facies_determination

August 30, 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.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
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
```

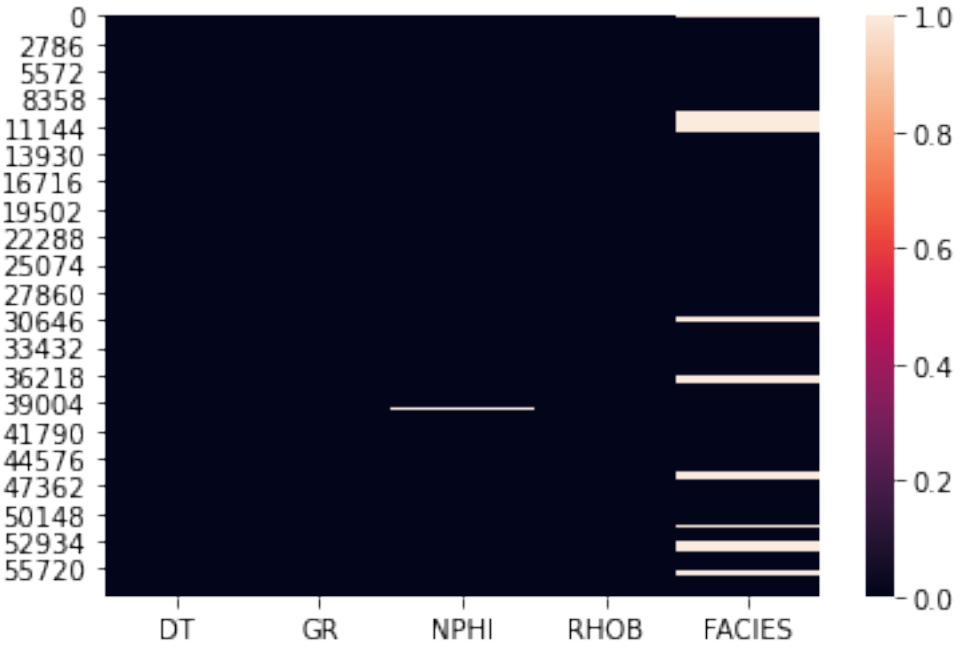
[28]:
```
(58499, 5)
```

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

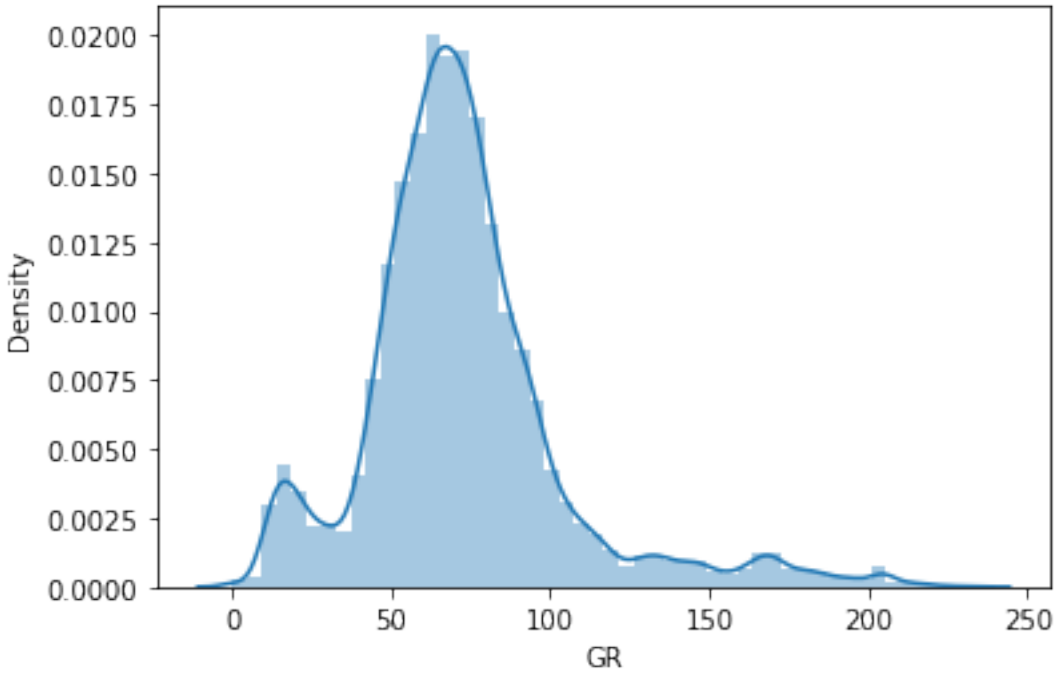
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58499 entries, 0 to 58498
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   DT      58499 non-null  float64
 1   GR      58379 non-null  float64
 2   NPHI    58172 non-null  float64
 3 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



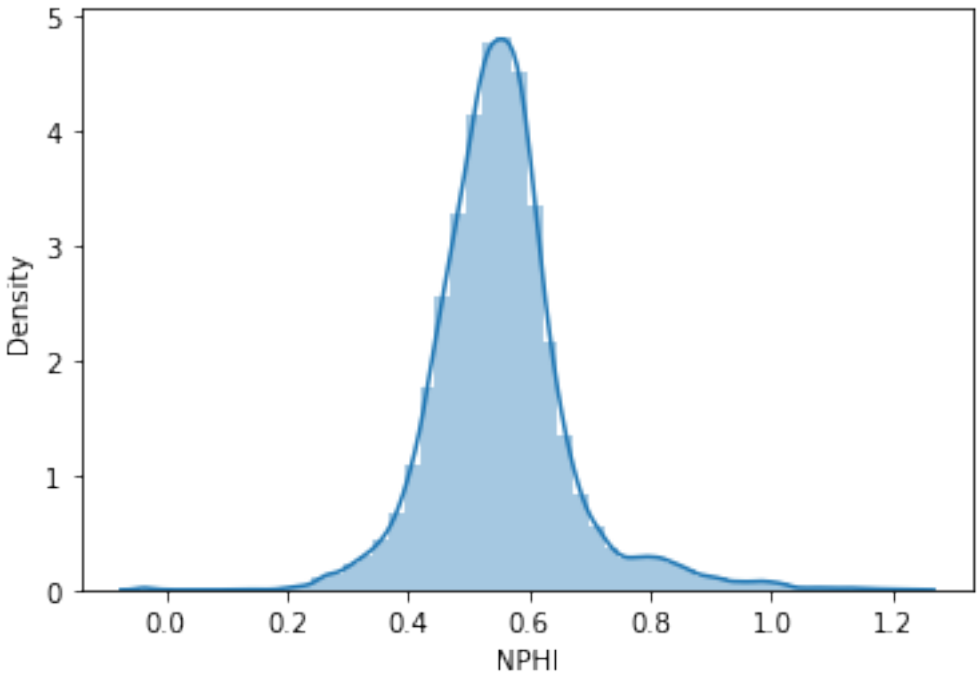
[31]:
```
null_gr = sns.distplot(df.GR.dropna())
```



[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())
```

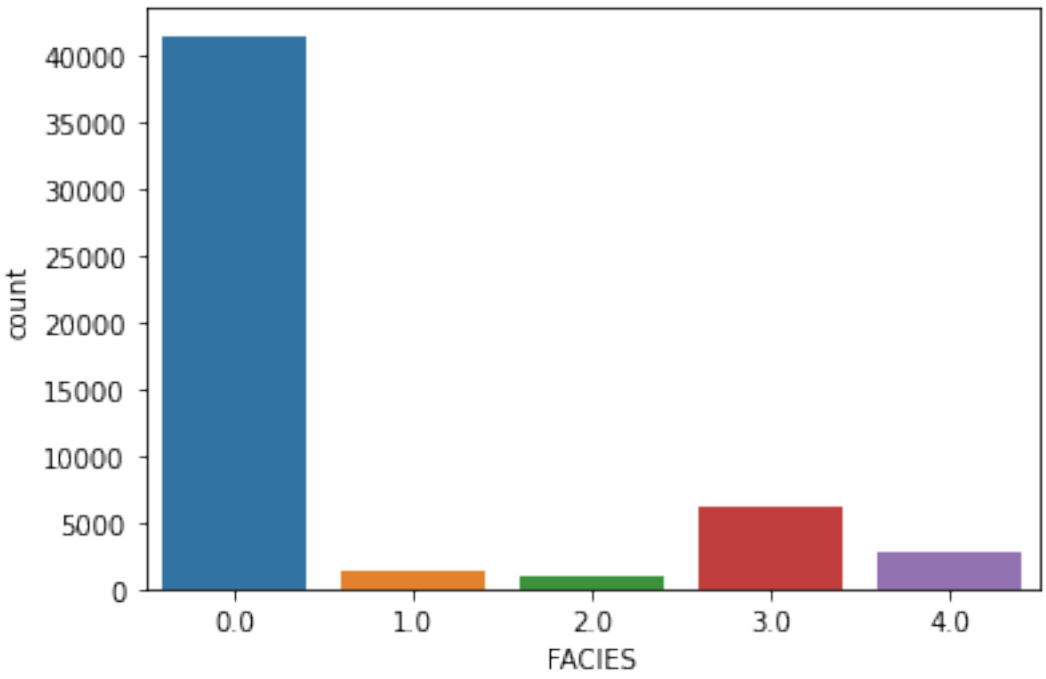


[34]:
```
df.NPHI.describe()
```

[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=4
```

```
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
```

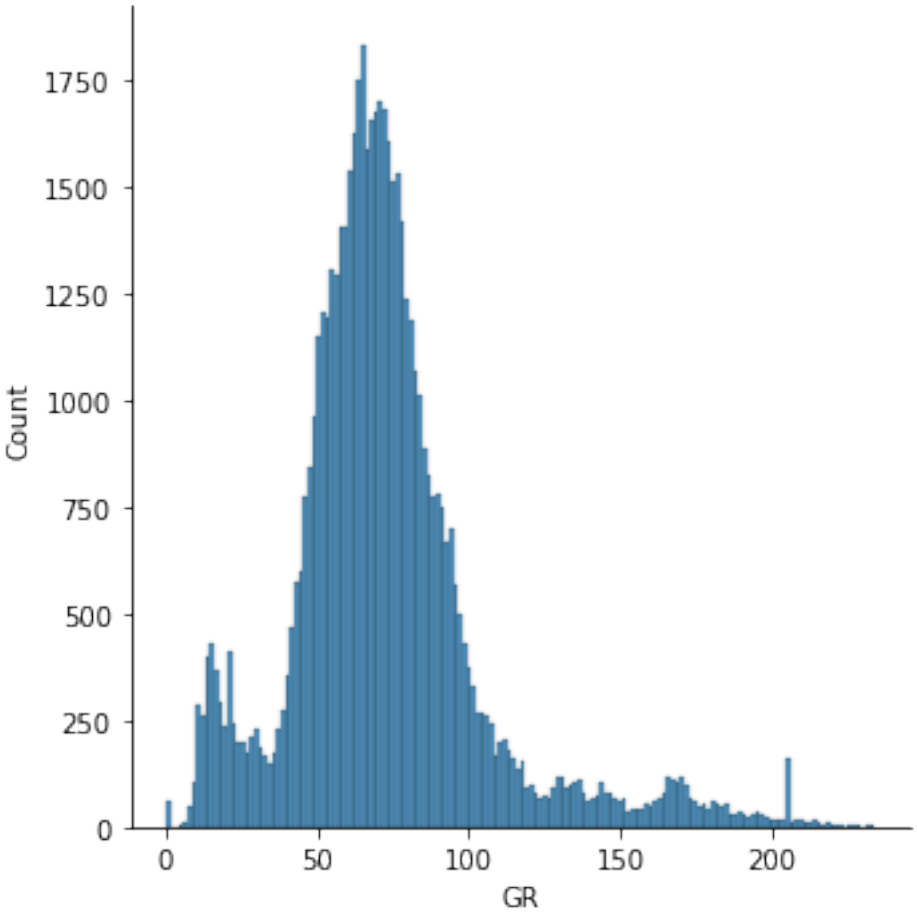
[41]:
```
df.isnull().sum()
```

[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())
```

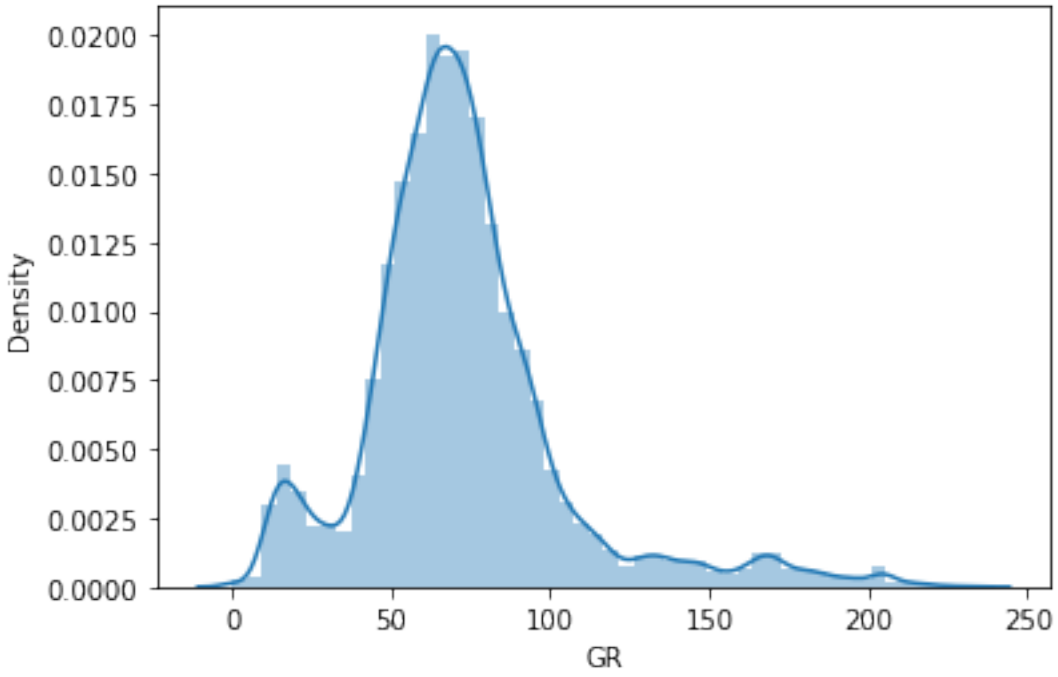
[43]:
```
<seaborn.axisgrid.FacetGrid at 0x7f6dd3946b20>
```



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

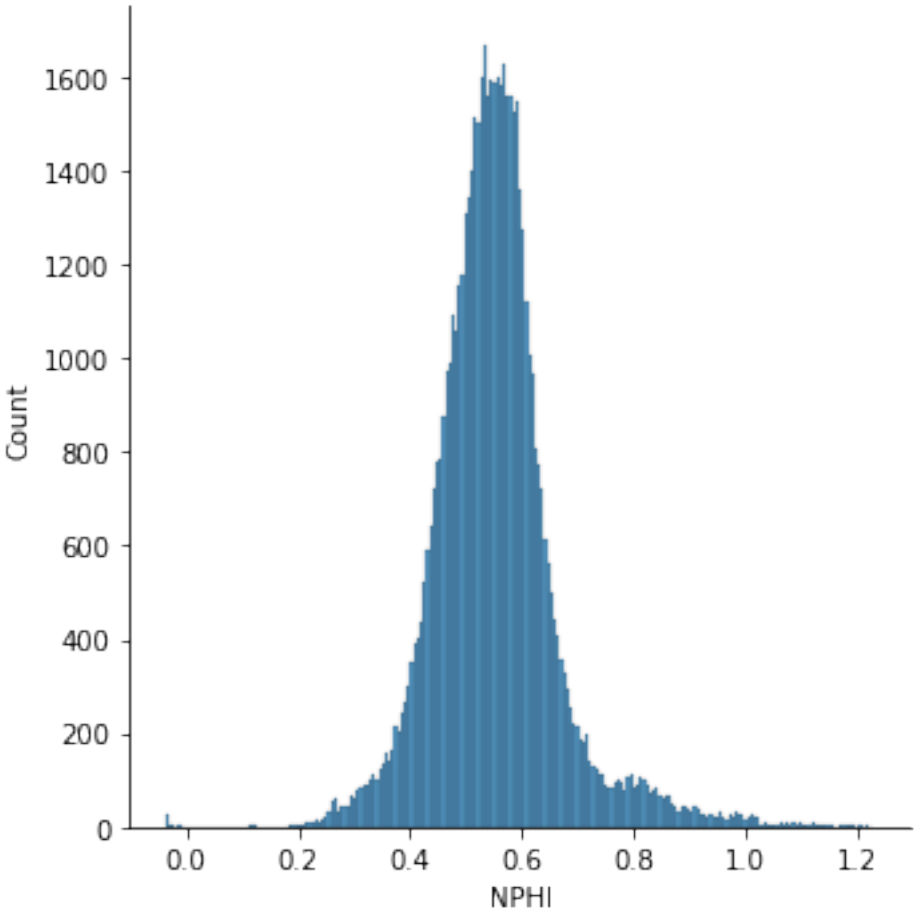
```
WHEN GR WAS NULL
```

[44]:



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

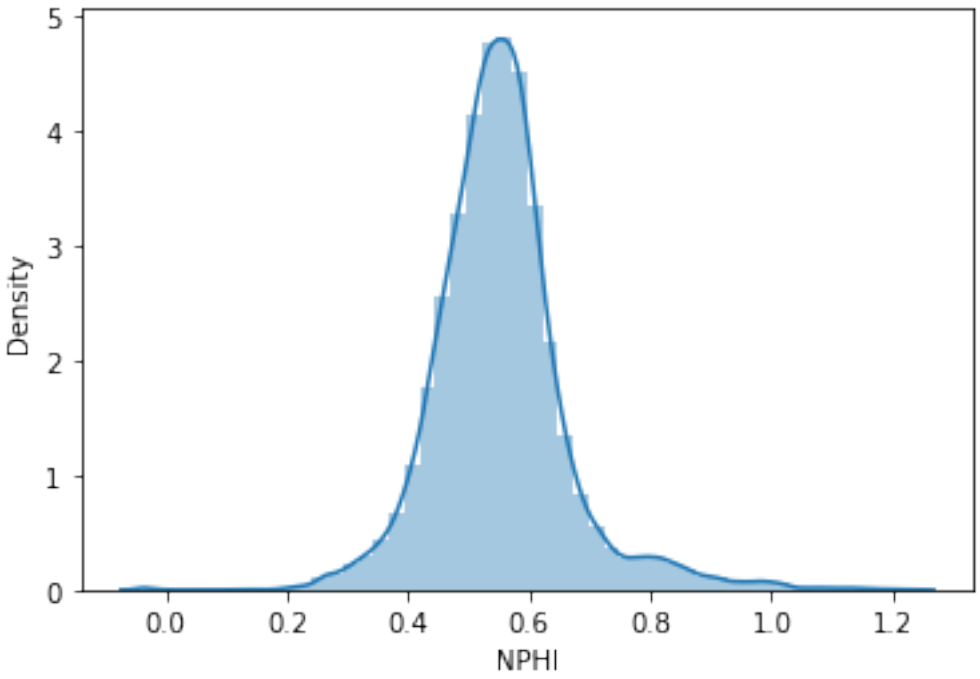
[45]:
```
<seaborn.axisgrid.FacetGrid at 0x7f6dd3cd06d0>
```



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

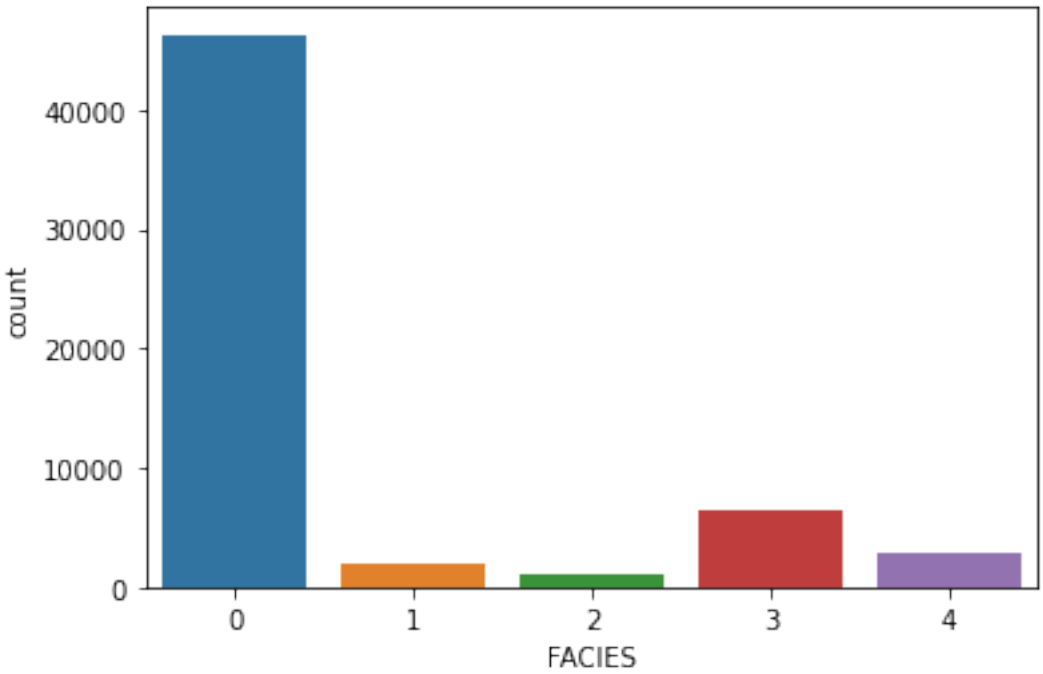
```
WHEN NPHI WAS NULL
```

[46]:



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

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



4 DATA CONDITIONING / OUTLIER REMOVAL

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

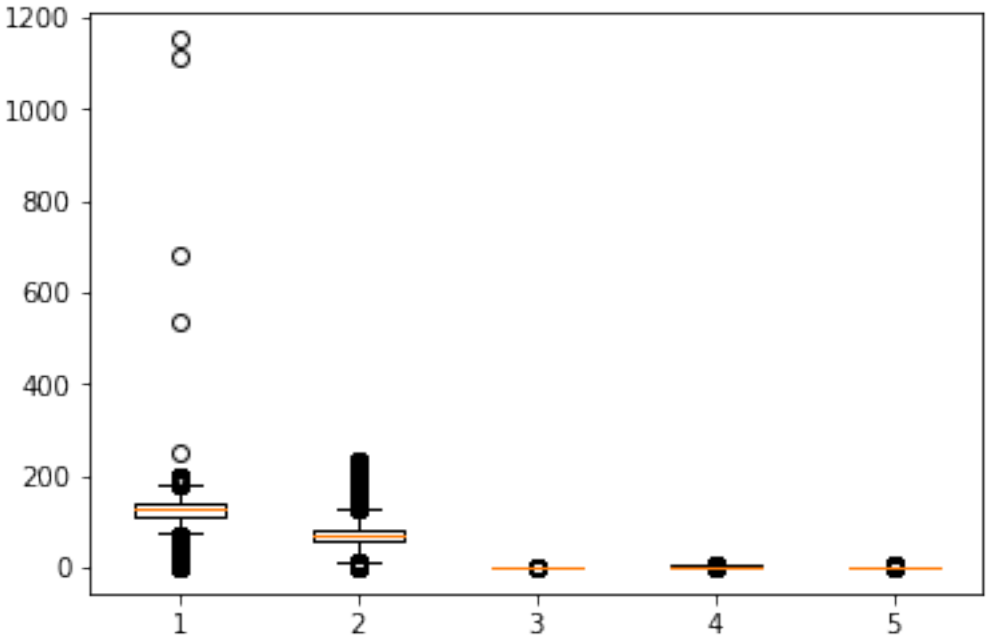
[48]:
```
<bound method NDFrame.head of              DT          GR    NPHI    RHOB
FACIES
0       50.2544   50.212800  0.5340  2.1228       2
1       50.3881   49.750900  0.5316  2.1250       3
2       49.8852   48.251300  0.5126  2.1316       3
3       49.9032   46.821200  0.5137  2.1437       3
4       50.0157   45.346300  0.5472  2.1611       3
…          …          …      …       …     …
58494  123.7404  130.872833  0.4993  2.4639       0
58495  123.8728   92.579667  0.5313  2.4660       0
58496  123.3722   81.624267  0.5448  2.4714       0
58497  122.6038  118.991767  0.5364  2.4750       0
58498  122.3045   70.033400  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 0x7f6dd365b250>,
  <matplotlib.lines.Line2D at 0x7f6dd365b5e0>,
  <matplotlib.lines.Line2D at 0x7f6dd3667bb0>,
  <matplotlib.lines.Line2D at 0x7f6dd3667f40>,
  <matplotlib.lines.Line2D at 0x7f6dd3680520>,
  <matplotlib.lines.Line2D at 0x7f6dd36808b0>,
  <matplotlib.lines.Line2D at 0x7f6dd3688e50>,
  <matplotlib.lines.Line2D at 0x7f6dd35d1220>,
  <matplotlib.lines.Line2D at 0x7f6dd35de7c0>,
  <matplotlib.lines.Line2D at 0x7f6dd35deb50>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dd365b970>,
  <matplotlib.lines.Line2D at 0x7f6dd365bd00>,
  <matplotlib.lines.Line2D at 0x7f6dd3673310>,
  <matplotlib.lines.Line2D at 0x7f6dd36736a0>,
  <matplotlib.lines.Line2D at 0x7f6dd3680c40>,
  <matplotlib.lines.Line2D at 0x7f6dd3680fd0>,
  <matplotlib.lines.Line2D at 0x7f6dd35d15b0>,
  <matplotlib.lines.Line2D at 0x7f6dd35d1940>,
  <matplotlib.lines.Line2D at 0x7f6dd35deee0>,
  <matplotlib.lines.Line2D at 0x7f6dd35ea2b0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dd370ce80>,
```

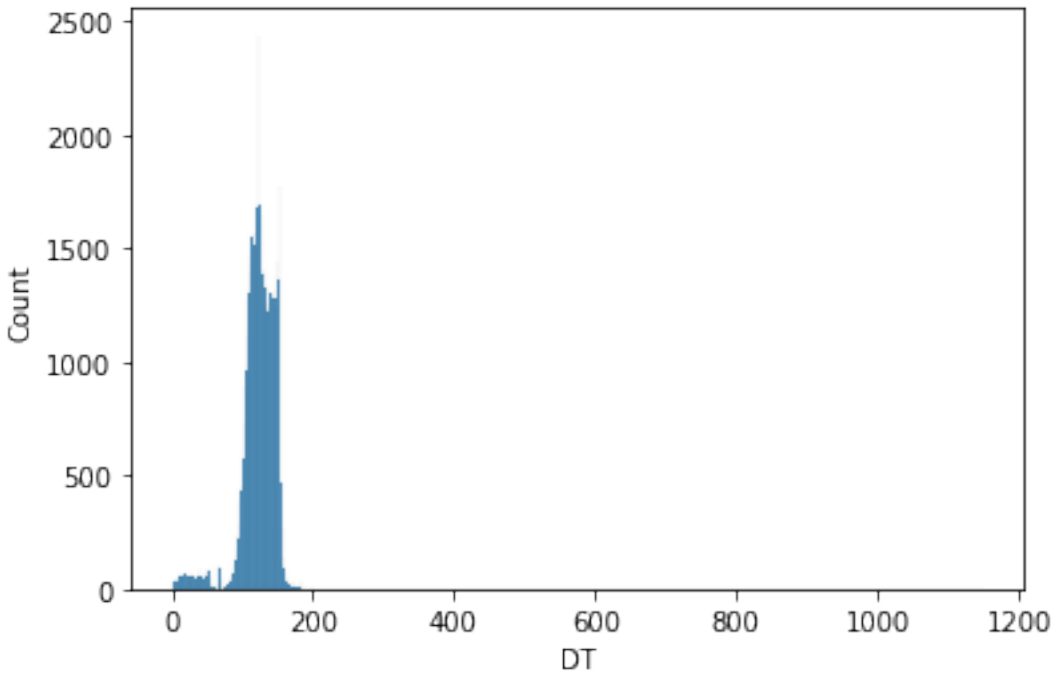
```
 <matplotlib.lines.Line2D at 0x7f6dd3667820>,
 <matplotlib.lines.Line2D at 0x7f6dd3680190>,
 <matplotlib.lines.Line2D at 0x7f6dd3688ac0>,
 <matplotlib.lines.Line2D at 0x7f6dd35de430>],
'medians': [<matplotlib.lines.Line2D at 0x7f6dd36670d0>,
 <matplotlib.lines.Line2D at 0x7f6dd3673a30>,
 <matplotlib.lines.Line2D at 0x7f6dd36883a0>,
 <matplotlib.lines.Line2D at 0x7f6dd35d1cd0>,
 <matplotlib.lines.Line2D at 0x7f6dd35ea640>],
'fliers': [<matplotlib.lines.Line2D at 0x7f6dd3667460>,
 <matplotlib.lines.Line2D at 0x7f6dd3673dc0>,
 <matplotlib.lines.Line2D at 0x7f6dd3688730>,
 <matplotlib.lines.Line2D at 0x7f6dd35de0a0>,
 <matplotlib.lines.Line2D at 0x7f6dd35eaa00>],
'means': []}
```



4.2 DT VISUALIZATION

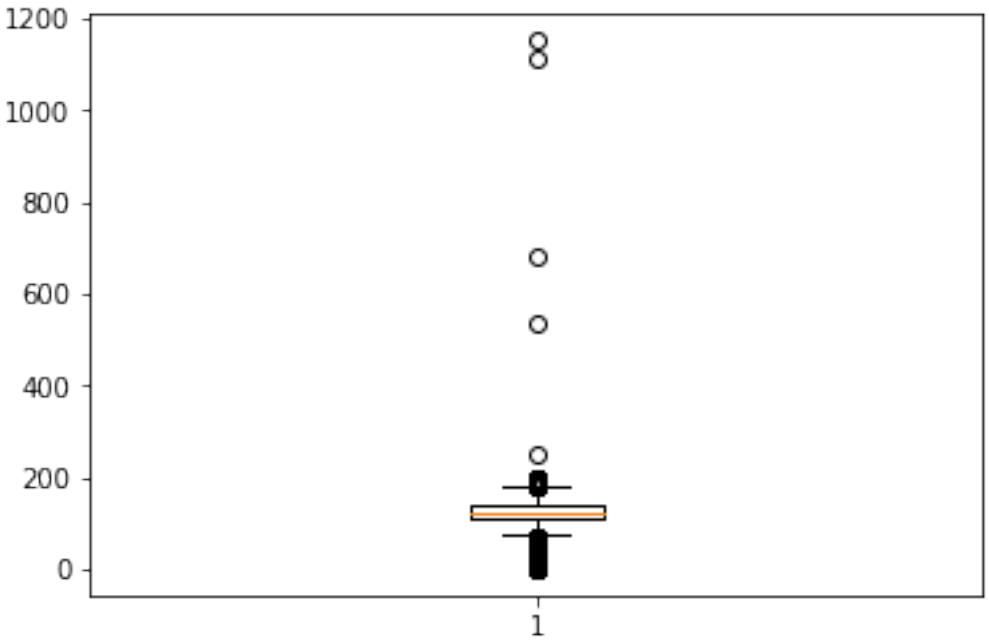
[50]:
```
sns.histplot(df.DT)
```

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



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

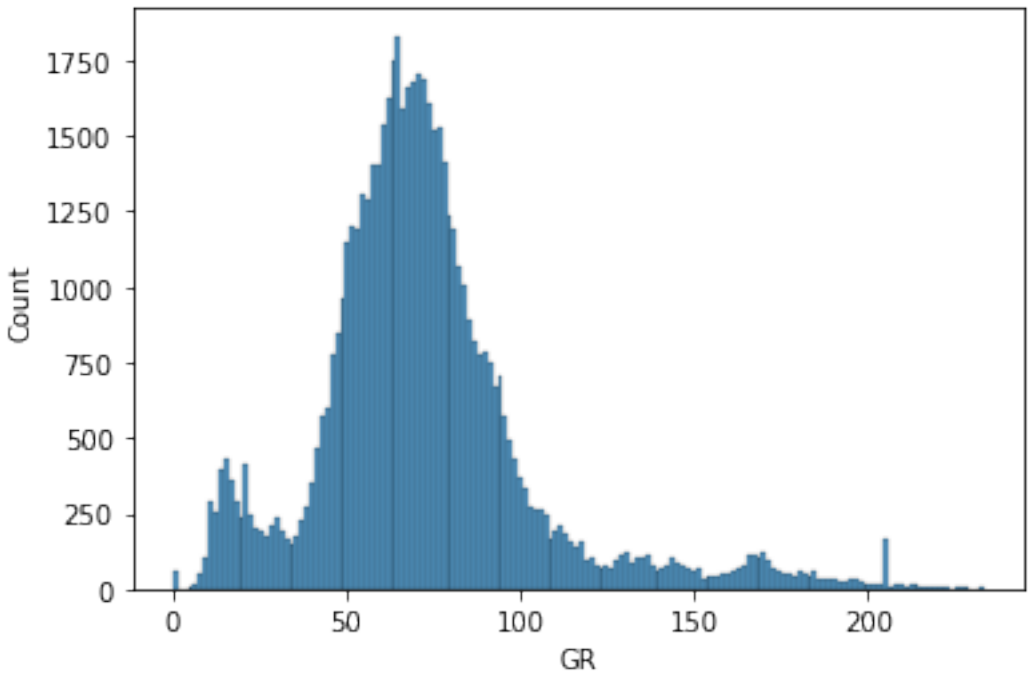
[51]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dd1e2c1c0>,
  <matplotlib.lines.Line2D at 0x7f6dd1e2c550>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dd1e2c8e0>,
  <matplotlib.lines.Line2D at 0x7f6dd1e2cc70>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dd1df0df0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dd1e06040>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dd1e063d0>],
 'means': []}
```



4.3 GR VISUALIZATION

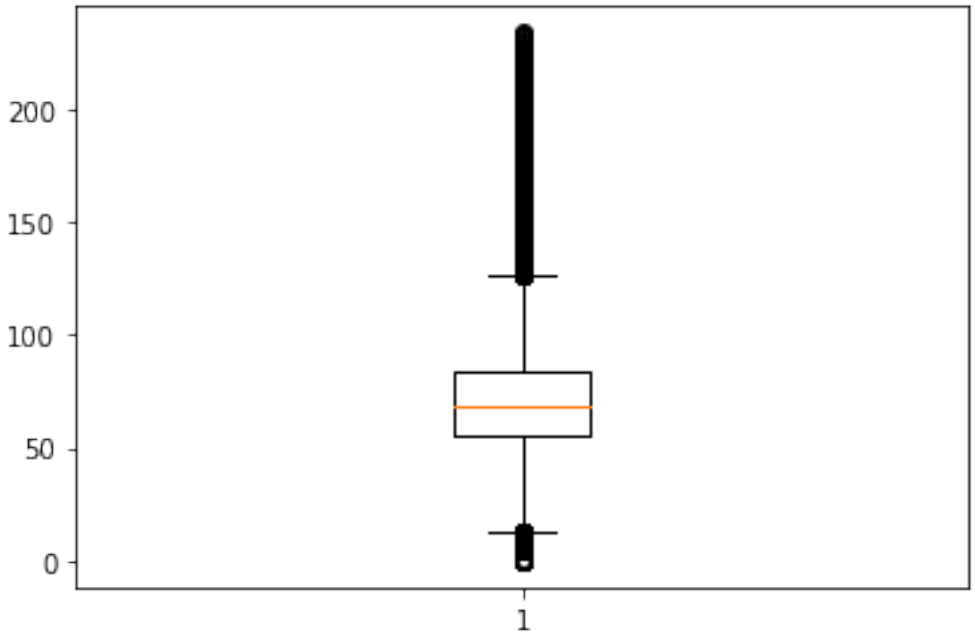
[52]:
```
sns.histplot(df.GR)
```

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



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

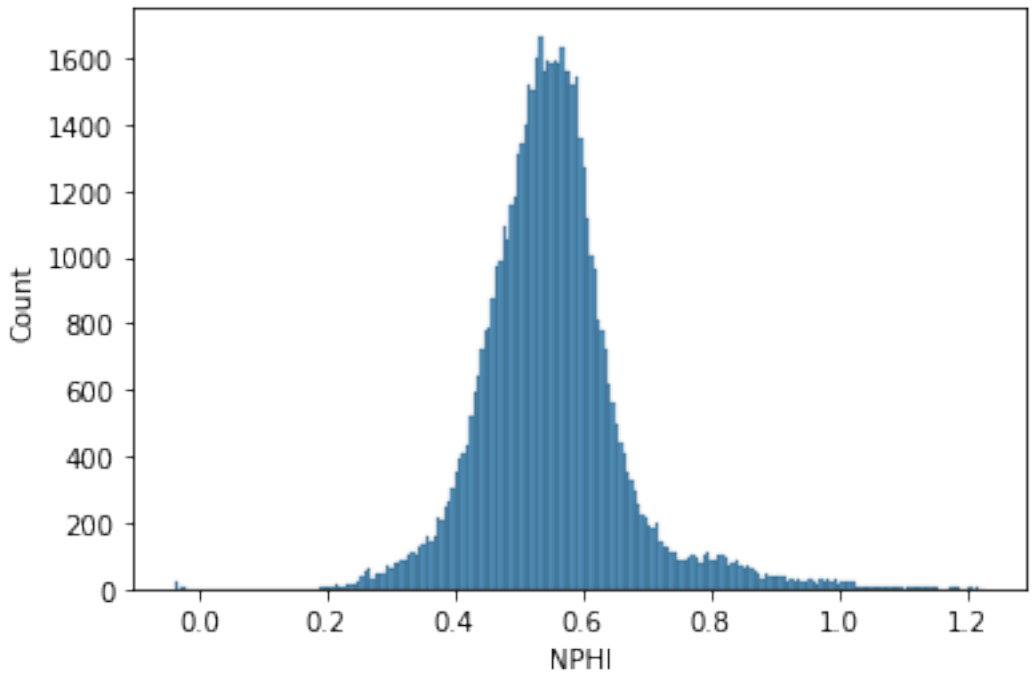
[53]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc5773550>,
  <matplotlib.lines.Line2D at 0x7f6dc57738e0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc5773c70>,
  <matplotlib.lines.Line2D at 0x7f6dc5780040>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc57731c0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc57803d0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc5780760>],
 'means': []}
```



