First of all let's look at the data we have. This will help as to estimate what methods we will use for model implementation.

Ввод [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import missingno as msno
from matplotlib import pyplot as plt
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
```

Ввод [2]:
```
from matplotlib import rcParams

# figure size in inches
rcParams['figure.figsize'] = 15,12
```

Ввод [3]:
```
#from google.colab import drive
#drive.mount('drive')
```

Ввод [4]:
```
data = pd.read_csv('../CSV/Norwey data.csv', sep=';')
data
```

Out[4]:

	WELL	DEPTH_MD	X_LOC	Y_LOC	Z_LOC	GROUP	FORMATION	CALI	RSHA	RMED	...	ROP	DTS	DCAL	DRHO
0	15/9-13	494.5280	437641.96875	6470972.5	-469.501831	NORDLAND GP.	NaN	19.480835	NaN	1.611410	...	34.636410	NaN	NaN	-0.574928
1	15/9-13	494.6800	437641.96875	6470972.5	-469.653809	NORDLAND GP.	NaN	19.468800	NaN	1.618070	...	34.636410	NaN	NaN	-0.570188
2	15/9-13	494.8320	437641.96875	6470972.5	-469.805786	NORDLAND GP.	NaN	19.468800	NaN	1.626459	...	34.779556	NaN	NaN	-0.574245
3	15/9-13	494.9840	437641.96875	6470972.5	-469.957794	NORDLAND GP.	NaN	19.459282	NaN	1.621594	...	39.965164	NaN	NaN	-0.586315
4	15/9-13	495.1360	437641.96875	6470972.5	-470.109772	NORDLAND GP.	NaN	19.453100	NaN	1.602679	...	57.483765	NaN	NaN	-0.597914
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1170506	7/1-2 S	3169.3124	NaN	NaN	NaN	VESTLAND GP.	Bryne Fm.	8.423170	NaN	NaN	...	27.674368	NaN	NaN	-0.001763
1170507	7/1-2 S	3169.4644	NaN	NaN	NaN	VESTLAND GP.	Bryne Fm.	8.379244	NaN	NaN	...	28.024338	NaN	NaN	-0.007600
1170508	7/1-2 S	3169.6164	NaN	NaN	NaN	VESTLAND GP.	Bryne Fm.	8.350248	NaN	NaN	...	28.091282	NaN	NaN	-0.018297
1170509	7/1-2 S	3169.7684	NaN	NaN	NaN	VESTLAND GP.	Bryne Fm.	8.313779	NaN	NaN	...	28.019775	NaN	NaN	-0.011438
1170510	7/1-2 S	3169.9204	NaN	NaN	NaN	VESTLAND GP.	Bryne Fm.	8.294910	NaN	NaN	...	25.985943	NaN	NaN	-0.011398

1170511 rows × 29 columns

We are interested in 20 features from CALI to RXO. Let's sclice data

