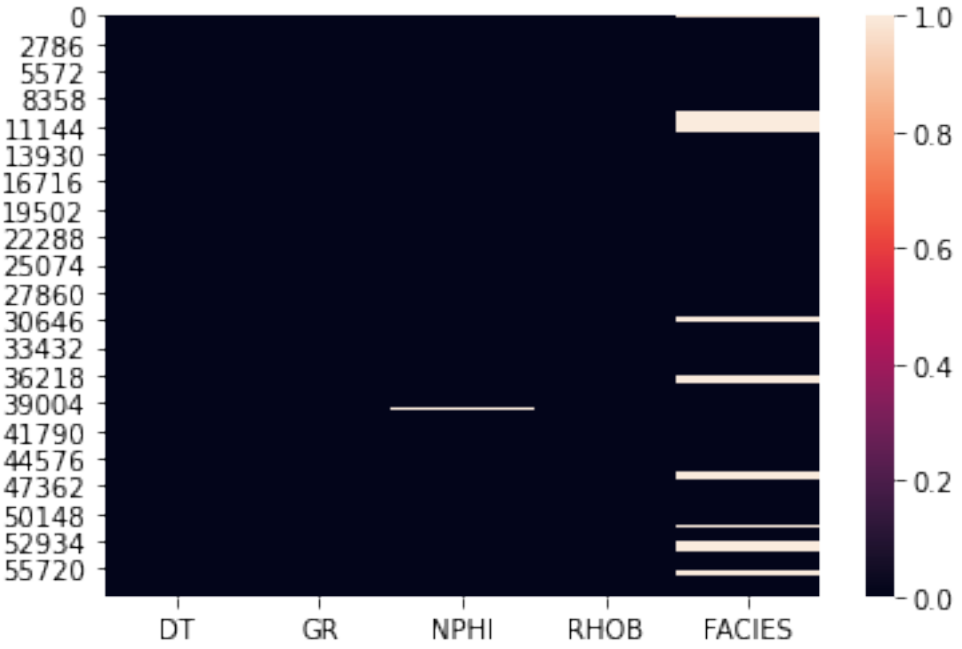
[28]:
```
(58499, 5)
```

[29]:
```
df.info()
```

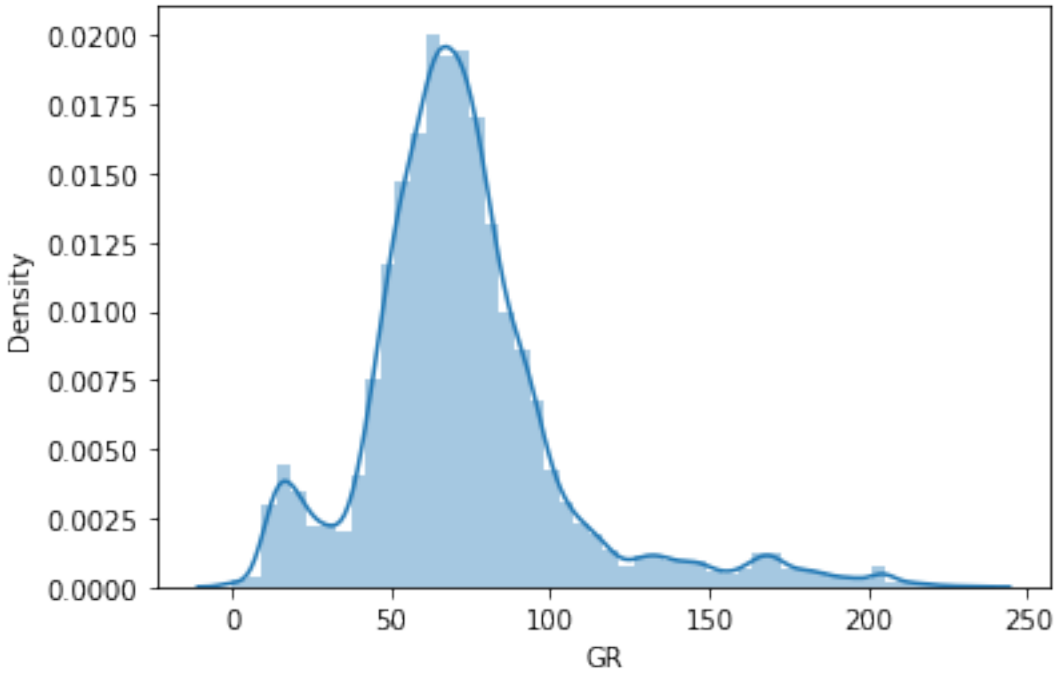
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58499 entries, 0 to 58498
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   DT      58499 non-null  float64
 1   GR      58379 non-null  float64
 2   NPHI    58172 non-null  float64
 3   RHOB    58499 non-null  float64
 4   FACIES  52641 non-null  float64
dtypes: float64(5)
memory usage: 2.2 MB
```

[30]:
```
sns.heatmap(df.isnull())
```

[30]: <AxesSubplot:>



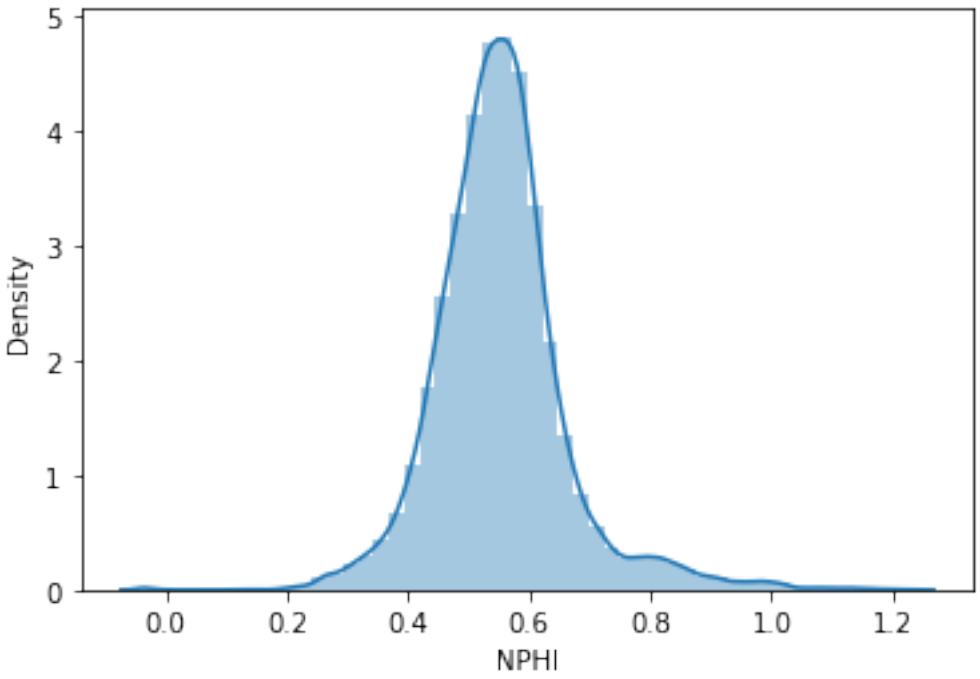
[31]:
```
null_gr = sns.distplot(df.GR.dropna())
```



[32]:
```
df.GR.describe()
```

[32]:
```
count    58379.000000
mean        72.610942
std         32.140407
min          0.000000
25%         55.340300
50%         68.939700
75%         83.758300
max        233.707400
Name: GR, dtype: float64
```

[33]:
```
null_nphi=sns.distplot(df.NPHI.dropna())
```

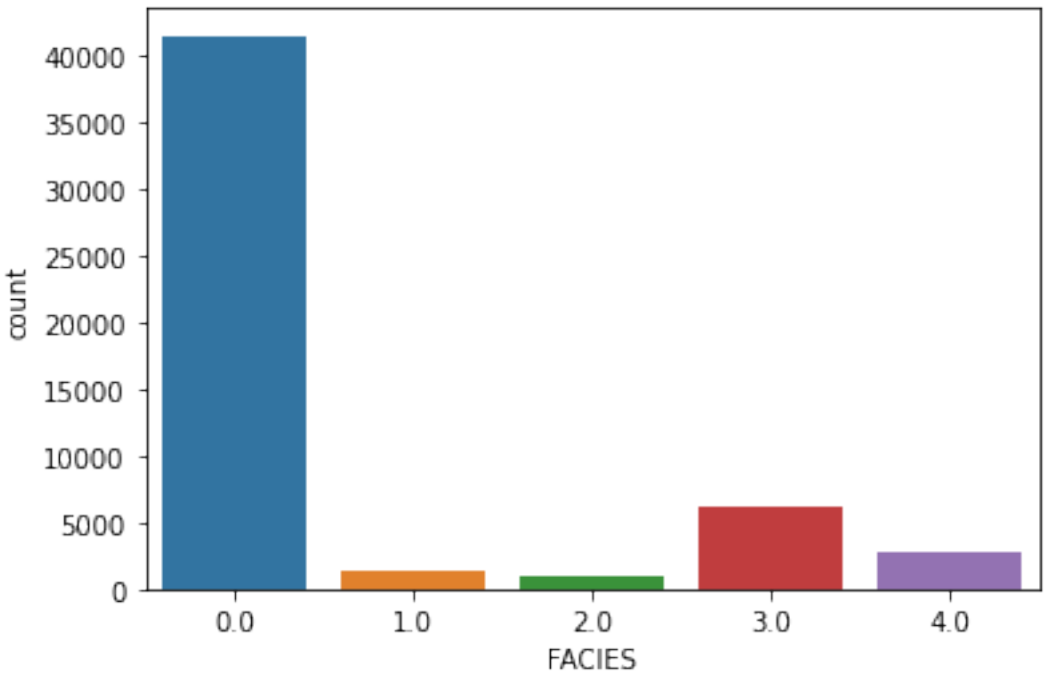


[34]:
```
df.NPHI.describe()
```

[34]:
```
count    58172.000000
mean         0.551710
std          0.109983
min         -0.038000
25%          0.489275
50%          0.546600
75%          0.600500
max          1.231200
Name: NPHI, dtype: float64
```

[35]:
```
sns.countplot(x="FACIES",data=df)
```

[35]:
```
<AxesSubplot:xlabel='FACIES', ylabel='count'>
```



[36]:
```
df.FACIES.value_counts(dropna=False)
```

[36]:
```
0.0    41514
3.0     6138
NaN     5858
4.0     2798
1.0     1281
2.0      910
Name: FACIES, dtype: int64
```

[37]:
```
def imputing(imputation_strategy,imputing_data):
    df=imputing_data
    if imputation_strategy == "Mean":
        df.GR.fillna(df.GR.mean(),inplace=True)
        print( df.GR.isnull().sum())
        print("Graph (GR) after filling null values with mean")
        sns.displot(df.GR.dropna())
        df.NPHI.fillna(df.NPHI.mean(),inplace=True)
        print("Graph (NPHI) after filling null values with mean")
        print(df.NPHI.isnull().sum())
        sns.displot(df.NPHI.dropna())
        #dropping FACIES rows with null
        df.dropna(axis=0,inplace=True)
        print(df.isnull().sum())
        df['FACIES'] = df.FACIES.astype(np.int64)
```

```
        df.info()
        df.FACIES.describe()
        return df

    elif imputation_strategy == "bffill":
        df = df.ffill(axis = 0)
        df = df.bfill(axis = 0)
        df['FACIES'] = df.FACIES.astype(np.int64)
        print(df.isnull().sum())
        return df

    elif imputation_strategy == "KNNImputer":
        knn= KNNImputer(n_neighbors=3)
        X=df.drop('FACIES',1)
        t=knn.fit_transform(X)
        X=pd.DataFrame(t)
        Y=df['FACIES']
        Y=Y.ffill(axis=0)
        Y=Y.bfill(axis=0)
        X['FACIES']=Y
        df=X
        df['FACIES'] = df.FACIES.astype(np.int64)
        d=['DT','GR','NPHI','RHOB']
        for i in range(4):
            df.columns.values[i]=d[i]
        return df

    elif imputation_strategy == "IterativeImputer":
        lr=LinearRegression()    #can use other regressions too. / default is␣
↪beysian
        imp=IterativeImputer(max_iter=3)
        X=df.drop('FACIES',1)
        t=imp.fit_transform(X)
        X=pd.DataFrame(t)
        Y=df['FACIES']
        Y=Y.ffill(axis=0)
        Y=Y.bfill(axis=0)
        X['FACIES']=Y
        df=X
        df['FACIES'] = df.FACIES.astype(np.int64)
        d=['DT','GR','NPHI','RHOB']
        for i in range(4):
            df.columns.values[i]=d[i]
        return df

    elif imputation_strategy == "KNNimputer_floor" :
        X=df
```

```
        knn= KNNImputer(n_neighbors=3)
        t=knn.fit_transform(df)
        df=pd.DataFrame(t)
        d=['DT','GR','NPHI','RHOB','FACIES']
        df['FACIES1'] = X.FACIES
        for i in range(5):
            df.columns.values[i]=d[i]
        df=df.drop('FACIES1',1)
        df['FACIES'] = df.FACIES.astype(np.int64)
        return df

    elif imputation_strategy == "IterativeImputer_floor" :
        X=df
        lr=LinearRegression()
        imp= IterativeImputer(max_iter=3)
        t=imp.fit_transform(df)
        df=pd.DataFrame(t)
        d=['DT','GR','NPHI','RHOB','FACIES']
        df['FACIES1'] = X.FACIES
        for i in range(5):
            df.columns.values[i]=d[i]
        df=df.drop('FACIES1',1)
        df['FACIES'] = df.FACIES.astype(np.int64)
        return df

    elif imputation_strategy == "KNNBinning" :
        X=df
        knn= KNNImputer(n_neighbors=3)
        t=knn.fit_transform(df)
        df=pd.DataFrame(t)
        d=['DT','GR','NPHI','RHOB','FACIES']
        df['FACIES1'] = X.FACIES
        for i in range(5):
            df.columns.values[i]=d[i]
        df=df.drop('FACIES1',1)
        #df['FACIES'] = pd.cut(x=df['FACIES'],bins=[0,0.5,1.5,2.5,3.5,4.0],␣
↪labels=['0','1','2','3','4'])
        return df

    elif imputation_strategy == "dropna":
        df=df.dropna(axis=0)
        return df
```

[38]:
```
imputation_strategy = ["Mean" , "bffill" , "KNNImputer" , "IterativeImputer" ,␣
↪"KNNimputer_floor" , "IterativeImputer_floor" , "KNNBinning","dropna"]
#select option from 0-7 (6 is experimental)
optionimputation=5
```

```
df=imputing(imputation_strategy[optionimputation],df)
```

[39]:
```
#if option==6:
#    df['FACIES'] = pd.cut(x=df['FACIES'],bins=[0.0,0.5,1.5,2.5,3.5,4.0],␣
 ↪labels=['0','1','2','3','4'])
```

[40]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58499 entries, 0 to 58498
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   DT      58499 non-null  float64
 1   GR      58499 non-null  float64
 2   NPHI    58499 non-null  float64
 3   RHOB    58499 non-null  float64
 4   FACIES  58499 non-null  int64
dtypes: float64(4), int64(1)
memory usage: 2.2 MB
```

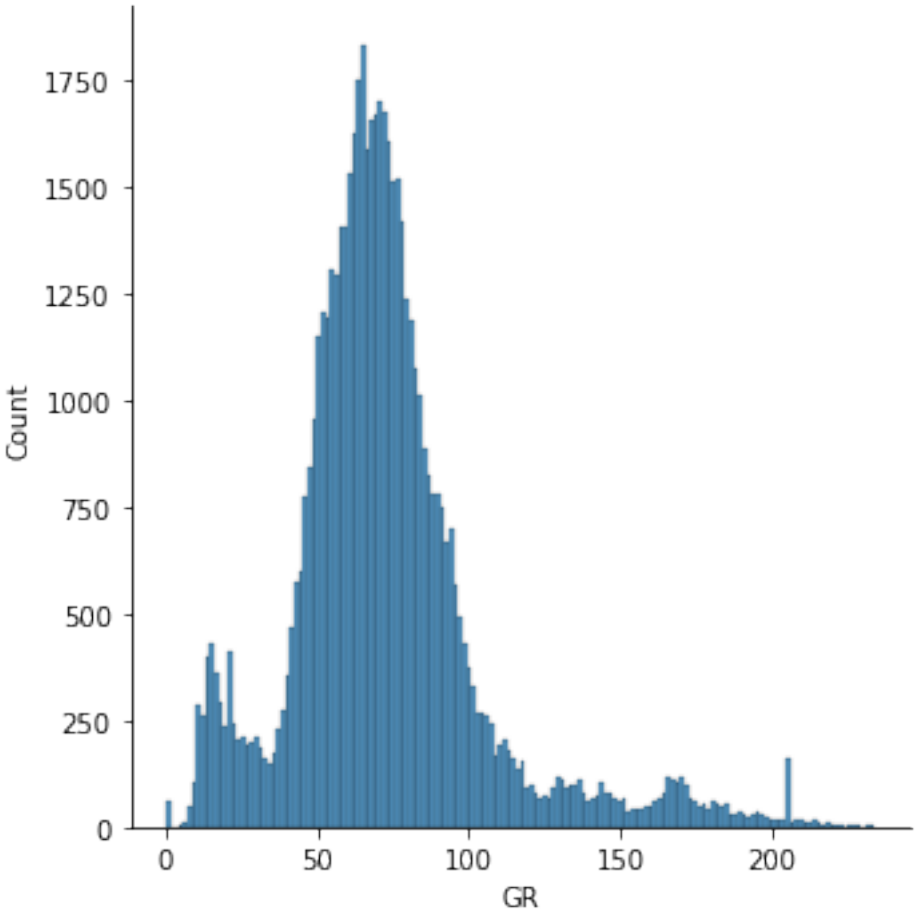
[41]:
```
df.isnull().sum()
```

[41]:
```
DT        0
GR        0
NPHI      0
RHOB      0
FACIES    0
dtype: int64
```

[42]:
```
df.to_csv("FACIES_imputed.csv",index=False)
df=pd.read_csv("FACIES_imputed.csv")
```

[43]:
```
sns.displot(df.GR.dropna())
```

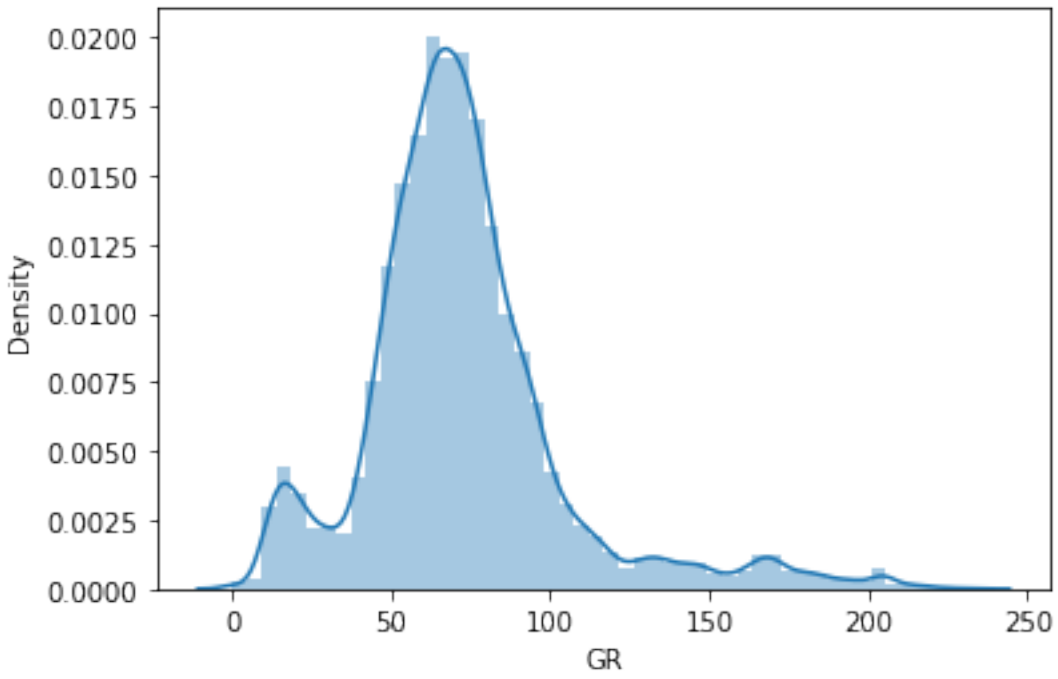
[43]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4844300c40>
```



[44]:
```
print("WHEN GR WAS NULL")
null_gr.figure
```

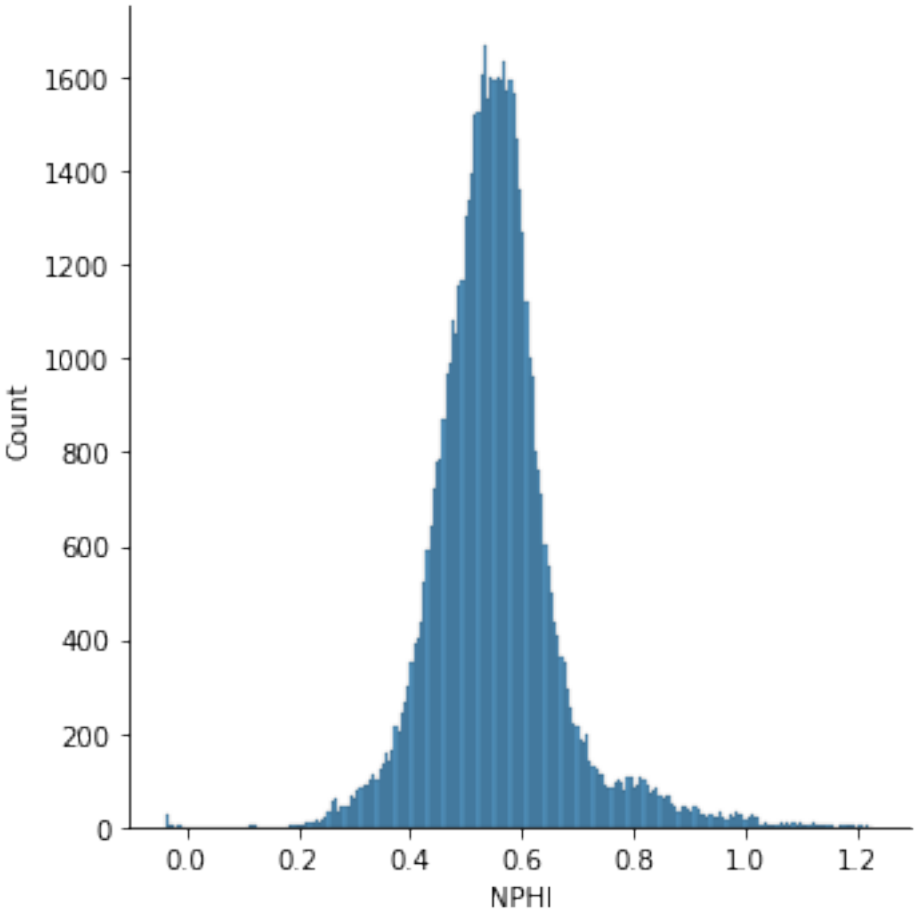
```
WHEN GR WAS NULL
```

[44]:



[45]:
```
sns.displot(df.NPHI.dropna())
```

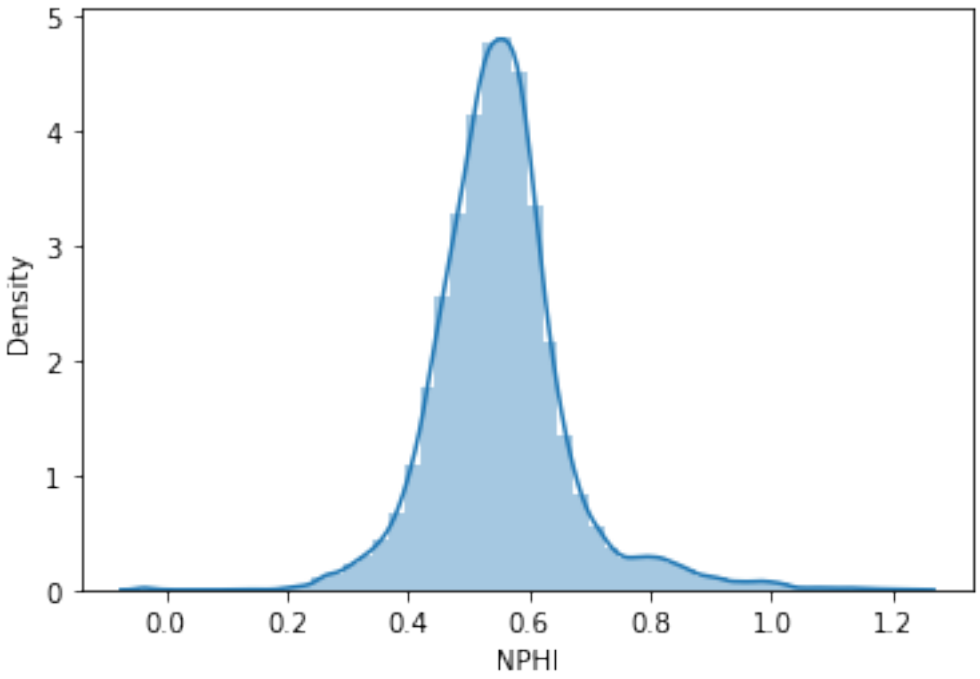
[45]: <seaborn.axisgrid.FacetGrid at 0x7f4843e2b520>



[46]:
```
print("WHEN NPHI WAS NULL")
null_nphi.figure
```

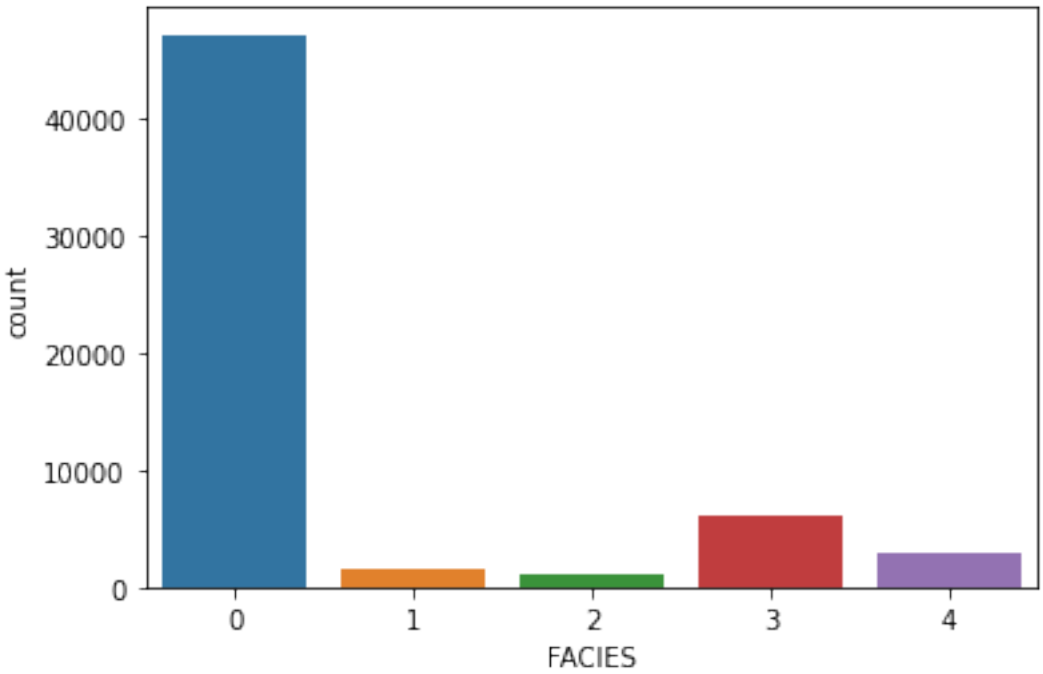
```
WHEN NPHI WAS NULL
```

[46]:



[47]:
```
sns.countplot(x="FACIES",data=df)
```

[47]: <AxesSubplot:xlabel='FACIES', ylabel='count'>



4 DATA CONDITIONING / OUTLIER REMOVAL

[48]:
```
df.head
```

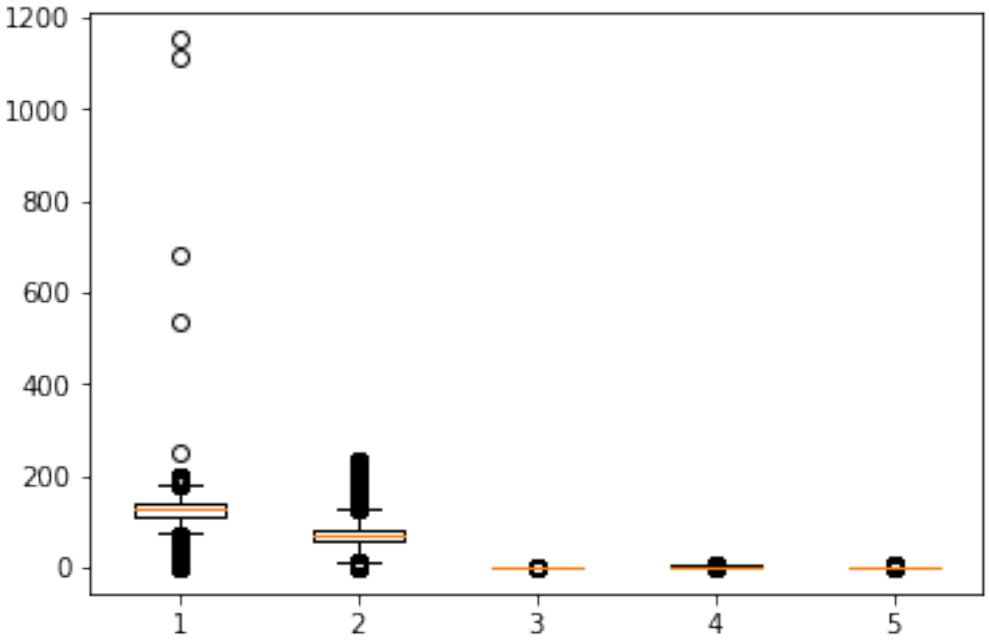
[48]:
```
<bound method NDFrame.head of              DT         GR    NPHI    RHOB  FACIES
0       50.2544  50.212800  0.5340  2.1228       1
1       50.3881  49.750900  0.5316  2.1250       1
2       49.8852  48.251300  0.5126  2.1316       1
3       49.9032  46.821200  0.5137  2.1437       1
4       50.0157  45.346300  0.5472  2.1611       1
…          …        …       …       …       …
58494  123.7404  80.913653  0.4993  2.4639       0
58495  123.8728  82.952576  0.5313  2.4660       0
58496  123.3722  84.044079  0.5448  2.4714       0
58497  122.6038  83.725389  0.5364  2.4750       0
58498  122.3045  83.329152  0.5331  2.4709       0