4.4 NPHI VISUALIZATION

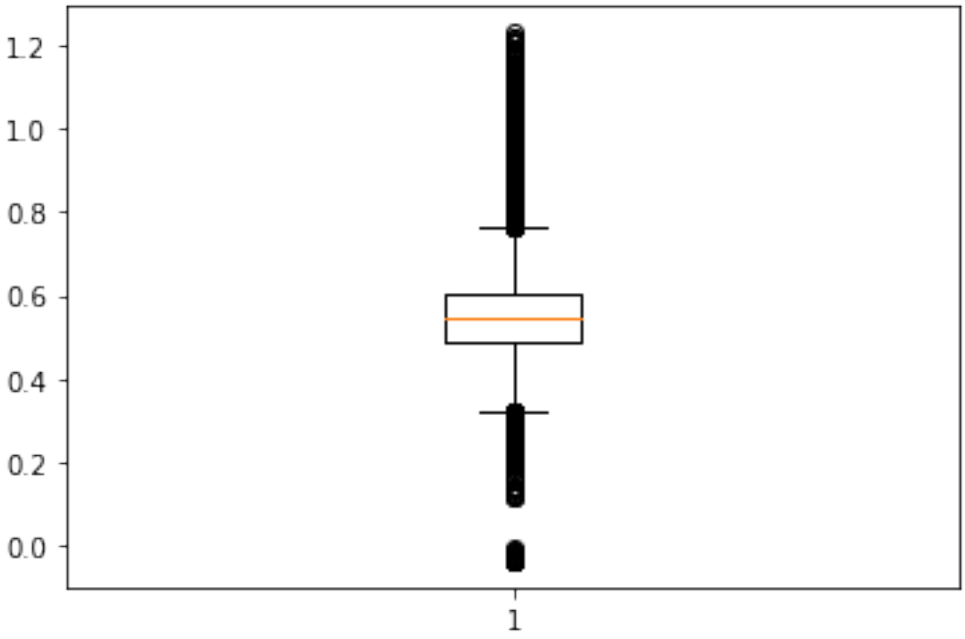
[54]:
```
sns.histplot(df.NPHI)
```

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



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

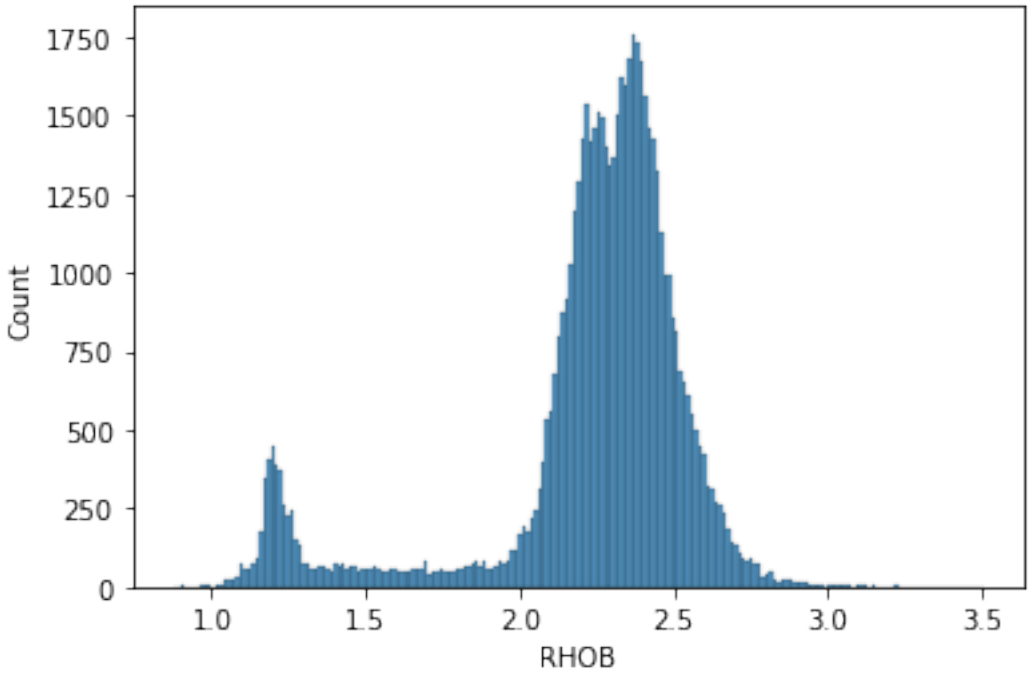
[55]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc545a400>,
  <matplotlib.lines.Line2D at 0x7f6dc545a790>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc545ab20>,
  <matplotlib.lines.Line2D at 0x7f6dc545aeb0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc545a070>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc5464280>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc5464610>],
 'means': []}
```



4.5 RHOB VISUALIZATION

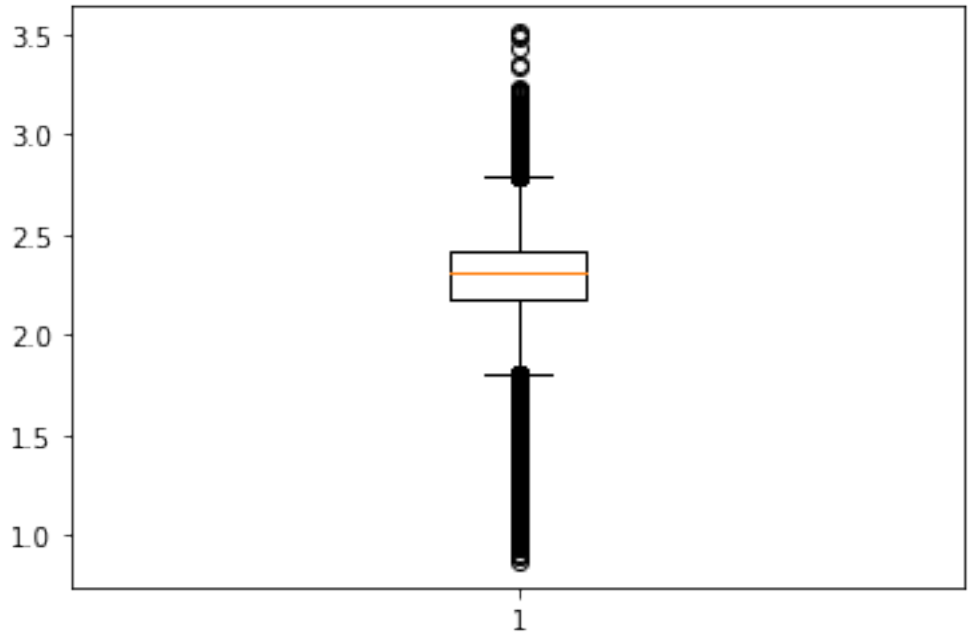
[56]:
```
sns.histplot(df.RHOB)
```

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



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

[57]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc5196430>,
  <matplotlib.lines.Line2D at 0x7f6dc51967c0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc5196b50>,
  <matplotlib.lines.Line2D at 0x7f6dc5196ee0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc51960a0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc51a02b0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc51a0640>],
 '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       2
1      50.3881  49.7509  0.5316  2.1250       3
2      49.8852  48.2513  0.5126  2.1316       3
3      49.9032  46.8212  0.5137  2.1437       3
4      50.0157  45.3463  0.5472  2.1611       3
…        …       …     …       …      …
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  130.872833  0.4993  2.4639       0
58495  123.8728   92.579667  0.5313  2.4660       0
58496  123.3722   81.624267  0.5448  2.4714       0
58497  122.6038  118.991767  0.5364  2.4750       0
58498  122.3045   70.033400  0.5331  2.4709       0

[55907 rows x 5 columns]
column GR
Percentiles: 25th=55.447, 75th=84.382, IQR=28.935
InterQuartile Range Outliers-:
             DT          GR    NPHI    RHOB  FACIES
4029   151.3950   11.621800  0.8730  1.1941       3
4030   151.2614   11.706100  0.8996  1.2056       3
4039   152.8249   11.756300  0.7718  1.1963       3
4040   152.8680   11.590300  0.7690  1.1947       3
9974   141.8031  153.032300  0.6077  2.1543       1
…         …         …     …       …      …
58180  110.9551  130.679400  0.5160  2.3705       0
58181  114.0812  131.847300  0.4959  2.3630       0
58182  115.8771  127.830000  0.4907  2.3684       0
58493  123.4216  159.013200  0.4626  2.4620       0
58494  123.7404  130.872833  0.4993  2.4639       0

[4130 rows x 5 columns]
```

```
(4130, 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
…          …         …     …     …     …
58492  123.1318   89.947733  0.4492  2.4574       0
58495  123.8728   92.579667  0.5313  2.4660       0
58496  123.3722   81.624267  0.5448  2.4714       0
58497  122.6038  118.991767  0.5364  2.4750       0
58498  122.3045   70.033400  0.5331  2.4709       0

[51777 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

[2890 rows x 5 columns]
(2890, 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
…          …         …     …     …     …
58492  123.1318   89.947733  0.4492  2.4574       0
58495  123.8728   92.579667  0.5313  2.4660       0
58496  123.3722   81.624267  0.5448  2.4714       0
58497  122.6038  118.991767  0.5364  2.4750       0
58498  122.3045   70.033400  0.5331  2.4709       0

[48887 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  58.763333  0.4365  2.7816       0
58478   92.1297  55.115400  0.4509  2.8974       0
58479   92.0023  58.263400  0.4585  2.7846       0

[3505 rows x 5 columns]
(3505, 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
…           …          …      …       …     …
58492  123.1318   89.947733  0.4492  2.4574       0
58495  123.8728   92.579667  0.5313  2.4660       0
58496  123.3722   81.624267  0.5448  2.4714       0
58497  122.6038  118.991767  0.5364  2.4750       0
58498  122.3045   70.033400  0.5331  2.4709       0

[45382 rows x 5 columns]
```

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

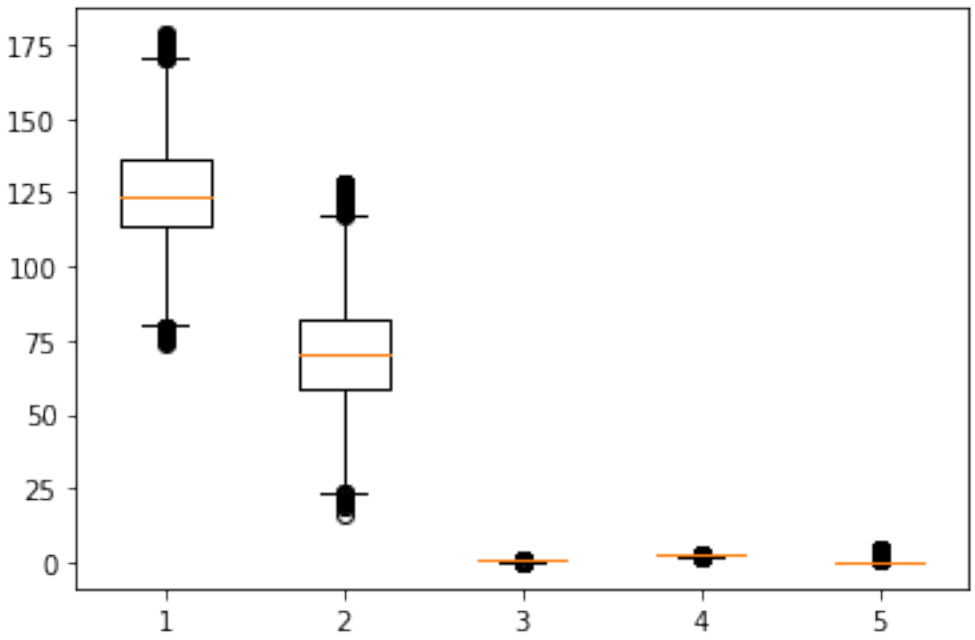
[60]:
```
(45382, 5)
```

4.6 WHOLE DATA AFTER REMOVING OUTLIERS

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

[61]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc517bcd0>,
  <matplotlib.lines.Line2D at 0x7f6dc4d4a0a0>,
  <matplotlib.lines.Line2D at 0x7f6dc4d56670>,
  <matplotlib.lines.Line2D at 0x7f6dc4d56a00>,
  <matplotlib.lines.Line2D at 0x7f6dc4d61fa0>,
  <matplotlib.lines.Line2D at 0x7f6dc4d6c370>,
  <matplotlib.lines.Line2D at 0x7f6dc4d76910>,
  <matplotlib.lines.Line2D at 0x7f6dc4d76ca0>,
```

```
 <matplotlib.lines.Line2D at 0x7f6dc510d280>,
 <matplotlib.lines.Line2D at 0x7f6dc510d610>],
'caps': [<matplotlib.lines.Line2D at 0x7f6dc4d4a460>,
 <matplotlib.lines.Line2D at 0x7f6dc4d4a7f0>,
 <matplotlib.lines.Line2D at 0x7f6dc4d56d90>,
 <matplotlib.lines.Line2D at 0x7f6dc4d61160>,
 <matplotlib.lines.Line2D at 0x7f6dc4d6c700>,
 <matplotlib.lines.Line2D at 0x7f6dc4d6ca90>,
 <matplotlib.lines.Line2D at 0x7f6dc4d81070>,
 <matplotlib.lines.Line2D at 0x7f6dc4d81400>,
 <matplotlib.lines.Line2D at 0x7f6dc510d9a0>,
 <matplotlib.lines.Line2D at 0x7f6dc510dd30>],
'boxes': [<matplotlib.lines.Line2D at 0x7f6dc517b910>,
 <matplotlib.lines.Line2D at 0x7f6dc4d562e0>,
 <matplotlib.lines.Line2D at 0x7f6dc4d61c10>,
 <matplotlib.lines.Line2D at 0x7f6dc4d76580>,
 <matplotlib.lines.Line2D at 0x7f6dc4d81eb0>],
'medians': [<matplotlib.lines.Line2D at 0x7f6dc4d4ab80>,
 <matplotlib.lines.Line2D at 0x7f6dc4d614f0>,
 <matplotlib.lines.Line2D at 0x7f6dc4d6ce20>,
 <matplotlib.lines.Line2D at 0x7f6dc4d81790>,
 <matplotlib.lines.Line2D at 0x7f6dc5116100>],
'fliers': [<matplotlib.lines.Line2D at 0x7f6dc4d4af10>,
 <matplotlib.lines.Line2D at 0x7f6dc4d61880>,
 <matplotlib.lines.Line2D at 0x7f6dc4d761f0>,
 <matplotlib.lines.Line2D at 0x7f6dc4d81b20>,
 <matplotlib.lines.Line2D at 0x7f6dc5116490>],
'means': []}
```



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

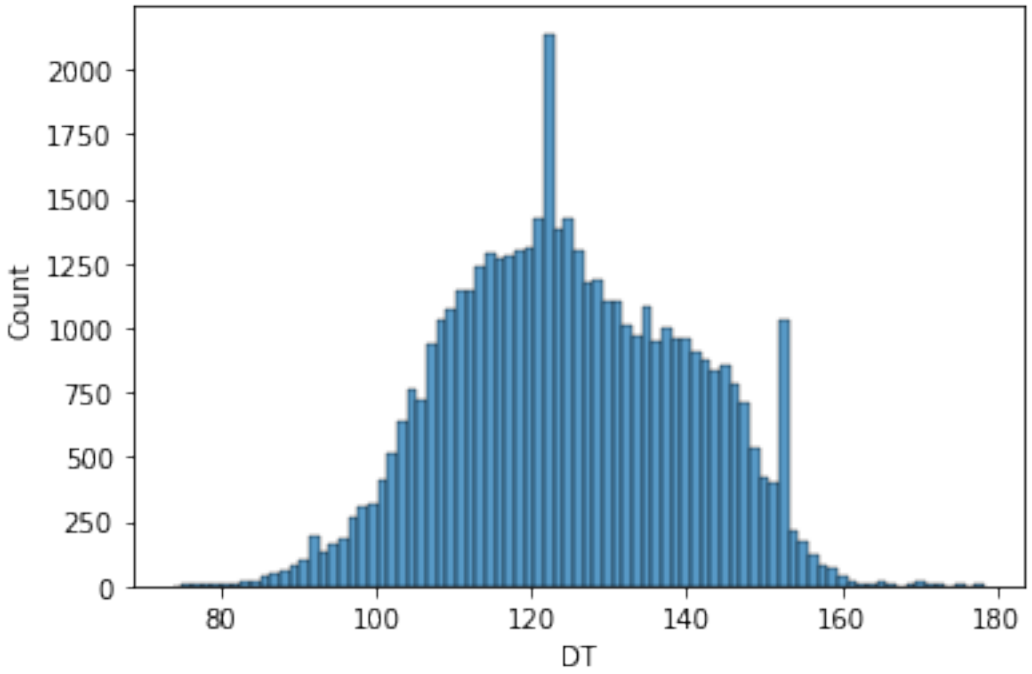
[62]:

	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)
```

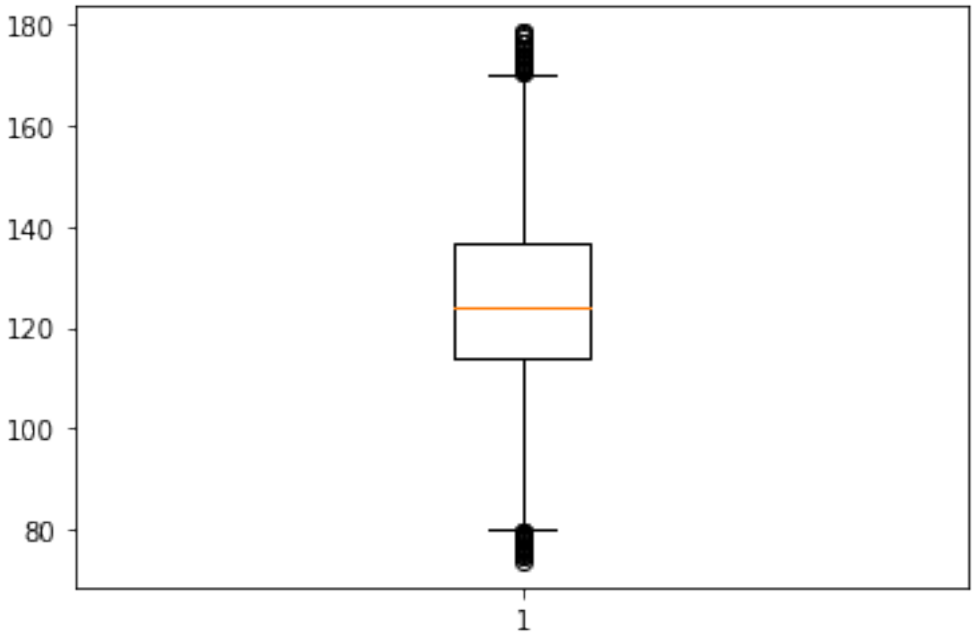
[63]:
```
<AxesSubplot:xlabel='DT', ylabel='Count'>
```



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

[64]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc5013a90>,
  <matplotlib.lines.Line2D at 0x7f6dc5013e20>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc50211f0>,
  <matplotlib.lines.Line2D at 0x7f6dc5021580>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc5013700>],
```

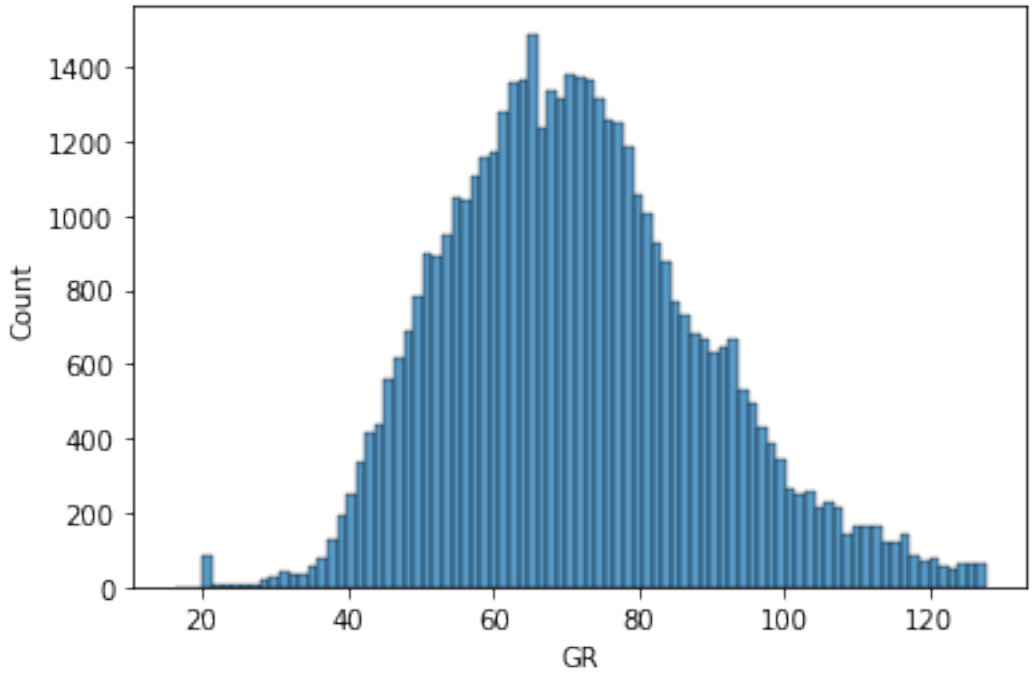
```
'medians': [<matplotlib.lines.Line2D at 0x7f6dc5021910>],
'fliers': [<matplotlib.lines.Line2D at 0x7f6dc5021ca0>],
'means': []}
```



4.8 GR AFTER REMOVING OUTLIER

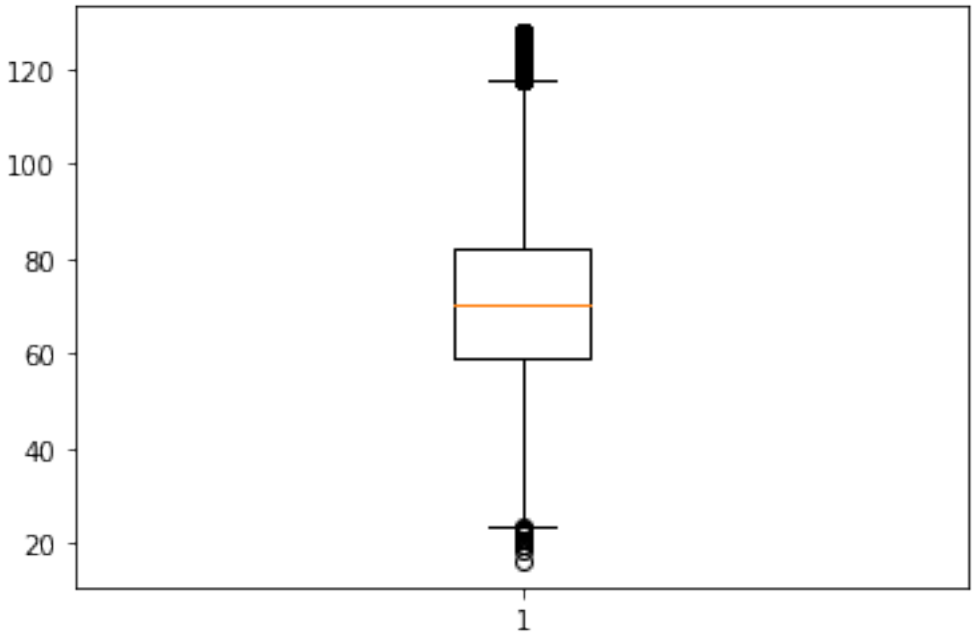
[65]:
```
sns.histplot(df.GR)
```

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



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

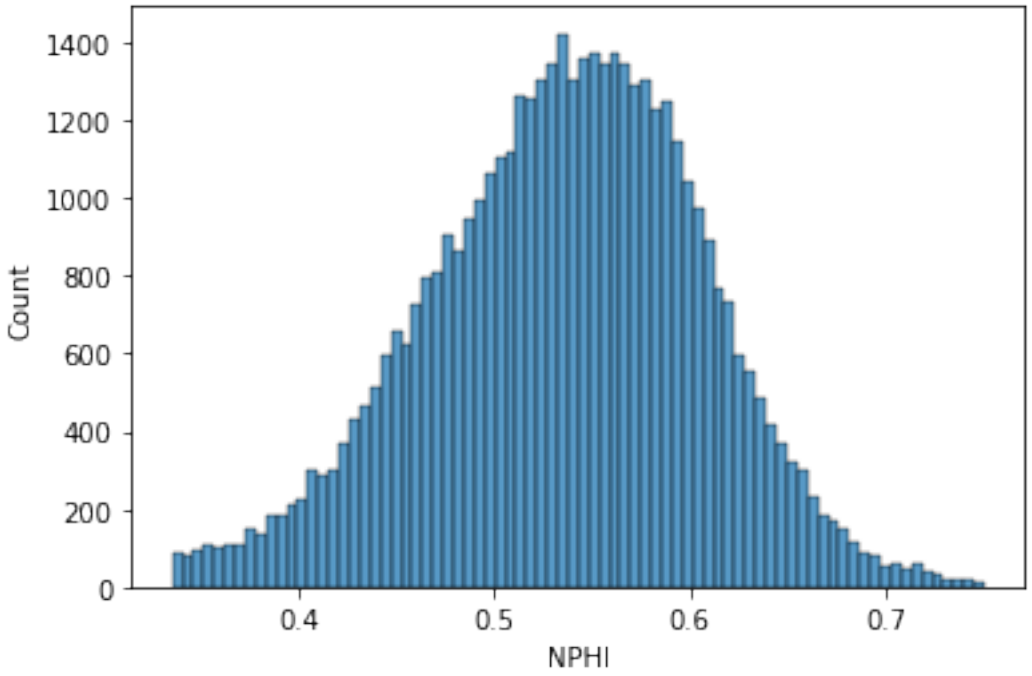
[66]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc4e98490>,
  <matplotlib.lines.Line2D at 0x7f6dc4e98820>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc4e98bb0>,
  <matplotlib.lines.Line2D at 0x7f6dc4e98f40>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc4e98100>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc4ea2310>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc4ea26a0>],
 'means': []}
```