Ввод [5]:
```
# Select featuresfrom data. We will use from "CALI" to "RXO"
features = data.loc[:, "CALI":"RXO"]
features
```

Out[5]:

	CALI	RSHA	RMED	RDEP	RHOB	GR	SGR	NPHI	PEF	DTC	SP	BS	ROP	DTS	DCAL	DRHO	MU
0	19.480835	NaN	1.611410	1.798681	1.884186	80.200851	NaN	NaN	20.915468	161.131180	24.612379	NaN	34.636410	NaN	NaN	-0.574928	
1	19.468800	NaN	1.618070	1.795641	1.889794	79.262886	NaN	NaN	19.383013	160.603470	23.895531	NaN	34.636410	NaN	NaN	-0.570188	
2	19.468800	NaN	1.626459	1.800733	1.896523	74.821999	NaN	NaN	22.591518	160.173615	23.916357	NaN	34.779556	NaN	NaN	-0.574245	
3	19.459282	NaN	1.621594	1.801517	1.891913	72.878922	NaN	NaN	32.191910	160.149429	23.793688	NaN	39.965164	NaN	NaN	-0.586315	
4	19.453100	NaN	1.602679	1.795299	1.880034	71.729141	NaN	NaN	38.495632	160.128342	24.104078	NaN	57.483765	NaN	NaN	-0.597914	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1170506	8.423170	NaN	NaN	NaN	2.527984	77.654900	NaN	NaN	4.586425	NaN	NaN	8.5	27.674368	NaN	NaN	-0.001763	
1170507	8.379244	NaN	NaN	NaN	2.537613	75.363937	NaN	NaN	7.019858	NaN	NaN	8.5	28.024338	NaN	NaN	-0.007600	
1170508	8.350248	NaN	NaN	NaN	2.491860	66.452843	NaN	NaN	9.049782	NaN	NaN	8.5	28.091282	NaN	NaN	-0.018297	
1170509	8.313779	NaN	NaN	NaN	2.447539	55.784817	NaN	NaN	8.903917	NaN	NaN	8.5	28.019775	NaN	NaN	-0.011438	
1170510	8.294910	NaN	NaN	NaN	2.430716	48.432129	NaN	NaN	9.150043	NaN	NaN	8.5	25.985943	NaN	NaN	-0.011398	

1170511 rows × 20 columns

We have 20 features and a population of 1,170,511

Ввод [6]:
```
features.describe()
```

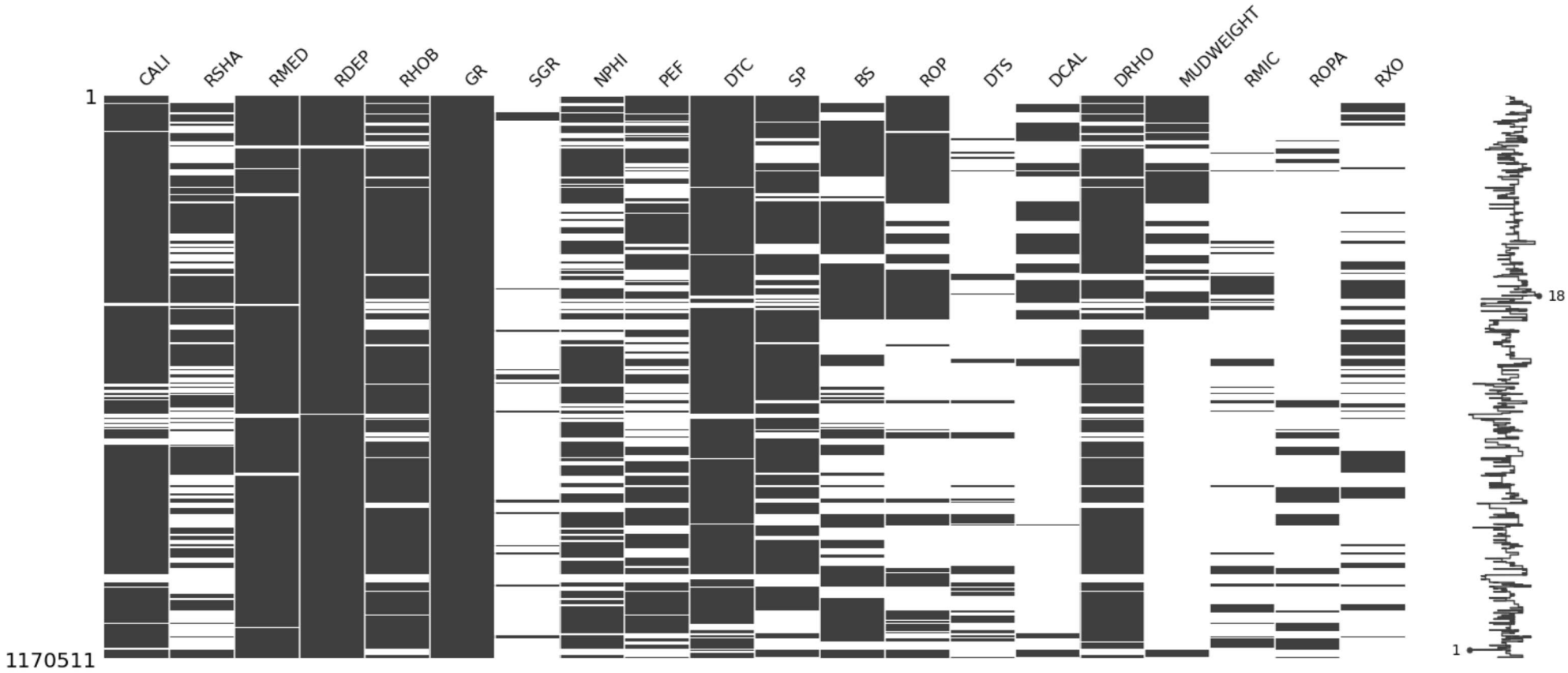
Out[6]:

	CALI	RSHA	RMED	RDEP	RHOB	GR	SGR	NPHI	PEF	DTC	
count	1.082634e+06	630650.000000	1.131518e+06	1.159496e+06	1.009242e+06	1.170511e+06	69353.000000	765409.000000	671692.000000	1.089648e+06	86424
mean	1.318568e+01	10.694664	4.986978e+00	1.069103e+01	2.284987e+00	7.091370e+01	64.895910	0.331966	6.319719	1.133581e+02	6