[58499 rows x 5 columns]>
```

4.1 WHOLE DATA OUTLIER VISUALIZATION

[49]:
```
plt.boxplot(df)
```

[49]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4843cd41f0>,
  <matplotlib.lines.Line2D at 0x7f4843cd4580>,
  <matplotlib.lines.Line2D at 0x7f4843cdeb50>,
  <matplotlib.lines.Line2D at 0x7f4843cdeee0>,
  <matplotlib.lines.Line2D at 0x7f4843cf74c0>,
  <matplotlib.lines.Line2D at 0x7f4843cf7850>,
  <matplotlib.lines.Line2D at 0x7f4843d00df0>,
  <matplotlib.lines.Line2D at 0x7f4843c4b1c0>,
  <matplotlib.lines.Line2D at 0x7f4843c56760>,
  <matplotlib.lines.Line2D at 0x7f4843c56af0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4843cd4910>,
  <matplotlib.lines.Line2D at 0x7f4843cd4ca0>,
  <matplotlib.lines.Line2D at 0x7f4843cea2b0>,
  <matplotlib.lines.Line2D at 0x7f4843cea640>,
  <matplotlib.lines.Line2D at 0x7f4843cf7be0>,
  <matplotlib.lines.Line2D at 0x7f4843cf7f70>,
  <matplotlib.lines.Line2D at 0x7f4843c4b550>,
  <matplotlib.lines.Line2D at 0x7f4843c4b8e0>,
  <matplotlib.lines.Line2D at 0x7f4843c56e80>,
  <matplotlib.lines.Line2D at 0x7f4843c61250>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4843d44e20>,
  <matplotlib.lines.Line2D at 0x7f4843cde7c0>,
```

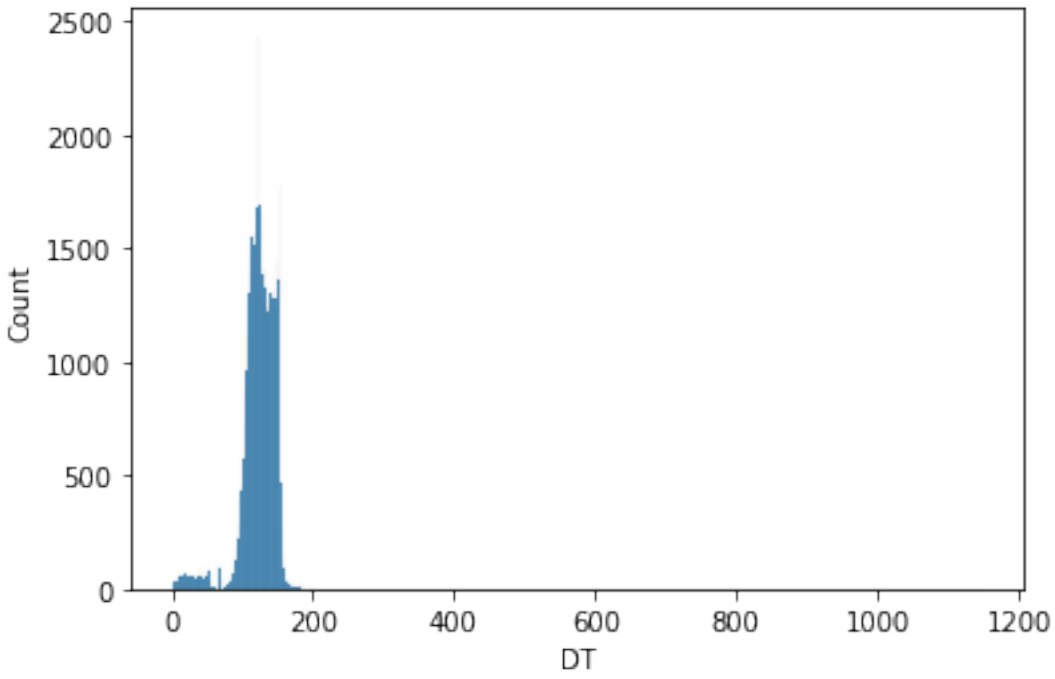
```
 <matplotlib.lines.Line2D at 0x7f4843cf7130>,
 <matplotlib.lines.Line2D at 0x7f4843d00a60>,
 <matplotlib.lines.Line2D at 0x7f4843c563d0>],
'medians': [<matplotlib.lines.Line2D at 0x7f4843cde070>,
 <matplotlib.lines.Line2D at 0x7f4843cea9d0>,
 <matplotlib.lines.Line2D at 0x7f4843d00340>,
 <matplotlib.lines.Line2D at 0x7f4843c4bc70>,
 <matplotlib.lines.Line2D at 0x7f4843c615e0>],
'fliers': [<matplotlib.lines.Line2D at 0x7f4843cde400>,
 <matplotlib.lines.Line2D at 0x7f4843cead60>,
 <matplotlib.lines.Line2D at 0x7f4843d006d0>,
 <matplotlib.lines.Line2D at 0x7f4843c56040>,
 <matplotlib.lines.Line2D at 0x7f4843c619a0>],
'means': []}
```



4.2 DT VISUALIZATION

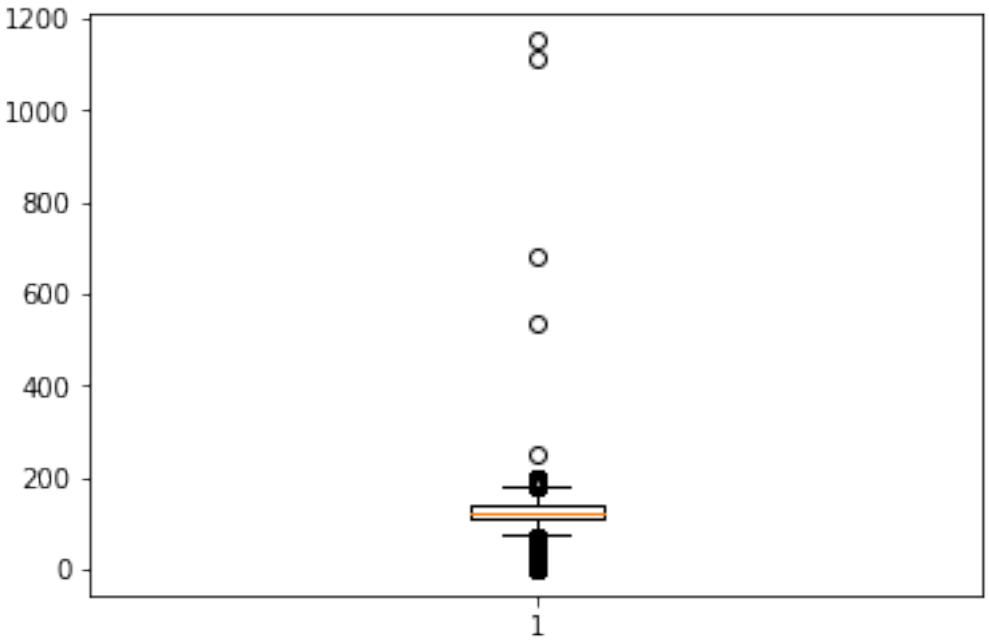
[50]:
```
sns.histplot(df.DT)
```

[50]:
```
<AxesSubplot:xlabel='DT', ylabel='Count'>
```



[51]:
```
plt.boxplot(df["DT"])
```

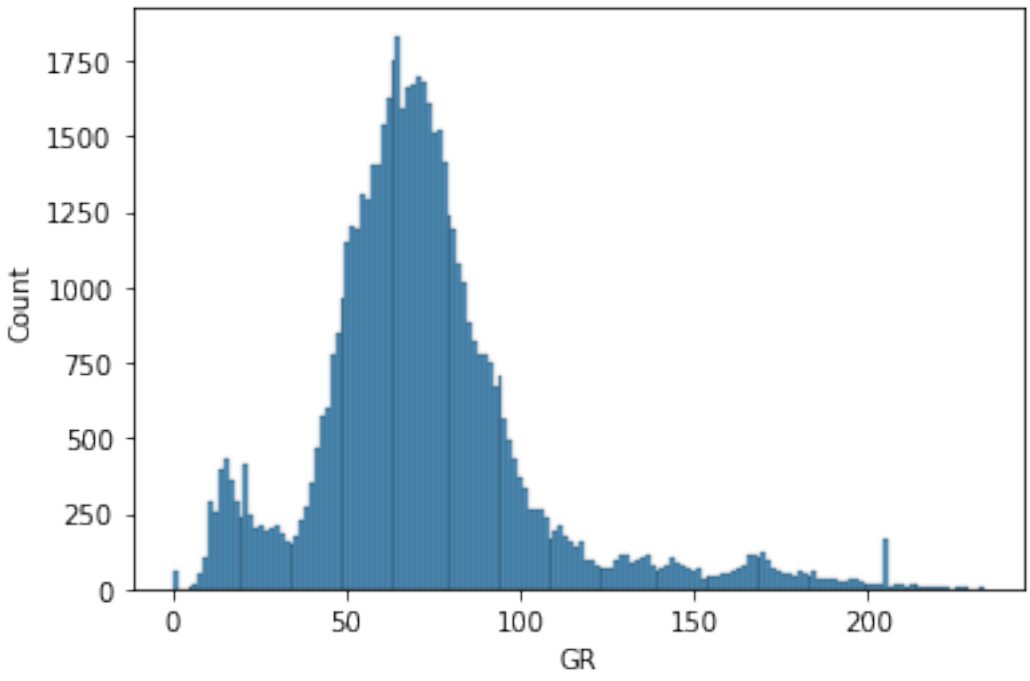
[51]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f48424731c0>,
  <matplotlib.lines.Line2D at 0x7f4842473550>],
 'caps': [<matplotlib.lines.Line2D at 0x7f48424738e0>,
  <matplotlib.lines.Line2D at 0x7f4842473c70>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4842467df0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f484247c040>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f484247c3d0>],
 'means': []}
```



4.3 GR VISUALIZATION

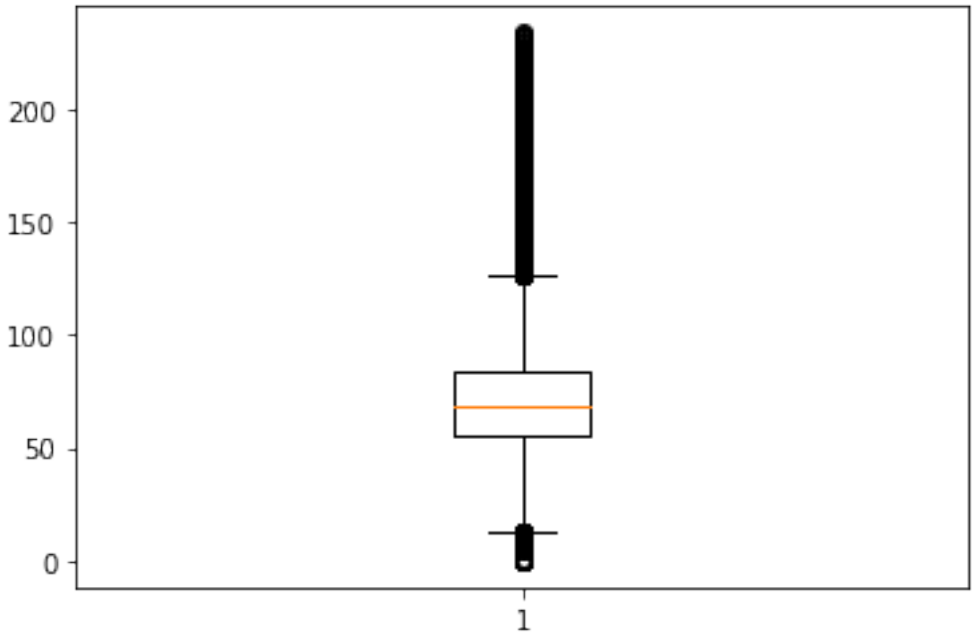
[52]:
```
sns.histplot(df.GR)
```

[52]:
```
<AxesSubplot:xlabel='GR', ylabel='Count'>
```



[53]:
```
plt.boxplot(df.GR)
```

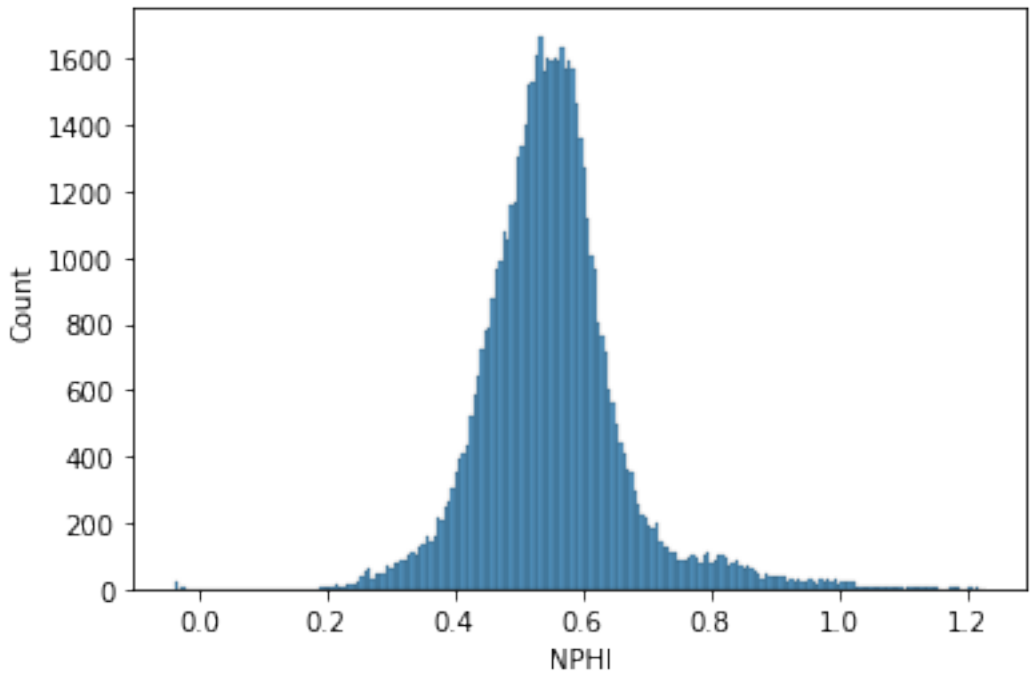
[53]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4835deb550>,
  <matplotlib.lines.Line2D at 0x7f4835deb8e0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4835debc70>,
  <matplotlib.lines.Line2D at 0x7f4835df7040>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4835deb1c0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4835df73d0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f4835df7760>],
 'means': []}
```



4.4 NPHI VISUALIZATION

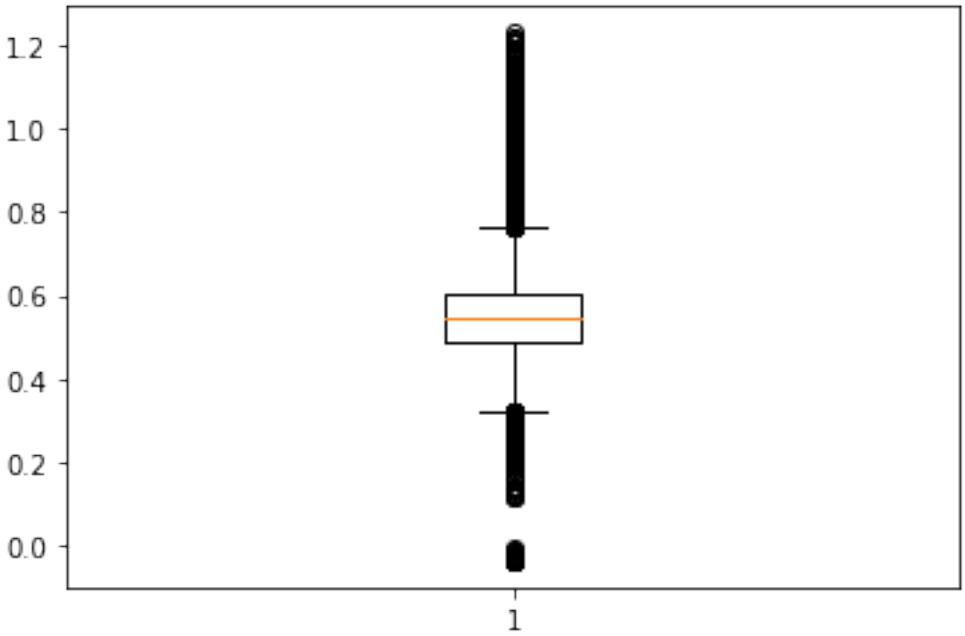
[54]:
```
sns.histplot(df.NPHI)
```

[54]:
```
<AxesSubplot:xlabel='NPHI', ylabel='Count'>
```



[55]:
```
plt.boxplot(df.NPHI)
```

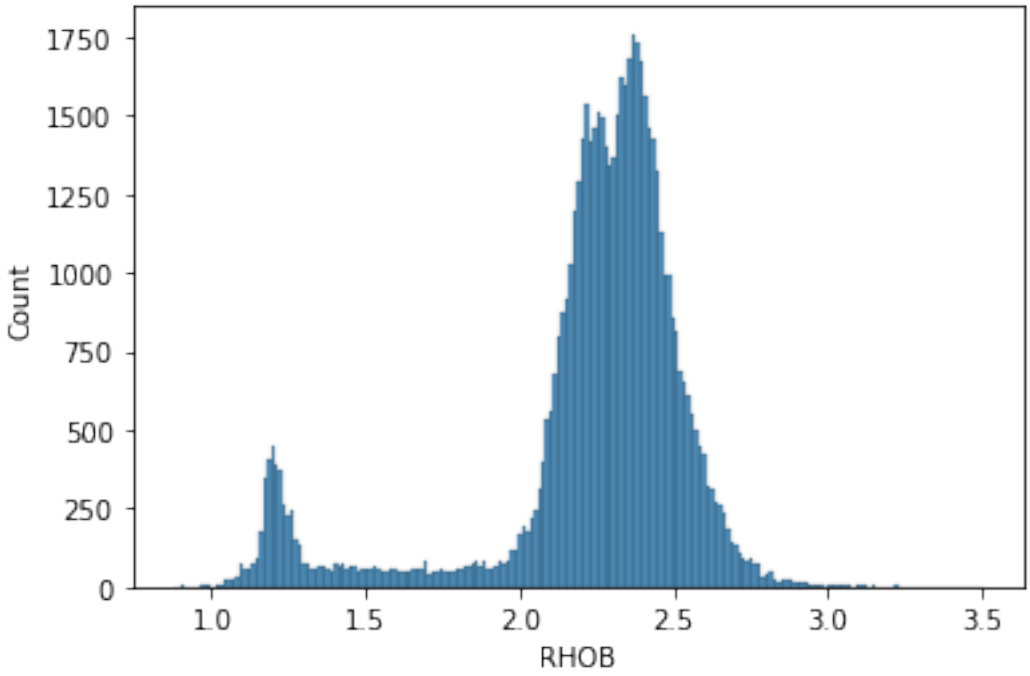
[55]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4835ad13d0>,
  <matplotlib.lines.Line2D at 0x7f4835ad1760>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4835ad1af0>,
  <matplotlib.lines.Line2D at 0x7f4835ad1e80>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4835ad1040>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4835adb250>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f4835adb5e0>],
 'means': []}
```



4.5 RHOB VISUALIZATION

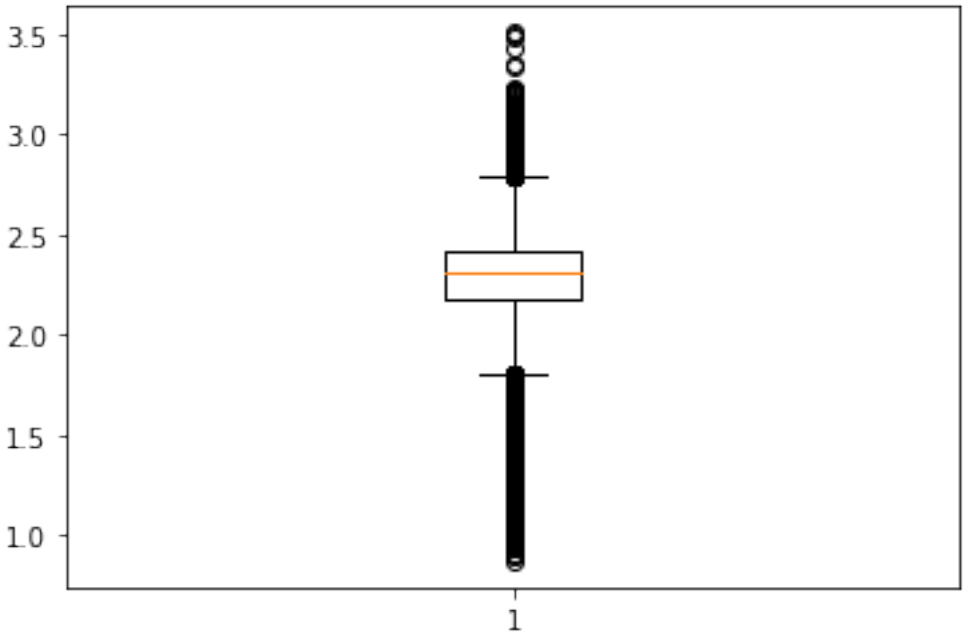
[56]:
```
sns.histplot(df.RHOB)
```

[56]:
```
<AxesSubplot:xlabel='RHOB', ylabel='Count'>
```



[57]:
```
plt.boxplot(df.RHOB)
```

[57]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f483580d3a0>,
  <matplotlib.lines.Line2D at 0x7f483580d730>],
 'caps': [<matplotlib.lines.Line2D at 0x7f483580dac0>,
  <matplotlib.lines.Line2D at 0x7f483580de50>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4835800fd0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f4835818220>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f48358185b0>],
 'means': []}
```