4.9 NPHI AFTER REMOVING OUTLIER

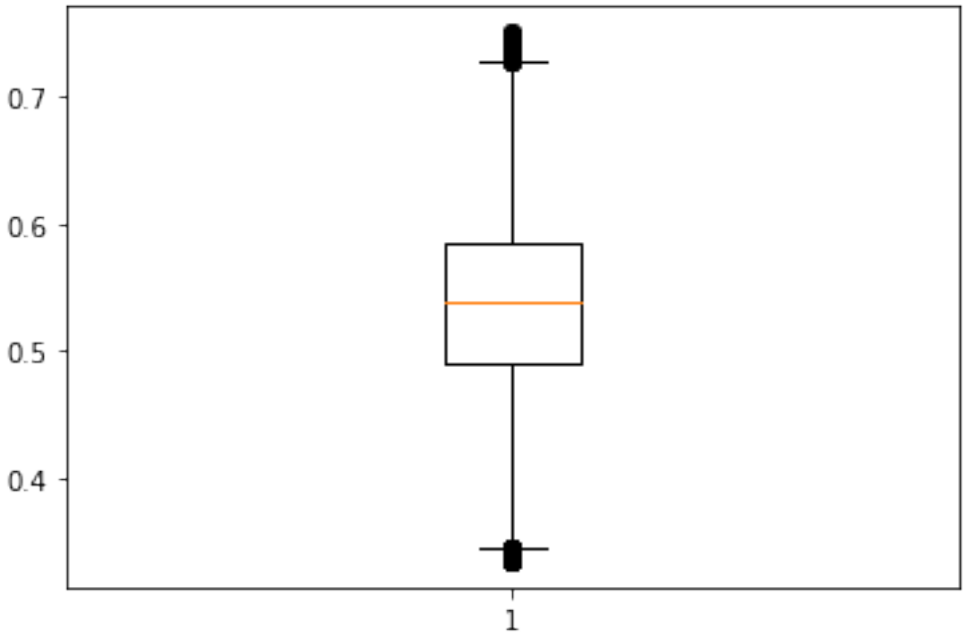
[67]:
```
sns.histplot(df.NPHI)
```

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



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

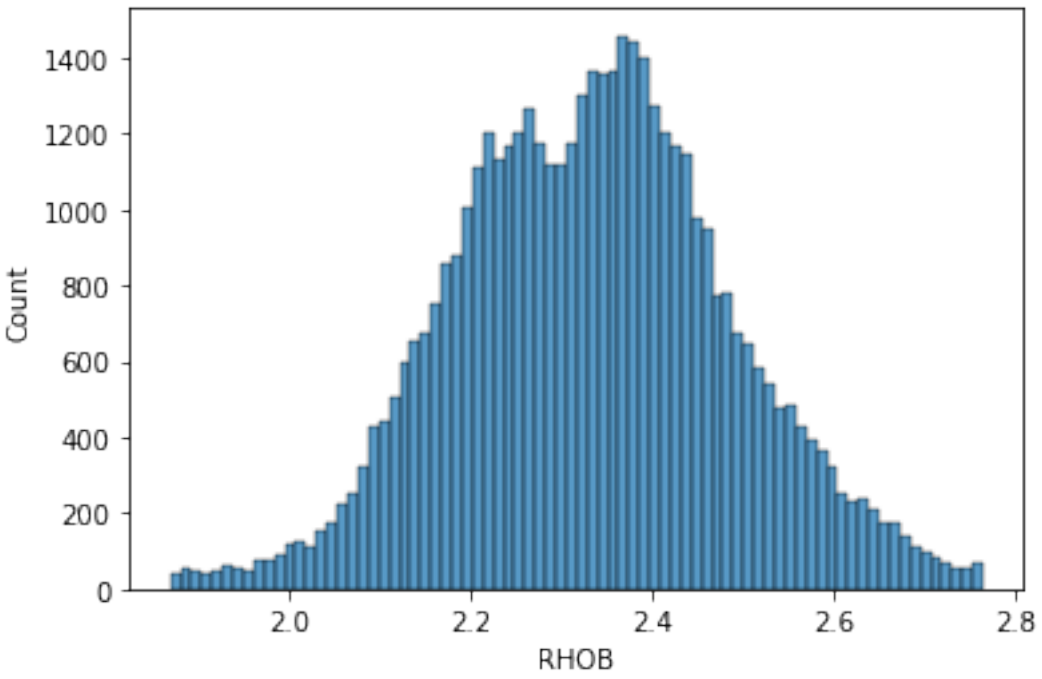
[68]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc4d380a0>,
  <matplotlib.lines.Line2D at 0x7f6dc4d38430>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc4d387c0>,
  <matplotlib.lines.Line2D at 0x7f6dc4d38b50>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc4d2acd0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc4d38ee0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc4d432b0>],
 'means': []}
```



4.10 RHOB AFTER REMOVING OUTLIER

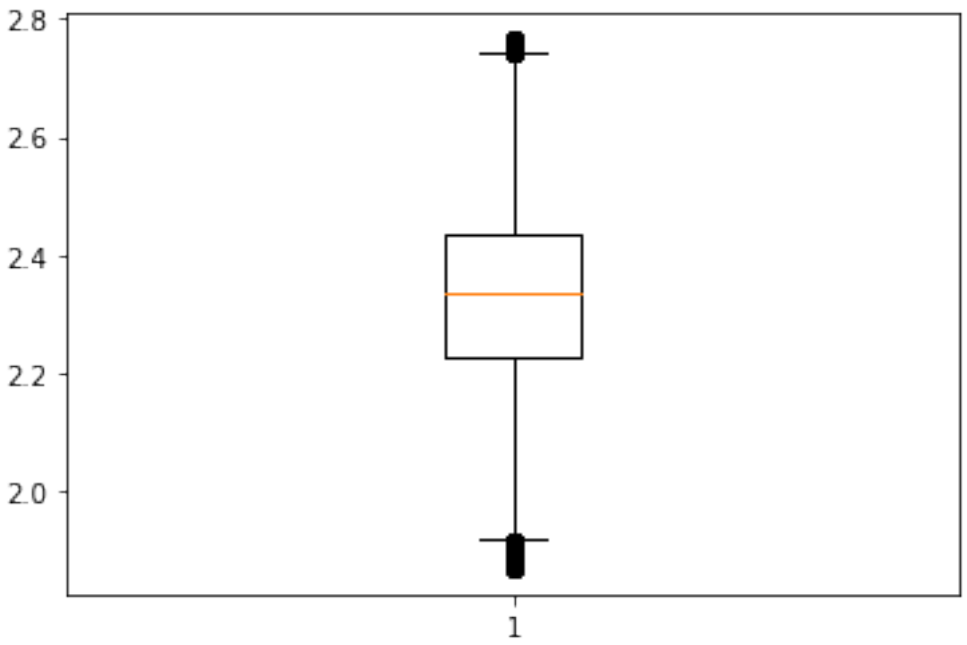
[69]:
```
sns.histplot(df.RHOB)
```

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



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

[70]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f6dc4b56a60>,
  <matplotlib.lines.Line2D at 0x7f6dc4b56df0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f6dc4b651c0>,
  <matplotlib.lines.Line2D at 0x7f6dc4b65550>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f6dc4b566d0>],
 'medians': [<matplotlib.lines.Line2D at 0x7f6dc4b658e0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f6dc4b65c70>],
 '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
…	…	…	…	…	…
58492	123.1318	89.947733	0.4492	2.4574	0
58495	123.8728	92.579667	0.5313	2.4660	0
58496	123.3722	81.624267	0.5448	2.4714	0
58497	122.6038	118.991767	0.5364	2.4750	0
58498	122.3045	70.033400	0.5331	2.4709	0

[45382 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]:
```
(45382, 5)
```

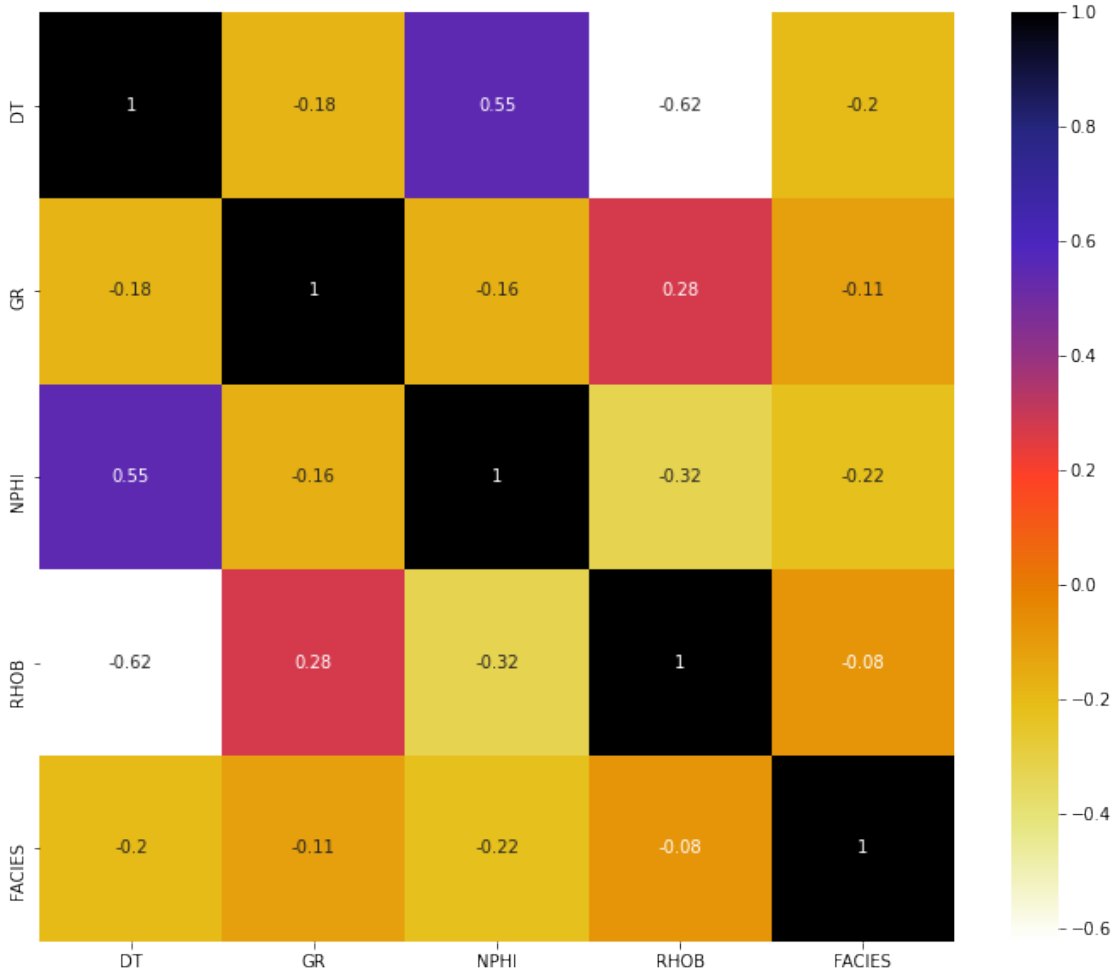
[74]:
```
features = df.shape[1]
features
```

[74]:
```
5
```

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

[75]:
```
DT        230.983102
GR        313.280377
NPHI        0.004941
RHOB        0.023272
FACIES      1.045660
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
…	…	…	…	…	…
58492	123.1318	89.947733	0.4492	2.4574	0
58495	123.8728	92.579667	0.5313	2.4660	0
58496	123.3722	81.624267	0.5448	2.4714	0
58497	122.6038	118.991767	0.5364	2.4750	0
58498	122.3045	70.033400	0.5331	2.4709	0

[45382 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   -2.124306 -0.959885 -0.908473  0.465409       0
219   -2.108481 -0.987369 -0.921025  0.513304       0
2250   0.615641 -0.379246  0.259937 -0.723270       0
2251   0.694378 -0.350878  0.226464 -0.769231       0
2252   0.713445 -0.286145  0.246339 -0.680213       0
…           …        …        …        …      …
58492 -0.033240  0.836880 -0.944038  0.591195       0
58495 -0.000475  0.948717 -0.085251  0.632801       0
58496 -0.022611  0.483197  0.055962  0.658926       0
58497 -0.056587  2.071027 -0.031904  0.676343       0
58498 -0.069821 -0.009325 -0.066423  0.656507       0

[45382 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 -2.124306 -0.959885 -0.908473  0.465409       0
1 -2.108481 -0.987369 -0.921025  0.513304       0
2  0.615641 -0.379246  0.259937 -0.723270       0
3  0.694378 -0.350878  0.226464 -0.769231       0
4  0.713445 -0.286145  0.246339 -0.680213       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]:
```
(31767, 4)
```

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

[90]:
```
(13615, 4)
```

[91]:
```
X_test
```

[91]:
```
             DT        GR      NPHI      RHOB
12426 -0.611997 -0.279801 -0.782950  0.364780
28889 -0.518721  1.098954  0.212866  0.943396
44033  0.491306  0.855792  0.134414  0.009192
8745   0.909116 -0.408790  0.718096 -1.192066
39849  0.403486  0.645060 -1.158473 -0.006773
…           …         …         …         …
23183  0.601655 -0.980226  0.178347 -0.124819
38398  0.257383  0.658645 -0.575837 -0.701500
1059  -0.679521 -0.525126 -1.781904 -0.685535
9662  -0.573669  0.135718  0.109310  0.110789
6669  -0.613257  1.159616  1.119770  0.870827

[13615 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: 0.889057 using {'C': 1.0, 'penalty': 'l2', 'solver': 'lbfgs'}
0.889025 (0.002086) with: {'C': 100, 'penalty': 'l2', 'solver': 'newton-cg'}
0.889025 (0.002086) with: {'C': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
0.887756 (0.001713) with: {'C': 100, 'penalty': 'l2', 'solver': 'liblinear'}
0.889025 (0.002086) with: {'C': 10, 'penalty': 'l2', 'solver': 'newton-cg'}
0.889025 (0.002086) with: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
0.887777 (0.001705) with: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}
0.889046 (0.002072) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'newton-cg'}
0.889057 (0.002075) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'lbfgs'}
0.887840 (0.001744) with: {'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}
0.888889 (0.002038) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'newton-cg'}
0.888889 (0.002038) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'lbfgs'}
0.887871 (0.001592) with: {'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'}
0.888490 (0.001355) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'newton-cg'}
0.888490 (0.001355) with: {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
0.887252 (0.001042) 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]:
```
#neigh = KNeighborsClassifier(n_neighbors=3)
```

[100]:
```
rdmclf = RandomForestClassifier(n_estimators=494,max_depth=5)
```

[101]:
```
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))
#estimator.append(('KNN',neigh))
```

[102]:
```
vot_soft = VotingClassifier(estimators = estimator, voting ='soft')
```

[103]:
```
vot_soft.fit(X_train,y_train)
```

```
Learning rate set to 0.09439
0:      learn: 1.3367956        total: 56.8ms   remaining: 56.7s
1:      learn: 1.1602766        total: 63.3ms   remaining: 31.6s
2:      learn: 1.0298253        total: 69.4ms   remaining: 23.1s
3:      learn: 0.9292459        total: 75.5ms   remaining: 18.8s
4:      learn: 0.8483811        total: 82.5ms   remaining: 16.4s
5:      learn: 0.7831321        total: 88.3ms   remaining: 14.6s
6:      learn: 0.7299435        total: 95.2ms   remaining: 13.5s
7:      learn: 0.6829198        total: 101ms    remaining: 12.6s
8:      learn: 0.6439571        total: 108ms    remaining: 11.9s
9:      learn: 0.6095197        total: 114ms    remaining: 11.3s
10:     learn: 0.5801260        total: 120ms    remaining: 10.8s
11:     learn: 0.5552812        total: 127ms    remaining: 10.4s
12:     learn: 0.5327087        total: 133ms    remaining: 10.1s
13:     learn: 0.5132747        total: 140ms    remaining: 9.89s
14:     learn: 0.4964109        total: 146ms    remaining: 9.61s
15:     learn: 0.4805574        total: 152ms    remaining: 9.38s
16:     learn: 0.4666538        total: 159ms    remaining: 9.19s
17:     learn: 0.4543748        total: 165ms    remaining: 8.99s
18:     learn: 0.4441595        total: 171ms    remaining: 8.82s
19:     learn: 0.4347972        total: 178ms    remaining: 8.7s
20:     learn: 0.4261594        total: 183ms    remaining: 8.55s
21:     learn: 0.4186246        total: 190ms    remaining: 8.43s
22:     learn: 0.4120922        total: 197ms    remaining: 8.36s
23:     learn: 0.4052560        total: 203ms    remaining: 8.27s
24:     learn: 0.3997226        total: 210ms    remaining: 8.19s
25:     learn: 0.3944293        total: 216ms    remaining: 8.11s
26:     learn: 0.3894524        total: 223ms    remaining: 8.04s
27:     learn: 0.3849400        total: 230ms    remaining: 7.99s
28:     learn: 0.3806713        total: 237ms    remaining: 7.94s
29:     learn: 0.3770841        total: 244ms    remaining: 7.87s
30:     learn: 0.3745258        total: 250ms    remaining: 7.81s
31:     learn: 0.3719056        total: 256ms    remaining: 7.75s
32:     learn: 0.3690093        total: 263ms    remaining: 7.7s
33:     learn: 0.3663647        total: 269ms    remaining: 7.65s
34:     learn: 0.3638133        total: 278ms    remaining: 7.66s
35:     learn: 0.3615098        total: 285ms    remaining: 7.64s
36:     learn: 0.3595725        total: 292ms    remaining: 7.61s
37:     learn: 0.3583474        total: 301ms    remaining: 7.63s
```