std	3.798907e+00	100.642597	5.467269e+01	1.139480e+02	2.532835e-01	3.423149e+01	38.435818	0.130483	10.955360	2.999050e+01	7
min	2.344000e+00	0.000100	-8.418695e-03	3.170056e-02	7.209712e-01	1.092843e-01	-777.985962	-0.035822	0.099718	7.415132e+00	-99
25%	9.429712e+00	0.854120	9.140862e-01	9.102396e-01	2.092203e+00	4.762722e+01	42.962429	0.241365	3.414440	8.782584e+01	3
50%	1.255575e+01	1.399020	1.443584e+00	1.439000e+00	2.321228e+00	6.836763e+01	69.562714	0.326800	4.313530	1.095852e+02	5
75%	1.671075e+01	3.099348	2.680930e+00	2.557220e+00	2.488580e+00	8.903551e+01	87.910156	0.422951	5.968794	1.407745e+02	8
max	2.827900e+01	2193.904541	1.988616e+03	1.999887e+03	3.457820e+00	1.076964e+03	963.608582	0.999570	383.129974	3.204789e+02	52

All features are numerical with difference in distribution. That's why we need normalization

1. MISSING VALUES

Ввод [7]:
```
msno.matrix(features);
```



Ввод [8]:
```
# Percent of missing values in data
features_entirety_pct = (features.isnull().sum()/features.shape[0]*100).astype('int').sort_values(ascending=False)
features_entirety_pct
```

Out[8]:
```
SGR          94
DTS          85
RMIC         84
ROPA         83
DCAL         74
RXO          72
MUDWEIGHT    72
ROP          54
RSHA         46
PEF          42
BS           41
NPHI         34
SP           26
DRHO         15
RHOB         13
CALI          7
DTC           6
RMED          3
GR            0
RDEP          0
dtype: int32
```

We have huge amount of missing values up to 94%

2. FEATURES CORELLATION

Let's start with checking the correlation with target value:

Ввод [9]:
```
features_n_target = features.join(data['FORCE_2020_LITHOFACIES_LITHOLOGY'])
features_n_target_corellation = features_n_target.corr()

#Correlation with output variable
cor_with_target = abs(features_n_target_corellation["FORCE_2020_LITHOFACIES_LITHOLOGY"])
#Selecting highly correlated features
relevant_features = cor_with_target[cor_with_target>0.5]
relevant_features
```

Out[9]:
```
FORCE_2020_LITHOFACIES_LITHOLOGY    1.0