[58]:
```
def outliers(dataConditioningStrategy,dataframe, dataconditioningcolumns):
    df=dataframe
    if dataConditioningStrategy == "3_Standard_Deviation":
        for column in dataconditioningcolumns:
            print("column",column )
            upperlimit = df[column].mean() + 3*df[column].std()
            lowerlimit = df[column].mean() - 3*df[column].std()

            print("3 standard deviation outliers -:")
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)])
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)].
 ↪shape)
```

```
            df= df[(df[column] < upperlimit) & (df[column] > lowerlimit) & (df.
↪FACIES >= 0) & (df.FACIES <= 4)]
            print(df)

    elif dataConditioningStrategy == "4_Standard_Deviation":
        for column in dataconditioningcolumns:
            print("column",column )
            upperlimit = df[column].mean() + 4*df[column].std()
            lowerlimit = df[column].mean() - 4*df[column].std()

            print("4 standard deviation outliers -:")
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)])
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)].
↪shape)
            df= df[(df[column] < upperlimit) & (df[column] > lowerlimit) & (df.
↪FACIES >= 0) & (df.FACIES <= 4)]
            print(df)

    elif dataConditioningStrategy == "InterquartileRange":
        for column in dataconditioningcolumns:
            print("column",column )
            q25, q75 = percentile(df[column], 25), percentile(df[column], 75)
            iqr = q75 - q25
            print('Percentiles: 25th=%.3f, 75th=%.3f, IQR=%.3f' % (q25, q75,␣
↪iqr))
            cut_off = iqr * 1.5
            lowerlimit, upperlimit = q25 - cut_off, q75 + cut_off

            print("InterQuartile Range Outliers-:")
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)])
            print(df[(df[column] > upperlimit) | (df[column] < lowerlimit)].
↪shape)
            df= df[(df[column] < upperlimit) & (df[column] > lowerlimit) & (df.
↪FACIES >= 0) & (df.FACIES <= 4)]
            print(df)


    return df
```

[59]:
```
DATAConditioningStrategy =␣
↪["3_Standard_Deviation","4_Standard_Deviation","InterquartileRange"]
DATAConditioningColumns = ["DT","GR","NPHI","RHOB"]
optionoutlier = 2
df = outliers(DATAConditioningStrategy[optionoutlier] , df,␣
↪DATAConditioningColumns)
```

```
column DT
```

```
Percentiles: 25th=112.649, 75th=139.678, IQR=27.029
InterQuartile Range Outliers-:
             DT       GR    NPHI    RHOB  FACIES
0       50.2544  50.2128  0.5340  2.1228       1
1       50.3881  49.7509  0.5316  2.1250       1
2       49.8852  48.2513  0.5126  2.1316       1
3       49.9032  46.8212  0.5137  2.1437       1
4       50.0157  45.3463  0.5472  2.1611       1
…          …       …     …       …     …
44912   71.0756  39.1722  0.3397  3.1791       0
44913   71.3734  39.3511  0.3455  2.9875       0
44929   71.2182  55.9609  0.4199  2.7743       0
44930   70.1539  52.4927  0.3936  2.9376       0
44931   67.9970  48.9224  0.3727  3.0912       0

[2592 rows x 5 columns]
(2592, 5)
              DT          GR    NPHI    RHOB  FACIES
218      75.8412  47.663200  0.4526  2.4314       0
219      76.1991  47.016400  0.4514  2.4413       0
2026     76.4115  48.396700  0.5571  1.0846       0
2027     78.0536  47.637300  0.5496  1.1340       0
2028     75.2216  48.504000  0.5402  1.1749       0
…           …         …     …       …     …
58494   123.7404  80.913653  0.4993  2.4639       0
58495   123.8728  82.952576  0.5313  2.4660       0
58496   123.3722  84.044079  0.5448  2.4714       0
58497   122.6038  83.725389  0.5364  2.4750       0
58498   122.3045  83.329152  0.5331  2.4709       0

[55907 rows x 5 columns]
column GR
Percentiles: 25th=55.447, 75th=84.350, IQR=28.902
InterQuartile Range Outliers-:
              DT        GR    NPHI    RHOB  FACIES
4029    151.3950   11.6218  0.8730  1.1941       3
4030    151.2614   11.7061  0.8996  1.2056       3
4039    152.8249   11.7563  0.7718  1.1963       3
4040    152.8680   11.5903  0.7690  1.1947       3
4041    152.9320   12.0709  0.7689  1.1923       3
…          …        …     …       …     …
57812   116.8102  136.5899  0.5287  2.4344       0
58179   110.8288  128.6649  0.5213  2.3846       0
58180   110.9551  130.6794  0.5160  2.3705       0
58181   114.0812  131.8473  0.4959  2.3630       0
58182   115.8771  127.8300  0.4907  2.3684       0

[4132 rows x 5 columns]
```

```
(4132, 5)
             DT          GR    NPHI    RHOB  FACIES
218     75.8412  47.663200  0.4526  2.4314       0
219     76.1991  47.016400  0.4514  2.4413       0
2026    76.4115  48.396700  0.5571  1.0846       0
2027    78.0536  47.637300  0.5496  1.1340       0
2028    75.2216  48.504000  0.5402  1.1749       0
…          …         …      …       …      …
58494  123.7404  80.913653  0.4993  2.4639       0
58495  123.8728  82.952576  0.5313  2.4660       0
58496  123.3722  84.044079  0.5448  2.4714       0
58497  122.6038  83.725389  0.5364  2.4750       0
58498  122.3045  83.329152  0.5331  2.4709       0

[51775 rows x 5 columns]
column NPHI
Percentiles: 25th=0.491, 75th=0.595, IQR=0.104
InterQuartile Range Outliers-:
             DT        GR    NPHI    RHOB  FACIES
2361   151.4359   44.2168  0.7608  1.3596       3
2362   149.7643   36.0403  0.7885  1.2673       3
2363   149.5450   28.3286  0.7905  1.2324       3
2364   150.3661   22.7745  0.7713  1.2522       3
3039   143.1059   35.7501  0.7585  1.2089       3
…          …         …      …       …      …
54941  114.6628  114.2647  0.3314  2.2033       1
54953  109.6688  104.5008  0.3327  2.2693       1
57287  106.0689   97.8201  0.3325  2.2712       4
57981  150.8674   23.8442  0.7894  1.1197       3
58290  152.3449   17.4243  0.7641  1.1663       3

[2885 rows x 5 columns]
(2885, 5)
             DT          GR    NPHI    RHOB  FACIES
218     75.8412  47.663200  0.4526  2.4314       0
219     76.1991  47.016400  0.4514  2.4413       0
2026    76.4115  48.396700  0.5571  1.0846       0
2027    78.0536  47.637300  0.5496  1.1340       0
2028    75.2216  48.504000  0.5402  1.1749       0
…          …         …      …       …      …
58494  123.7404  80.913653  0.4993  2.4639       0
58495  123.8728  82.952576  0.5313  2.4660       0
58496  123.3722  84.044079  0.5448  2.4714       0
58497  122.6038  83.725389  0.5364  2.4750       0
58498  122.3045  83.329152  0.5331  2.4709       0

[48890 rows x 5 columns]
column RHOB
```

```
Percentiles: 25th=2.205, 75th=2.429, IQR=0.224
InterQuartile Range Outliers-:
             DT         GR    NPHI    RHOB  FACIES
2026    76.4115  48.396700  0.5571  1.0846       0
2027    78.0536  47.637300  0.5496  1.1340       0
2028    75.2216  48.504000  0.5402  1.1749       0
2359   153.0665  56.560300  0.6720  1.6982       3
2360   153.1740  51.458100  0.7148  1.5046       3
…           …         …      …       …     …
58400   94.9099  59.051400  0.4770  2.9270       0
58401   96.4064  57.049500  0.4644  2.7995       0
58477  100.5518  93.119065  0.4365  2.7816       0
58478   92.1297  99.825730  0.4509  2.8974       0
58479   92.0023  94.744734  0.4585  2.7846       0

[3498 rows x 5 columns]
(3498, 5)
             DT         GR    NPHI    RHOB  FACIES
218     75.8412  47.663200  0.4526  2.4314       0
219     76.1991  47.016400  0.4514  2.4413       0
2250   137.8066  61.327800  0.5643  2.1857       0
2251   139.5873  61.995400  0.5611  2.1762       0
2252   140.0185  63.518800  0.5630  2.1946       0
…           …         …      …       …     …
58494  123.7404  80.913653  0.4993  2.4639       0
58495  123.8728  82.952576  0.5313  2.4660       0
58496  123.3722  84.044079  0.5448  2.4714       0
58497  122.6038  83.725389  0.5364  2.4750       0
58498  122.3045  83.329152  0.5331  2.4709       0

[45392 rows x 5 columns]
```

[60]:
```
df.shape
```

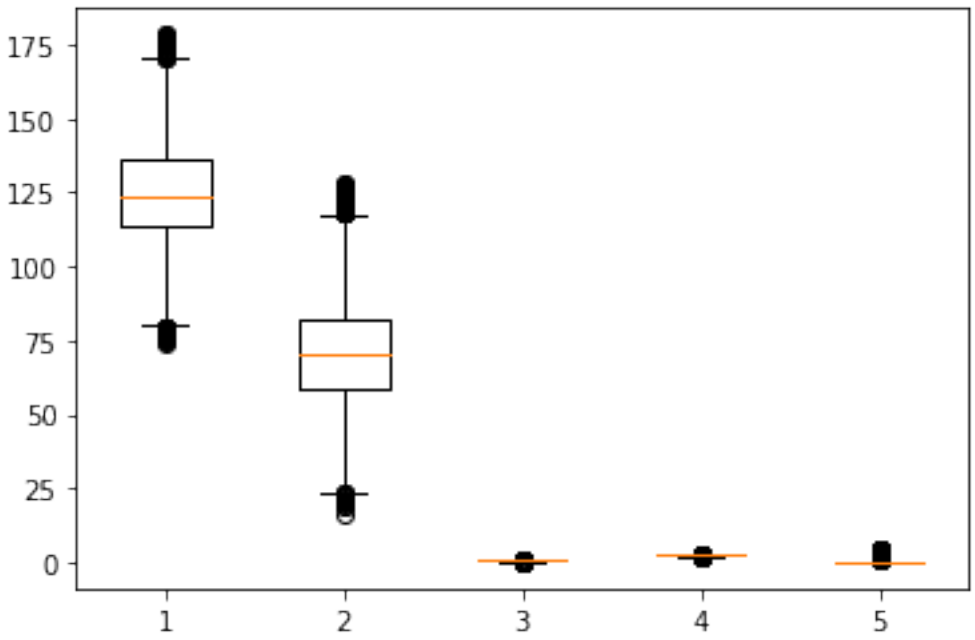
[60]:
```
(45392, 5)
```

4.6 WHOLE DATA AFTER REMOVING OUTLIERS

[61]:
```
plt.boxplot(df)
```

[61]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f48357f5c40>,
  <matplotlib.lines.Line2D at 0x7f48357f5fd0>,
  <matplotlib.lines.Line2D at 0x7f48353cd5e0>,
  <matplotlib.lines.Line2D at 0x7f48353cd970>,
  <matplotlib.lines.Line2D at 0x7f48353d8f10>,
  <matplotlib.lines.Line2D at 0x7f48353e32e0>,
  <matplotlib.lines.Line2D at 0x7f48353f0880>,
  <matplotlib.lines.Line2D at 0x7f48353f0c10>,
```

```
 <matplotlib.lines.Line2D at 0x7f48357861f0>,
 <matplotlib.lines.Line2D at 0x7f4835786580>],
'caps': [<matplotlib.lines.Line2D at 0x7f48353c23d0>,
 <matplotlib.lines.Line2D at 0x7f48353c2760>,
 <matplotlib.lines.Line2D at 0x7f48353cdd00>,
 <matplotlib.lines.Line2D at 0x7f48353d80d0>,
 <matplotlib.lines.Line2D at 0x7f48353e3670>,
 <matplotlib.lines.Line2D at 0x7f48353e3a00>,
 <matplotlib.lines.Line2D at 0x7f48353f0fa0>,
 <matplotlib.lines.Line2D at 0x7f48353f9370>,
 <matplotlib.lines.Line2D at 0x7f4835786910>,
 <matplotlib.lines.Line2D at 0x7f4835786ca0>],
'boxes': [<matplotlib.lines.Line2D at 0x7f48357f58b0>,
 <matplotlib.lines.Line2D at 0x7f48353cd250>,
 <matplotlib.lines.Line2D at 0x7f48353d8b80>,
 <matplotlib.lines.Line2D at 0x7f48353f04f0>,
 <matplotlib.lines.Line2D at 0x7f48353f9e20>],
'medians': [<matplotlib.lines.Line2D at 0x7f48353c2af0>,
 <matplotlib.lines.Line2D at 0x7f48353d8460>,
 <matplotlib.lines.Line2D at 0x7f48353e3d90>,
 <matplotlib.lines.Line2D at 0x7f48353f9700>,
 <matplotlib.lines.Line2D at 0x7f4835790070>],
'fliers': [<matplotlib.lines.Line2D at 0x7f48353c2e80>,
 <matplotlib.lines.Line2D at 0x7f48353d87f0>,
 <matplotlib.lines.Line2D at 0x7f48353f0160>,
 <matplotlib.lines.Line2D at 0x7f48353f9a90>,
 <matplotlib.lines.Line2D at 0x7f4835790400>],
'means': []}
```



[62]:
```
df.head(5)
```

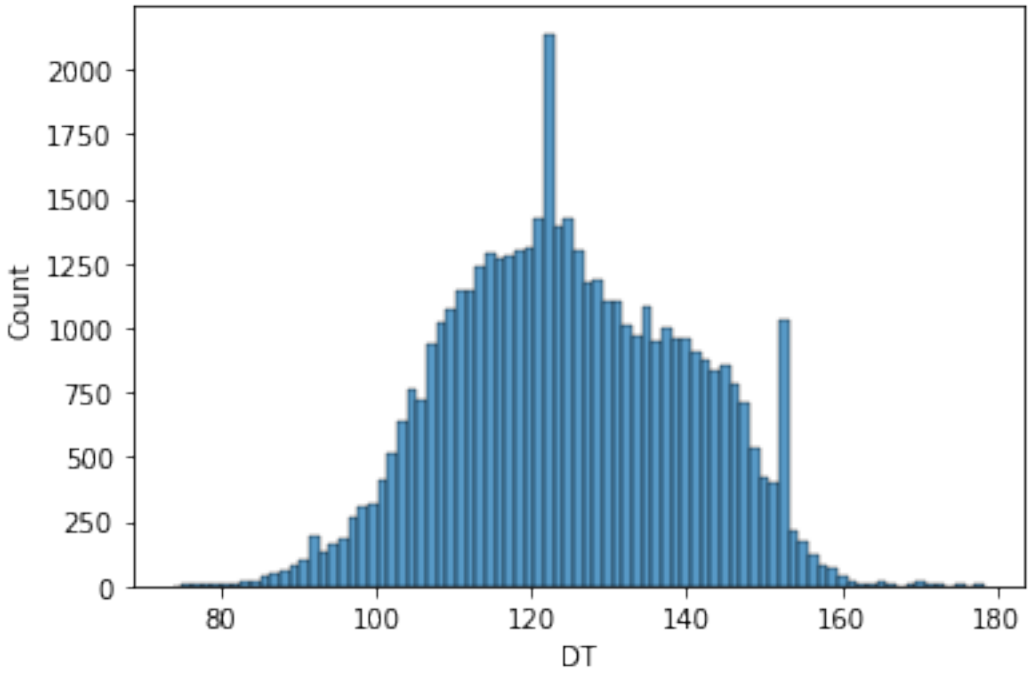
[62]:

	DT	GR	NPHI	RHOB	FACIES
218	75.8412	47.6632	0.4526	2.4314	0
219	76.1991	47.0164	0.4514	2.4413	0
2250	137.8066	61.3278	0.5643	2.1857	0
2251	139.5873	61.9954	0.5611	2.1762	0
2252	140.0185	63.5188	0.5630	2.1946	0

4.7 DT AFTER REMOVING OUTLIER

[63]:
```
sns.histplot(df.DT)
```

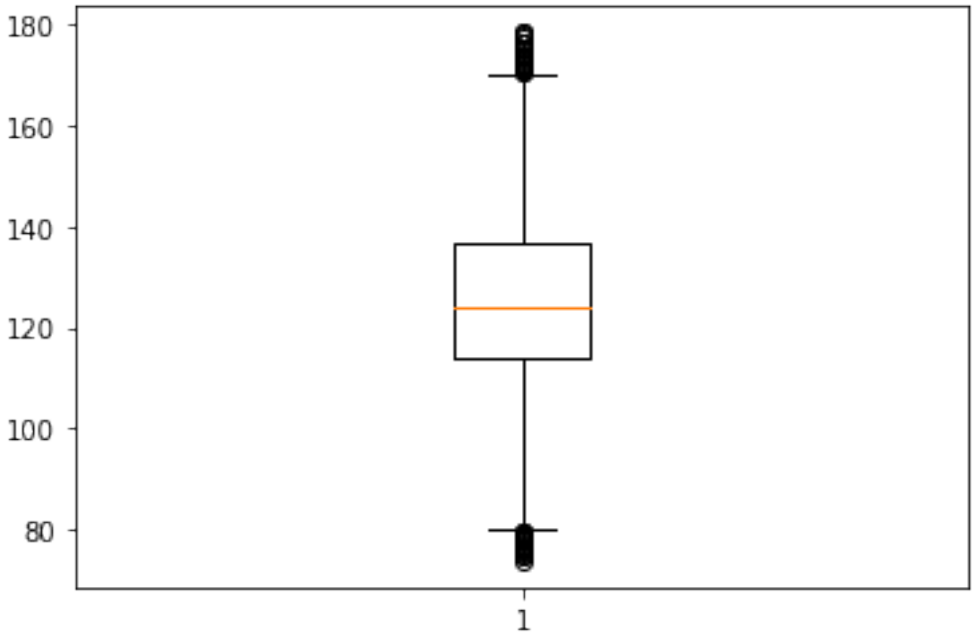
[63]:
```
<AxesSubplot:xlabel='DT', ylabel='Count'>
```



[64]:
```
plt.boxplot(df["DT"])
```

[64]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f483568c9d0>,
  <matplotlib.lines.Line2D at 0x7f483568cd60>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4835699130>,
  <matplotlib.lines.Line2D at 0x7f48356994c0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f483568c640>],
```

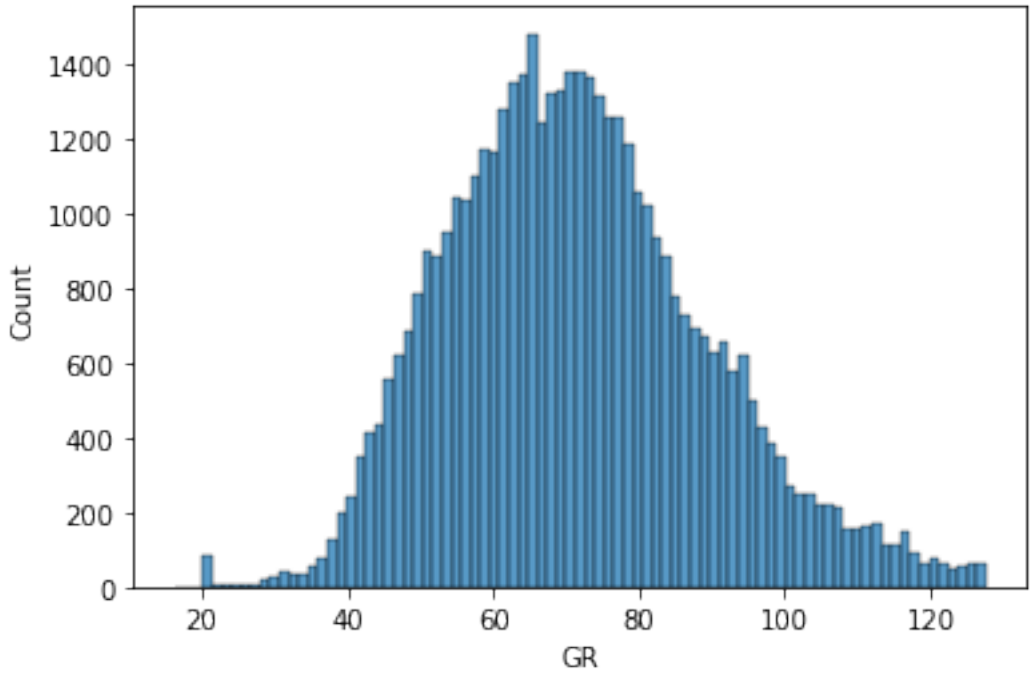
```
'medians': [<matplotlib.lines.Line2D at 0x7f4835699850>],
'fliers': [<matplotlib.lines.Line2D at 0x7f4835699be0>],
'means': []}
```