```
38:     learn: 0.3568645        total: 309ms    remaining: 7.6s
39:     learn: 0.3553813        total: 315ms    remaining: 7.56s
40:     learn: 0.3538665        total: 322ms    remaining: 7.52s
41:     learn: 0.3522937        total: 329ms    remaining: 7.51s
42:     learn: 0.3510341        total: 336ms    remaining: 7.48s
43:     learn: 0.3497485        total: 342ms    remaining: 7.43s
44:     learn: 0.3488629        total: 349ms    remaining: 7.4s
45:     learn: 0.3478060        total: 355ms    remaining: 7.36s
46:     learn: 0.3469715        total: 362ms    remaining: 7.33s
47:     learn: 0.3457592        total: 368ms    remaining: 7.3s
48:     learn: 0.3443386        total: 375ms    remaining: 7.28s
49:     learn: 0.3434576        total: 382ms    remaining: 7.26s
50:     learn: 0.3425910        total: 388ms    remaining: 7.22s
51:     learn: 0.3414779        total: 399ms    remaining: 7.27s
52:     learn: 0.3405872        total: 406ms    remaining: 7.25s
53:     learn: 0.3399649        total: 413ms    remaining: 7.23s
54:     learn: 0.3390589        total: 419ms    remaining: 7.2s
55:     learn: 0.3386036        total: 426ms    remaining: 7.17s
56:     learn: 0.3374969        total: 433ms    remaining: 7.17s
57:     learn: 0.3370021        total: 441ms    remaining: 7.16s
58:     learn: 0.3362960        total: 448ms    remaining: 7.14s
59:     learn: 0.3358938        total: 455ms    remaining: 7.12s
60:     learn: 0.3350114        total: 461ms    remaining: 7.1s
61:     learn: 0.3342788        total: 467ms    remaining: 7.07s
62:     learn: 0.3336403        total: 475ms    remaining: 7.06s
63:     learn: 0.3330846        total: 480ms    remaining: 7.03s
64:     learn: 0.3325209        total: 487ms    remaining: 7.01s
65:     learn: 0.3320510        total: 494ms    remaining: 6.99s
66:     learn: 0.3316196        total: 501ms    remaining: 6.98s
67:     learn: 0.3311977        total: 507ms    remaining: 6.95s
68:     learn: 0.3304369        total: 513ms    remaining: 6.93s
69:     learn: 0.3299930        total: 521ms    remaining: 6.92s
70:     learn: 0.3294389        total: 527ms    remaining: 6.89s
71:     learn: 0.3290934        total: 533ms    remaining: 6.87s
72:     learn: 0.3284825        total: 539ms    remaining: 6.85s
73:     learn: 0.3280491        total: 545ms    remaining: 6.82s
74:     learn: 0.3277599        total: 553ms    remaining: 6.82s
75:     learn: 0.3271653        total: 559ms    remaining: 6.79s
76:     learn: 0.3266328        total: 566ms    remaining: 6.78s
77:     learn: 0.3261874        total: 572ms    remaining: 6.76s
78:     learn: 0.3258351        total: 579ms    remaining: 6.75s
79:     learn: 0.3252825        total: 586ms    remaining: 6.74s
80:     learn: 0.3250073        total: 593ms    remaining: 6.72s
81:     learn: 0.3246601        total: 600ms    remaining: 6.71s
82:     learn: 0.3242268        total: 606ms    remaining: 6.7s
83:     learn: 0.3237858        total: 613ms    remaining: 6.68s
84:     learn: 0.3234897        total: 622ms    remaining: 6.69s
85:     learn: 0.3231829        total: 629ms    remaining: 6.68s
```

```
86:     learn: 0.3229708        total: 635ms    remaining: 6.67s
87:     learn: 0.3226775        total: 641ms    remaining: 6.65s
88:     learn: 0.3222597        total: 648ms    remaining: 6.64s
89:     learn: 0.3219338        total: 655ms    remaining: 6.62s
90:     learn: 0.3215500        total: 664ms    remaining: 6.64s
91:     learn: 0.3211525        total: 671ms    remaining: 6.62s
92:     learn: 0.3204700        total: 678ms    remaining: 6.61s
93:     learn: 0.3203048        total: 684ms    remaining: 6.6s
94:     learn: 0.3200545        total: 692ms    remaining: 6.59s
95:     learn: 0.3197951        total: 697ms    remaining: 6.57s
96:     learn: 0.3194174        total: 704ms    remaining: 6.55s
97:     learn: 0.3191680        total: 710ms    remaining: 6.54s
98:     learn: 0.3188592        total: 717ms    remaining: 6.52s
99:     learn: 0.3183763        total: 724ms    remaining: 6.51s
100:    learn: 0.3180059        total: 730ms    remaining: 6.49s
101:    learn: 0.3178073        total: 737ms    remaining: 6.49s
102:    learn: 0.3175562        total: 743ms    remaining: 6.47s
103:    learn: 0.3172459        total: 750ms    remaining: 6.46s
104:    learn: 0.3169708        total: 756ms    remaining: 6.45s
105:    learn: 0.3165167        total: 763ms    remaining: 6.44s
106:    learn: 0.3162868        total: 772ms    remaining: 6.45s
107:    learn: 0.3159375        total: 779ms    remaining: 6.44s
108:    learn: 0.3157671        total: 787ms    remaining: 6.43s
109:    learn: 0.3155149        total: 794ms    remaining: 6.43s
110:    learn: 0.3152318        total: 803ms    remaining: 6.43s
111:    learn: 0.3150669        total: 809ms    remaining: 6.42s
112:    learn: 0.3147893        total: 817ms    remaining: 6.41s
113:    learn: 0.3145836        total: 823ms    remaining: 6.4s
114:    learn: 0.3143425        total: 829ms    remaining: 6.38s
115:    learn: 0.3141059        total: 836ms    remaining: 6.37s
116:    learn: 0.3138628        total: 843ms    remaining: 6.36s
117:    learn: 0.3135587        total: 850ms    remaining: 6.35s
118:    learn: 0.3133880        total: 856ms    remaining: 6.33s
119:    learn: 0.3130235        total: 862ms    remaining: 6.32s
120:    learn: 0.3127985        total: 869ms    remaining: 6.31s
121:    learn: 0.3124523        total: 876ms    remaining: 6.3s
122:    learn: 0.3122157        total: 883ms    remaining: 6.29s
123:    learn: 0.3119864        total: 889ms    remaining: 6.28s
124:    learn: 0.3116617        total: 896ms    remaining: 6.27s
125:    learn: 0.3113634        total: 902ms    remaining: 6.26s
126:    learn: 0.3111308        total: 909ms    remaining: 6.25s
127:    learn: 0.3109688        total: 915ms    remaining: 6.23s
128:    learn: 0.3105632        total: 921ms    remaining: 6.22s
129:    learn: 0.3102893        total: 928ms    remaining: 6.21s
130:    learn: 0.3101044        total: 934ms    remaining: 6.2s
131:    learn: 0.3097649        total: 941ms    remaining: 6.19s
132:    learn: 0.3093394        total: 948ms    remaining: 6.18s
133:    learn: 0.3090570        total: 954ms    remaining: 6.17s
```

```
134:    learn: 0.3088196        total: 962ms    remaining: 6.16s
135:    learn: 0.3086459        total: 971ms    remaining: 6.17s
136:    learn: 0.3083507        total: 978ms    remaining: 6.16s
137:    learn: 0.3081912        total: 984ms    remaining: 6.15s
138:    learn: 0.3080075        total: 994ms    remaining: 6.15s
139:    learn: 0.3077525        total: 999ms    remaining: 6.14s
140:    learn: 0.3074994        total: 1s       remaining: 6.13s
141:    learn: 0.3072512        total: 1.01s    remaining: 6.11s
142:    learn: 0.3070955        total: 1.02s    remaining: 6.09s
143:    learn: 0.3069701        total: 1.02s    remaining: 6.08s
144:    learn: 0.3067112        total: 1.03s    remaining: 6.07s
145:    learn: 0.3064985        total: 1.04s    remaining: 6.06s
146:    learn: 0.3062773        total: 1.04s    remaining: 6.05s
147:    learn: 0.3061042        total: 1.05s    remaining: 6.05s
148:    learn: 0.3058253        total: 1.06s    remaining: 6.04s
149:    learn: 0.3056653        total: 1.06s    remaining: 6.02s
150:    learn: 0.3054483        total: 1.07s    remaining: 6.01s
151:    learn: 0.3053141        total: 1.07s    remaining: 6s
152:    learn: 0.3050191        total: 1.08s    remaining: 5.99s
153:    learn: 0.3048245        total: 1.09s    remaining: 5.98s
154:    learn: 0.3046940        total: 1.09s    remaining: 5.97s
155:    learn: 0.3044304        total: 1.1s     remaining: 5.95s
156:    learn: 0.3041373        total: 1.11s    remaining: 5.94s
157:    learn: 0.3038548        total: 1.11s    remaining: 5.93s
158:    learn: 0.3037035        total: 1.12s    remaining: 5.92s
159:    learn: 0.3034388        total: 1.13s    remaining: 5.91s
160:    learn: 0.3032959        total: 1.13s    remaining: 5.9s
161:    learn: 0.3029703        total: 1.14s    remaining: 5.89s
162:    learn: 0.3028534        total: 1.15s    remaining: 5.9s
163:    learn: 0.3027141        total: 1.16s    remaining: 5.89s
164:    learn: 0.3025312        total: 1.16s    remaining: 5.88s
165:    learn: 0.3023283        total: 1.17s    remaining: 5.87s
166:    learn: 0.3021731        total: 1.18s    remaining: 5.86s
167:    learn: 0.3018942        total: 1.18s    remaining: 5.85s
168:    learn: 0.3015168        total: 1.19s    remaining: 5.84s
169:    learn: 0.3013187        total: 1.2s     remaining: 5.84s
170:    learn: 0.3011623        total: 1.2s     remaining: 5.83s
171:    learn: 0.3009444        total: 1.21s    remaining: 5.82s
172:    learn: 0.3007655        total: 1.22s    remaining: 5.81s
173:    learn: 0.3005106        total: 1.22s    remaining: 5.8s
174:    learn: 0.3001136        total: 1.23s    remaining: 5.79s
175:    learn: 0.2996040        total: 1.24s    remaining: 5.78s
176:    learn: 0.2994882        total: 1.24s    remaining: 5.78s
177:    learn: 0.2991650        total: 1.25s    remaining: 5.77s
178:    learn: 0.2988848        total: 1.25s    remaining: 5.76s
179:    learn: 0.2986654        total: 1.26s    remaining: 5.75s
180:    learn: 0.2984920        total: 1.27s    remaining: 5.74s
181:    learn: 0.2981041        total: 1.27s    remaining: 5.73s
```