Name: FORCE_2020_LITHOFACIES_LITHOLOGY, dtype: float64
```

No features highly corellated with target value

We will create function that helps to estimate relative features

Ввод [10]:
```
def handling_multicollinear_features(data, target_name: str) -> list:
  features_to_remove = []
  data_columns = data.columns.to_list()
  features = data.drop(columns=[target_name])
  features_n_target_corr = data.corr()
  cor_target = abs(features_n_target_corr[target_name])
  for col_name in features.columns:
    cor_feature = abs(features_n_target_corr[col_name])
    relevant_features = cor_feature[cor_feature > 0.5].drop(col_name)
    if relevant_features.empty:
      continue
    feature_with_max_corr_with_target = cor_target[relevant_features.index].idxmax()
    list_to_drop = relevant_features.index.to_list()
    list_to_drop.remove(feature_with_max_corr_with_target)

    if feature_with_max_corr_with_target != col_name:
      list_to_drop += [col_name]
    features_to_remove += list_to_drop

  return list(set(features_to_remove))
```

Ввод [11]:
```
features_to_remove = handling_multicollinear_features(features_n_target, 'FORCE_2020_LITHOFACIES_LITHOLOGY')
features_to_remove
```

Out[11]:
```
['GR', 'DTC', 'DTS', 'RHOB', 'NPHI', 'BS', 'DCAL', 'CALI', 'SGR']
```

There are 9 highly corellated features with corr_values > 0.5

Ввод [12]:
```
features_for_use = [el for el in features.columns if el not in features_to_remove]
features_for_use
```

Out[12]:
```
['RSHA',
 'RMED',
 'RDEP',
 'PEF',
 'SP',
 'ROP',
 'DRHO',
 'MUDWEIGHT',
 'RMIC',
 'ROPA',
 'RXO']
```

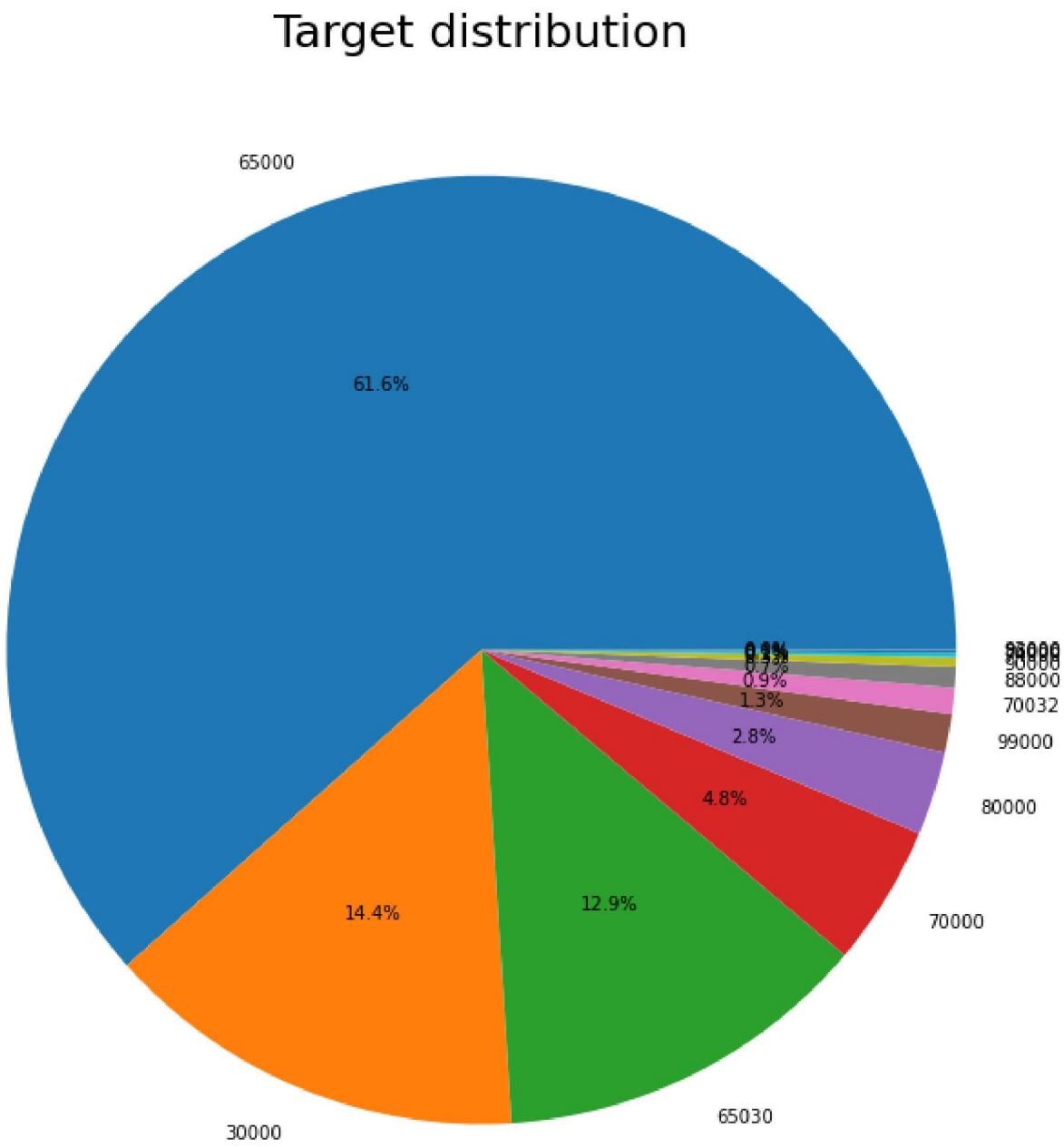
3. TARGET ANALYSIS

Ввод [13]:
```
# Target
target = data['FORCE_2020_LITHOFACIES_LITHOLOGY']
sorted(set(target))
```

Out[13]:
```
[30000,
 65000,
 65030,
 70000,
 70032,
 74000,
 80000,
 86000,
 88000,
 90000,
 93000,
 99000]
```

We can resume from the target that we have a task of multi-label classification. There are 12 classes

Ввод [14]:
```