4.8 GR AFTER REMOVING OUTLIER

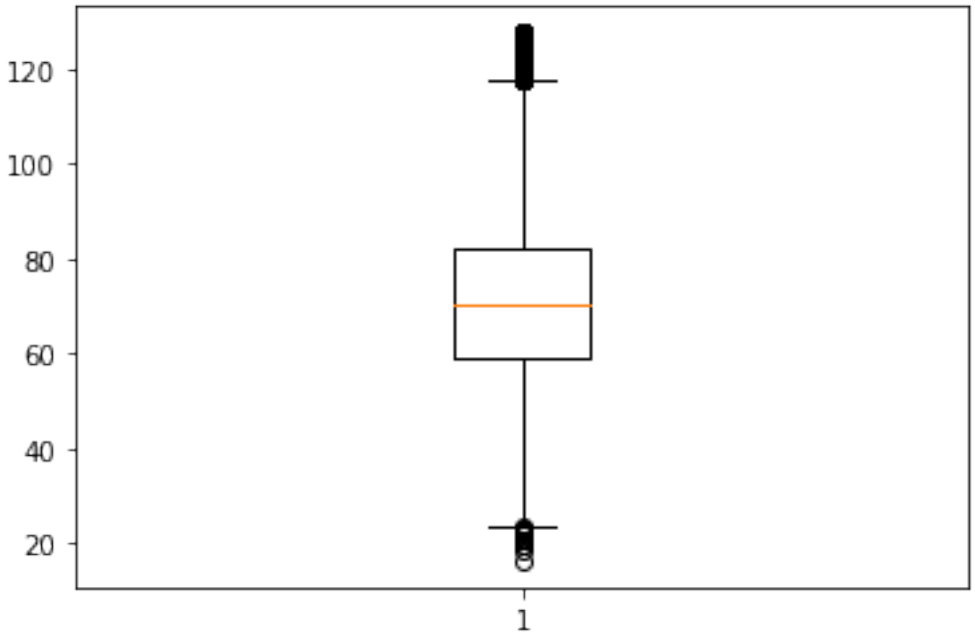
[65]:
```
sns.histplot(df.GR)
```

[65]:
```
<AxesSubplot:xlabel='GR', ylabel='Count'>
```



[66]:
```
plt.boxplot(df.GR)
```

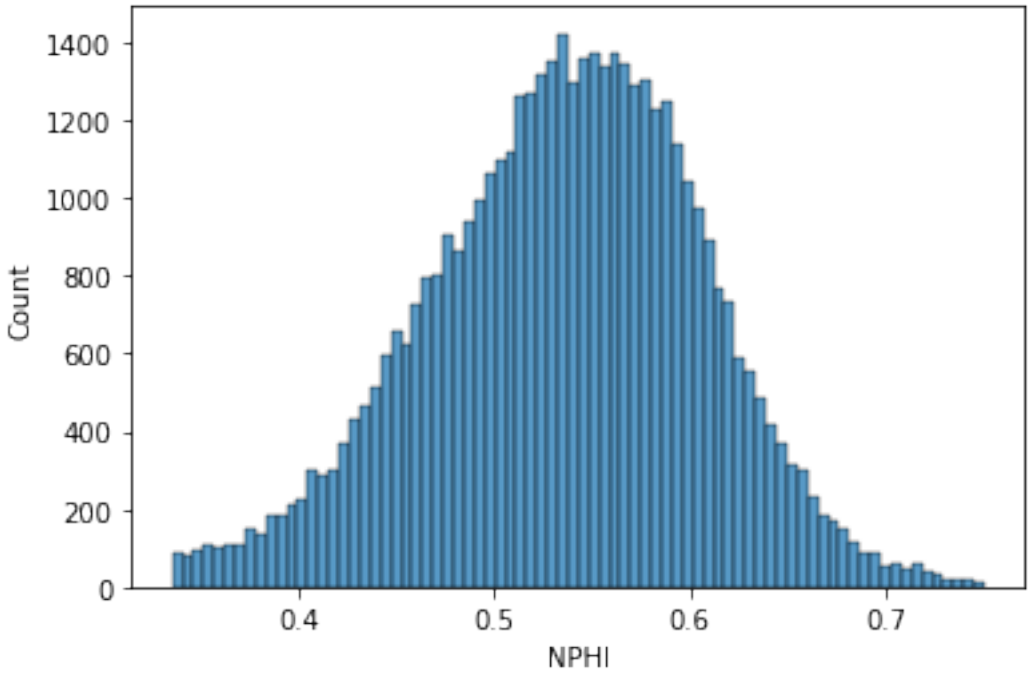
[66]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f48354cf3a0>,
  <matplotlib.lines.Line2D at 0x7f48354cf730>],
 'caps': [<matplotlib.lines.Line2D at 0x7f48354cfac0>,
  <matplotlib.lines.Line2D at 0x7f48354cfe50>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f48354c2fd0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f48354db220>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f48354db5b0>],
 'means': []}
```



4.9 NPHI AFTER REMOVING OUTLIER

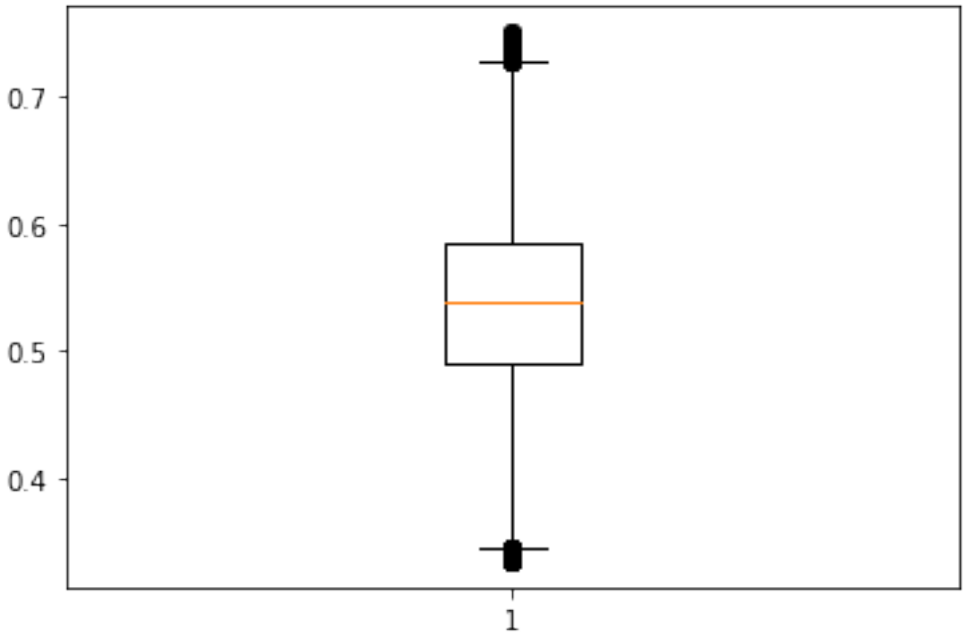
[67]:
```
sns.histplot(df.NPHI)
```

[67]:
```
<AxesSubplot:xlabel='NPHI', ylabel='Count'>
```



[68]:
```
plt.boxplot(df.NPHI)
```

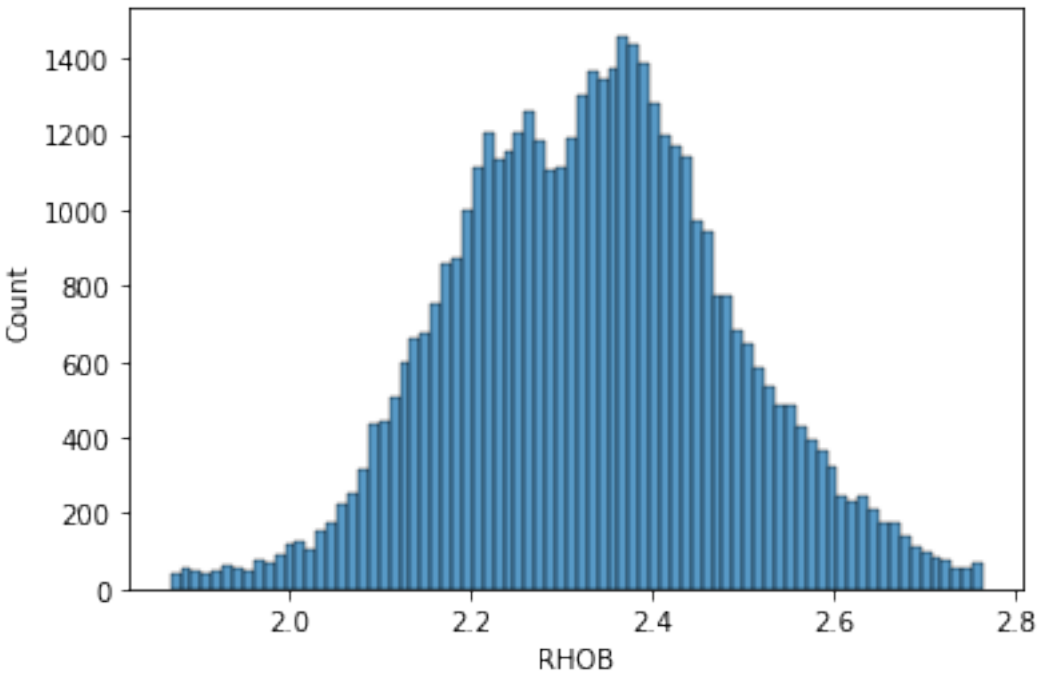
[68]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f48353b00d0>,
  <matplotlib.lines.Line2D at 0x7f48353b0460>],
 'caps': [<matplotlib.lines.Line2D at 0x7f48353b07f0>,
  <matplotlib.lines.Line2D at 0x7f48353b0b80>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f48353a2d00>],
 'medians': [<matplotlib.lines.Line2D at 0x7f48353b0f10>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f48353ba2e0>],
 'means': []}
```



4.10 RHOB AFTER REMOVING OUTLIER

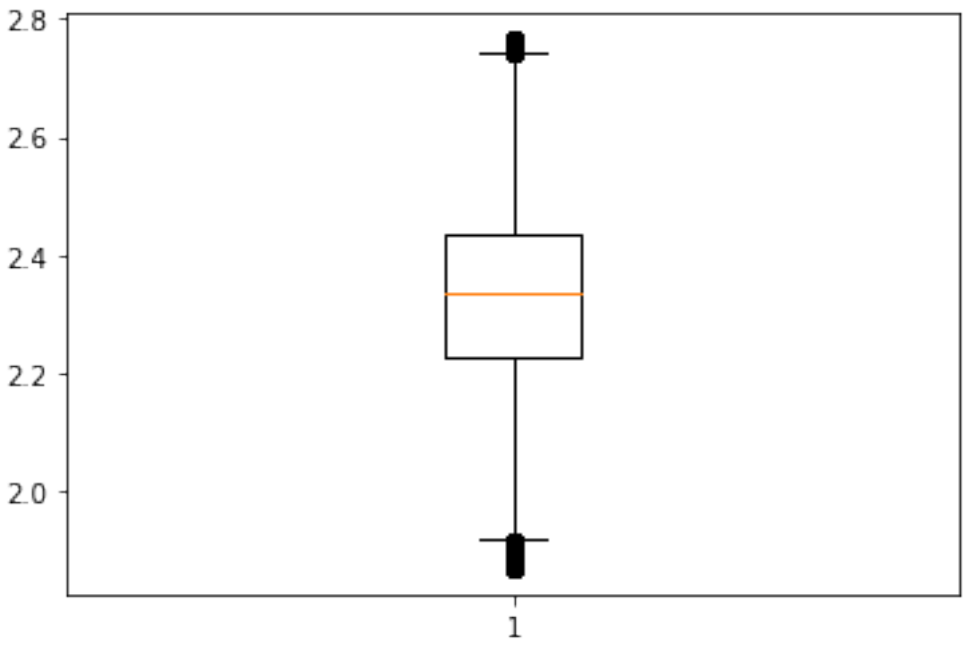
[69]:
```
sns.histplot(df.RHOB)
```

[69]:
```
<AxesSubplot:xlabel='RHOB', ylabel='Count'>
```



[70]:
```
plt.boxplot(df.RHOB)
```

[70]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f48351cfa30>,
  <matplotlib.lines.Line2D at 0x7f48351cfdc0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f48351dd190>,
  <matplotlib.lines.Line2D at 0x7f48351dd520>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f48351cf6a0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f48351dd8b0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f48351ddc40>],
 'means': []}
```



[71]:
```
df
```

[71]:

	DT	GR	NPHI	RHOB	FACIES
218	75.8412	47.663200	0.4526	2.4314	0
219	76.1991	47.016400	0.4514	2.4413	0
2250	137.8066	61.327800	0.5643	2.1857	0
2251	139.5873	61.995400	0.5611	2.1762	0
2252	140.0185	63.518800	0.5630	2.1946	0
…	…	…	…	…	…
58494	123.7404	80.913653	0.4993	2.4639	0
58495	123.8728	82.952576	0.5313	2.4660	0
58496	123.3722	84.044079	0.5448	2.4714	0
58497	122.6038	83.725389	0.5364	2.4750	0
58498	122.3045	83.329152	0.5331	2.4709	0

[45392 rows x 5 columns]

5 FEATURE SELECTION

[72]:
```
df.head(10)
```

[72]:

	DT	GR	NPHI	RHOB	FACIES
218	75.8412	47.6632	0.4526	2.4314	0
219	76.1991	47.0164	0.4514	2.4413	0
2250	137.8066	61.3278	0.5643	2.1857	0

```
2251  139.5873  61.9954  0.5611  2.1762       0
2252  140.0185  63.5188  0.5630  2.1946       0
2253  139.3474  64.9925  0.5677  2.1992       0
2254  138.8638  65.6985  0.5743  2.1992       0
2255  139.0847  65.1353  0.5844  2.2009       0
2256  139.2288  63.4583  0.5984  2.2021       0
2257  138.7143  61.7829  0.6146  2.2090       0
```

[73]:
```
df.shape
```

[73]:
```
(45392, 5)
```

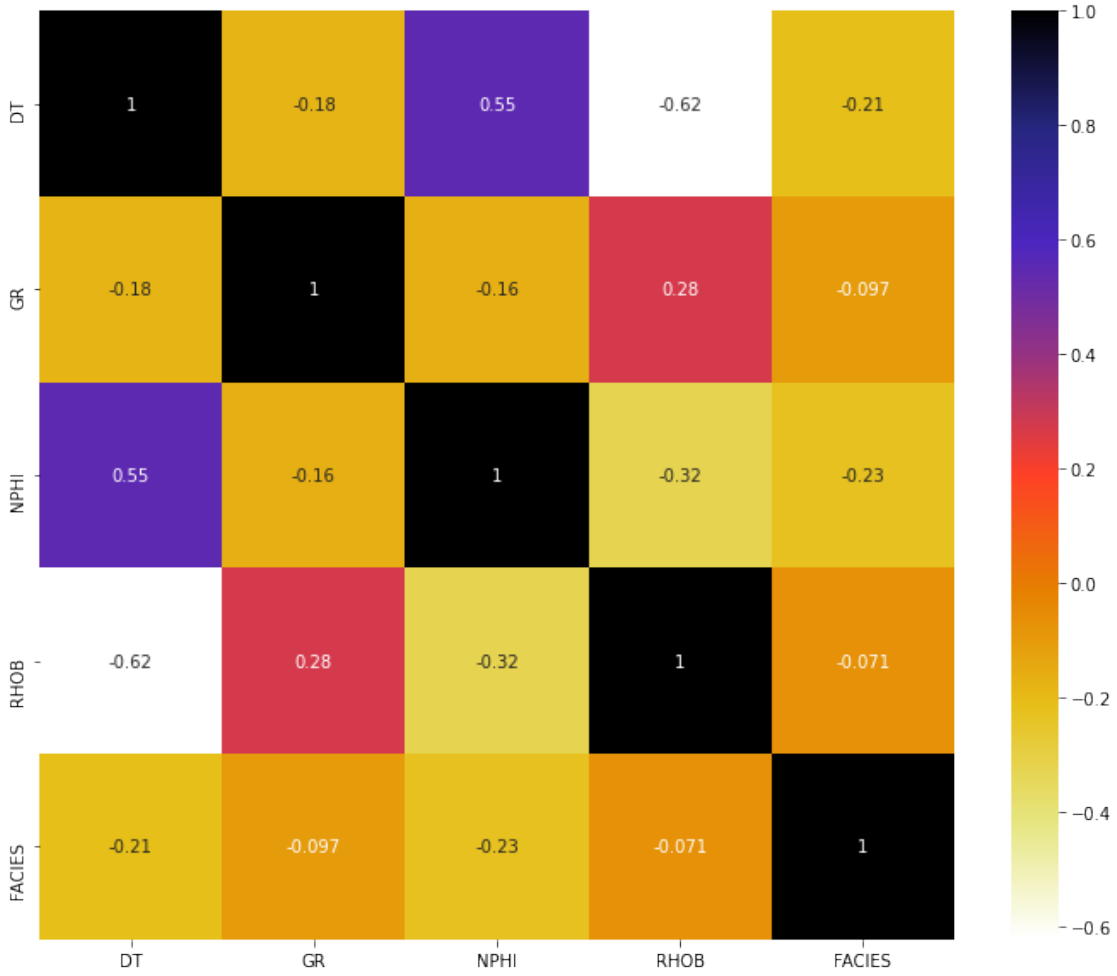
[74]:
```
features = df.shape[1]
features
```

[74]:
```
5
```

[75]:
```
df.var()
```

[75]:
```
DT        230.988291
GR        312.562035
NPHI        0.004939
RHOB        0.023286
FACIES      1.026135
dtype: float64
```

[76]:
```
plt.figure(figsize=(12,10))
cor = df.corr()
sns.heatmap(cor , annot=True , cmap=plt.cm.CMRmap_r)
plt.show()
```



[77]:
```
def FeatureSelection(FeatureSelectionStrategy,dataframe):
    df=dataframe

    if(FeatureSelectionStrategy=="Variance_Threshold"):
        var_thres=VarianceThreshold(threshold=0.0)
        var_thres.fit(df)
        df.columns[var_thres.get_support()]
        cols = [column for column in df.columns
                    if column not in df.columns[var_thres.get_support()]]
        print(cols)
        df = df.drop(cols,axis=1)
        return df

    if(FeatureSelectionStrategy=="Absolute_Correlation"):
        threshold = 0.6
        col_corr = set()
```

```
        corr_matrix = df.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]
                    print(colname)
                    col_corr.add(colname)
        df = df.drop(col_corr,axis=1)
        return df

    if(FeatureSelectionStrategy=="Correlation"):
        threshold = 0.6
        col_corr = set()
        corr_matrix = df.corr()
        for i in range(len(corr_matrix.columns)):
            for j in range(i):
                if (corr_matrix.iloc[i,j]) > threshold :
                    colname = corr_matrix.columns[i]
                    print(colname)
                    col_corr.add(colname)
        df = df.drop(col_corr,axis=1)
        return df

    if(FeatureSelectionStrategy == "SelectKBest"):
        x = df.drop("FACIES",1)
        y = df["FACIES"]
        mutual_info = mutual_info_classif(x,y)
        print(mutual_info)
        mutual_info=pd.Series(mutual_info)
        mutual_info.sort_values(ascending=False)
        mutual_info.sort_values(ascending=False).plot.bar(figsize=(20,8))
        select_col = SelectKBest(mutual_info_classif,k=1)
        select_col.fit(x,y)
        column1 = df.columns[select_col.get_support()]
        df = df.drop(column1,axis=1)
        return df

    if(FeatureSelectionStrategy == "Mutual_Info_Class"):
        x = df.drop("FACIES",1)
        y = df["FACIES"]
        mutual_info = mutual_info_classif(x,y)
        print(mutual_info)
        mutual_info=pd.Series(mutual_info)
        mutual_info.sort_values(ascending=False)
        mutual_info.sort_values(ascending=False).plot.bar(figsize=(20,8))
        return df
```

[78]:
```
FeatureSelectionStrategy=["Variance_Threshold","Absolute_Correlation","Correlation","SelectKBe
optionfeature = 0
df=FeatureSelection(FeatureSelectionStrategy[optionfeature],df)
```

```
[]
```

[79]:
```
print("Deleted feature(s) = " + str(features-df.shape[1]))
```

```
Deleted feature(s) = 0
```

[80]:
```
df
```

[80]:

	DT	GR	NPHI	RHOB	FACIES
218	75.8412	47.663200	0.4526	2.4314	0
219	76.1991	47.016400	0.4514	2.4413	0
2250	137.8066	61.327800	0.5643	2.1857	0
2251	139.5873	61.995400	0.5611	2.1762	0
2252	140.0185	63.518800	0.5630	2.1946	0
…	…	…	…	…	…
58494	123.7404	80.913653	0.4993	2.4639	0
58495	123.8728	82.952576	0.5313	2.4660	0
58496	123.3722	84.044079	0.5448	2.4714	0
58497	122.6038	83.725389	0.5364	2.4750	0
58498	122.3045	83.329152	0.5331	2.4709	0

[45392 rows x 5 columns]

6 SCALING DATA

[81]:
```
def data_scaling( scaling_strategy , scaling_data , scaling_columns ):

    if scaling_strategy =="RobustScaler" :
        scaling_data[scaling_columns] = RobustScaler().
↪fit_transform(scaling_data[scaling_columns])

    elif scaling_strategy =="MinMaxScaler" :
        scaling_data[scaling_columns] = MinMaxScaler().
↪fit_transform(scaling_data[scaling_columns])

    else : # If any other scaling send by mistake still perform Robust Scalar
        scaling_data[scaling_columns] = RobustScaler().
↪fit_transform(scaling_data[scaling_columns])

    return scaling_data
```

[82]:
```
scaling_strategy = ["RobustScaler","MinMaxScaler"]
optionscaling = 0
```

```
df = data_scaling( scaling_strategy[optionscaling] , df ,␣
↪DATAConditioningColumns )
```

[83]:
```
df
```

[83]:
```
              DT        GR      NPHI      RHOB  FACIES
218   -2.123320 -0.960120 -0.908901  0.465184       0
219   -2.107499 -0.987602 -0.921466  0.513056       0
2250   0.615845 -0.379535  0.260733 -0.722921       0
2251   0.694561 -0.351170  0.227225 -0.768859       0
2252   0.713622 -0.286443  0.247120 -0.679884       0
…           …        …         …         …       …
58494 -0.005948  0.452634 -0.419895  0.622340       0
58495 -0.000095  0.539265 -0.084817  0.632495       0
58496 -0.022224  0.585641  0.056545  0.658607       0
58497 -0.056191  0.572100 -0.031414  0.676015       0
58498 -0.069421  0.555265 -0.065969  0.656190       0

[45392 rows x 5 columns]
```

[84]:
```
df.to_csv("Preprocessed_data.csv",index=False)
```

7 SPLITTING DATA USING TRAIN_TEST_SPLIT

[85]:
```
df=pd.read_csv('Preprocessed_data.csv')
```

[86]:
```
df.head()
```

[86]:
```
         DT        GR      NPHI      RHOB  FACIES
0 -2.123320 -0.960120 -0.908901  0.465184       0
1 -2.107499 -0.987602 -0.921466  0.513056       0
2  0.615845 -0.379535  0.260733 -0.722921       0
3  0.694561 -0.351170  0.227225 -0.768859       0
4  0.713622 -0.286443  0.247120 -0.679884       0
```

[87]:
```
df.isnull().sum()
```

[87]:
```
DT        0
GR        0
NPHI      0
RHOB      0
FACIES    0
dtype: int64
```

[88]:
```
x = df.drop("FACIES",1)
y = df["FACIES"]
```

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=8)
```

[89]:
```
X_train.shape
```

[89]:
```
(31774, 4)
```

[90]:
```
X_test.shape
```

[90]:
```
(13618, 4)
```

[91]:
```
X_test
```

[91]:
```
             DT        GR      NPHI      RHOB
13107  0.585512  0.618141  0.524607  1.169729
24761 -0.492187 -0.387412  0.144503  1.200193
44043  0.314996  0.928135  0.108901  0.179400
17707  0.409511  0.461954  0.432461  0.064797
39859  0.550480  0.761862 -0.366492 -0.692456
…           …         …         …         …
17881  0.034243 -0.048364  0.727749  0.693907
43199  0.641064  0.074669  0.531937 -0.492263
1059  -0.678947 -0.525402 -1.783246 -0.685203
9662  -0.699114 -0.065674 -0.014660 -0.001934
6669  -0.587117  1.145858  1.061780  0.933752

[13618 rows x 4 columns]
```

8 MODEL TRAINING

[92]:
```
estimator=[]
```

[93]:
```
gnb = GaussianNB()
```

[94]:
```
model = LogisticRegression()
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]

grid = {'solver':solvers,'penalty':penalty,'C':c_values}
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv,␣
↪scoring='accuracy',error_score=0)
grid_result = grid_search.fit(X_train, y_train)

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
```

```
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.902321 using {'C': 0.1, 'penalty': 'l2', 'solver': 'newton-cg'}
0.902216 (0.002300) with: {'C': 100, 'penalty': 'l2', 'solver': 'newton-cg'}
0.902205 (0.002308) with: {'C': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
0.900401 (0.001923) with: {'C': 100, 'penalty': 'l2', 'solver': 'liblinear'}
0.902226 (0.002296) with: {'C': 10, 'penalty': 'l2', 'solver': 'newton-cg'}
0.902216 (0.002304) with: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
0.900390 (0.001977) with: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}
0.902279 (0.002317) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'newton-cg'}
0.902279 (0.002317) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'lbfgs'}
0.900275 (0.001884) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}
0.902321 (0.002006) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'newton-cg'}
0.902321 (0.002006) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'lbfgs'}
0.899624 (0.001890) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'}
0.900716 (0.001635) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'newton-cg'}
0.900716 (0.001635) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
0.899541 (0.001054) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'liblinear'}
```