```
182:    learn: 0.2979483        total: 1.28s    remaining: 5.72s
183:    learn: 0.2977568        total: 1.29s    remaining: 5.71s
184:    learn: 0.2976276        total: 1.29s    remaining: 5.7s
185:    learn: 0.2973269        total: 1.3s     remaining: 5.7s
186:    learn: 0.2972515        total: 1.31s    remaining: 5.69s
187:    learn: 0.2969509        total: 1.31s    remaining: 5.68s
188:    learn: 0.2967110        total: 1.32s    remaining: 5.67s
189:    learn: 0.2965108        total: 1.33s    remaining: 5.66s
190:    learn: 0.2961612        total: 1.33s    remaining: 5.65s
191:    learn: 0.2960441        total: 1.34s    remaining: 5.64s
192:    learn: 0.2957567        total: 1.35s    remaining: 5.64s
193:    learn: 0.2954925        total: 1.35s    remaining: 5.63s
194:    learn: 0.2952942        total: 1.36s    remaining: 5.62s
195:    learn: 0.2951111        total: 1.37s    remaining: 5.61s
196:    learn: 0.2949726        total: 1.37s    remaining: 5.6s
197:    learn: 0.2947348        total: 1.38s    remaining: 5.6s
198:    learn: 0.2945600        total: 1.39s    remaining: 5.59s
199:    learn: 0.2943188        total: 1.4s     remaining: 5.59s
200:    learn: 0.2942151        total: 1.4s     remaining: 5.58s
201:    learn: 0.2938776        total: 1.41s    remaining: 5.57s
202:    learn: 0.2936503        total: 1.42s    remaining: 5.56s
203:    learn: 0.2933281        total: 1.42s    remaining: 5.55s
204:    learn: 0.2932160        total: 1.43s    remaining: 5.54s
205:    learn: 0.2931260        total: 1.44s    remaining: 5.53s
206:    learn: 0.2929757        total: 1.44s    remaining: 5.52s
207:    learn: 0.2927186        total: 1.45s    remaining: 5.51s
208:    learn: 0.2925597        total: 1.45s    remaining: 5.5s
209:    learn: 0.2923648        total: 1.46s    remaining: 5.5s
210:    learn: 0.2920692        total: 1.47s    remaining: 5.49s
211:    learn: 0.2918583        total: 1.47s    remaining: 5.47s
212:    learn: 0.2917624        total: 1.48s    remaining: 5.47s
213:    learn: 0.2916380        total: 1.49s    remaining: 5.46s
214:    learn: 0.2914396        total: 1.49s    remaining: 5.45s
215:    learn: 0.2912095        total: 1.5s     remaining: 5.44s
216:    learn: 0.2909976        total: 1.5s     remaining: 5.43s
217:    learn: 0.2908663        total: 1.51s    remaining: 5.43s
218:    learn: 0.2907407        total: 1.52s    remaining: 5.42s
219:    learn: 0.2905774        total: 1.52s    remaining: 5.41s
220:    learn: 0.2903015        total: 1.53s    remaining: 5.4s
221:    learn: 0.2901868        total: 1.54s    remaining: 5.39s
222:    learn: 0.2899107        total: 1.54s    remaining: 5.38s
223:    learn: 0.2896550        total: 1.55s    remaining: 5.37s
224:    learn: 0.2894536        total: 1.56s    remaining: 5.37s
225:    learn: 0.2892752        total: 1.56s    remaining: 5.36s
226:    learn: 0.2892170        total: 1.57s    remaining: 5.36s
227:    learn: 0.2890366        total: 1.58s    remaining: 5.35s
228:    learn: 0.2889054        total: 1.59s    remaining: 5.34s
229:    learn: 0.2887696        total: 1.59s    remaining: 5.33s
```

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230:    learn: 0.2886497        total: 1.6s     remaining: 5.33s
231:    learn: 0.2885708        total: 1.61s    remaining: 5.32s
232:    learn: 0.2884563        total: 1.61s    remaining: 5.31s
233:    learn: 0.2883899        total: 1.62s    remaining: 5.3s
234:    learn: 0.2881081        total: 1.63s    remaining: 5.29s
235:    learn: 0.2879521        total: 1.63s    remaining: 5.29s
236:    learn: 0.2877339        total: 1.64s    remaining: 5.28s
237:    learn: 0.2875652        total: 1.65s    remaining: 5.27s
238:    learn: 0.2874907        total: 1.65s    remaining: 5.26s
239:    learn: 0.2873773        total: 1.66s    remaining: 5.25s
240:    learn: 0.2872232        total: 1.67s    remaining: 5.25s
241:    learn: 0.2870978        total: 1.67s    remaining: 5.24s
242:    learn: 0.2869705        total: 1.68s    remaining: 5.23s
243:    learn: 0.2868598        total: 1.69s    remaining: 5.22s
244:    learn: 0.2866931        total: 1.69s    remaining: 5.21s
245:    learn: 0.2865765        total: 1.7s     remaining: 5.21s
246:    learn: 0.2864405        total: 1.71s    remaining: 5.2s
247:    learn: 0.2862633        total: 1.71s    remaining: 5.19s
248:    learn: 0.2860142        total: 1.72s    remaining: 5.18s
249:    learn: 0.2857744        total: 1.73s    remaining: 5.18s
250:    learn: 0.2856757        total: 1.73s    remaining: 5.17s
251:    learn: 0.2855731        total: 1.74s    remaining: 5.17s
252:    learn: 0.2854208        total: 1.75s    remaining: 5.17s
253:    learn: 0.2853023        total: 1.76s    remaining: 5.16s
254:    learn: 0.2851977        total: 1.76s    remaining: 5.16s
255:    learn: 0.2850590        total: 1.77s    remaining: 5.15s
256:    learn: 0.2849114        total: 1.78s    remaining: 5.14s
257:    learn: 0.2847444        total: 1.78s    remaining: 5.13s
258:    learn: 0.2846577        total: 1.79s    remaining: 5.13s
259:    learn: 0.2845010        total: 1.8s     remaining: 5.12s
260:    learn: 0.2842627        total: 1.81s    remaining: 5.11s
261:    learn: 0.2841076        total: 1.81s    remaining: 5.11s
262:    learn: 0.2839592        total: 1.82s    remaining: 5.1s
263:    learn: 0.2838281        total: 1.83s    remaining: 5.09s
264:    learn: 0.2837066        total: 1.83s    remaining: 5.09s
265:    learn: 0.2835626        total: 1.84s    remaining: 5.08s
266:    learn: 0.2833237        total: 1.85s    remaining: 5.07s
267:    learn: 0.2832175        total: 1.85s    remaining: 5.07s
268:    learn: 0.2831187        total: 1.86s    remaining: 5.06s
269:    learn: 0.2829665        total: 1.87s    remaining: 5.05s
270:    learn: 0.2827940        total: 1.87s    remaining: 5.04s
271:    learn: 0.2827198        total: 1.88s    remaining: 5.03s
272:    learn: 0.2825885        total: 1.89s    remaining: 5.02s
273:    learn: 0.2824501        total: 1.89s    remaining: 5.01s
274:    learn: 0.2823199        total: 1.9s     remaining: 5.01s
275:    learn: 0.2821785        total: 1.91s    remaining: 5s
276:    learn: 0.2820174        total: 1.91s    remaining: 4.99s
277:    learn: 0.2818062        total: 1.92s    remaining: 4.99s
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278:    learn: 0.2815752        total: 1.93s    remaining: 4.98s
279:    learn: 0.2814820        total: 1.93s    remaining: 4.97s
280:    learn: 0.2812939        total: 1.94s    remaining: 4.97s
281:    learn: 0.2810843        total: 1.95s    remaining: 4.96s
282:    learn: 0.2809318        total: 1.95s    remaining: 4.95s
283:    learn: 0.2807730        total: 1.96s    remaining: 4.95s
284:    learn: 0.2804447        total: 1.97s    remaining: 4.94s
285:    learn: 0.2803105        total: 1.97s    remaining: 4.93s
286:    learn: 0.2802235        total: 1.98s    remaining: 4.92s
287:    learn: 0.2800613        total: 1.99s    remaining: 4.91s
288:    learn: 0.2799600        total: 1.99s    remaining: 4.91s
289:    learn: 0.2798184        total: 2s       remaining: 4.9s
290:    learn: 0.2796161        total: 2.01s    remaining: 4.89s
291:    learn: 0.2795185        total: 2.01s    remaining: 4.88s
292:    learn: 0.2793586        total: 2.02s    remaining: 4.87s
293:    learn: 0.2791426        total: 2.03s    remaining: 4.87s
294:    learn: 0.2789122        total: 2.03s    remaining: 4.86s
295:    learn: 0.2786988        total: 2.04s    remaining: 4.85s
296:    learn: 0.2786184        total: 2.04s    remaining: 4.84s
297:    learn: 0.2785593        total: 2.05s    remaining: 4.83s
298:    learn: 0.2784718        total: 2.06s    remaining: 4.83s
299:    learn: 0.2782639        total: 2.06s    remaining: 4.82s
300:    learn: 0.2782007        total: 2.07s    remaining: 4.81s
301:    learn: 0.2780756        total: 2.08s    remaining: 4.8s
302:    learn: 0.2779471        total: 2.08s    remaining: 4.8s
303:    learn: 0.2775524        total: 2.09s    remaining: 4.79s
304:    learn: 0.2774668        total: 2.1s     remaining: 4.78s
305:    learn: 0.2772705        total: 2.1s     remaining: 4.78s
306:    learn: 0.2771690        total: 2.11s    remaining: 4.77s
307:    learn: 0.2770358        total: 2.12s    remaining: 4.76s
308:    learn: 0.2769417        total: 2.13s    remaining: 4.75s
309:    learn: 0.2768011        total: 2.13s    remaining: 4.75s
310:    learn: 0.2766834        total: 2.14s    remaining: 4.74s
311:    learn: 0.2765089        total: 2.15s    remaining: 4.73s
312:    learn: 0.2763590        total: 2.15s    remaining: 4.73s
313:    learn: 0.2762599        total: 2.16s    remaining: 4.72s
314:    learn: 0.2761610        total: 2.17s    remaining: 4.72s
315:    learn: 0.2760224        total: 2.17s    remaining: 4.71s
316:    learn: 0.2758999        total: 2.18s    remaining: 4.7s
317:    learn: 0.2757953        total: 2.19s    remaining: 4.69s
318:    learn: 0.2756507        total: 2.19s    remaining: 4.68s
319:    learn: 0.2755430        total: 2.2s     remaining: 4.68s
320:    learn: 0.2754516        total: 2.21s    remaining: 4.67s
321:    learn: 0.2753148        total: 2.21s    remaining: 4.66s
322:    learn: 0.2752186        total: 2.22s    remaining: 4.65s
323:    learn: 0.2750016        total: 2.23s    remaining: 4.64s
324:    learn: 0.2749380        total: 2.23s    remaining: 4.64s
325:    learn: 0.2748031        total: 2.24s    remaining: 4.63s
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326:    learn: 0.2746812        total: 2.25s    remaining: 4.62s
327:    learn: 0.2745749        total: 2.25s    remaining: 4.61s
328:    learn: 0.2743892        total: 2.26s    remaining: 4.61s
329:    learn: 0.2743152        total: 2.26s    remaining: 4.6s
330:    learn: 0.2741740        total: 2.27s    remaining: 4.59s
331:    learn: 0.2740444        total: 2.28s    remaining: 4.58s
332:    learn: 0.2738985        total: 2.28s    remaining: 4.57s
333:    learn: 0.2737223        total: 2.29s    remaining: 4.57s
334:    learn: 0.2735650        total: 2.29s    remaining: 4.56s
335:    learn: 0.2733959        total: 2.3s     remaining: 4.55s
336:    learn: 0.2731180        total: 2.31s    remaining: 4.54s
337:    learn: 0.2730099        total: 2.31s    remaining: 4.53s
338:    learn: 0.2729531        total: 2.32s    remaining: 4.53s
339:    learn: 0.2728817        total: 2.33s    remaining: 4.52s
340:    learn: 0.2727492        total: 2.34s    remaining: 4.51s
341:    learn: 0.2726345        total: 2.34s    remaining: 4.51s
342:    learn: 0.2724753        total: 2.35s    remaining: 4.5s
343:    learn: 0.2723593        total: 2.36s    remaining: 4.5s
344:    learn: 0.2722565        total: 2.37s    remaining: 4.49s
345:    learn: 0.2721841        total: 2.37s    remaining: 4.48s
346:    learn: 0.2720513        total: 2.38s    remaining: 4.47s
347:    learn: 0.2719258        total: 2.38s    remaining: 4.47s
348:    learn: 0.2718248        total: 2.39s    remaining: 4.46s
349:    learn: 0.2717345        total: 2.4s     remaining: 4.45s
350:    learn: 0.2716310        total: 2.4s     remaining: 4.44s
351:    learn: 0.2715329        total: 2.41s    remaining: 4.44s
352:    learn: 0.2713853        total: 2.42s    remaining: 4.43s
353:    learn: 0.2712704        total: 2.42s    remaining: 4.42s
354:    learn: 0.2712007        total: 2.43s    remaining: 4.41s
355:    learn: 0.2710623        total: 2.43s    remaining: 4.4s
356:    learn: 0.2709516        total: 2.44s    remaining: 4.4s
357:    learn: 0.2708063        total: 2.45s    remaining: 4.39s
358:    learn: 0.2706784        total: 2.45s    remaining: 4.38s
359:    learn: 0.2705619        total: 2.46s    remaining: 4.37s
360:    learn: 0.2704923        total: 2.47s    remaining: 4.37s
361:    learn: 0.2704005        total: 2.47s    remaining: 4.36s
362:    learn: 0.2702751        total: 2.48s    remaining: 4.35s
363:    learn: 0.2701480        total: 2.49s    remaining: 4.34s
364:    learn: 0.2700718        total: 2.49s    remaining: 4.34s
365:    learn: 0.2699038        total: 2.5s     remaining: 4.33s
366:    learn: 0.2697065        total: 2.51s    remaining: 4.32s
367:    learn: 0.2695748        total: 2.51s    remaining: 4.32s
368:    learn: 0.2694936        total: 2.52s    remaining: 4.31s
369:    learn: 0.2693984        total: 2.53s    remaining: 4.3s
370:    learn: 0.2692990        total: 2.53s    remaining: 4.3s
371:    learn: 0.2691059        total: 2.54s    remaining: 4.29s
372:    learn: 0.2690015        total: 2.55s    remaining: 4.28s
373:    learn: 0.2689173        total: 2.55s    remaining: 4.28s
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374:    learn: 0.2688303        total: 2.56s    remaining: 4.27s
375:    learn: 0.2687481        total: 2.57s    remaining: 4.26s
376:    learn: 0.2686564        total: 2.58s    remaining: 4.26s
377:    learn: 0.2685327        total: 2.58s    remaining: 4.25s
378:    learn: 0.2684668        total: 2.59s    remaining: 4.25s
379:    learn: 0.2683571        total: 2.6s     remaining: 4.24s
380:    learn: 0.2682622        total: 2.6s     remaining: 4.23s
381:    learn: 0.2682010        total: 2.61s    remaining: 4.22s
382:    learn: 0.2680836        total: 2.62s    remaining: 4.22s
383:    learn: 0.2679303        total: 2.62s    remaining: 4.21s
384:    learn: 0.2678129        total: 2.63s    remaining: 4.2s
385:    learn: 0.2677309        total: 2.64s    remaining: 4.2s
386:    learn: 0.2676421        total: 2.64s    remaining: 4.19s
387:    learn: 0.2675883        total: 2.65s    remaining: 4.19s
388:    learn: 0.2673997        total: 2.66s    remaining: 4.18s
389:    learn: 0.2671956        total: 2.67s    remaining: 4.18s
390:    learn: 0.2670907        total: 2.68s    remaining: 4.17s
391:    learn: 0.2669769        total: 2.69s    remaining: 4.17s
392:    learn: 0.2668648        total: 2.69s    remaining: 4.16s
393:    learn: 0.2667405        total: 2.71s    remaining: 4.16s
394:    learn: 0.2666316        total: 2.71s    remaining: 4.16s
395:    learn: 0.2665452        total: 2.72s    remaining: 4.15s
396:    learn: 0.2664881        total: 2.73s    remaining: 4.14s
397:    learn: 0.2663782        total: 2.73s    remaining: 4.14s
398:    learn: 0.2663286        total: 2.74s    remaining: 4.13s
399:    learn: 0.2662265        total: 2.75s    remaining: 4.12s
400:    learn: 0.2661619        total: 2.75s    remaining: 4.11s
401:    learn: 0.2660834        total: 2.76s    remaining: 4.11s
402:    learn: 0.2659274        total: 2.77s    remaining: 4.1s
403:    learn: 0.2657917        total: 2.78s    remaining: 4.09s
404:    learn: 0.2656862        total: 2.78s    remaining: 4.09s
405:    learn: 0.2656121        total: 2.79s    remaining: 4.08s
406:    learn: 0.2655104        total: 2.8s     remaining: 4.07s
407:    learn: 0.2653870        total: 2.8s     remaining: 4.07s
408:    learn: 0.2653328        total: 2.81s    remaining: 4.06s
409:    learn: 0.2652230        total: 2.81s    remaining: 4.05s
410:    learn: 0.2651407        total: 2.82s    remaining: 4.05s
411:    learn: 0.2650402        total: 2.83s    remaining: 4.04s
412:    learn: 0.2648654        total: 2.84s    remaining: 4.03s
413:    learn: 0.2647231        total: 2.84s    remaining: 4.03s
414:    learn: 0.2646342        total: 2.85s    remaining: 4.02s
415:    learn: 0.2645008        total: 2.86s    remaining: 4.01s
416:    learn: 0.2643958        total: 2.86s    remaining: 4s
417:    learn: 0.2643196        total: 2.87s    remaining: 4s
418:    learn: 0.2642114        total: 2.88s    remaining: 3.99s
419:    learn: 0.2641582        total: 2.88s    remaining: 3.98s
420:    learn: 0.2640704        total: 2.89s    remaining: 3.97s
421:    learn: 0.2638255        total: 2.9s     remaining: 3.97s
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422:    learn: 0.2637427        total: 2.9s     remaining: 3.96s
423:    learn: 0.2635994        total: 2.91s    remaining: 3.96s
424:    learn: 0.2634996        total: 2.92s    remaining: 3.95s
425:    learn: 0.2634363        total: 2.92s    remaining: 3.94s
426:    learn: 0.2633764        total: 2.93s    remaining: 3.94s
427:    learn: 0.2632237        total: 2.94s    remaining: 3.93s
428:    learn: 0.2631362        total: 2.95s    remaining: 3.92s
429:    learn: 0.2630197        total: 2.96s    remaining: 3.92s
430:    learn: 0.2629168        total: 2.96s    remaining: 3.91s
431:    learn: 0.2628323        total: 2.97s    remaining: 3.91s
432:    learn: 0.2627103        total: 2.98s    remaining: 3.9s
433:    learn: 0.2626552        total: 2.99s    remaining: 3.9s
434:    learn: 0.2625413        total: 3s       remaining: 3.89s
435:    learn: 0.2624752        total: 3s       remaining: 3.89s
436:    learn: 0.2623947        total: 3.01s    remaining: 3.88s
437:    learn: 0.2622653        total: 3.02s    remaining: 3.88s
438:    learn: 0.2622003        total: 3.03s    remaining: 3.87s
439:    learn: 0.2621552        total: 3.04s    remaining: 3.87s
440:    learn: 0.2621076        total: 3.05s    remaining: 3.86s
441:    learn: 0.2619954        total: 3.05s    remaining: 3.85s
442:    learn: 0.2619243        total: 3.06s    remaining: 3.85s
443:    learn: 0.2617870        total: 3.07s    remaining: 3.84s
444:    learn: 0.2617091        total: 3.08s    remaining: 3.84s
445:    learn: 0.2615964        total: 3.09s    remaining: 3.84s
446:    learn: 0.2615205        total: 3.1s     remaining: 3.83s
447:    learn: 0.2614178        total: 3.1s     remaining: 3.83s
448:    learn: 0.2612950        total: 3.11s    remaining: 3.82s
449:    learn: 0.2612002        total: 3.12s    remaining: 3.81s
450:    learn: 0.2611347        total: 3.13s    remaining: 3.81s
451:    learn: 0.2610463        total: 3.14s    remaining: 3.8s
452:    learn: 0.2608777        total: 3.15s    remaining: 3.8s
453:    learn: 0.2607636        total: 3.16s    remaining: 3.8s
454:    learn: 0.2606813        total: 3.17s    remaining: 3.79s
455:    learn: 0.2604076        total: 3.17s    remaining: 3.79s
456:    learn: 0.2602625        total: 3.18s    remaining: 3.78s
457:    learn: 0.2601186        total: 3.19s    remaining: 3.77s
458:    learn: 0.2600762        total: 3.2s     remaining: 3.77s
459:    learn: 0.2599852        total: 3.21s    remaining: 3.76s
460:    learn: 0.2598507        total: 3.21s    remaining: 3.76s
461:    learn: 0.2598201        total: 3.22s    remaining: 3.75s
462:    learn: 0.2597180        total: 3.23s    remaining: 3.75s
463:    learn: 0.2596171        total: 3.24s    remaining: 3.74s
464:    learn: 0.2594738        total: 3.25s    remaining: 3.73s
465:    learn: 0.2592503        total: 3.26s    remaining: 3.73s
466:    learn: 0.2591417        total: 3.27s    remaining: 3.73s
467:    learn: 0.2590521        total: 3.27s    remaining: 3.72s
468:    learn: 0.2589964        total: 3.28s    remaining: 3.72s
469:    learn: 0.2589497        total: 3.29s    remaining: 3.71s
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470:    learn: 0.2588905        total: 3.3s     remaining: 3.7s
471:    learn: 0.2588037        total: 3.3s     remaining: 3.7s
472:    learn: 0.2587408        total: 3.31s    remaining: 3.69s
473:    learn: 0.2586714        total: 3.32s    remaining: 3.68s
474:    learn: 0.2586189        total: 3.33s    remaining: 3.68s
475:    learn: 0.2584936        total: 3.34s    remaining: 3.67s
476:    learn: 0.2584323        total: 3.35s    remaining: 3.67s
477:    learn: 0.2583432        total: 3.35s    remaining: 3.66s
478:    learn: 0.2582333        total: 3.36s    remaining: 3.66s
479:    learn: 0.2581367        total: 3.37s    remaining: 3.65s
480:    learn: 0.2580089        total: 3.38s    remaining: 3.65s
481:    learn: 0.2579155        total: 3.39s    remaining: 3.64s
482:    learn: 0.2578158        total: 3.4s     remaining: 3.63s
483:    learn: 0.2577281        total: 3.4s     remaining: 3.63s
484:    learn: 0.2576124        total: 3.41s    remaining: 3.62s
485:    learn: 0.2574869        total: 3.42s    remaining: 3.62s
486:    learn: 0.2573964        total: 3.43s    remaining: 3.61s
487:    learn: 0.2573201        total: 3.44s    remaining: 3.61s
488:    learn: 0.2571804        total: 3.45s    remaining: 3.6s
489:    learn: 0.2570901        total: 3.46s    remaining: 3.6s
490:    learn: 0.2569869        total: 3.46s    remaining: 3.59s
491:    learn: 0.2569291        total: 3.47s    remaining: 3.59s
492:    learn: 0.2567042        total: 3.48s    remaining: 3.58s
493:    learn: 0.2566493        total: 3.49s    remaining: 3.58s
494:    learn: 0.2565020        total: 3.5s     remaining: 3.57s
495:    learn: 0.2563995        total: 3.51s    remaining: 3.56s
496:    learn: 0.2563222        total: 3.52s    remaining: 3.56s
497:    learn: 0.2562671        total: 3.52s    remaining: 3.55s
498:    learn: 0.2561604        total: 3.53s    remaining: 3.55s
499:    learn: 0.2560843        total: 3.54s    remaining: 3.54s
500:    learn: 0.2560038        total: 3.55s    remaining: 3.53s
501:    learn: 0.2559036        total: 3.55s    remaining: 3.53s
502:    learn: 0.2558095        total: 3.56s    remaining: 3.52s
503:    learn: 0.2557170        total: 3.57s    remaining: 3.51s
504:    learn: 0.2556188        total: 3.58s    remaining: 3.5s
505:    learn: 0.2555331        total: 3.58s    remaining: 3.5s
506:    learn: 0.2555090        total: 3.59s    remaining: 3.49s
507:    learn: 0.2554205        total: 3.59s    remaining: 3.48s
508:    learn: 0.2553227        total: 3.6s     remaining: 3.47s
509:    learn: 0.2552442        total: 3.61s    remaining: 3.46s
510:    learn: 0.2551481        total: 3.62s    remaining: 3.46s
511:    learn: 0.2550837        total: 3.62s    remaining: 3.45s
512:    learn: 0.2550166        total: 3.63s    remaining: 3.44s
513:    learn: 0.2549379        total: 3.63s    remaining: 3.44s
514:    learn: 0.2548620        total: 3.64s    remaining: 3.43s
515:    learn: 0.2547962        total: 3.65s    remaining: 3.42s
516:    learn: 0.2546910        total: 3.66s    remaining: 3.42s
517:    learn: 0.2546081        total: 3.66s    remaining: 3.41s
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518:    learn: 0.2544975        total: 3.67s    remaining: 3.4s
519:    learn: 0.2544199        total: 3.68s    remaining: 3.4s
520:    learn: 0.2543803        total: 3.69s    remaining: 3.39s
521:    learn: 0.2543131        total: 3.7s     remaining: 3.38s
522:    learn: 0.2542394        total: 3.7s     remaining: 3.38s
523:    learn: 0.2541603        total: 3.71s    remaining: 3.37s
524:    learn: 0.2540938        total: 3.72s    remaining: 3.36s
525:    learn: 0.2538871        total: 3.72s    remaining: 3.36s
526:    learn: 0.2537980        total: 3.73s    remaining: 3.35s
527:    learn: 0.2536619        total: 3.74s    remaining: 3.34s
528:    learn: 0.2535848        total: 3.74s    remaining: 3.33s
529:    learn: 0.2534846        total: 3.75s    remaining: 3.33s
530:    learn: 0.2534489        total: 3.75s    remaining: 3.32s
531:    learn: 0.2532777        total: 3.76s    remaining: 3.31s
532:    learn: 0.2532103        total: 3.77s    remaining: 3.3s
533:    learn: 0.2531271        total: 3.77s    remaining: 3.29s
534:    learn: 0.2529207        total: 3.78s    remaining: 3.29s
535:    learn: 0.2527685        total: 3.79s    remaining: 3.28s
536:    learn: 0.2526413        total: 3.79s    remaining: 3.27s
537:    learn: 0.2525089        total: 3.8s     remaining: 3.26s
538:    learn: 0.2523284        total: 3.81s    remaining: 3.25s
539:    learn: 0.2522780        total: 3.81s    remaining: 3.25s
540:    learn: 0.2522395        total: 3.82s    remaining: 3.24s
541:    learn: 0.2521524        total: 3.83s    remaining: 3.23s
542:    learn: 0.2520933        total: 3.83s    remaining: 3.22s
543:    learn: 0.2520166        total: 3.84s    remaining: 3.22s
544:    learn: 0.2519416        total: 3.84s    remaining: 3.21s
545:    learn: 0.2518710        total: 3.85s    remaining: 3.2s
546:    learn: 0.2517758        total: 3.86s    remaining: 3.19s
547:    learn: 0.2516452        total: 3.86s    remaining: 3.19s
548:    learn: 0.2515885        total: 3.87s    remaining: 3.18s
549:    learn: 0.2514847        total: 3.88s    remaining: 3.17s
550:    learn: 0.2514331        total: 3.89s    remaining: 3.17s
551:    learn: 0.2513382        total: 3.89s    remaining: 3.16s
552:    learn: 0.2511431        total: 3.9s     remaining: 3.15s
553:    learn: 0.2510455        total: 3.91s    remaining: 3.14s
554:    learn: 0.2509824        total: 3.91s    remaining: 3.14s
555:    learn: 0.2509060        total: 3.92s    remaining: 3.13s
556:    learn: 0.2507642        total: 3.92s    remaining: 3.12s
557:    learn: 0.2506752        total: 3.93s    remaining: 3.11s
558:    learn: 0.2505516        total: 3.94s    remaining: 3.11s
559:    learn: 0.2505055        total: 3.94s    remaining: 3.1s
560:    learn: 0.2504134        total: 3.95s    remaining: 3.09s
561:    learn: 0.2503059        total: 3.96s    remaining: 3.08s
562:    learn: 0.2501826        total: 3.97s    remaining: 3.08s
563:    learn: 0.2501198        total: 3.97s    remaining: 3.07s
564:    learn: 0.2500592        total: 3.98s    remaining: 3.06s
565:    learn: 0.2500024        total: 3.98s    remaining: 3.05s
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566:    learn: 0.2499604        total: 3.99s    remaining: 3.05s
567:    learn: 0.2498728        total: 4s       remaining: 3.04s
568:    learn: 0.2498032        total: 4s       remaining: 3.03s
569:    learn: 0.2496540        total: 4.01s    remaining: 3.02s
570:    learn: 0.2495724        total: 4.01s    remaining: 3.02s
571:    learn: 0.2494451        total: 4.02s    remaining: 3.01s
572:    learn: 0.2493327        total: 4.03s    remaining: 3s
573:    learn: 0.2492647        total: 4.04s    remaining: 3s
574:    learn: 0.2491882        total: 4.04s    remaining: 2.99s
575:    learn: 0.2490807        total: 4.05s    remaining: 2.98s
576:    learn: 0.2489841        total: 4.05s    remaining: 2.97s
577:    learn: 0.2489482        total: 4.06s    remaining: 2.97s
578:    learn: 0.2488927        total: 4.07s    remaining: 2.96s
579:    learn: 0.2488102        total: 4.08s    remaining: 2.95s
580:    learn: 0.2487541        total: 4.08s    remaining: 2.94s
581:    learn: 0.2486643        total: 4.09s    remaining: 2.94s
582:    learn: 0.2484859        total: 4.09s    remaining: 2.93s
583:    learn: 0.2484295        total: 4.1s     remaining: 2.92s
584:    learn: 0.2483018        total: 4.11s    remaining: 2.91s
585:    learn: 0.2482065        total: 4.12s    remaining: 2.91s
586:    learn: 0.2481333        total: 4.12s    remaining: 2.9s
587:    learn: 0.2480836        total: 4.13s    remaining: 2.89s
588:    learn: 0.2479980        total: 4.13s    remaining: 2.88s
589:    learn: 0.2479136        total: 4.14s    remaining: 2.88s
590:    learn: 0.2477979        total: 4.15s    remaining: 2.87s
591:    learn: 0.2477116        total: 4.15s    remaining: 2.86s
592:    learn: 0.2476033        total: 4.16s    remaining: 2.85s
593:    learn: 0.2475288        total: 4.16s    remaining: 2.85s
594:    learn: 0.2474709        total: 4.17s    remaining: 2.84s
595:    learn: 0.2473696        total: 4.18s    remaining: 2.83s
596:    learn: 0.2472432        total: 4.18s    remaining: 2.82s
597:    learn: 0.2471214        total: 4.19s    remaining: 2.82s
598:    learn: 0.2470466        total: 4.2s     remaining: 2.81s
599:    learn: 0.2469823        total: 4.2s     remaining: 2.8s
600:    learn: 0.2469287        total: 4.21s    remaining: 2.79s
601:    learn: 0.2468413        total: 4.21s    remaining: 2.79s
602:    learn: 0.2467535        total: 4.22s    remaining: 2.78s
603:    learn: 0.2466709        total: 4.23s    remaining: 2.77s
604:    learn: 0.2465446        total: 4.24s    remaining: 2.77s
605:    learn: 0.2464751        total: 4.24s    remaining: 2.76s
606:    learn: 0.2463954        total: 4.25s    remaining: 2.75s
607:    learn: 0.2462520        total: 4.26s    remaining: 2.75s
608:    learn: 0.2462011        total: 4.26s    remaining: 2.74s
609:    learn: 0.2461367        total: 4.27s    remaining: 2.73s
610:    learn: 0.2460300        total: 4.28s    remaining: 2.72s
611:    learn: 0.2459615        total: 4.28s    remaining: 2.71s
612:    learn: 0.2458399        total: 4.29s    remaining: 2.71s
613:    learn: 0.2457985        total: 4.29s    remaining: 2.7s
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614:    learn: 0.2457246        total: 4.3s     remaining: 2.69s
615:    learn: 0.2456538        total: 4.31s    remaining: 2.69s
616:    learn: 0.2455295        total: 4.31s    remaining: 2.68s
617:    learn: 0.2454038        total: 4.32s    remaining: 2.67s
618:    learn: 0.2453181        total: 4.33s    remaining: 2.66s
619:    learn: 0.2452490        total: 4.33s    remaining: 2.65s
620:    learn: 0.2451567        total: 4.34s    remaining: 2.65s
621:    learn: 0.2450922        total: 4.34s    remaining: 2.64s
622:    learn: 0.2450215        total: 4.35s    remaining: 2.63s
623:    learn: 0.2449133        total: 4.36s    remaining: 2.62s
624:    learn: 0.2448119        total: 4.36s    remaining: 2.62s
625:    learn: 0.2446947        total: 4.37s    remaining: 2.61s
626:    learn: 0.2446392        total: 4.37s    remaining: 2.6s
627:    learn: 0.2445249        total: 4.38s    remaining: 2.59s
628:    learn: 0.2444434        total: 4.39s    remaining: 2.59s
629:    learn: 0.2443596        total: 4.39s    remaining: 2.58s
630:    learn: 0.2443059        total: 4.4s     remaining: 2.57s
631:    learn: 0.2441549        total: 4.41s    remaining: 2.57s
632:    learn: 0.2441040        total: 4.41s    remaining: 2.56s
633:    learn: 0.2440266        total: 4.42s    remaining: 2.55s
634:    learn: 0.2439436        total: 4.43s    remaining: 2.54s
635:    learn: 0.2438812        total: 4.43s    remaining: 2.54s
636:    learn: 0.2437569        total: 4.44s    remaining: 2.53s
637:    learn: 0.2436947        total: 4.45s    remaining: 2.52s
638:    learn: 0.2436206        total: 4.46s    remaining: 2.52s
639:    learn: 0.2435426        total: 4.46s    remaining: 2.51s
640:    learn: 0.2433920        total: 4.47s    remaining: 2.5s
641:    learn: 0.2433449        total: 4.48s    remaining: 2.5s
642:    learn: 0.2432299        total: 4.48s    remaining: 2.49s
643:    learn: 0.2431250        total: 4.49s    remaining: 2.48s
644:    learn: 0.2430396        total: 4.5s     remaining: 2.47s
645:    learn: 0.2429292        total: 4.5s     remaining: 2.47s
646:    learn: 0.2428473        total: 4.51s    remaining: 2.46s
647:    learn: 0.2427629        total: 4.51s    remaining: 2.45s
648:    learn: 0.2427147        total: 4.52s    remaining: 2.44s
649:    learn: 0.2426303        total: 4.53s    remaining: 2.44s
650:    learn: 0.2425118        total: 4.53s    remaining: 2.43s
651:    learn: 0.2424726        total: 4.54s    remaining: 2.42s
652:    learn: 0.2424422        total: 4.54s    remaining: 2.41s
653:    learn: 0.2423798        total: 4.55s    remaining: 2.41s
654:    learn: 0.2423368        total: 4.56s    remaining: 2.4s
655:    learn: 0.2422963        total: 4.56s    remaining: 2.39s
656:    learn: 0.2422347        total: 4.57s    remaining: 2.38s
657:    learn: 0.2421959        total: 4.58s    remaining: 2.38s
658:    learn: 0.2421487        total: 4.58s    remaining: 2.37s
659:    learn: 0.2420713        total: 4.59s    remaining: 2.36s
660:    learn: 0.2419673        total: 4.59s    remaining: 2.36s
661:    learn: 0.2419033        total: 4.6s     remaining: 2.35s
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662:    learn: 0.2418503        total: 4.61s    remaining: 2.34s
663:    learn: 0.2416912        total: 4.62s    remaining: 2.33s
664:    learn: 0.2416049        total: 4.62s    remaining: 2.33s
665:    learn: 0.2415561        total: 4.63s    remaining: 2.32s
666:    learn: 0.2414929        total: 4.64s    remaining: 2.31s
667:    learn: 0.2414186        total: 4.65s    remaining: 2.31s
668:    learn: 0.2413266        total: 4.65s    remaining: 2.3s
669:    learn: 0.2412428        total: 4.66s    remaining: 2.29s
670:    learn: 0.2411898        total: 4.67s    remaining: 2.29s
671:    learn: 0.2411216        total: 4.67s    remaining: 2.28s
672:    learn: 0.2410094        total: 4.68s    remaining: 2.27s
673:    learn: 0.2409216        total: 4.69s    remaining: 2.27s
674:    learn: 0.2408690        total: 4.69s    remaining: 2.26s
675:    learn: 0.2407428        total: 4.7s     remaining: 2.25s
676:    learn: 0.2406709        total: 4.71s    remaining: 2.25s
677:    learn: 0.2406149        total: 4.71s    remaining: 2.24s
678:    learn: 0.2405519        total: 4.72s    remaining: 2.23s
679:    learn: 0.2405014        total: 4.72s    remaining: 2.22s
680:    learn: 0.2403895        total: 4.73s    remaining: 2.21s
681:    learn: 0.2402308        total: 4.74s    remaining: 2.21s
682:    learn: 0.2401826        total: 4.74s    remaining: 2.2s
683:    learn: 0.2400005        total: 4.75s    remaining: 2.19s
684:    learn: 0.2399029        total: 4.75s    remaining: 2.19s
685:    learn: 0.2397791        total: 4.76s    remaining: 2.18s
686:    learn: 0.2397364        total: 4.78s    remaining: 2.17s
687:    learn: 0.2396854        total: 4.78s    remaining: 2.17s
688:    learn: 0.2396217        total: 4.79s    remaining: 2.16s
689:    learn: 0.2395792        total: 4.79s    remaining: 2.15s
690:    learn: 0.2395413        total: 4.8s     remaining: 2.15s
691:    learn: 0.2394504        total: 4.81s    remaining: 2.14s
692:    learn: 0.2393753        total: 4.82s    remaining: 2.13s
693:    learn: 0.2393297        total: 4.82s    remaining: 2.13s
694:    learn: 0.2392802        total: 4.83s    remaining: 2.12s
695:    learn: 0.2391343        total: 4.84s    remaining: 2.11s
696:    learn: 0.2390281        total: 4.85s    remaining: 2.11s
697:    learn: 0.2389856        total: 4.85s    remaining: 2.1s
698:    learn: 0.2389111        total: 4.86s    remaining: 2.09s
699:    learn: 0.2388349        total: 4.87s    remaining: 2.08s
700:    learn: 0.2387774        total: 4.87s    remaining: 2.08s
701:    learn: 0.2386921        total: 4.88s    remaining: 2.07s
702:    learn: 0.2385191        total: 4.88s    remaining: 2.06s
703:    learn: 0.2384420        total: 4.89s    remaining: 2.06s
704:    learn: 0.2383801        total: 4.9s     remaining: 2.05s
705:    learn: 0.2382425        total: 4.9s     remaining: 2.04s
706:    learn: 0.2381665        total: 4.91s    remaining: 2.03s
707:    learn: 0.2381411        total: 4.92s    remaining: 2.03s
708:    learn: 0.2380394        total: 4.92s    remaining: 2.02s
709:    learn: 0.2379921        total: 4.93s    remaining: 2.01s
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710:    learn: 0.2379602        total: 4.93s    remaining: 2s
711:    learn: 0.2378902        total: 4.94s    remaining: 2s
712:    learn: 0.2378513        total: 4.95s    remaining: 1.99s
713:    learn: 0.2377523        total: 4.95s    remaining: 1.98s
714:    learn: 0.2376835        total: 4.96s    remaining: 1.98s
715:    learn: 0.2375807        total: 4.96s    remaining: 1.97s
716:    learn: 0.2375266        total: 4.97s    remaining: 1.96s
717:    learn: 0.2373979        total: 4.98s    remaining: 1.96s
718:    learn: 0.2373111        total: 4.98s    remaining: 1.95s
719:    learn: 0.2372269        total: 4.99s    remaining: 1.94s
720:    learn: 0.2371601        total: 5s       remaining: 1.93s
721:    learn: 0.2370757        total: 5s       remaining: 1.93s
722:    learn: 0.2370337        total: 5.01s    remaining: 1.92s
723:    learn: 0.2369889        total: 5.03s    remaining: 1.92s
724:    learn: 0.2369318        total: 5.05s    remaining: 1.91s
725:    learn: 0.2368698        total: 5.06s    remaining: 1.91s
726:    learn: 0.2368038        total: 5.06s    remaining: 1.9s
727:    learn: 0.2367750        total: 5.07s    remaining: 1.89s
728:    learn: 0.2367120        total: 5.08s    remaining: 1.89s
729:    learn: 0.2366281        total: 5.08s    remaining: 1.88s
730:    learn: 0.2365741        total: 5.09s    remaining: 1.87s
731:    learn: 0.2364302        total: 5.1s     remaining: 1.87s
732:    learn: 0.2363615        total: 5.11s    remaining: 1.86s
733:    learn: 0.2363141        total: 5.11s    remaining: 1.85s
734:    learn: 0.2362371        total: 5.12s    remaining: 1.85s
735:    learn: 0.2361416        total: 5.13s    remaining: 1.84s
736:    learn: 0.2360844        total: 5.13s    remaining: 1.83s
737:    learn: 0.2360398        total: 5.14s    remaining: 1.82s
738:    learn: 0.2359805        total: 5.14s    remaining: 1.82s
739:    learn: 0.2359010        total: 5.15s    remaining: 1.81s
740:    learn: 0.2358213        total: 5.16s    remaining: 1.8s
741:    learn: 0.2357256        total: 5.16s    remaining: 1.79s
742:    learn: 0.2356862        total: 5.17s    remaining: 1.79s
743:    learn: 0.2356294        total: 5.18s    remaining: 1.78s
744:    learn: 0.2355027        total: 5.18s    remaining: 1.77s
745:    learn: 0.2354547        total: 5.2s     remaining: 1.77s
746:    learn: 0.2354058        total: 5.2s     remaining: 1.76s
747:    learn: 0.2353392        total: 5.21s    remaining: 1.75s
748:    learn: 0.2352817        total: 5.21s    remaining: 1.75s
749:    learn: 0.2352325        total: 5.22s    remaining: 1.74s
750:    learn: 0.2351765        total: 5.23s    remaining: 1.73s
751:    learn: 0.2350930        total: 5.23s    remaining: 1.73s
752:    learn: 0.2350414        total: 5.24s    remaining: 1.72s
753:    learn: 0.2349765        total: 5.25s    remaining: 1.71s
754:    learn: 0.2349296        total: 5.25s    remaining: 1.7s
755:    learn: 0.2348586        total: 5.26s    remaining: 1.7s
756:    learn: 0.2347831        total: 5.26s    remaining: 1.69s
757:    learn: 0.2347161        total: 5.27s    remaining: 1.68s
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758:    learn: 0.2345511        total: 5.28s    remaining: 1.68s
759:    learn: 0.2344571        total: 5.28s    remaining: 1.67s
760:    learn: 0.2344288        total: 5.29s    remaining: 1.66s
761:    learn: 0.2343687        total: 5.3s     remaining: 1.65s
762:    learn: 0.2342749        total: 5.3s     remaining: 1.65s
763:    learn: 0.2342094        total: 5.31s    remaining: 1.64s
764:    learn: 0.2341608        total: 5.32s    remaining: 1.63s
765:    learn: 0.2340881        total: 5.32s    remaining: 1.63s
766:    learn: 0.2340276        total: 5.33s    remaining: 1.62s
767:    learn: 0.2339892        total: 5.33s    remaining: 1.61s
768:    learn: 0.2339423        total: 5.34s    remaining: 1.6s
769:    learn: 0.2338938        total: 5.35s    remaining: 1.6s
770:    learn: 0.2336964        total: 5.35s    remaining: 1.59s
771:    learn: 0.2336250        total: 5.36s    remaining: 1.58s
772:    learn: 0.2335590        total: 5.37s    remaining: 1.58s
773:    learn: 0.2334825        total: 5.37s    remaining: 1.57s
774:    learn: 0.2334219        total: 5.38s    remaining: 1.56s
775:    learn: 0.2333646        total: 5.39s    remaining: 1.55s
776:    learn: 0.2332788        total: 5.39s    remaining: 1.55s
777:    learn: 0.2332277        total: 5.4s     remaining: 1.54s
778:    learn: 0.2331811        total: 5.41s    remaining: 1.53s
779:    learn: 0.2330965        total: 5.41s    remaining: 1.53s
780:    learn: 0.2330133        total: 5.42s    remaining: 1.52s
781:    learn: 0.2329399        total: 5.43s    remaining: 1.51s
782:    learn: 0.2328938        total: 5.43s    remaining: 1.5s
783:    learn: 0.2328374        total: 5.44s    remaining: 1.5s
784:    learn: 0.2327445        total: 5.45s    remaining: 1.49s
785:    learn: 0.2326466        total: 5.46s    remaining: 1.49s
786:    learn: 0.2326024        total: 5.46s    remaining: 1.48s
787:    learn: 0.2324894        total: 5.47s    remaining: 1.47s
788:    learn: 0.2324066        total: 5.47s    remaining: 1.46s
789:    learn: 0.2323237        total: 5.48s    remaining: 1.46s
790:    learn: 0.2322340        total: 5.49s    remaining: 1.45s
791:    learn: 0.2320852        total: 5.49s    remaining: 1.44s
792:    learn: 0.2320587        total: 5.5s     remaining: 1.44s
793:    learn: 0.2320297        total: 5.51s    remaining: 1.43s
794:    learn: 0.2319652        total: 5.51s    remaining: 1.42s
795:    learn: 0.2318766        total: 5.52s    remaining: 1.41s
796:    learn: 0.2318297        total: 5.53s    remaining: 1.41s
797:    learn: 0.2317367        total: 5.53s    remaining: 1.4s
798:    learn: 0.2316809        total: 5.54s    remaining: 1.39s
799:    learn: 0.2315868        total: 5.54s    remaining: 1.39s
800:    learn: 0.2315204        total: 5.55s    remaining: 1.38s
801:    learn: 0.2314833        total: 5.56s    remaining: 1.37s
802:    learn: 0.2314281        total: 5.57s    remaining: 1.36s
803:    learn: 0.2313624        total: 5.57s    remaining: 1.36s
804:    learn: 0.2312753        total: 5.58s    remaining: 1.35s
805:    learn: 0.2311553        total: 5.59s    remaining: 1.34s
```