target_values_count = target.value_counts()
plt.figure(figsize = (12,12))
plt.pie(target_values_count.values, labels=target_values_count.index, autopct='%1.1f%%')
plt.title('Target distribution', fontsize = 25)
plt.show()
```



Ввод [15]:
```
target.value_counts()
```

Out[15]:
```
65000    720803
30000    168937
65030    150455
70000     56320
80000     33329
99000     15245
70032     10513
88000      8213
90000      3820
74000      1688
86000      1085
93000       103
Name: FORCE_2020_LITHOFACIES_LITHOLOGY, dtype: int64
```

We have a **high disbalance** of classes here. The biggest class exceeds the smallest one in about 7e3 and we have only 100 examples of minority class. With Confidence level of 95% and the Confidence Interval of 5 we need at least 384 examples of the smallest class to get any kind of meaningful result. Also we will use **Stratified Split by Labels** for train test splitting

There is possibility to implement the **oversampling technique** called **SMOTE** to increase the amount of data (for population of 1170511 we should get between 384 to 117051 examples of certain class). But in this case we have to keep the distribution of data in authentic state.

Also we should answer **the question**: what for a metric to use? Is it important to have high accuracy for the smallest class prediction? Or is it ok to use the accuracy as metric? **Macro/Micro** metric depending on the task

The next question is how to process missing values in data? There are 3 most popular methods: removing NANs, replacing them with some value (mean value or -1) or to create a model which will fill gaps with values based on KNN technique or with using of NN. Methods 1 and 3 are not suitable in our situation when we have about 50% features missing 50% of data. Therefore, we will filling missing data with -1

As a model I suppose to use **Gradient Boosting from CatBoost**. It works great with chart data and has all benefits of Gradient Boosting technique