[95]:
```
dtclf = DecisionTreeClassifier(max_depth=5)
```

[96]:
```
cat = CatBoostClassifier()
```

[97]:
```
xgb= XGBClassifier(learning_rate =0.09,
n_estimators=494,
max_depth=5,
subsample = 0.70,
verbosity = 0,)
```

[98]:
```
lgbm=LGBMClassifier(importance_type = "gain",
verbosity = -1,
max_bin = 60,
num_leaves=300,
boosting_type = 'dart',
learning_rate=0.1,
n_estimators=494,
max_depth=5, )
```

[99]:
```
rdmclf = RandomForestClassifier(n_estimators=494,max_depth=5)
```

[100]:
```
estimator.append(('gaussian',gnb))
estimator.append(('Gridlogistic',grid_search))
estimator.append(('catboost_classifier',cat))
estimator.append(('decision_tree',dtclf))
estimator.append(('xgbclassifier',xgb))
```

```
estimator.append(('LGBMclassifier',lgbm))
```

[101]:
```
vot_soft = VotingClassifier(estimators = estimator, voting ='soft')
```

[102]:
```
vot_soft.fit(X_train,y_train)
```

```
Learning rate set to 0.094391
0:      learn: 1.3265685        total: 59.1ms   remaining: 59s
1:      learn: 1.1441447        total: 66.8ms   remaining: 33.3s
2:      learn: 1.0098936        total: 73.7ms   remaining: 24.5s
3:      learn: 0.9070909        total: 80.4ms   remaining: 20s
4:      learn: 0.8233265        total: 87.1ms   remaining: 17.3s
5:      learn: 0.7555721        total: 93.9ms   remaining: 15.6s
6:      learn: 0.7003256        total: 101ms    remaining: 14.4s
7:      learn: 0.6518884        total: 108ms    remaining: 13.4s
8:      learn: 0.6107570        total: 116ms    remaining: 12.8s
9:      learn: 0.5748652        total: 122ms    remaining: 12.1s
10:     learn: 0.5440267        total: 129ms    remaining: 11.6s
11:     learn: 0.5172645        total: 135ms    remaining: 11.1s
12:     learn: 0.4945976        total: 141ms    remaining: 10.7s
13:     learn: 0.4744959        total: 151ms    remaining: 10.6s
14:     learn: 0.4563637        total: 157ms    remaining: 10.3s
15:     learn: 0.4395808        total: 164ms    remaining: 10.1s
16:     learn: 0.4252144        total: 170ms    remaining: 9.84s
17:     learn: 0.4125212        total: 176ms    remaining: 9.62s
18:     learn: 0.4014292        total: 183ms    remaining: 9.45s
19:     learn: 0.3912449        total: 190ms    remaining: 9.29s
20:     learn: 0.3819971        total: 197ms    remaining: 9.2s
21:     learn: 0.3739274        total: 204ms    remaining: 9.05s
22:     learn: 0.3671660        total: 210ms    remaining: 8.93s
23:     learn: 0.3607492        total: 217ms    remaining: 8.83s
24:     learn: 0.3546127        total: 224ms    remaining: 8.74s
25:     learn: 0.3493236        total: 231ms    remaining: 8.64s
26:     learn: 0.3445168        total: 238ms    remaining: 8.56s
27:     learn: 0.3396638        total: 246ms    remaining: 8.53s
28:     learn: 0.3348014        total: 253ms    remaining: 8.46s
29:     learn: 0.3314200        total: 260ms    remaining: 8.39s
30:     learn: 0.3277385        total: 267ms    remaining: 8.36s
31:     learn: 0.3249679        total: 275ms    remaining: 8.31s
32:     learn: 0.3221409        total: 282ms    remaining: 8.26s
33:     learn: 0.3194326        total: 289ms    remaining: 8.22s
34:     learn: 0.3163122        total: 297ms    remaining: 8.18s
35:     learn: 0.3139723        total: 304ms    remaining: 8.13s
36:     learn: 0.3118089        total: 311ms    remaining: 8.09s
37:     learn: 0.3099771        total: 317ms    remaining: 8.03s
38:     learn: 0.3081699        total: 324ms    remaining: 7.98s
39:     learn: 0.3065539        total: 330ms    remaining: 7.93s
40:     learn: 0.3053255        total: 338ms    remaining: 7.9s
```

```
41:     learn: 0.3039021        total: 345ms    remaining: 7.87s
42:     learn: 0.3025759        total: 352ms    remaining: 7.83s
43:     learn: 0.3014233        total: 358ms    remaining: 7.79s
44:     learn: 0.2997517        total: 365ms    remaining: 7.75s
45:     learn: 0.2985515        total: 372ms    remaining: 7.71s
46:     learn: 0.2976736        total: 379ms    remaining: 7.68s
47:     learn: 0.2962642        total: 386ms    remaining: 7.66s
48:     learn: 0.2952980        total: 393ms    remaining: 7.64s
49:     learn: 0.2944012        total: 400ms    remaining: 7.6s
50:     learn: 0.2937763        total: 407ms    remaining: 7.57s
51:     learn: 0.2930726        total: 414ms    remaining: 7.54s
52:     learn: 0.2922601        total: 420ms    remaining: 7.51s
53:     learn: 0.2913897        total: 427ms    remaining: 7.48s
54:     learn: 0.2908381        total: 434ms    remaining: 7.46s
55:     learn: 0.2901412        total: 441ms    remaining: 7.43s
56:     learn: 0.2894886        total: 447ms    remaining: 7.4s
57:     learn: 0.2887200        total: 453ms    remaining: 7.36s
58:     learn: 0.2879917        total: 463ms    remaining: 7.38s
59:     learn: 0.2873456        total: 470ms    remaining: 7.37s
60:     learn: 0.2868916        total: 477ms    remaining: 7.34s
61:     learn: 0.2862890        total: 484ms    remaining: 7.33s
62:     learn: 0.2857701        total: 491ms    remaining: 7.3s
63:     learn: 0.2851188        total: 497ms    remaining: 7.27s
64:     learn: 0.2845449        total: 504ms    remaining: 7.25s
65:     learn: 0.2841480        total: 510ms    remaining: 7.22s
66:     learn: 0.2836590        total: 516ms    remaining: 7.18s
67:     learn: 0.2824413        total: 523ms    remaining: 7.17s
68:     learn: 0.2820536        total: 529ms    remaining: 7.13s
69:     learn: 0.2815608        total: 535ms    remaining: 7.11s
70:     learn: 0.2811326        total: 542ms    remaining: 7.09s
71:     learn: 0.2803515        total: 549ms    remaining: 7.07s
72:     learn: 0.2798132        total: 555ms    remaining: 7.05s
73:     learn: 0.2793368        total: 562ms    remaining: 7.03s
74:     learn: 0.2787849        total: 568ms    remaining: 7.01s
75:     learn: 0.2783549        total: 576ms    remaining: 7s
76:     learn: 0.2778664        total: 583ms    remaining: 6.99s
77:     learn: 0.2774651        total: 590ms    remaining: 6.97s
78:     learn: 0.2771077        total: 596ms    remaining: 6.95s
79:     learn: 0.2767508        total: 603ms    remaining: 6.93s
80:     learn: 0.2764223        total: 610ms    remaining: 6.92s
81:     learn: 0.2760075        total: 616ms    remaining: 6.89s
82:     learn: 0.2754035        total: 623ms    remaining: 6.88s
83:     learn: 0.2751105        total: 629ms    remaining: 6.86s
84:     learn: 0.2748215        total: 636ms    remaining: 6.85s
85:     learn: 0.2745139        total: 644ms    remaining: 6.84s
86:     learn: 0.2740358        total: 650ms    remaining: 6.82s
87:     learn: 0.2735845        total: 657ms    remaining: 6.8s
88:     learn: 0.2732176        total: 663ms    remaining: 6.79s
```

```
89:     learn: 0.2728186        total: 670ms    remaining: 6.77s
90:     learn: 0.2724885        total: 676ms    remaining: 6.75s
91:     learn: 0.2718692        total: 683ms    remaining: 6.74s
92:     learn: 0.2716402        total: 690ms    remaining: 6.73s
93:     learn: 0.2713018        total: 697ms    remaining: 6.71s
94:     learn: 0.2710079        total: 703ms    remaining: 6.69s
95:     learn: 0.2707728        total: 709ms    remaining: 6.67s
96:     learn: 0.2705703        total: 715ms    remaining: 6.66s
97:     learn: 0.2701709        total: 722ms    remaining: 6.64s
98:     learn: 0.2698516        total: 729ms    remaining: 6.63s
99:     learn: 0.2695801        total: 735ms    remaining: 6.61s
100:    learn: 0.2692980        total: 741ms    remaining: 6.59s
101:    learn: 0.2689943        total: 748ms    remaining: 6.58s
102:    learn: 0.2686165        total: 755ms    remaining: 6.57s
103:    learn: 0.2683034        total: 763ms    remaining: 6.58s
104:    learn: 0.2679960        total: 770ms    remaining: 6.57s
105:    learn: 0.2676761        total: 778ms    remaining: 6.56s
106:    learn: 0.2673879        total: 785ms    remaining: 6.55s
107:    learn: 0.2672502        total: 795ms    remaining: 6.56s
108:    learn: 0.2669644        total: 801ms    remaining: 6.55s
109:    learn: 0.2665695        total: 808ms    remaining: 6.54s
110:    learn: 0.2660552        total: 815ms    remaining: 6.53s
111:    learn: 0.2659019        total: 824ms    remaining: 6.53s
112:    learn: 0.2656889        total: 830ms    remaining: 6.52s
113:    learn: 0.2655331        total: 837ms    remaining: 6.51s
114:    learn: 0.2652994        total: 844ms    remaining: 6.49s
115:    learn: 0.2650709        total: 851ms    remaining: 6.48s
116:    learn: 0.2648800        total: 857ms    remaining: 6.47s
117:    learn: 0.2646628        total: 864ms    remaining: 6.46s
118:    learn: 0.2644057        total: 870ms    remaining: 6.44s
119:    learn: 0.2642081        total: 877ms    remaining: 6.43s
120:    learn: 0.2637376        total: 885ms    remaining: 6.43s
121:    learn: 0.2635814        total: 891ms    remaining: 6.41s
122:    learn: 0.2633007        total: 897ms    remaining: 6.39s
123:    learn: 0.2630463        total: 904ms    remaining: 6.38s
124:    learn: 0.2625436        total: 910ms    remaining: 6.37s
125:    learn: 0.2623534        total: 917ms    remaining: 6.36s
126:    learn: 0.2620983        total: 924ms    remaining: 6.35s
127:    learn: 0.2619562        total: 930ms    remaining: 6.33s
128:    learn: 0.2616396        total: 938ms    remaining: 6.33s
129:    learn: 0.2614650        total: 944ms    remaining: 6.32s
130:    learn: 0.2613639        total: 950ms    remaining: 6.3s
131:    learn: 0.2611495        total: 957ms    remaining: 6.29s
132:    learn: 0.2609170        total: 963ms    remaining: 6.28s
133:    learn: 0.2606897        total: 971ms    remaining: 6.27s
134:    learn: 0.2602264        total: 978ms    remaining: 6.27s
135:    learn: 0.2600640        total: 985ms    remaining: 6.25s
136:    learn: 0.2597188        total: 991ms    remaining: 6.24s
```

```
137:    learn: 0.2595349        total: 997ms    remaining: 6.23s
138:    learn: 0.2592843        total: 1s       remaining: 6.21s
139:    learn: 0.2590630        total: 1.01s    remaining: 6.2s
140:    learn: 0.2588638        total: 1.01s    remaining: 6.19s
141:    learn: 0.2585916        total: 1.02s    remaining: 6.18s
142:    learn: 0.2581374        total: 1.03s    remaining: 6.17s
143:    learn: 0.2579750        total: 1.03s    remaining: 6.15s
144:    learn: 0.2577894        total: 1.04s    remaining: 6.14s
145:    learn: 0.2575293        total: 1.05s    remaining: 6.13s
146:    learn: 0.2573961        total: 1.05s    remaining: 6.12s
147:    learn: 0.2571889        total: 1.06s    remaining: 6.11s
148:    learn: 0.2567704        total: 1.07s    remaining: 6.09s
149:    learn: 0.2566223        total: 1.07s    remaining: 6.08s
150:    learn: 0.2563600        total: 1.08s    remaining: 6.08s
151:    learn: 0.2561895        total: 1.09s    remaining: 6.06s
152:    learn: 0.2558380        total: 1.09s    remaining: 6.06s
153:    learn: 0.2555814        total: 1.1s     remaining: 6.05s
154:    learn: 0.2554083        total: 1.11s    remaining: 6.04s
155:    learn: 0.2552984        total: 1.11s    remaining: 6.03s
156:    learn: 0.2551474        total: 1.12s    remaining: 6.02s
157:    learn: 0.2549385        total: 1.13s    remaining: 6.01s
158:    learn: 0.2547784        total: 1.13s    remaining: 6s
159:    learn: 0.2544535        total: 1.14s    remaining: 5.99s
160:    learn: 0.2541922        total: 1.15s    remaining: 5.98s
161:    learn: 0.2539903        total: 1.16s    remaining: 5.98s
162:    learn: 0.2537715        total: 1.16s    remaining: 5.97s
163:    learn: 0.2535303        total: 1.17s    remaining: 5.96s
164:    learn: 0.2533616        total: 1.18s    remaining: 5.95s
165:    learn: 0.2532041        total: 1.18s    remaining: 5.94s
166:    learn: 0.2529416        total: 1.19s    remaining: 5.93s
167:    learn: 0.2525866        total: 1.2s     remaining: 5.92s
168:    learn: 0.2525007        total: 1.2s     remaining: 5.92s
169:    learn: 0.2523330        total: 1.21s    remaining: 5.91s
170:    learn: 0.2521521        total: 1.22s    remaining: 5.89s
171:    learn: 0.2519040        total: 1.22s    remaining: 5.88s
172:    learn: 0.2516926        total: 1.23s    remaining: 5.87s
173:    learn: 0.2514995        total: 1.23s    remaining: 5.86s
174:    learn: 0.2512817        total: 1.24s    remaining: 5.85s
175:    learn: 0.2511407        total: 1.25s    remaining: 5.84s
176:    learn: 0.2510292        total: 1.25s    remaining: 5.83s
177:    learn: 0.2509016        total: 1.26s    remaining: 5.82s
178:    learn: 0.2507685        total: 1.26s    remaining: 5.81s
179:    learn: 0.2505808        total: 1.27s    remaining: 5.79s
180:    learn: 0.2504170        total: 1.28s    remaining: 5.78s
181:    learn: 0.2502518        total: 1.28s    remaining: 5.78s
182:    learn: 0.2500816        total: 1.29s    remaining: 5.77s
183:    learn: 0.2498906        total: 1.3s     remaining: 5.76s
184:    learn: 0.2497381        total: 1.3s     remaining: 5.75s
```

```
185:    learn: 0.2494736        total: 1.31s    remaining: 5.74s
186:    learn: 0.2492397        total: 1.32s    remaining: 5.73s
187:    learn: 0.2490249        total: 1.32s    remaining: 5.72s
188:    learn: 0.2488902        total: 1.33s    remaining: 5.71s
189:    learn: 0.2487012        total: 1.34s    remaining: 5.7s
190:    learn: 0.2484632        total: 1.34s    remaining: 5.69s
191:    learn: 0.2483583        total: 1.35s    remaining: 5.68s
192:    learn: 0.2482601        total: 1.36s    remaining: 5.68s
193:    learn: 0.2481310        total: 1.36s    remaining: 5.67s
194:    learn: 0.2480393        total: 1.37s    remaining: 5.66s
195:    learn: 0.2478056        total: 1.38s    remaining: 5.65s
196:    learn: 0.2476306        total: 1.39s    remaining: 5.65s
197:    learn: 0.2474531        total: 1.39s    remaining: 5.64s
198:    learn: 0.2473607        total: 1.4s     remaining: 5.64s
199:    learn: 0.2472163        total: 1.41s    remaining: 5.63s
200:    learn: 0.2470767        total: 1.41s    remaining: 5.62s
201:    learn: 0.2469456        total: 1.42s    remaining: 5.61s
202:    learn: 0.2467708        total: 1.43s    remaining: 5.6s
203:    learn: 0.2465132        total: 1.43s    remaining: 5.59s
204:    learn: 0.2463698        total: 1.44s    remaining: 5.58s
205:    learn: 0.2462758        total: 1.44s    remaining: 5.57s
206:    learn: 0.2460621        total: 1.45s    remaining: 5.56s
207:    learn: 0.2459294        total: 1.46s    remaining: 5.55s
208:    learn: 0.2457998        total: 1.46s    remaining: 5.54s
209:    learn: 0.2457208        total: 1.47s    remaining: 5.53s
210:    learn: 0.2456269        total: 1.48s    remaining: 5.52s
211:    learn: 0.2455251        total: 1.48s    remaining: 5.51s
212:    learn: 0.2454213        total: 1.49s    remaining: 5.5s
213:    learn: 0.2452242        total: 1.5s     remaining: 5.5s
214:    learn: 0.2451108        total: 1.5s     remaining: 5.49s
215:    learn: 0.2450393        total: 1.51s    remaining: 5.48s
216:    learn: 0.2449533        total: 1.51s    remaining: 5.47s
217:    learn: 0.2448301        total: 1.52s    remaining: 5.46s
218:    learn: 0.2445710        total: 1.53s    remaining: 5.45s
219:    learn: 0.2444952        total: 1.53s    remaining: 5.44s
220:    learn: 0.2443948        total: 1.54s    remaining: 5.43s
221:    learn: 0.2443132        total: 1.55s    remaining: 5.43s
222:    learn: 0.2441354        total: 1.55s    remaining: 5.42s
223:    learn: 0.2438815        total: 1.56s    remaining: 5.41s
224:    learn: 0.2437099        total: 1.57s    remaining: 5.4s
225:    learn: 0.2436042        total: 1.58s    remaining: 5.4s
226:    learn: 0.2433821        total: 1.58s    remaining: 5.39s
227:    learn: 0.2431384        total: 1.59s    remaining: 5.39s
228:    learn: 0.2429660        total: 1.6s     remaining: 5.38s
229:    learn: 0.2427872        total: 1.6s     remaining: 5.37s
230:    learn: 0.2425999        total: 1.61s    remaining: 5.37s
231:    learn: 0.2425140        total: 1.62s    remaining: 5.36s
232:    learn: 0.2422695        total: 1.62s    remaining: 5.35s
```

```
233:    learn: 0.2421520        total: 1.63s    remaining: 5.34s
234:    learn: 0.2420232        total: 1.64s    remaining: 5.33s
235:    learn: 0.2418425        total: 1.64s    remaining: 5.32s
236:    learn: 0.2417145        total: 1.65s    remaining: 5.31s
237:    learn: 0.2415322        total: 1.66s    remaining: 5.3s
238:    learn: 0.2413079        total: 1.66s    remaining: 5.29s
239:    learn: 0.2410921        total: 1.67s    remaining: 5.29s
240:    learn: 0.2406247        total: 1.68s    remaining: 5.28s
241:    learn: 0.2405484        total: 1.68s    remaining: 5.27s
242:    learn: 0.2403969        total: 1.69s    remaining: 5.26s
243:    learn: 0.2402799        total: 1.7s     remaining: 5.26s
244:    learn: 0.2402060        total: 1.7s     remaining: 5.25s
245:    learn: 0.2401171        total: 1.71s    remaining: 5.24s
246:    learn: 0.2399426        total: 1.72s    remaining: 5.24s
247:    learn: 0.2397320        total: 1.73s    remaining: 5.23s
248:    learn: 0.2396716        total: 1.73s    remaining: 5.23s
249:    learn: 0.2395485        total: 1.74s    remaining: 5.22s
250:    learn: 0.2394654        total: 1.75s    remaining: 5.22s
251:    learn: 0.2393852        total: 1.75s    remaining: 5.21s
252:    learn: 0.2392479        total: 1.76s    remaining: 5.2s
253:    learn: 0.2391280        total: 1.77s    remaining: 5.2s
254:    learn: 0.2390591        total: 1.77s    remaining: 5.19s
255:    learn: 0.2388890        total: 1.78s    remaining: 5.18s
256:    learn: 0.2386931        total: 1.79s    remaining: 5.18s
257:    learn: 0.2385642        total: 1.8s     remaining: 5.17s
258:    learn: 0.2383739        total: 1.8s     remaining: 5.16s
259:    learn: 0.2381171        total: 1.81s    remaining: 5.16s
260:    learn: 0.2379443        total: 1.82s    remaining: 5.15s
261:    learn: 0.2378468        total: 1.83s    remaining: 5.14s
262:    learn: 0.2375667        total: 1.83s    remaining: 5.14s
263:    learn: 0.2373650        total: 1.84s    remaining: 5.13s
264:    learn: 0.2372930        total: 1.85s    remaining: 5.12s
265:    learn: 0.2371216        total: 1.85s    remaining: 5.12s
266:    learn: 0.2370675        total: 1.86s    remaining: 5.11s
267:    learn: 0.2368375        total: 1.87s    remaining: 5.1s
268:    learn: 0.2367015        total: 1.87s    remaining: 5.09s
269:    learn: 0.2364558        total: 1.88s    remaining: 5.08s
270:    learn: 0.2363646        total: 1.89s    remaining: 5.07s
271:    learn: 0.2363036        total: 1.89s    remaining: 5.07s
272:    learn: 0.2360773        total: 1.9s     remaining: 5.06s
273:    learn: 0.2359868        total: 1.91s    remaining: 5.07s
274:    learn: 0.2358526        total: 1.92s    remaining: 5.07s
275:    learn: 0.2357256        total: 1.93s    remaining: 5.06s
276:    learn: 0.2355491        total: 1.94s    remaining: 5.06s
277:    learn: 0.2354738        total: 1.95s    remaining: 5.06s
278:    learn: 0.2352435        total: 1.96s    remaining: 5.05s
279:    learn: 0.2351142        total: 1.96s    remaining: 5.05s
280:    learn: 0.2350460        total: 1.97s    remaining: 5.04s
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281:    learn: 0.2349202        total: 1.98s    remaining: 5.04s
282:    learn: 0.2348326        total: 1.99s    remaining: 5.03s
283:    learn: 0.2346826        total: 1.99s    remaining: 5.03s
284:    learn: 0.2346046        total: 2s       remaining: 5.02s
285:    learn: 0.2345158        total: 2.01s    remaining: 5.01s
286:    learn: 0.2344149        total: 2.02s    remaining: 5.01s
287:    learn: 0.2343082        total: 2.02s    remaining: 5s
288:    learn: 0.2341964        total: 2.03s    remaining: 5s
289:    learn: 0.2340399        total: 2.04s    remaining: 5s
290:    learn: 0.2339014        total: 2.05s    remaining: 5s
291:    learn: 0.2338514        total: 2.06s    remaining: 4.99s
292:    learn: 0.2337334        total: 2.07s    remaining: 4.99s
293:    learn: 0.2335168        total: 2.07s    remaining: 4.98s
294:    learn: 0.2334100        total: 2.08s    remaining: 4.97s
295:    learn: 0.2332535        total: 2.09s    remaining: 4.96s
296:    learn: 0.2331561        total: 2.09s    remaining: 4.96s
297:    learn: 0.2330767        total: 2.1s     remaining: 4.95s
298:    learn: 0.2329214        total: 2.11s    remaining: 4.95s
299:    learn: 0.2328660        total: 2.12s    remaining: 4.94s
300:    learn: 0.2327600        total: 2.13s    remaining: 4.93s
301:    learn: 0.2325710        total: 2.13s    remaining: 4.93s
302:    learn: 0.2324730        total: 2.14s    remaining: 4.92s
303:    learn: 0.2322987        total: 2.15s    remaining: 4.92s
304:    learn: 0.2322007        total: 2.15s    remaining: 4.91s
305:    learn: 0.2321026        total: 2.16s    remaining: 4.9s
306:    learn: 0.2319058        total: 2.17s    remaining: 4.89s
307:    learn: 0.2318392        total: 2.17s    remaining: 4.88s
308:    learn: 0.2317533        total: 2.18s    remaining: 4.88s
309:    learn: 0.2316300        total: 2.19s    remaining: 4.87s
310:    learn: 0.2315107        total: 2.19s    remaining: 4.86s
311:    learn: 0.2314088        total: 2.2s     remaining: 4.85s
312:    learn: 0.2312854        total: 2.21s    remaining: 4.84s
313:    learn: 0.2312056        total: 2.21s    remaining: 4.83s
314:    learn: 0.2310590        total: 2.22s    remaining: 4.83s
315:    learn: 0.2309510        total: 2.23s    remaining: 4.82s
316:    learn: 0.2308020        total: 2.23s    remaining: 4.81s
317:    learn: 0.2307294        total: 2.24s    remaining: 4.8s
318:    learn: 0.2306022        total: 2.24s    remaining: 4.79s
319:    learn: 0.2304457        total: 2.25s    remaining: 4.79s
320:    learn: 0.2303706        total: 2.26s    remaining: 4.78s
321:    learn: 0.2301776        total: 2.27s    remaining: 4.77s
322:    learn: 0.2300760        total: 2.27s    remaining: 4.76s
323:    learn: 0.2299269        total: 2.28s    remaining: 4.75s
324:    learn: 0.2298565        total: 2.28s    remaining: 4.74s
325:    learn: 0.2297747        total: 2.29s    remaining: 4.73s
326:    learn: 0.2296641        total: 2.3s     remaining: 4.73s
327:    learn: 0.2295321        total: 2.3s     remaining: 4.72s
328:    learn: 0.2293651        total: 2.31s    remaining: 4.71s
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329:    learn: 0.2292387        total: 2.32s    remaining: 4.71s
330:    learn: 0.2291054        total: 2.33s    remaining: 4.7s
331:    learn: 0.2289381        total: 2.33s    remaining: 4.7s
332:    learn: 0.2288299        total: 2.34s    remaining: 4.69s
333:    learn: 0.2286605        total: 2.35s    remaining: 4.68s
334:    learn: 0.2285349        total: 2.35s    remaining: 4.67s
335:    learn: 0.2284535        total: 2.36s    remaining: 4.66s
336:    learn: 0.2283536        total: 2.37s    remaining: 4.65s
337:    learn: 0.2282592        total: 2.37s    remaining: 4.65s
338:    learn: 0.2279756        total: 2.38s    remaining: 4.64s
339:    learn: 0.2278969        total: 2.38s    remaining: 4.63s
340:    learn: 0.2278449        total: 2.39s    remaining: 4.62s
341:    learn: 0.2277673        total: 2.4s     remaining: 4.61s
342:    learn: 0.2276390        total: 2.4s     remaining: 4.6s
343:    learn: 0.2275845        total: 2.41s    remaining: 4.59s
344:    learn: 0.2274582        total: 2.41s    remaining: 4.58s
345:    learn: 0.2274200        total: 2.42s    remaining: 4.58s
346:    learn: 0.2273298        total: 2.43s    remaining: 4.57s
347:    learn: 0.2272161        total: 2.43s    remaining: 4.56s
348:    learn: 0.2270976        total: 2.44s    remaining: 4.55s
349:    learn: 0.2270232        total: 2.44s    remaining: 4.54s
350:    learn: 0.2268901        total: 2.45s    remaining: 4.53s
351:    learn: 0.2267488        total: 2.46s    remaining: 4.53s
352:    learn: 0.2266618        total: 2.46s    remaining: 4.52s
353:    learn: 0.2265505        total: 2.47s    remaining: 4.51s
354:    learn: 0.2264771        total: 2.48s    remaining: 4.5s
355:    learn: 0.2263983        total: 2.48s    remaining: 4.49s
356:    learn: 0.2263505        total: 2.49s    remaining: 4.48s
357:    learn: 0.2262671        total: 2.5s     remaining: 4.48s
358:    learn: 0.2261118        total: 2.5s     remaining: 4.47s
359:    learn: 0.2260468        total: 2.51s    remaining: 4.46s
360:    learn: 0.2259924        total: 2.52s    remaining: 4.45s
361:    learn: 0.2258496        total: 2.52s    remaining: 4.45s
362:    learn: 0.2257988        total: 2.53s    remaining: 4.44s
363:    learn: 0.2256857        total: 2.54s    remaining: 4.43s
364:    learn: 0.2256119        total: 2.54s    remaining: 4.42s
365:    learn: 0.2254031        total: 2.55s    remaining: 4.42s
366:    learn: 0.2251951        total: 2.56s    remaining: 4.41s
367:    learn: 0.2251213        total: 2.56s    remaining: 4.4s
368:    learn: 0.2250513        total: 2.57s    remaining: 4.39s
369:    learn: 0.2249376        total: 2.58s    remaining: 4.38s
370:    learn: 0.2248535        total: 2.58s    remaining: 4.38s
371:    learn: 0.2247426        total: 2.59s    remaining: 4.37s
372:    learn: 0.2246487        total: 2.59s    remaining: 4.36s
373:    learn: 0.2245474        total: 2.6s     remaining: 4.35s
374:    learn: 0.2243712        total: 2.61s    remaining: 4.34s
375:    learn: 0.2243207        total: 2.61s    remaining: 4.33s
376:    learn: 0.2242267        total: 2.62s    remaining: 4.33s
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377:    learn: 0.2241480        total: 2.62s    remaining: 4.32s
378:    learn: 0.2240364        total: 2.63s    remaining: 4.31s
379:    learn: 0.2239902        total: 2.64s    remaining: 4.3s
380:    learn: 0.2239568        total: 2.64s    remaining: 4.29s
381:    learn: 0.2238940        total: 2.65s    remaining: 4.29s
382:    learn: 0.2238190        total: 2.66s    remaining: 4.28s
383:    learn: 0.2237454        total: 2.66s    remaining: 4.27s
384:    learn: 0.2236104        total: 2.67s    remaining: 4.26s
385:    learn: 0.2235448        total: 2.67s    remaining: 4.25s
386:    learn: 0.2234451        total: 2.68s    remaining: 4.25s
387:    learn: 0.2233694        total: 2.69s    remaining: 4.25s
388:    learn: 0.2231778        total: 2.7s     remaining: 4.24s
389:    learn: 0.2230817        total: 2.71s    remaining: 4.23s
390:    learn: 0.2229973        total: 2.71s    remaining: 4.22s
391:    learn: 0.2228756        total: 2.72s    remaining: 4.22s
392:    learn: 0.2227837        total: 2.73s    remaining: 4.21s
393:    learn: 0.2226789        total: 2.74s    remaining: 4.21s
394:    learn: 0.2225873        total: 2.74s    remaining: 4.2s
395:    learn: 0.2224891        total: 2.75s    remaining: 4.19s
396:    learn: 0.2223921        total: 2.75s    remaining: 4.18s
397:    learn: 0.2223288        total: 2.76s    remaining: 4.18s
398:    learn: 0.2221911        total: 2.77s    remaining: 4.17s
399:    learn: 0.2220904        total: 2.77s    remaining: 4.16s
400:    learn: 0.2220063        total: 2.78s    remaining: 4.16s
401:    learn: 0.2218881        total: 2.79s    remaining: 4.15s
402:    learn: 0.2218155        total: 2.79s    remaining: 4.14s
403:    learn: 0.2216986        total: 2.8s     remaining: 4.13s
404:    learn: 0.2216620        total: 2.81s    remaining: 4.13s
405:    learn: 0.2215218        total: 2.81s    remaining: 4.12s
406:    learn: 0.2214495        total: 2.82s    remaining: 4.11s
407:    learn: 0.2213840        total: 2.83s    remaining: 4.1s
408:    learn: 0.2212938        total: 2.83s    remaining: 4.09s
409:    learn: 0.2211536        total: 2.84s    remaining: 4.08s
410:    learn: 0.2210424        total: 2.85s    remaining: 4.08s
411:    learn: 0.2209620        total: 2.85s    remaining: 4.07s
412:    learn: 0.2208763        total: 2.86s    remaining: 4.06s
413:    learn: 0.2207857        total: 2.86s    remaining: 4.05s
414:    learn: 0.2207325        total: 2.87s    remaining: 4.05s
415:    learn: 0.2206513        total: 2.88s    remaining: 4.04s
416:    learn: 0.2205462        total: 2.88s    remaining: 4.03s
417:    learn: 0.2204792        total: 2.89s    remaining: 4.02s
418:    learn: 0.2204360        total: 2.9s     remaining: 4.02s
419:    learn: 0.2202566        total: 2.9s     remaining: 4.01s
420:    learn: 0.2201897        total: 2.91s    remaining: 4s
421:    learn: 0.2200053        total: 2.92s    remaining: 4s
422:    learn: 0.2199119        total: 2.92s    remaining: 3.99s
423:    learn: 0.2198538        total: 2.93s    remaining: 3.98s
424:    learn: 0.2196806        total: 2.94s    remaining: 3.98s
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425:    learn: 0.2195446        total: 2.95s    remaining: 3.97s
426:    learn: 0.2194325        total: 2.95s    remaining: 3.96s
427:    learn: 0.2193998        total: 2.96s    remaining: 3.95s
428:    learn: 0.2192857        total: 2.96s    remaining: 3.94s
429:    learn: 0.2191101        total: 2.97s    remaining: 3.94s
430:    learn: 0.2189795        total: 2.98s    remaining: 3.93s
431:    learn: 0.2189000        total: 2.98s    remaining: 3.92s
432:    learn: 0.2187997        total: 2.99s    remaining: 3.91s
433:    learn: 0.2187450        total: 3s       remaining: 3.9s
434:    learn: 0.2186719        total: 3s       remaining: 3.9s
435:    learn: 0.2185494        total: 3.01s    remaining: 3.89s
436:    learn: 0.2183277        total: 3.01s    remaining: 3.88s
437:    learn: 0.2182696        total: 3.02s    remaining: 3.88s
438:    learn: 0.2180881        total: 3.03s    remaining: 3.87s
439:    learn: 0.2179389        total: 3.03s    remaining: 3.86s
440:    learn: 0.2178397        total: 3.04s    remaining: 3.85s
441:    learn: 0.2177451        total: 3.05s    remaining: 3.85s
442:    learn: 0.2175836        total: 3.05s    remaining: 3.84s
443:    learn: 0.2174961        total: 3.06s    remaining: 3.83s
444:    learn: 0.2174097        total: 3.06s    remaining: 3.82s
445:    learn: 0.2172442        total: 3.07s    remaining: 3.81s
446:    learn: 0.2171339        total: 3.08s    remaining: 3.81s
447:    learn: 0.2170263        total: 3.08s    remaining: 3.8s
448:    learn: 0.2168717        total: 3.09s    remaining: 3.79s
449:    learn: 0.2167817        total: 3.1s     remaining: 3.79s
450:    learn: 0.2166920        total: 3.11s    remaining: 3.78s
451:    learn: 0.2166008        total: 3.12s    remaining: 3.78s
452:    learn: 0.2165132        total: 3.12s    remaining: 3.77s
453:    learn: 0.2163766        total: 3.13s    remaining: 3.76s
454:    learn: 0.2161928        total: 3.14s    remaining: 3.76s
455:    learn: 0.2160550        total: 3.14s    remaining: 3.75s
456:    learn: 0.2159512        total: 3.15s    remaining: 3.74s
457:    learn: 0.2158766        total: 3.15s    remaining: 3.73s
458:    learn: 0.2157677        total: 3.16s    remaining: 3.73s
459:    learn: 0.2156778        total: 3.17s    remaining: 3.72s
460:    learn: 0.2156335        total: 3.17s    remaining: 3.71s
461:    learn: 0.2155545        total: 3.18s    remaining: 3.7s
462:    learn: 0.2154547        total: 3.19s    remaining: 3.69s
463:    learn: 0.2153413        total: 3.19s    remaining: 3.69s
464:    learn: 0.2152417        total: 3.2s     remaining: 3.68s
465:    learn: 0.2151660        total: 3.2s     remaining: 3.67s
466:    learn: 0.2150671        total: 3.21s    remaining: 3.66s
467:    learn: 0.2149759        total: 3.22s    remaining: 3.66s
468:    learn: 0.2148777        total: 3.22s    remaining: 3.65s
469:    learn: 0.2148264        total: 3.23s    remaining: 3.64s
470:    learn: 0.2147377        total: 3.23s    remaining: 3.63s
471:    learn: 0.2146307        total: 3.24s    remaining: 3.63s
472:    learn: 0.2145233        total: 3.25s    remaining: 3.62s
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473:    learn: 0.2144755        total: 3.25s    remaining: 3.61s
474:    learn: 0.2143416        total: 3.26s    remaining: 3.6s
475:    learn: 0.2142608        total: 3.27s    remaining: 3.59s
476:    learn: 0.2141369        total: 3.27s    remaining: 3.59s
477:    learn: 0.2140400        total: 3.28s    remaining: 3.58s
478:    learn: 0.2139744        total: 3.29s    remaining: 3.57s
479:    learn: 0.2138870        total: 3.29s    remaining: 3.57s
480:    learn: 0.2137787        total: 3.3s     remaining: 3.56s
481:    learn: 0.2137266        total: 3.31s    remaining: 3.55s
482:    learn: 0.2136642        total: 3.31s    remaining: 3.55s
483:    learn: 0.2136163        total: 3.32s    remaining: 3.54s
484:    learn: 0.2134952        total: 3.33s    remaining: 3.53s
485:    learn: 0.2134634        total: 3.33s    remaining: 3.52s
486:    learn: 0.2134009        total: 3.34s    remaining: 3.52s
487:    learn: 0.2132641        total: 3.35s    remaining: 3.51s
488:    learn: 0.2132161        total: 3.35s    remaining: 3.5s
489:    learn: 0.2131495        total: 3.36s    remaining: 3.49s
490:    learn: 0.2130005        total: 3.36s    remaining: 3.49s
491:    learn: 0.2128442        total: 3.37s    remaining: 3.48s
492:    learn: 0.2127390        total: 3.38s    remaining: 3.47s
493:    learn: 0.2126422        total: 3.38s    remaining: 3.46s
494:    learn: 0.2125131        total: 3.39s    remaining: 3.46s
495:    learn: 0.2123999        total: 3.39s    remaining: 3.45s
496:    learn: 0.2123438        total: 3.4s     remaining: 3.44s
497:    learn: 0.2122668        total: 3.41s    remaining: 3.43s
498:    learn: 0.2121514        total: 3.41s    remaining: 3.43s
499:    learn: 0.2120527        total: 3.42s    remaining: 3.42s
500:    learn: 0.2119999        total: 3.42s    remaining: 3.41s
501:    learn: 0.2119371        total: 3.43s    remaining: 3.4s
502:    learn: 0.2118923        total: 3.44s    remaining: 3.4s
503:    learn: 0.2118240        total: 3.44s    remaining: 3.39s
504:    learn: 0.2117593        total: 3.45s    remaining: 3.38s
505:    learn: 0.2116512        total: 3.46s    remaining: 3.37s
506:    learn: 0.2115866        total: 3.46s    remaining: 3.37s
507:    learn: 0.2115161        total: 3.47s    remaining: 3.36s
508:    learn: 0.2113917        total: 3.47s    remaining: 3.35s
509:    learn: 0.2113214        total: 3.48s    remaining: 3.34s
510:    learn: 0.2112496        total: 3.49s    remaining: 3.34s
511:    learn: 0.2111018        total: 3.5s     remaining: 3.33s
512:    learn: 0.2109492        total: 3.5s     remaining: 3.33s
513:    learn: 0.2108762        total: 3.51s    remaining: 3.32s
514:    learn: 0.2108162        total: 3.52s    remaining: 3.31s
515:    learn: 0.2107745        total: 3.52s    remaining: 3.3s
516:    learn: 0.2107079        total: 3.53s    remaining: 3.29s
517:    learn: 0.2106499        total: 3.53s    remaining: 3.29s
518:    learn: 0.2106001        total: 3.54s    remaining: 3.28s
519:    learn: 0.2105139        total: 3.54s    remaining: 3.27s
520:    learn: 0.2104720        total: 3.55s    remaining: 3.27s
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521:    learn: 0.2103790        total: 3.56s    remaining: 3.26s
522:    learn: 0.2103389        total: 3.56s    remaining: 3.25s
523:    learn: 0.2102202        total: 3.57s    remaining: 3.24s
524:    learn: 0.2100753        total: 3.58s    remaining: 3.24s
525:    learn: 0.2099908        total: 3.58s    remaining: 3.23s
526:    learn: 0.2098948        total: 3.59s    remaining: 3.22s
527:    learn: 0.2097867        total: 3.6s     remaining: 3.22s
528:    learn: 0.2097522        total: 3.6s     remaining: 3.21s
529:    learn: 0.2096978        total: 3.61s    remaining: 3.2s
530:    learn: 0.2096082        total: 3.62s    remaining: 3.19s
531:    learn: 0.2095653        total: 3.62s    remaining: 3.19s
532:    learn: 0.2094684        total: 3.63s    remaining: 3.18s
533:    learn: 0.2093117        total: 3.64s    remaining: 3.17s
534:    learn: 0.2092354        total: 3.64s    remaining: 3.17s
535:    learn: 0.2091436        total: 3.65s    remaining: 3.16s
536:    learn: 0.2090864        total: 3.66s    remaining: 3.15s
537:    learn: 0.2089512        total: 3.67s    remaining: 3.15s
538:    learn: 0.2088497        total: 3.67s    remaining: 3.14s
539:    learn: 0.2087798        total: 3.68s    remaining: 3.14s
540:    learn: 0.2086202        total: 3.69s    remaining: 3.13s
541:    learn: 0.2085208        total: 3.7s     remaining: 3.12s
542:    learn: 0.2084385        total: 3.7s     remaining: 3.12s
543:    learn: 0.2083634        total: 3.71s    remaining: 3.11s
544:    learn: 0.2082971        total: 3.72s    remaining: 3.1s
545:    learn: 0.2081810        total: 3.72s    remaining: 3.1s
546:    learn: 0.2079915        total: 3.73s    remaining: 3.09s
547:    learn: 0.2079285        total: 3.74s    remaining: 3.08s
548:    learn: 0.2078454        total: 3.74s    remaining: 3.08s
549:    learn: 0.2077833        total: 3.75s    remaining: 3.07s
550:    learn: 0.2077211        total: 3.76s    remaining: 3.06s
551:    learn: 0.2076747        total: 3.76s    remaining: 3.05s
552:    learn: 0.2076155        total: 3.77s    remaining: 3.05s
553:    learn: 0.2075145        total: 3.77s    remaining: 3.04s
554:    learn: 0.2074651        total: 3.78s    remaining: 3.03s
555:    learn: 0.2073812        total: 3.79s    remaining: 3.02s
556:    learn: 0.2072993        total: 3.79s    remaining: 3.02s
557:    learn: 0.2071930        total: 3.8s     remaining: 3.01s
558:    learn: 0.2071185        total: 3.81s    remaining: 3s
559:    learn: 0.2070510        total: 3.81s    remaining: 3s
560:    learn: 0.2068170        total: 3.82s    remaining: 2.99s
561:    learn: 0.2067595        total: 3.83s    remaining: 2.98s
562:    learn: 0.2066856        total: 3.83s    remaining: 2.97s
563:    learn: 0.2065821        total: 3.84s    remaining: 2.97s
564:    learn: 0.2065028        total: 3.85s    remaining: 2.96s
565:    learn: 0.2064569        total: 3.85s    remaining: 2.95s
566:    learn: 0.2063768        total: 3.86s    remaining: 2.95s
567:    learn: 0.2063010        total: 3.87s    remaining: 2.94s
568:    learn: 0.2061286        total: 3.87s    remaining: 2.93s
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569:    learn: 0.2060233        total: 3.88s    remaining: 2.93s
570:    learn: 0.2059153        total: 3.89s    remaining: 2.92s
571:    learn: 0.2058480        total: 3.89s    remaining: 2.91s
572:    learn: 0.2056988        total: 3.9s     remaining: 2.91s
573:    learn: 0.2055973        total: 3.91s    remaining: 2.9s
574:    learn: 0.2055389        total: 3.91s    remaining: 2.89s
575:    learn: 0.2054888        total: 3.92s    remaining: 2.88s
576:    learn: 0.2054406        total: 3.92s    remaining: 2.88s
577:    learn: 0.2053376        total: 3.93s    remaining: 2.87s
578:    learn: 0.2053066        total: 3.94s    remaining: 2.86s
579:    learn: 0.2052102        total: 3.94s    remaining: 2.86s
580:    learn: 0.2051722        total: 3.95s    remaining: 2.85s
581:    learn: 0.2051036        total: 3.96s    remaining: 2.84s
582:    learn: 0.2050620        total: 3.96s    remaining: 2.83s
583:    learn: 0.2050266        total: 3.97s    remaining: 2.83s
584:    learn: 0.2049465        total: 3.98s    remaining: 2.82s
585:    learn: 0.2048190        total: 3.98s    remaining: 2.81s
586:    learn: 0.2047287        total: 3.99s    remaining: 2.81s
587:    learn: 0.2046807        total: 4s       remaining: 2.8s
588:    learn: 0.2045474        total: 4s       remaining: 2.79s
589:    learn: 0.2044338        total: 4.01s    remaining: 2.79s
590:    learn: 0.2043946        total: 4.01s    remaining: 2.78s
591:    learn: 0.2043238        total: 4.02s    remaining: 2.77s
592:    learn: 0.2042665        total: 4.03s    remaining: 2.76s
593:    learn: 0.2041527        total: 4.03s    remaining: 2.76s
594:    learn: 0.2040958        total: 4.04s    remaining: 2.75s
595:    learn: 0.2039872        total: 4.05s    remaining: 2.74s
596:    learn: 0.2038833        total: 4.05s    remaining: 2.74s
597:    learn: 0.2038104        total: 4.06s    remaining: 2.73s
598:    learn: 0.2037615        total: 4.07s    remaining: 2.72s
599:    learn: 0.2036613        total: 4.08s    remaining: 2.72s
600:    learn: 0.2035668        total: 4.09s    remaining: 2.71s
601:    learn: 0.2034867        total: 4.09s    remaining: 2.71s
602:    learn: 0.2034659        total: 4.1s     remaining: 2.7s
603:    learn: 0.2033558        total: 4.11s    remaining: 2.69s
604:    learn: 0.2032621        total: 4.12s    remaining: 2.69s
605:    learn: 0.2031786        total: 4.13s    remaining: 2.68s
606:    learn: 0.2030911        total: 4.14s    remaining: 2.68s
607:    learn: 0.2029989        total: 4.14s    remaining: 2.67s
608:    learn: 0.2029045        total: 4.15s    remaining: 2.67s
609:    learn: 0.2028255        total: 4.16s    remaining: 2.66s
610:    learn: 0.2027479        total: 4.17s    remaining: 2.65s
611:    learn: 0.2026813        total: 4.18s    remaining: 2.65s
612:    learn: 0.2026205        total: 4.18s    remaining: 2.64s
613:    learn: 0.2025210        total: 4.19s    remaining: 2.63s
614:    learn: 0.2024570        total: 4.2s     remaining: 2.63s
615:    learn: 0.2023572        total: 4.21s    remaining: 2.62s
616:    learn: 0.2022534        total: 4.21s    remaining: 2.62s
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617:    learn: 0.2021801        total: 4.22s    remaining: 2.61s
618:    learn: 0.2021383        total: 4.23s    remaining: 2.6s
619:    learn: 0.2020917        total: 4.24s    remaining: 2.6s
620:    learn: 0.2019920        total: 4.25s    remaining: 2.59s
621:    learn: 0.2018590        total: 4.25s    remaining: 2.58s
622:    learn: 0.2017607        total: 4.26s    remaining: 2.58s
623:    learn: 0.2016948        total: 4.27s    remaining: 2.57s
624:    learn: 0.2015345        total: 4.28s    remaining: 2.57s
625:    learn: 0.2014788        total: 4.29s    remaining: 2.56s
626:    learn: 0.2014067        total: 4.3s     remaining: 2.56s
627:    learn: 0.2013413        total: 4.3s     remaining: 2.55s
628:    learn: 0.2012455        total: 4.31s    remaining: 2.54s
629:    learn: 0.2012018        total: 4.32s    remaining: 2.54s
630:    learn: 0.2011478        total: 4.33s    remaining: 2.53s
631:    learn: 0.2010356        total: 4.33s    remaining: 2.52s
632:    learn: 0.2009691        total: 4.34s    remaining: 2.52s
633:    learn: 0.2009022        total: 4.35s    remaining: 2.51s
634:    learn: 0.2008306        total: 4.36s    remaining: 2.5s
635:    learn: 0.2007926        total: 4.36s    remaining: 2.5s
636:    learn: 0.2007445        total: 4.37s    remaining: 2.49s
637:    learn: 0.2006610        total: 4.38s    remaining: 2.48s
638:    learn: 0.2005908        total: 4.39s    remaining: 2.48s
639:    learn: 0.2005211        total: 4.4s     remaining: 2.47s
640:    learn: 0.2004693        total: 4.41s    remaining: 2.47s
641:    learn: 0.2004018        total: 4.41s    remaining: 2.46s
642:    learn: 0.2003394        total: 4.42s    remaining: 2.46s
643:    learn: 0.2002736        total: 4.43s    remaining: 2.45s
644:    learn: 0.2002289        total: 4.44s    remaining: 2.44s
645:    learn: 0.2001750        total: 4.44s    remaining: 2.44s
646:    learn: 0.2001379        total: 4.45s    remaining: 2.43s
647:    learn: 0.2000654        total: 4.46s    remaining: 2.42s
648:    learn: 0.1999964        total: 4.47s    remaining: 2.42s
649:    learn: 0.1999407        total: 4.47s    remaining: 2.41s
650:    learn: 0.1998783        total: 4.48s    remaining: 2.4s
651:    learn: 0.1997949        total: 4.49s    remaining: 2.4s
652:    learn: 0.1997280        total: 4.5s     remaining: 2.39s
653:    learn: 0.1996323        total: 4.5s     remaining: 2.38s
654:    learn: 0.1995662        total: 4.51s    remaining: 2.38s
655:    learn: 0.1995313        total: 4.52s    remaining: 2.37s
656:    learn: 0.1994082        total: 4.53s    remaining: 2.36s
657:    learn: 0.1993488        total: 4.54s    remaining: 2.36s
658:    learn: 0.1992498        total: 4.55s    remaining: 2.35s
659:    learn: 0.1992097        total: 4.56s    remaining: 2.35s
660:    learn: 0.1991774        total: 4.56s    remaining: 2.34s
661:    learn: 0.1990894        total: 4.57s    remaining: 2.33s
662:    learn: 0.1990365        total: 4.58s    remaining: 2.33s
663:    learn: 0.1989641        total: 4.59s    remaining: 2.32s
664:    learn: 0.1989173        total: 4.6s     remaining: 2.32s
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665:    learn: 0.1988548        total: 4.61s    remaining: 2.31s
666:    learn: 0.1988125        total: 4.62s    remaining: 2.31s
667:    learn: 0.1986869        total: 4.63s    remaining: 2.3s
668:    learn: 0.1986417        total: 4.64s    remaining: 2.29s
669:    learn: 0.1986112        total: 4.65s    remaining: 2.29s
670:    learn: 0.1985652        total: 4.66s    remaining: 2.28s
671:    learn: 0.1984814        total: 4.66s    remaining: 2.28s
672:    learn: 0.1984098        total: 4.67s    remaining: 2.27s
673:    learn: 0.1983605        total: 4.68s    remaining: 2.26s
674:    learn: 0.1982421        total: 4.69s    remaining: 2.26s
675:    learn: 0.1980866        total: 4.7s     remaining: 2.25s
676:    learn: 0.1980079        total: 4.71s    remaining: 2.24s
677:    learn: 0.1978641        total: 4.71s    remaining: 2.24s
678:    learn: 0.1977948        total: 4.72s    remaining: 2.23s
679:    learn: 0.1976980        total: 4.73s    remaining: 2.22s
680:    learn: 0.1976036        total: 4.73s    remaining: 2.22s
681:    learn: 0.1975447        total: 4.74s    remaining: 2.21s
682:    learn: 0.1974716        total: 4.75s    remaining: 2.2s
683:    learn: 0.1974157        total: 4.75s    remaining: 2.19s
684:    learn: 0.1973268        total: 4.76s    remaining: 2.19s
685:    learn: 0.1972638        total: 4.76s    remaining: 2.18s
686:    learn: 0.1972139        total: 4.77s    remaining: 2.17s
687:    learn: 0.1971788        total: 4.78s    remaining: 2.17s
688:    learn: 0.1971374        total: 4.78s    remaining: 2.16s
689:    learn: 0.1970828        total: 4.79s    remaining: 2.15s
690:    learn: 0.1970310        total: 4.8s     remaining: 2.15s
691:    learn: 0.1969840        total: 4.8s     remaining: 2.14s
692:    learn: 0.1969072        total: 4.81s    remaining: 2.13s
693:    learn: 0.1968492        total: 4.82s    remaining: 2.12s
694:    learn: 0.1966983        total: 4.83s    remaining: 2.12s
695:    learn: 0.1966088        total: 4.83s    remaining: 2.11s
696:    learn: 0.1965760        total: 4.84s    remaining: 2.1s
697:    learn: 0.1965173        total: 4.85s    remaining: 2.1s
698:    learn: 0.1964285        total: 4.86s    remaining: 2.09s
699:    learn: 0.1963442        total: 4.86s    remaining: 2.08s
700:    learn: 0.1961963        total: 4.87s    remaining: 2.08s
701:    learn: 0.1961272        total: 4.88s    remaining: 2.07s
702:    learn: 0.1960599        total: 4.88s    remaining: 2.06s
703:    learn: 0.1959964        total: 4.89s    remaining: 2.06s
704:    learn: 0.1959371        total: 4.9s     remaining: 2.05s
705:    learn: 0.1958750        total: 4.9s     remaining: 2.04s
706:    learn: 0.1958235        total: 4.91s    remaining: 2.03s
707:    learn: 0.1957617        total: 4.92s    remaining: 2.03s
708:    learn: 0.1956646        total: 4.92s    remaining: 2.02s
709:    learn: 0.1956086        total: 4.93s    remaining: 2.01s
710:    learn: 0.1955558        total: 4.94s    remaining: 2.01s
711:    learn: 0.1954574        total: 4.94s    remaining: 2s
712:    learn: 0.1953871        total: 4.95s    remaining: 1.99s
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713:    learn: 0.1953299        total: 4.96s    remaining: 1.99s
714:    learn: 0.1952887        total: 4.96s    remaining: 1.98s
715:    learn: 0.1952297        total: 4.97s    remaining: 1.97s
716:    learn: 0.1951415        total: 4.98s    remaining: 1.96s
717:    learn: 0.1950738        total: 4.98s    remaining: 1.96s
718:    learn: 0.1950161        total: 4.99s    remaining: 1.95s
719:    learn: 0.1949749        total: 5s       remaining: 1.94s
720:    learn: 0.1948462        total: 5s       remaining: 1.94s
721:    learn: 0.1947736        total: 5.01s    remaining: 1.93s
722:    learn: 0.1947256        total: 5.02s    remaining: 1.92s
723:    learn: 0.1946693        total: 5.02s    remaining: 1.91s
724:    learn: 0.1945913        total: 5.03s    remaining: 1.91s
725:    learn: 0.1945653        total: 5.04s    remaining: 1.9s
726:    learn: 0.1945068        total: 5.05s    remaining: 1.9s
727:    learn: 0.1944264        total: 5.05s    remaining: 1.89s
728:    learn: 0.1943877        total: 5.06s    remaining: 1.88s
729:    learn: 0.1943467        total: 5.07s    remaining: 1.87s
730:    learn: 0.1942933        total: 5.07s    remaining: 1.87s
731:    learn: 0.1942501        total: 5.08s    remaining: 1.86s
732:    learn: 0.1941951        total: 5.09s    remaining: 1.85s
733:    learn: 0.1941275        total: 5.09s    remaining: 1.84s
734:    learn: 0.1940436        total: 5.1s     remaining: 1.84s
735:    learn: 0.1939957        total: 5.11s    remaining: 1.83s
736:    learn: 0.1939473        total: 5.11s    remaining: 1.82s
737:    learn: 0.1938955        total: 5.12s    remaining: 1.82s
738:    learn: 0.1938517        total: 5.13s    remaining: 1.81s
739:    learn: 0.1937896        total: 5.13s    remaining: 1.8s
740:    learn: 0.1937389        total: 5.14s    remaining: 1.8s
741:    learn: 0.1936824        total: 5.14s    remaining: 1.79s
742:    learn: 0.1936308        total: 5.15s    remaining: 1.78s
743:    learn: 0.1935848        total: 5.16s    remaining: 1.77s
744:    learn: 0.1935553        total: 5.16s    remaining: 1.77s
745:    learn: 0.1934806        total: 5.17s    remaining: 1.76s
746:    learn: 0.1934124        total: 5.18s    remaining: 1.75s
747:    learn: 0.1933741        total: 5.18s    remaining: 1.75s
748:    learn: 0.1932505        total: 5.19s    remaining: 1.74s
749:    learn: 0.1932073        total: 5.2s     remaining: 1.73s
750:    learn: 0.1931790        total: 5.2s     remaining: 1.73s
751:    learn: 0.1931243        total: 5.21s    remaining: 1.72s
752:    learn: 0.1930409        total: 5.22s    remaining: 1.71s
753:    learn: 0.1929782        total: 5.22s    remaining: 1.7s
754:    learn: 0.1929231        total: 5.23s    remaining: 1.7s
755:    learn: 0.1928767        total: 5.24s    remaining: 1.69s
756:    learn: 0.1927564        total: 5.24s    remaining: 1.68s
757:    learn: 0.1926995        total: 5.25s    remaining: 1.68s
758:    learn: 0.1926468        total: 5.26s    remaining: 1.67s
759:    learn: 0.1925954        total: 5.26s    remaining: 1.66s
760:    learn: 0.1925582        total: 5.27s    remaining: 1.65s
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761:    learn: 0.1925032        total: 5.28s    remaining: 1.65s
762:    learn: 0.1924362        total: 5.28s    remaining: 1.64s
763:    learn: 0.1923957        total: 5.29s    remaining: 1.63s
764:    learn: 0.1923231        total: 5.3s     remaining: 1.63s
765:    learn: 0.1922752        total: 5.3s     remaining: 1.62s
766:    learn: 0.1922166        total: 5.31s    remaining: 1.61s
767:    learn: 0.1921601        total: 5.32s    remaining: 1.6s
768:    learn: 0.1921294        total: 5.32s    remaining: 1.6s
769:    learn: 0.1920539        total: 5.33s    remaining: 1.59s
770:    learn: 0.1919381        total: 5.33s    remaining: 1.58s
771:    learn: 0.1918772        total: 5.34s    remaining: 1.58s
772:    learn: 0.1918145        total: 5.35s    remaining: 1.57s
773:    learn: 0.1917487        total: 5.35s    remaining: 1.56s
774:    learn: 0.1916815        total: 5.36s    remaining: 1.56s
775:    learn: 0.1916249        total: 5.37s    remaining: 1.55s
776:    learn: 0.1915275        total: 5.37s    remaining: 1.54s
777:    learn: 0.1914847        total: 5.38s    remaining: 1.53s
778:    learn: 0.1914462        total: 5.38s    remaining: 1.53s
779:    learn: 0.1913790        total: 5.39s    remaining: 1.52s
780:    learn: 0.1913073        total: 5.4s     remaining: 1.51s
781:    learn: 0.1912337        total: 5.41s    remaining: 1.51s
782:    learn: 0.1911011        total: 5.41s    remaining: 1.5s
783:    learn: 0.1909886        total: 5.42s    remaining: 1.49s
784:    learn: 0.1909409        total: 5.43s    remaining: 1.49s
785:    learn: 0.1908991        total: 5.43s    remaining: 1.48s
786:    learn: 0.1908315        total: 5.44s    remaining: 1.47s
787:    learn: 0.1908022        total: 5.45s    remaining: 1.47s
788:    learn: 0.1907172        total: 5.45s    remaining: 1.46s
789:    learn: 0.1906736        total: 5.46s    remaining: 1.45s
790:    learn: 0.1905327        total: 5.47s    remaining: 1.45s
791:    learn: 0.1904500        total: 5.48s    remaining: 1.44s
792:    learn: 0.1904218        total: 5.48s    remaining: 1.43s
793:    learn: 0.1903906        total: 5.49s    remaining: 1.42s
794:    learn: 0.1902471        total: 5.5s     remaining: 1.42s
795:    learn: 0.1901935        total: 5.5s     remaining: 1.41s
796:    learn: 0.1900416        total: 5.51s    remaining: 1.4s
797:    learn: 0.1900122        total: 5.52s    remaining: 1.4s
798:    learn: 0.1899747        total: 5.53s    remaining: 1.39s
799:    learn: 0.1899227        total: 5.53s    remaining: 1.38s
800:    learn: 0.1898807        total: 5.54s    remaining: 1.38s
801:    learn: 0.1898421        total: 5.54s    remaining: 1.37s
802:    learn: 0.1897930        total: 5.55s    remaining: 1.36s
803:    learn: 0.1897610        total: 5.56s    remaining: 1.35s
804:    learn: 0.1896710        total: 5.57s    remaining: 1.35s
805:    learn: 0.1896135        total: 5.57s    remaining: 1.34s
806:    learn: 0.1895601        total: 5.58s    remaining: 1.33s
807:    learn: 0.1895369        total: 5.59s    remaining: 1.33s
808:    learn: 0.1894627        total: 5.6s     remaining: 1.32s
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809:    learn: 0.1893839        total: 5.6s     remaining: 1.31s
810:    learn: 0.1893088        total: 5.61s    remaining: 1.31s
811:    learn: 0.1892817        total: 5.62s    remaining: 1.3s
812:    learn: 0.1891631        total: 5.62s    remaining: 1.29s
813:    learn: 0.1891230        total: 5.63s    remaining: 1.29s
814:    learn: 0.1890854        total: 5.64s    remaining: 1.28s
815:    learn: 0.1889219        total: 5.64s    remaining: 1.27s
816:    learn: 0.1888709        total: 5.65s    remaining: 1.27s
817:    learn: 0.1888247        total: 5.66s    remaining: 1.26s
818:    learn: 0.1887144        total: 5.67s    remaining: 1.25s
819:    learn: 0.1886630        total: 5.67s    remaining: 1.24s
820:    learn: 0.1886179        total: 5.68s    remaining: 1.24s
821:    learn: 0.1885825        total: 5.68s    remaining: 1.23s
822:    learn: 0.1885123        total: 5.69s    remaining: 1.22s
823:    learn: 0.1884517        total: 5.7s     remaining: 1.22s
824:    learn: 0.1883777        total: 5.7s     remaining: 1.21s
825:    learn: 0.1883313        total: 5.71s    remaining: 1.2s
826:    learn: 0.1882942        total: 5.72s    remaining: 1.2s
827:    learn: 0.1882472        total: 5.72s    remaining: 1.19s
828:    learn: 0.1881965        total: 5.73s    remaining: 1.18s
829:    learn: 0.1880825        total: 5.74s    remaining: 1.18s
830:    learn: 0.1880234        total: 5.74s    remaining: 1.17s
831:    learn: 0.1879763        total: 5.75s    remaining: 1.16s
832:    learn: 0.1879248        total: 5.76s    remaining: 1.15s
833:    learn: 0.1878405        total: 5.76s    remaining: 1.15s
834:    learn: 0.1877591        total: 5.77s    remaining: 1.14s
835:    learn: 0.1877115        total: 5.78s    remaining: 1.13s
836:    learn: 0.1876571        total: 5.78s    remaining: 1.13s
837:    learn: 0.1876166        total: 5.79s    remaining: 1.12s
838:    learn: 0.1875605        total: 5.8s     remaining: 1.11s
839:    learn: 0.1874875        total: 5.8s     remaining: 1.1s
840:    learn: 0.1874378        total: 5.81s    remaining: 1.1s
841:    learn: 0.1873431        total: 5.82s    remaining: 1.09s
842:    learn: 0.1873156        total: 5.83s    remaining: 1.08s
843:    learn: 0.1872790        total: 5.83s    remaining: 1.08s
844:    learn: 0.1872330        total: 5.84s    remaining: 1.07s
845:    learn: 0.1871534        total: 5.85s    remaining: 1.06s
846:    learn: 0.1870521        total: 5.85s    remaining: 1.06s
847:    learn: 0.1869520        total: 5.86s    remaining: 1.05s
848:    learn: 0.1869020        total: 5.87s    remaining: 1.04s
849:    learn: 0.1868210        total: 5.87s    remaining: 1.04s
850:    learn: 0.1867953        total: 5.88s    remaining: 1.03s
851:    learn: 0.1867432        total: 5.89s    remaining: 1.02s
852:    learn: 0.1867011        total: 5.89s    remaining: 1.01s
853:    learn: 0.1866362        total: 5.9s     remaining: 1.01s
854:    learn: 0.1865869        total: 5.91s    remaining: 1s
855:    learn: 0.1865473        total: 5.91s    remaining: 995ms
856:    learn: 0.1864878        total: 5.92s    remaining: 988ms
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857:    learn: 0.1863979        total: 5.92s    remaining: 981ms
858:    learn: 0.1863061        total: 5.93s    remaining: 974ms
859:    learn: 0.1862172        total: 5.94s    remaining: 967ms
860:    learn: 0.1861699        total: 5.95s    remaining: 960ms
861:    learn: 0.1861276        total: 5.95s    remaining: 953ms
862:    learn: 0.1860910        total: 5.96s    remaining: 946ms
863:    learn: 0.1860256        total: 5.97s    remaining: 939ms
864:    learn: 0.1859875        total: 5.97s    remaining: 932ms
865:    learn: 0.1858766        total: 5.98s    remaining: 925ms
866:    learn: 0.1858215        total: 5.99s    remaining: 918ms
867:    learn: 0.1857580        total: 6s       remaining: 912ms
868:    learn: 0.1857137        total: 6s       remaining: 905ms
869:    learn: 0.1856185        total: 6.01s    remaining: 898ms
870:    learn: 0.1855621        total: 6.02s    remaining: 892ms
871:    learn: 0.1854975        total: 6.03s    remaining: 885ms
872:    learn: 0.1854594        total: 6.03s    remaining: 878ms
873:    learn: 0.1853966        total: 6.04s    remaining: 871ms
874:    learn: 0.1853544        total: 6.05s    remaining: 864ms
875:    learn: 0.1852546        total: 6.05s    remaining: 857ms
876:    learn: 0.1852105        total: 6.06s    remaining: 850ms
877:    learn: 0.1851749        total: 6.07s    remaining: 843ms
878:    learn: 0.1851255        total: 6.08s    remaining: 836ms
879:    learn: 0.1850571        total: 6.08s    remaining: 829ms
880:    learn: 0.1849887        total: 6.09s    remaining: 822ms
881:    learn: 0.1849271        total: 6.09s    remaining: 815ms
882:    learn: 0.1848930        total: 6.1s     remaining: 808ms
883:    learn: 0.1848156        total: 6.11s    remaining: 801ms
884:    learn: 0.1847537        total: 6.11s    remaining: 794ms
885:    learn: 0.1847240        total: 6.12s    remaining: 788ms
886:    learn: 0.1846561        total: 6.13s    remaining: 781ms
887:    learn: 0.1846367        total: 6.13s    remaining: 774ms
888:    learn: 0.1846023        total: 6.14s    remaining: 767ms
889:    learn: 0.1845636        total: 6.15s    remaining: 760ms
890:    learn: 0.1845252        total: 6.15s    remaining: 753ms
891:    learn: 0.1844703        total: 6.16s    remaining: 746ms
892:    learn: 0.1844277        total: 6.17s    remaining: 739ms
893:    learn: 0.1843491        total: 6.17s    remaining: 732ms
894:    learn: 0.1842706        total: 6.18s    remaining: 725ms
895:    learn: 0.1841790        total: 6.19s    remaining: 718ms
896:    learn: 0.1841322        total: 6.19s    remaining: 711ms
897:    learn: 0.1840940        total: 6.2s     remaining: 704ms
898:    learn: 0.1840513        total: 6.21s    remaining: 697ms
899:    learn: 0.1839500        total: 6.21s    remaining: 691ms
900:    learn: 0.1839051        total: 6.22s    remaining: 684ms
901:    learn: 0.1838690        total: 6.23s    remaining: 677ms
902:    learn: 0.1838340        total: 6.23s    remaining: 670ms
903:    learn: 0.1838107        total: 6.24s    remaining: 663ms
904:    learn: 0.1837625        total: 6.25s    remaining: 656ms
```

```
905:    learn: 0.1836721        total: 6.25s    remaining: 649ms
906:    learn: 0.1835911        total: 6.26s    remaining: 642ms
907:    learn: 0.1834980        total: 6.27s    remaining: 635ms
908:    learn: 0.1834220        total: 6.27s    remaining: 628ms
909:    learn: 0.1833429        total: 6.28s    remaining: 621ms
910:    learn: 0.1832808        total: 6.29s    remaining: 614ms
911:    learn: 0.1832510        total: 6.29s    remaining: 607ms
912:    learn: 0.1832091        total: 6.3s     remaining: 600ms
913:    learn: 0.1830306        total: 6.3s     remaining: 593ms
914:    learn: 0.1829526        total: 6.31s    remaining: 586ms
915:    learn: 0.1828862        total: 6.32s    remaining: 579ms
916:    learn: 0.1828156        total: 6.33s    remaining: 573ms
917:    learn: 0.1827643        total: 6.33s    remaining: 566ms
918:    learn: 0.1827074        total: 6.34s    remaining: 559ms
919:    learn: 0.1826764        total: 6.34s    remaining: 552ms
920:    learn: 0.1826378        total: 6.35s    remaining: 545ms
921:    learn: 0.1825923        total: 6.36s    remaining: 538ms
922:    learn: 0.1825187        total: 6.37s    remaining: 531ms
923:    learn: 0.1824676        total: 6.37s    remaining: 524ms
924:    learn: 0.1824365        total: 6.38s    remaining: 517ms
925:    learn: 0.1824101        total: 6.39s    remaining: 510ms
926:    learn: 0.1823213        total: 6.39s    remaining: 504ms
927:    learn: 0.1822724        total: 6.4s     remaining: 497ms
928:    learn: 0.1822111        total: 6.41s    remaining: 490ms
929:    learn: 0.1821301        total: 6.42s    remaining: 483ms
930:    learn: 0.1820535        total: 6.42s    remaining: 476ms
931:    learn: 0.1819781        total: 6.43s    remaining: 469ms
932:    learn: 0.1819033        total: 6.44s    remaining: 462ms
933:    learn: 0.1818579        total: 6.44s    remaining: 455ms
934:    learn: 0.1817432        total: 6.45s    remaining: 448ms
935:    learn: 0.1817179        total: 6.46s    remaining: 442ms
936:    learn: 0.1816418        total: 6.46s    remaining: 435ms
937:    learn: 0.1816005        total: 6.47s    remaining: 428ms
938:    learn: 0.1815598        total: 6.48s    remaining: 421ms
939:    learn: 0.1815208        total: 6.49s    remaining: 414ms
940:    learn: 0.1814883        total: 6.49s    remaining: 407ms
941:    learn: 0.1814144        total: 6.5s     remaining: 400ms
942:    learn: 0.1813459        total: 6.5s     remaining: 393ms
943:    learn: 0.1813011        total: 6.51s    remaining: 386ms
944:    learn: 0.1812364        total: 6.52s    remaining: 379ms
945:    learn: 0.1811484        total: 6.53s    remaining: 373ms
946:    learn: 0.1811265        total: 6.54s    remaining: 366ms
947:    learn: 0.1810627        total: 6.54s    remaining: 359ms
948:    learn: 0.1810274        total: 6.55s    remaining: 352ms
949:    learn: 0.1809470        total: 6.56s    remaining: 345ms
950:    learn: 0.1808604        total: 6.57s    remaining: 338ms
951:    learn: 0.1808094        total: 6.57s    remaining: 331ms
952:    learn: 0.1807565        total: 6.58s    remaining: 324ms
```

```
953:    learn: 0.1806931        total: 6.59s    remaining: 318ms
954:    learn: 0.1806400        total: 6.59s    remaining: 311ms
955:    learn: 0.1806084        total: 6.6s     remaining: 304ms
956:    learn: 0.1805417        total: 6.61s    remaining: 297ms
957:    learn: 0.1804648        total: 6.61s    remaining: 290ms
958:    learn: 0.1804367        total: 6.62s    remaining: 283ms
959:    learn: 0.1803765        total: 6.63s    remaining: 276ms
960:    learn: 0.1803410        total: 6.63s    remaining: 269ms
961:    learn: 0.1803168        total: 6.64s    remaining: 262ms
962:    learn: 0.1802625        total: 6.65s    remaining: 255ms
963:    learn: 0.1801915        total: 6.65s    remaining: 248ms
964:    learn: 0.1801313        total: 6.66s    remaining: 242ms
965:    learn: 0.1801005        total: 6.67s    remaining: 235ms
966:    learn: 0.1799676        total: 6.67s    remaining: 228ms
967:    learn: 0.1799060        total: 6.68s    remaining: 221ms
968:    learn: 0.1798571        total: 6.69s    remaining: 214ms
969:    learn: 0.1798203        total: 6.69s    remaining: 207ms
970:    learn: 0.1797556        total: 6.7s     remaining: 200ms
971:    learn: 0.1797036        total: 6.71s    remaining: 193ms
972:    learn: 0.1796488        total: 6.71s    remaining: 186ms
973:    learn: 0.1796218        total: 6.72s    remaining: 179ms
974:    learn: 0.1795801        total: 6.73s    remaining: 172ms
975:    learn: 0.1795017        total: 6.73s    remaining: 166ms
976:    learn: 0.1794816        total: 6.74s    remaining: 159ms
977:    learn: 0.1794352        total: 6.74s    remaining: 152ms
978:    learn: 0.1793843        total: 6.75s    remaining: 145ms
979:    learn: 0.1793591        total: 6.76s    remaining: 138ms
980:    learn: 0.1792623        total: 6.77s    remaining: 131ms
981:    learn: 0.1792027        total: 6.77s    remaining: 124ms
982:    learn: 0.1790638        total: 6.78s    remaining: 117ms
983:    learn: 0.1790086        total: 6.79s    remaining: 110ms
984:    learn: 0.1789560        total: 6.8s     remaining: 104ms
985:    learn: 0.1789085        total: 6.8s     remaining: 96.6ms
986:    learn: 0.1788723        total: 6.81s    remaining: 89.7ms
987:    learn: 0.1788502        total: 6.82s    remaining: 82.8ms
988:    learn: 0.1787975        total: 6.82s    remaining: 75.9ms
989:    learn: 0.1787243        total: 6.83s    remaining: 69ms
990:    learn: 0.1786958        total: 6.83s    remaining: 62.1ms
991:    learn: 0.1786443        total: 6.84s    remaining: 55.2ms
992:    learn: 0.1786059        total: 6.85s    remaining: 48.3ms
993:    learn: 0.1785555        total: 6.85s    remaining: 41.4ms
994:    learn: 0.1785192        total: 6.86s    remaining: 34.5ms
995:    learn: 0.1784798        total: 6.87s    remaining: 27.6ms
996:    learn: 0.1784028        total: 6.87s    remaining: 20.7ms
997:    learn: 0.1783568        total: 6.88s    remaining: 13.8ms
998:    learn: 0.1783011        total: 6.88s    remaining: 6.89ms
999:    learn: 0.1782462        total: 6.89s    remaining: 0us
```

[102]:
```
VotingClassifier(estimators=[('gaussian', GaussianNB()),
                             ('Gridlogistic',
GridSearchCV(cv=RepeatedStratifiedKFold(n_repeats=3, n_splits=10,
random_state=1),
                                         error_score=0,
                                         estimator=LogisticRegression(),
                                         n_jobs=-1,
                                         param_grid={'C': [100, 10, 1.0, 0.1,
                                                           0.01],
                                                     'penalty': ['l2'],
                                                     'solver': ['newton-cg',
                                                                'lbfgs',
                                                                'liblinear']},
                                         scoring='accuracy')),
                             ('catboost_classifier',
                              <…
                                          n_estimators=494, n_jobs=None,
                                          num_parallel_tree=None,
                                          random_state=None, reg_alpha=None,
                                          reg_lambda=None,
                                          scale_pos_weight=None,
                                          subsample=0.7, tree_method=None,
                                          validate_parameters=None,
                                          verbosity=0)),
                             ('LGBMclassifier',
                              LGBMClassifier(boosting_type='dart',
                                             importance_type='gain', max_bin=60,
                                             max_depth=5, n_estimators=494,
                                             num_leaves=300, verbosity=-1))],
                 voting='soft')
```

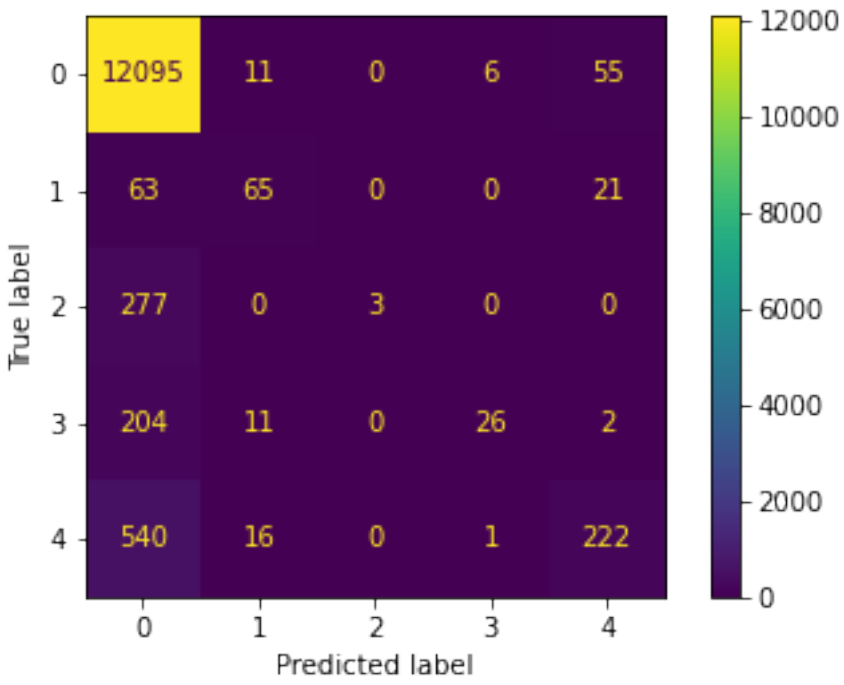
[103]:
```
y_pred = vot_soft.predict(X_test)
```

[104]:
```
metrics.accuracy_score(y_test, y_pred)*100
```

[104]:
```
91.13673079747393
```

[105]:
```
t = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= vot_soft.
 ↪classes_)
disp.plot()
```

[105]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f48350b8df0>
```



[106]:
```
#metrics.accuracy_score(y_test, y_pred_gnb)*100
```

[107]:
```
#confusion_matrix(y_test, y_pred_gnb)
```

[108]:
```
#t = confusion_matrix(y_test, y_pred_gnb)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= gnb.
 ↪classes_)
```

[109]:
```
#disp.plot()
```

[110]:
```
#metrics.accuracy_score(y_test, y_pred_log)*100
```

[111]:
```
#t = confusion_matrix(y_test, y_pred_log)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= grid_search.
 ↪classes_)
#disp.plot()
```

[112]:
```
#metrics.accuracy_score(y_test, y_pred_cat)*100
```

[113]:
```
#t = confusion_matrix(y_test, y_pred_cat)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= cat.
 ↪classes_)
#disp.plot()
```

[114]:
```
#metrics.accuracy_score(y_test, y_pred_dt)*100
```

[115]:
```
#t = confusion_matrix(y_test, y_pred_dt)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= dtclf.
 ↪classes_)
#disp.plot()
```

9 TESTING DATA

[116]:
```
path = '/media/mr-robot/Local Disk/summer_training/test'
os.chdir(path)
```

[117]:
```
# Converting all las files in csv by iterating using lasio
for file in os.listdir():
    if file.endswith(".las"):
        file_path = f"{path}/{file}"
        las=lasio.read(file_path)
        size=len(file_path)
        filepath1=file_path[:size-3]
        las.to_csv(filepath1+'csv', units=False)
```

[118]:
```
## To avoid furthur merging data and redundancy
if(os.path.isfile('./merged_data.csv') ):
    os.remove("merged_data.csv")

if(os.path.isfile('./FACIES_imputed.csv')):
    os.remove("FACIES_imputed.csv")

if(os.path.isfile('./FACIES_TRAIN.csv')):
    os.remove("FACIES_TRAIN.csv")
```

[119]:
```
# Merging all Well Log using Glob
filenames = glob.glob(path + "/*.csv")
dfs = []
for filename in filenames:
    dfs.append(pd.read_csv(filename))
big_frame = pd.concat(dfs, ignore_index=True)
big_frame.to_csv('merged_data.csv',index=False)
```

[120]:
```
df = pd.read_csv('merged_data.csv')
df
```

[120]:

	DEPTH	ACOUSTICIMPEDANCE1	AI	AVG_PIGN	BIT	CALI	\
0	1197.4072	5252.3882	5252388.0	NaN	0.2159	8.9012	
1	1197.5596	5289.7070	5289707.0	NaN	0.2159	8.9005	
2	1197.7120	5245.4429	5245443.0	NaN	0.2159	8.8957	
3	1197.8644	5181.9023	5181902.5	NaN	0.2159	8.8932	

```
4      1198.0168           5131.1343  5131134.5       NaN  0.2159  8.8980
…           …                   …          …         …      …       …
29560  1689.5065           6013.4722  6013472.5       NaN  0.2159     NaN
29561  1689.6589           5953.0059  5953006.0       NaN  0.2159     NaN
29562  1689.8113           5954.4824  5954482.0       NaN  0.2159     NaN
29563  1689.9637           5911.3301  5911330.0       NaN  0.2159     NaN
29564  1690.1161           5930.9585  5930958.5       NaN  0.2159     NaN

          NPHI        DT  FACIES  FLD1  …  SPSD  ZCOR  BS  CALI[DERIVED]1  \
0       0.4682  133.4417     NaN   NaN  …   NaN   NaN NaN             NaN
1       0.4585  132.4196     NaN   NaN  …   NaN   NaN NaN             NaN
2       0.4543  133.3569     NaN   NaN  …   NaN   NaN NaN             NaN
3       0.4827  134.7392     NaN   NaN  …   NaN   NaN NaN             NaN
4       0.5361  135.7694     NaN   NaN  …   NaN   NaN NaN             NaN
…          …         …     …    …   …   …   …  ..              …
29560      NaN  126.6800     NaN   NaN  …   NaN   NaN NaN             NaN
29561      NaN  127.9872     NaN   NaN  …   NaN   NaN NaN             NaN
29562      NaN  127.9657     NaN   NaN  …   NaN   NaN NaN             NaN
29563      NaN  128.9050     NaN   NaN  …   NaN   NaN NaN             NaN
29564      NaN  128.4784     NaN   NaN  …   NaN   NaN NaN             NaN

       DFL  GRCO  HDRS  HMRS  PHIT  TEMP1
0      NaN   NaN   NaN   NaN   NaN    NaN
1      NaN   NaN   NaN   NaN   NaN    NaN
2      NaN   NaN   NaN   NaN   NaN    NaN
3      NaN   NaN   NaN   NaN   NaN    NaN
4      NaN   NaN   NaN   NaN   NaN    NaN
…    …   …   …   …   …   …    …
29560  NaN   NaN   NaN   NaN   NaN    NaN
29561  NaN   NaN   NaN   NaN   NaN    NaN
29562  NaN   NaN   NaN   NaN   NaN    NaN
29563  NaN   NaN   NaN   NaN   NaN    NaN
29564  NaN   NaN   NaN   NaN   NaN    NaN

[29565 rows x 55 columns]
```

[121]:
```
#Selecting required feature
df=df[["DT","GR","NPHI","RHOB","FACIES"]]
```

[122]:
```
df
```

[122]:
```
             DT       GR    NPHI    RHOB  FACIES
0      133.4417  87.3154  0.4682  2.2995     NaN
1      132.4196  88.5412  0.4585  2.2981     NaN
2      133.3569  87.5764  0.4543  2.2950     NaN
3      134.7392  86.0361  0.4827  2.2907     NaN
4      135.7694  85.0393  0.5361  2.2856     NaN
```

```
…          …       …      …      …      …
29560  126.6800      NaN    NaN  2.4993    NaN
29561  127.9872      NaN    NaN  2.4997    NaN
29562  127.9657      NaN    NaN  2.4999    NaN
29563  128.9050      NaN    NaN  2.5000    NaN
29564  128.4784      NaN    NaN  2.5000    NaN

[29565 rows x 5 columns]
```

[123]:
```
df=imputing(imputation_strategy[optionimputation],df)
df
```

[123]:
```
              DT          GR      NPHI    RHOB  FACIES
0       133.4417   87.315400  0.468200  2.2995       0
1       132.4196   88.541200  0.458500  2.2981       0
2       133.3569   87.576400  0.454300  2.2950       0
3       134.7392   86.036100  0.482700  2.2907       0
4       135.7694   85.039300  0.536100  2.2856       0
…          …          …        …      …      …
29560   126.6800  102.326070  0.506785  2.4993       0
29561   127.9872  102.490830  0.510428  2.4997       0
29562   127.9657  102.498159  0.510361  2.4999       0
29563   128.9050  102.607440  0.512985  2.5000       0
29564   128.4784  102.560015  0.511792  2.5000       0

[29565 rows x 5 columns]
```

[124]:
```
df = outliers(DATAConditioningStrategy[optionoutlier] , df,␣
 ↪DATAConditioningColumns)
```

```
column DT
Percentiles: 25th=114.139, 75th=137.342, IQR=23.202
InterQuartile Range Outliers-:
             DT          GR    NPHI    RHOB  FACIES
2632    77.7408   55.287400  0.3062  2.6430       0
2633    77.3217   53.629600  0.3052  2.5920       1
3981    75.3027   73.368300  0.5153  2.5090       0
3982    73.6734   73.261800  0.5041  2.4475       0
6097    79.0923   87.085800  0.3700  2.8019       0
6110    76.3801   96.356900  0.3313  2.7004       0
6406    78.6538   59.692300  0.4038  2.6646       0
6448    79.3029   64.718200  0.3632  2.7212       0
13938   79.2984  108.679600  0.4490  2.8759       0
13939   70.9828   95.723000  0.4255  3.0317       0
13940   75.5917   94.711500  0.4245  2.9428       0
15679  175.1408   94.713206  0.5044  2.3501       0
15680  173.8879   96.256515  0.4875  2.3948       0
15706  172.7409   97.818285  0.5074  2.4185       0
```

```
15707  174.8540   97.349782  0.4967  2.4147       0
15708  172.7833   96.989636  0.4784  2.4165       0
16123   76.3119  121.788437  0.3927  3.0026       0
16907  173.0850   78.984443  0.6734  1.8918       0
23404   72.9019   86.674800  0.3879  2.6145       0
23405   73.6668   86.070200  0.3612  2.5231       0
25171   79.3205   78.216300  0.5893  2.2124       0
28926   78.1889   66.276900  0.4540  2.9479       0
(22, 5)
             DT          GR      NPHI    RHOB  FACIES
0      133.4417   87.315400  0.468200  2.2995       0
1      132.4196   88.541200  0.458500  2.2981       0
2      133.3569   87.576400  0.454300  2.2950       0
3      134.7392   86.036100  0.482700  2.2907       0
4      135.7694   85.039300  0.536100  2.2856       0
…         …         …       …     …     …
29560  126.6800  102.326070  0.506785  2.4993       0
29561  127.9872  102.490830  0.510428  2.4997       0
29562  127.9657  102.498159  0.510361  2.4999       0
29563  128.9050  102.607440  0.512985  2.5000       0
29564  128.4784  102.560015  0.511792  2.5000       0

[29534 rows x 5 columns]
column GR
Percentiles: 25th=77.174, 75th=102.911, IQR=25.736
InterQuartile Range Outliers-:
             DT       GR    NPHI    RHOB  FACIES
1342   144.1047  35.5685  0.6130  1.2752       3
1516   115.6053  37.5339  0.6715  1.1197       3
1517   116.5264  37.2150  0.6474  1.2269       3
1625   149.5008  36.3442  0.6133  1.1143       3
1626   150.9417  29.3642  0.6122  1.0951       3
…         …       …     …      …     …
28969  151.0522  27.8672  0.7510  1.0626       3
28970  152.6379  27.9862  0.7093  1.0935       3
28971  154.5247  28.4657  0.6571  1.1246       3
28972  155.4262  29.3424  0.6296  1.1451       3
28973  154.5691  32.9489  0.6210  1.1474       3

[1851 rows x 5 columns]
(1851, 5)
             DT          GR      NPHI    RHOB  FACIES
0      133.4417   87.315400  0.468200  2.2995       0
1      132.4196   88.541200  0.458500  2.2981       0
2      133.3569   87.576400  0.454300  2.2950       0
3      134.7392   86.036100  0.482700  2.2907       0
4      135.7694   85.039300  0.536100  2.2856       0
…         …          …       …     …     …
```

```
29560  126.6800  102.326070  0.506785  2.4993       0
29561  127.9872  102.490830  0.510428  2.4997       0
29562  127.9657  102.498159  0.510361  2.4999       0
29563  128.9050  102.607440  0.512985  2.5000       0
29564  128.4784  102.560015  0.511792  2.5000       0

[27683 rows x 5 columns]
column NPHI
Percentiles: 25th=0.468, 75th=0.550, IQR=0.083
InterQuartile Range Outliers-:
             DT       GR    NPHI    RHOB  FACIES
263    143.7784  72.7236  0.6766  2.1787       0
513    138.5944  75.0486  0.6775  2.2283       0
644    143.2483  78.0601  0.6805  1.9364       0
645    144.5881  78.3862  0.6749  1.7739       3
647    148.7089  60.5277  0.6966  1.3747       3
…         …       …     …      …     …
29028  105.8965  77.9666  0.2990  1.9829       1
29029  105.0871  73.8077  0.2886  1.9849       1
29030  105.3242  68.5815  0.2919  1.9918       1
29031  107.1987  64.1699  0.3269  2.0025       1
29038  113.2466  74.4795  0.3385  1.9897       1

[1568 rows x 5 columns]
(1568, 5)
             DT          GR      NPHI    RHOB  FACIES
0      133.4417   87.315400  0.468200  2.2995       0
1      132.4196   88.541200  0.458500  2.2981       0
2      133.3569   87.576400  0.454300  2.2950       0
3      134.7392   86.036100  0.482700  2.2907       0
4      135.7694   85.039300  0.536100  2.2856       0
…         …          …       …     …     …
29560  126.6800  102.326070  0.506785  2.4993       0
29561  127.9872  102.490830  0.510428  2.4997       0
29562  127.9657  102.498159  0.510361  2.4999       0
29563  128.9050  102.607440  0.512985  2.5000       0
29564  128.4784  102.560015  0.511792  2.5000       0

[26115 rows x 5 columns]
column RHOB
Percentiles: 25th=2.207, 75th=2.416, IQR=0.209
InterQuartile Range Outliers-:
             DT       GR    NPHI    RHOB  FACIES
646    146.9913  72.1231  0.6718  1.5568       3
1228   130.3615  77.5789  0.5451  1.6171       3
1229   133.5854  69.1480  0.5995  1.4461       3
1230   137.1125  58.9514  0.6035  1.4420       3
1231   139.1413  55.2131  0.5432  1.5727       3
```

```
…          …       …      …      …      …
29074   133.7901  78.6751  0.5387  1.8071       0
29125    96.3199  80.4237  0.4219  2.7614       0
29181   131.6097  94.2842  0.4822  1.8686       0
29182   130.0865  81.8287  0.4741  1.7645       0
29183   124.4891  75.3927  0.4875  1.7919       0

[1440 rows x 5 columns]
(1440, 5)
             DT          GR      NPHI    RHOB  FACIES
0      133.4417   87.315400  0.468200  2.2995       0
1      132.4196   88.541200  0.458500  2.2981       0
2      133.3569   87.576400  0.454300  2.2950       0
3      134.7392   86.036100  0.482700  2.2907       0
4      135.7694   85.039300  0.536100  2.2856       0
…          …          …       …     …     …
29560  126.6800  102.326070  0.506785  2.4993       0
29561  127.9872  102.490830  0.510428  2.4997       0
29562  127.9657  102.498159  0.510361  2.4999       0
29563  128.9050  102.607440  0.512985  2.5000       0
29564  128.4784  102.560015  0.511792  2.5000       0

[24675 rows x 5 columns]
```

[125]:
```
df = data_scaling( scaling_strategy[optionscaling] , df ,␣
↪DATAConditioningColumns )
```

[126]:
```
df.to_csv("testing_preprocessed.csv",index=False)
```

[127]:
```
df=pd.read_csv('testing_preprocessed.csv')
```

[128]:
```
df
```

[128]:
```
             DT        GR      NPHI      RHOB  FACIES
0      0.417594 -0.265769 -0.554201 -0.069035       0
1      0.368665 -0.208540 -0.685637 -0.076038       0
2      0.413534 -0.253584 -0.742547 -0.091546       0
3      0.479706 -0.325497 -0.357724 -0.113057       0
4      0.529023 -0.372035  0.365854 -0.138569       0
…           …         …         …         …     …
24670  0.093904  0.435043 -0.031369  0.930465       0
24671  0.156481  0.442736  0.017991  0.932466       0
24672  0.155452  0.443078  0.017092  0.933467       0
24673  0.200417  0.448180  0.052639  0.933967       0
24674  0.179995  0.445966  0.036476  0.933967       0

[24675 rows x 5 columns]
```

[129]:
```
X_testing=df[["DT","GR","NPHI","RHOB"]]
y_testing=df[["FACIES"]]
```

[130]:
```
X_testing.isnull().sum()
```

[130]:
```
DT      0
GR      0
NPHI    0
RHOB    0
dtype: int64
```

[131]:
```
#X_testing=FeatureSelection(FeatureSelectionStrategy[optionfeature],X_testing,y_testing)
```

[ ]:
```

```

[132]:
```
X_testing
```

[132]:

	DT	GR	NPHI	RHOB
0	0.417594	-0.265769	-0.554201	-0.069035
1	0.368665	-0.208540	-0.685637	-0.076038
2	0.413534	-0.253584	-0.742547	-0.091546
3	0.479706	-0.325497	-0.357724	-0.113057
4	0.529023	-0.372035	0.365854	-0.138569
…	…	…	…	…
24670	0.093904	0.435043	-0.031369	0.930465
24671	0.156481	0.442736	0.017991	0.932466
24672	0.155452	0.443078	0.017092	0.933467
24673	0.200417	0.448180	0.052639	0.933967
24674	0.179995	0.445966	0.036476	0.933967

[24675 rows x 4 columns]

[133]:
```
y_testing.describe()
```

[133]:

	FACIES
count	24675.000000
mean	0.327254
std	1.016689
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	4.000000

[134]:
```
y_predicted = vot_soft.predict(X_testing)
```

[135]:
```
y_predicted
```

[135]:
```
array([0, 0, 0, …, 0, 0, 0])
```

[136]:
```
metrics.accuracy_score(y_testing, y_predicted)*100
```

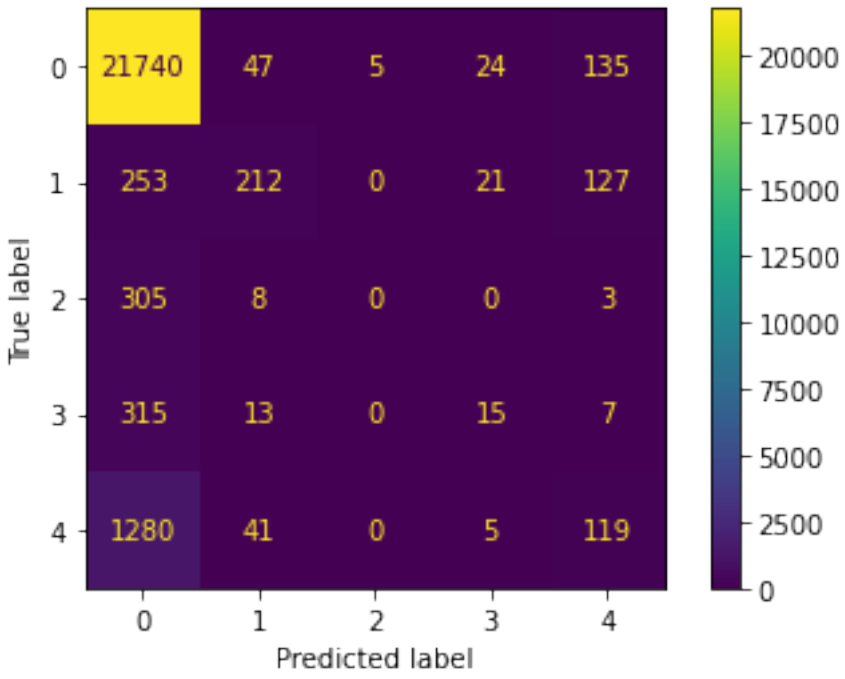
[136]:
```
89.50759878419453
```

[137]:
```
confusion_matrix(y_testing, y_predicted)
```

[137]:
```
array([[21740,    47,     5,    24,   135],
       [  253,   212,     0,    21,   127],
       [  305,     8,     0,     0,     3],
       [  315,    13,     0,    15,     7],
       [ 1280,    41,     0,     5,   119]])
```

[138]:
```
t = confusion_matrix(y_testing, y_predicted)
disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= vot_soft.
 ↪classes_)
disp.plot()
```

[138]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f48443debb0>
```



[139]:
```
t1=pd.DataFrame(y_testing)
```

[140]:
```
t1.to_csv('y_given.csv',index=False)
```

[141]:
```
t2=pd.DataFrame(y_predicted)
```

[142]:
```
t2.to_csv('y_predicted.csv',index=False)
```

[ ]:
```

```