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806:    learn: 0.2310921        total: 5.6s     remaining: 1.34s
807:    learn: 0.2310169        total: 5.6s     remaining: 1.33s
808:    learn: 0.2309759        total: 5.61s    remaining: 1.32s
809:    learn: 0.2309000        total: 5.62s    remaining: 1.32s
810:    learn: 0.2308211        total: 5.62s    remaining: 1.31s
811:    learn: 0.2307796        total: 5.63s    remaining: 1.3s
812:    learn: 0.2307301        total: 5.64s    remaining: 1.3s
813:    learn: 0.2305604        total: 5.64s    remaining: 1.29s
814:    learn: 0.2305217        total: 5.65s    remaining: 1.28s
815:    learn: 0.2305039        total: 5.66s    remaining: 1.27s
816:    learn: 0.2304133        total: 5.66s    remaining: 1.27s
817:    learn: 0.2303347        total: 5.67s    remaining: 1.26s
818:    learn: 0.2302789        total: 5.67s    remaining: 1.25s
819:    learn: 0.2302340        total: 5.68s    remaining: 1.25s
820:    learn: 0.2301928        total: 5.69s    remaining: 1.24s
821:    learn: 0.2301002        total: 5.69s    remaining: 1.23s
822:    learn: 0.2300324        total: 5.7s     remaining: 1.23s
823:    learn: 0.2299554        total: 5.71s    remaining: 1.22s
824:    learn: 0.2298069        total: 5.71s    remaining: 1.21s
825:    learn: 0.2296801        total: 5.72s    remaining: 1.2s
826:    learn: 0.2295831        total: 5.73s    remaining: 1.2s
827:    learn: 0.2295326        total: 5.73s    remaining: 1.19s
828:    learn: 0.2294043        total: 5.74s    remaining: 1.18s
829:    learn: 0.2293202        total: 5.75s    remaining: 1.18s
830:    learn: 0.2292573        total: 5.75s    remaining: 1.17s
831:    learn: 0.2291717        total: 5.76s    remaining: 1.16s
832:    learn: 0.2291218        total: 5.77s    remaining: 1.16s
833:    learn: 0.2290752        total: 5.77s    remaining: 1.15s
834:    learn: 0.2290012        total: 5.78s    remaining: 1.14s
835:    learn: 0.2289129        total: 5.79s    remaining: 1.14s
836:    learn: 0.2287635        total: 5.79s    remaining: 1.13s
837:    learn: 0.2286848        total: 5.8s     remaining: 1.12s
838:    learn: 0.2286533        total: 5.81s    remaining: 1.11s
839:    learn: 0.2285960        total: 5.81s    remaining: 1.11s
840:    learn: 0.2285215        total: 5.82s    remaining: 1.1s
841:    learn: 0.2284880        total: 5.83s    remaining: 1.09s
842:    learn: 0.2284395        total: 5.83s    remaining: 1.08s
843:    learn: 0.2283810        total: 5.84s    remaining: 1.08s
844:    learn: 0.2283137        total: 5.84s    remaining: 1.07s
845:    learn: 0.2282648        total: 5.85s    remaining: 1.06s
846:    learn: 0.2282006        total: 5.86s    remaining: 1.06s
847:    learn: 0.2281620        total: 5.86s    remaining: 1.05s
848:    learn: 0.2281181        total: 5.87s    remaining: 1.04s
849:    learn: 0.2280233        total: 5.87s    remaining: 1.04s
850:    learn: 0.2279703        total: 5.88s    remaining: 1.03s
851:    learn: 0.2278874        total: 5.89s    remaining: 1.02s
852:    learn: 0.2277998        total: 5.89s    remaining: 1.01s
853:    learn: 0.2277181        total: 5.9s     remaining: 1.01s
```

```
854:    learn: 0.2276485        total: 5.91s    remaining: 1s
855:    learn: 0.2275799        total: 5.91s    remaining: 994ms
856:    learn: 0.2274946        total: 5.92s    remaining: 987ms
857:    learn: 0.2274407        total: 5.92s    remaining: 980ms
858:    learn: 0.2274062        total: 5.93s    remaining: 973ms
859:    learn: 0.2273402        total: 5.94s    remaining: 966ms
860:    learn: 0.2272629        total: 5.94s    remaining: 960ms
861:    learn: 0.2271729        total: 5.95s    remaining: 953ms
862:    learn: 0.2271416        total: 5.96s    remaining: 946ms
863:    learn: 0.2271014        total: 5.96s    remaining: 939ms
864:    learn: 0.2269825        total: 5.97s    remaining: 932ms
865:    learn: 0.2269415        total: 5.98s    remaining: 925ms
866:    learn: 0.2268464        total: 5.99s    remaining: 918ms
867:    learn: 0.2267915        total: 5.99s    remaining: 911ms
868:    learn: 0.2266848        total: 6s       remaining: 904ms
869:    learn: 0.2265812        total: 6s       remaining: 897ms
870:    learn: 0.2265016        total: 6.01s    remaining: 890ms
871:    learn: 0.2264310        total: 6.02s    remaining: 883ms
872:    learn: 0.2263866        total: 6.02s    remaining: 876ms
873:    learn: 0.2263287        total: 6.03s    remaining: 869ms
874:    learn: 0.2262659        total: 6.04s    remaining: 862ms
875:    learn: 0.2262100        total: 6.04s    remaining: 855ms
876:    learn: 0.2261557        total: 6.05s    remaining: 848ms
877:    learn: 0.2261018        total: 6.05s    remaining: 841ms
878:    learn: 0.2260357        total: 6.06s    remaining: 834ms
879:    learn: 0.2259866        total: 6.07s    remaining: 827ms
880:    learn: 0.2258871        total: 6.07s    remaining: 820ms
881:    learn: 0.2258322        total: 6.08s    remaining: 814ms
882:    learn: 0.2257858        total: 6.09s    remaining: 807ms
883:    learn: 0.2257631        total: 6.09s    remaining: 800ms
884:    learn: 0.2256987        total: 6.1s     remaining: 793ms
885:    learn: 0.2256482        total: 6.11s    remaining: 786ms
886:    learn: 0.2255352        total: 6.11s    remaining: 779ms
887:    learn: 0.2254570        total: 6.12s    remaining: 772ms
888:    learn: 0.2254047        total: 6.13s    remaining: 765ms
889:    learn: 0.2253315        total: 6.13s    remaining: 758ms
890:    learn: 0.2252782        total: 6.14s    remaining: 751ms
891:    learn: 0.2252309        total: 6.15s    remaining: 744ms
892:    learn: 0.2251848        total: 6.15s    remaining: 737ms
893:    learn: 0.2251094        total: 6.16s    remaining: 730ms
894:    learn: 0.2250472        total: 6.17s    remaining: 724ms
895:    learn: 0.2249581        total: 6.17s    remaining: 717ms
896:    learn: 0.2248783        total: 6.18s    remaining: 710ms
897:    learn: 0.2248290        total: 6.19s    remaining: 703ms
898:    learn: 0.2247592        total: 6.19s    remaining: 696ms
899:    learn: 0.2246687        total: 6.2s     remaining: 689ms
900:    learn: 0.2246037        total: 6.21s    remaining: 682ms
901:    learn: 0.2244631        total: 6.21s    remaining: 675ms
```

```
902:    learn: 0.2243602        total: 6.22s    remaining: 668ms
903:    learn: 0.2242553        total: 6.22s    remaining: 661ms
904:    learn: 0.2242066        total: 6.23s    remaining: 654ms
905:    learn: 0.2241182        total: 6.24s    remaining: 647ms
906:    learn: 0.2240614        total: 6.24s    remaining: 640ms
907:    learn: 0.2239784        total: 6.25s    remaining: 633ms
908:    learn: 0.2239348        total: 6.26s    remaining: 626ms
909:    learn: 0.2238844        total: 6.26s    remaining: 619ms
910:    learn: 0.2238298        total: 6.27s    remaining: 612ms
911:    learn: 0.2237131        total: 6.28s    remaining: 606ms
912:    learn: 0.2236696        total: 6.28s    remaining: 599ms
913:    learn: 0.2235361        total: 6.29s    remaining: 592ms
914:    learn: 0.2234311        total: 6.29s    remaining: 585ms
915:    learn: 0.2233472        total: 6.3s     remaining: 578ms
916:    learn: 0.2233044        total: 6.31s    remaining: 571ms
917:    learn: 0.2232525        total: 6.31s    remaining: 564ms
918:    learn: 0.2231670        total: 6.32s    remaining: 557ms
919:    learn: 0.2230982        total: 6.33s    remaining: 550ms
920:    learn: 0.2230076        total: 6.33s    remaining: 543ms
921:    learn: 0.2229783        total: 6.34s    remaining: 536ms
922:    learn: 0.2229332        total: 6.35s    remaining: 530ms
923:    learn: 0.2228877        total: 6.36s    remaining: 523ms
924:    learn: 0.2228038        total: 6.36s    remaining: 516ms
925:    learn: 0.2227426        total: 6.37s    remaining: 509ms
926:    learn: 0.2226908        total: 6.37s    remaining: 502ms
927:    learn: 0.2226416        total: 6.38s    remaining: 495ms
928:    learn: 0.2225894        total: 6.39s    remaining: 488ms
929:    learn: 0.2225558        total: 6.39s    remaining: 481ms
930:    learn: 0.2224838        total: 6.4s     remaining: 474ms
931:    learn: 0.2224475        total: 6.41s    remaining: 467ms
932:    learn: 0.2223125        total: 6.41s    remaining: 461ms
933:    learn: 0.2222342        total: 6.42s    remaining: 454ms
934:    learn: 0.2221635        total: 6.43s    remaining: 447ms
935:    learn: 0.2221228        total: 6.43s    remaining: 440ms
936:    learn: 0.2220886        total: 6.44s    remaining: 433ms
937:    learn: 0.2220575        total: 6.45s    remaining: 426ms
938:    learn: 0.2220034        total: 6.45s    remaining: 419ms
939:    learn: 0.2219595        total: 6.46s    remaining: 412ms
940:    learn: 0.2219188        total: 6.47s    remaining: 406ms
941:    learn: 0.2218422        total: 6.47s    remaining: 399ms
942:    learn: 0.2217656        total: 6.48s    remaining: 392ms
943:    learn: 0.2216008        total: 6.49s    remaining: 385ms
944:    learn: 0.2214924        total: 6.5s     remaining: 378ms
945:    learn: 0.2213970        total: 6.5s     remaining: 371ms
946:    learn: 0.2213445        total: 6.51s    remaining: 364ms
947:    learn: 0.2212966        total: 6.52s    remaining: 357ms
948:    learn: 0.2212422        total: 6.52s    remaining: 351ms
949:    learn: 0.2211354        total: 6.53s    remaining: 344ms
```

```
950:    learn: 0.2210466        total: 6.54s    remaining: 337ms
951:    learn: 0.2209600        total: 6.55s    remaining: 330ms
952:    learn: 0.2208328        total: 6.55s    remaining: 323ms
953:    learn: 0.2207294        total: 6.56s    remaining: 316ms
954:    learn: 0.2206322        total: 6.57s    remaining: 310ms
955:    learn: 0.2205823        total: 6.58s    remaining: 303ms
956:    learn: 0.2205090        total: 6.58s    remaining: 296ms
957:    learn: 0.2204443        total: 6.59s    remaining: 289ms
958:    learn: 0.2203998        total: 6.59s    remaining: 282ms
959:    learn: 0.2203143        total: 6.6s     remaining: 275ms
960:    learn: 0.2202174        total: 6.61s    remaining: 268ms
961:    learn: 0.2201329        total: 6.61s    remaining: 261ms
962:    learn: 0.2200856        total: 6.62s    remaining: 254ms
963:    learn: 0.2200297        total: 6.63s    remaining: 247ms
964:    learn: 0.2199715        total: 6.63s    remaining: 241ms
965:    learn: 0.2199200        total: 6.64s    remaining: 234ms
966:    learn: 0.2198741        total: 6.64s    remaining: 227ms
967:    learn: 0.2198016        total: 6.65s    remaining: 220ms
968:    learn: 0.2197750        total: 6.66s    remaining: 213ms
969:    learn: 0.2197160        total: 6.66s    remaining: 206ms
970:    learn: 0.2196797        total: 6.67s    remaining: 199ms
971:    learn: 0.2196137        total: 6.67s    remaining: 192ms
972:    learn: 0.2195655        total: 6.68s    remaining: 185ms
973:    learn: 0.2195318        total: 6.69s    remaining: 179ms
974:    learn: 0.2194915        total: 6.69s    remaining: 172ms
975:    learn: 0.2194470        total: 6.7s     remaining: 165ms
976:    learn: 0.2194007        total: 6.71s    remaining: 158ms
977:    learn: 0.2193533        total: 6.71s    remaining: 151ms
978:    learn: 0.2192902        total: 6.72s    remaining: 144ms
979:    learn: 0.2192551        total: 6.73s    remaining: 137ms
980:    learn: 0.2192169        total: 6.73s    remaining: 130ms
981:    learn: 0.2191326        total: 6.74s    remaining: 124ms
982:    learn: 0.2191119        total: 6.75s    remaining: 117ms
983:    learn: 0.2190611        total: 6.75s    remaining: 110ms
984:    learn: 0.2190061        total: 6.76s    remaining: 103ms
985:    learn: 0.2189738        total: 6.76s    remaining: 96.1ms
986:    learn: 0.2189136        total: 6.77s    remaining: 89.2ms
987:    learn: 0.2188856        total: 6.78s    remaining: 82.3ms
988:    learn: 0.2188403        total: 6.78s    remaining: 75.5ms
989:    learn: 0.2187798        total: 6.79s    remaining: 68.6ms
990:    learn: 0.2187109        total: 6.8s     remaining: 61.7ms
991:    learn: 0.2186928        total: 6.8s     remaining: 54.9ms
992:    learn: 0.2186679        total: 6.81s    remaining: 48ms
993:    learn: 0.2185689        total: 6.82s    remaining: 41.1ms
994:    learn: 0.2185099        total: 6.82s    remaining: 34.3ms
995:    learn: 0.2184551        total: 6.83s    remaining: 27.4ms
996:    learn: 0.2184051        total: 6.83s    remaining: 20.6ms
997:    learn: 0.2183162        total: 6.84s    remaining: 13.7ms
```

```
998:    learn: 0.2182232        total: 6.84s    remaining: 6.85ms
999:    learn: 0.2181500        total: 6.85s    remaining: 0us
```

[103]:
```
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')
```

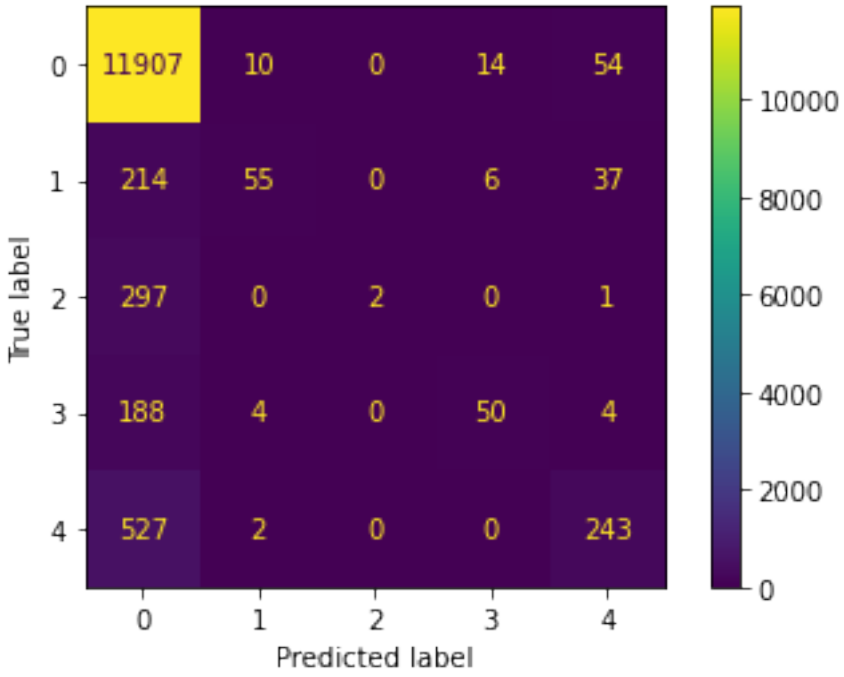
[104]:
```
y_pred = vot_soft.predict(X_test)
```

[105]:
```
metrics.accuracy_score(y_test, y_pred)*100
```

[105]:
```
90.02570694087404
```

[106]:
```
t = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= vot_soft.
 ↪classes_)
disp.plot()
```

[106]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f6dc4a3eb20>
```



[107]:
```
#metrics.accuracy_score(y_test, y_pred_gnb)*100
```

[108]:
```
#confusion_matrix(y_test, y_pred_gnb)
```

[109]:
```
#t = confusion_matrix(y_test, y_pred_gnb)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= gnb.
 ↪classes_)
```

[110]:
```
#disp.plot()
```

[111]:
```
#metrics.accuracy_score(y_test, y_pred_log)*100
```

[112]:
```
#t = confusion_matrix(y_test, y_pred_log)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= grid_search.
 ↪classes_)
#disp.plot()
```

[113]:
```
#metrics.accuracy_score(y_test, y_pred_cat)*100
```

[114]:
```
#t = confusion_matrix(y_test, y_pred_cat)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= cat.
 ↪classes_)
#disp.plot()
```

[115]:
```
#metrics.accuracy_score(y_test, y_pred_dt)*100
```

[116]:
```
#t = confusion_matrix(y_test, y_pred_dt)
#disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= dtclf.
 ↪classes_)
#disp.plot()
```

9 TESTING DATA

[117]:
```
path = '/media/mr-robot/Local Disk/summer_training/test'
os.chdir(path)
```

[118]:
```
# 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)
```

[119]:
```
## 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")
```

[120]:
```
# 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)
```

[121]:
```
df = pd.read_csv('merged_data.csv')
df
```

[121]:

	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]
```

[122]:
```
#Selecting required feature
df=df[["DT","GR","NPHI","RHOB","FACIES"]]
```

[123]:
```
df
```

[123]:
```
              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]
```

[124]:
```
df=imputing(imputation_strategy[optionimputation],df)
df
```

[124]:

	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	78.920533	0.530600	2.4993	0
29561	127.9872	84.668033	0.500300	2.4997	1
29562	127.9657	96.542533	0.524533	2.4999	1
29563	128.9050	95.799167	0.501867	2.5000	0
29564	128.4784	122.594467	0.606433	2.5000	0

[29565 rows x 5 columns]

[125]:
```
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	0
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	42.799200	0.5044	2.3501	0
15680	173.8879	42.799200	0.4875	2.3948	0
15706	172.7409	42.799200	0.5074	2.4185	0
15707	174.8540	42.799200	0.4967	2.4147	0
15708	172.7833	42.799200	0.4784	2.4165	0

```
16123   76.3119   88.145567  0.3927  3.0026       0
16907  173.0850   42.799200  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   78.920533  0.530600  2.4993       0
29561  127.9872   84.668033  0.500300  2.4997       1
29562  127.9657   96.542533  0.524533  2.4999       1
29563  128.9050   95.799167  0.501867  2.5000       0
29564  128.4784  122.594467  0.606433  2.5000       0

[29543 rows x 5 columns]
column GR
Percentiles: 25th=76.837, 75th=103.425, IQR=26.588
InterQuartile Range Outliers-:
             DT       GR    NPHI    RHOB  FACIES
1342   144.1047  35.5685  0.6130  1.2752       3
1625   149.5008  36.3442  0.6133  1.1143       3
1626   150.9417  29.3642  0.6122  1.0951       3
1627   149.6250  27.0870  0.6129  1.1136       3
1628   148.6148  28.5975  0.6274  1.2056       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

[1842 rows x 5 columns]
(1842, 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   78.920533  0.530600  2.4993       0
29561  127.9872   84.668033  0.500300  2.4997       1
```

```
29562  127.9657   96.542533  0.524533  2.4999       1
29563  128.9050   95.799167  0.501867  2.5000       0
29564  128.4784  122.594467  0.606433  2.5000       0

[27701 rows x 5 columns]
column NPHI
Percentiles: 25th=0.467, 75th=0.550, IQR=0.082
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

[1510 rows x 5 columns]
(1510, 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   78.920533  0.530600  2.4993       0
29561  127.9872   84.668033  0.500300  2.4997       1
29562  127.9657   96.542533  0.524533  2.4999       1
29563  128.9050   95.799167  0.501867  2.5000       0
29564  128.4784  122.594467  0.606433  2.5000       0

[26191 rows x 5 columns]
column RHOB
Percentiles: 25th=2.206, 75th=2.416, IQR=0.210
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

[1476 rows x 5 columns]
(1476, 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   78.920533  0.530600  2.4993       0
29561  127.9872   84.668033  0.500300  2.4997       1
29562  127.9657   96.542533  0.524533  2.4999       1
29563  128.9050   95.799167  0.501867  2.5000       0
29564  128.4784  122.594467  0.606433  2.5000       0

[24715 rows x 5 columns]
```

[126]:
```
df = data_scaling( scaling_strategy[optionscaling] , df ,␣
↪DATAConditioningColumns )
```

[127]:
```
df.to_csv("testing_preprocessed.csv",index=False)
```

[128]:
```
df=pd.read_csv('testing_preprocessed.csv')
```

[129]:
```
df
```

[129]:
```
             DT        GR      NPHI    RHOB  FACIES
0      0.419198 -0.251613 -0.555556 -0.0715       0
1      0.370230 -0.197525 -0.686992 -0.0785       0
2      0.415135 -0.240096 -0.743902 -0.0940       0
3      0.481360 -0.308062 -0.359079 -0.1155       0
4      0.530716 -0.352045  0.364499 -0.1410       0
…         …        …       …     …      …
24710  0.095252 -0.622034  0.289973  0.9275       0
24711  0.157879 -0.368427 -0.120596  0.9295       1
24712  0.156849  0.155533  0.207769  0.9305       1
24713  0.201850  0.122732 -0.099368  0.9310       0
24714  0.181412  1.305068  1.317525  0.9310       0

[24715 rows x 5 columns]
```

[130]:
```
X_testing=df[["DT","GR","NPHI","RHOB"]]
y_testing=df[["FACIES"]]
```

[131]:
```
X_testing.isnull().sum()
```

[131]:
```
DT      0
GR      0
NPHI    0
RHOB    0
dtype: int64
```

[132]:
```
#X_testing=FeatureSelection(FeatureSelectionStrategy[optionfeature],X_testing,y_testing)
```

[ ]:
```

```

[133]:
```
X_testing
```

[133]:

	DT	GR	NPHI	RHOB
0	0.419198	-0.251613	-0.555556	-0.0715
1	0.370230	-0.197525	-0.686992	-0.0785
2	0.415135	-0.240096	-0.743902	-0.0940
3	0.481360	-0.308062	-0.359079	-0.1155
4	0.530716	-0.352045	0.364499	-0.1410
…	…	…	…	…
24710	0.095252	-0.622034	0.289973	0.9275
24711	0.157879	-0.368427	-0.120596	0.9295
24712	0.156849	0.155533	0.207769	0.9305
24713	0.201850	0.122732	-0.099368	0.9310
24714	0.181412	1.305068	1.317525	0.9310

[24715 rows x 4 columns]

[134]:
```
y_testing.describe()
```

[134]:

	FACIES
count	24715.000000
mean	0.334776
std	1.018206
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	4.000000

[135]:
```
y_predicted = vot_soft.predict(X_testing)
```

[136]:
```
y_predicted
```

[136]:
```
array([0, 0, 0, …, 0, 0, 0])
```

[137]:
```
metrics.accuracy_score(y_testing, y_predicted)*100
```

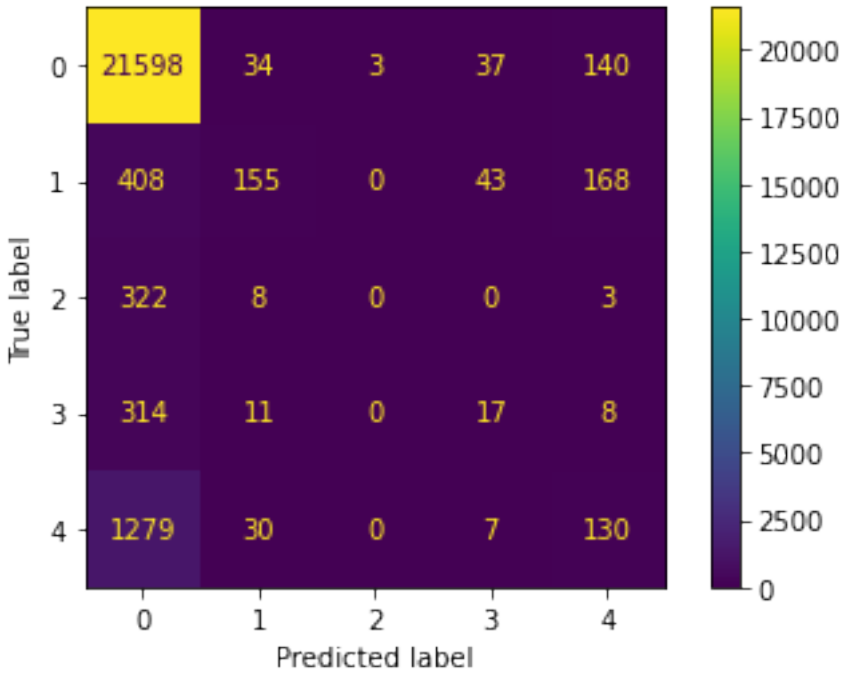
[137]: 88.61015577584462

[138]:
```
confusion_matrix(y_testing, y_predicted)
```

[138]:
```
array([[21598,    34,     3,    37,   140],
       [  408,   155,     0,    43,   168],
       [  322,     8,     0,     0,     3],
       [  314,    11,     0,    17,     8],
       [ 1279,    30,     0,     7,   130]])
```

[139]:
```
t = confusion_matrix(y_testing, y_predicted)
disp = ConfusionMatrixDisplay(confusion_matrix= t, display_labels= vot_soft.
 ↪classes_)
disp.plot()
```

[139]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f6dd3d6c100>



[140]:
```
t1=pd.DataFrame(y_testing)
```

[141]:
```
t1.to_csv('y_given.csv',index=False)
```

[142]:
```
t2=pd.DataFrame(y_predicted)
```

[143]:
```
t2.to_csv('y_predicted.csv',index=False)
```

[ ]: