phase-3-project

May 24, 2023

1 *Author*: *Yussuf Hersi*

2 *First Look to the Data and Cleaning & Exploring*

Tanzania is a developing country facing clean water challenges. With a population of over 59 million, there is a significant need to provide clean water to the population. Many existing water wells are either nonfunctional or in need of repair.

The objective is to develop a predictive model that can classify the status of water points as functional, nonfunctional, or functional but in need of repair. This model will assist the Tanzanian government in identifying maintenance requirements for existing wells and provide valuable insights for future well investments.

By accurately predicting the status of water points, the model will enable authorities to optimize the utilization of water sources and make informed decisions regarding well maintenance. This project aims to contribute towards ensuring sustainable access to clean water in Tanzania while supporting efficient resource allocation by the government.

2.1 Aim of This Notebook

The aim of this notebook is to perform data understanding, preparation, and exploration. We will download the necessary data and analyze the meanings of the columns. Our focus will be on identifying the required data cleaning steps. Through visualizations, we will examine certain features. Additionally, we will prepare the data for modeling by removing duplicate or unnecessary information, as well as handling null or irrelevant values.

The key findings from the initial data exploration will be summarized in a concise list at the end of the notebook.At the end of the notebook we would also do initial modelling and modelling tunning.

2.2 Data Source

The original data for this project is available from the DrivenData competition Pump it Up.The data consists of four different datasets: submission format, training set, test set, and train labels set. The training set contains 59,400 water point records with 40 features, while the train labels set provides the corresponding status of these water points.

2.3 Importing Necessary Libraries

[215]:
```
# Importing necessary libraries for data manipulation and visualization
import numpy as np       # To use np.arrays
import pandas as pd      # To use dataframes

# Importing libraries for plotting
import matplotlib.pyplot as plt  # To plot
%matplotlib inline                # To display plots inline in Jupyter Notebook
import seaborn as sns              # To enhance visualizations
```

```
UsageError: unrecognized arguments: # To display plots inline in Jupyter
Notebook
```

[216]:
```
# To see the hidden columns in dataframe
pd.options.display.max_columns=100
```

[217]:
```
df_train_set = pd.read_csv(r'C:\Users\Yussuf␣
↪Hersi\Music\Projects\phase-3-project\data1\Training-set-values.csv') # train␣
↪set data
```

[218]:
```
# train label dataframe
df_train_labels = pd.read_csv(r"C:\Users\Yussuf␣
↪Hersi\Music\Projects\phase-3-project\data1\Training-set-labels.csv") #train␣
↪set labels data
```

3 First Look to the Data and Merging Two Dataframes

[219]:
```
df_train_labels
```

[219]:
```
          id    status_group
0      69572      functional
1       8776      functional
2      34310      functional
3      67743  non functional
4      19728      functional
…        …             …
59395  60739      functional
59396  27263      functional
59397  37057      functional
59398  31282      functional
59399  26348      functional

[59400 rows x 2 columns]
```

[220]:
```
df_train_set
```

[220]:
```
          id  amount_tsh date_recorded        funder  gps_height  \
0      69572      6000.0    2011-03-14         Roman        1390
1       8776         0.0    2013-03-06       Grumeti        1399
2      34310        25.0    2013-02-25  Lottery Club         686
3      67743         0.0    2013-01-28        Unicef         263
4      19728         0.0    2011-07-13   Action In A           0
…        …          …           …             …         …
59395  60739        10.0    2013-05-03  Germany Republi       1210
59396  27263      4700.0    2011-05-07      Cefa-njombe        1212
59397  37057         0.0    2011-04-11              NaN           0
59398  31282         0.0    2011-03-08            Malec           0
59399  26348         0.0    2011-03-23       World Bank         191

          installer  longitude   latitude              wpt_name  num_private  \
0             Roman  34.938093  -9.856322                  none            0
1           GRUMETI  34.698766  -2.147466              Zahanati            0
2      World vision  37.460664  -3.821329           Kwa Mahundi            0
3            UNICEF  38.486161 -11.155298  Zahanati Ya Nanyumbu            0
4           Artisan  31.130847  -1.825359               Shuleni            0
…               …          …          …                     …          …
59395           CES  37.169807  -3.253847  Area Three Namba 27            0
59396          Cefa  35.249991  -9.070629     Kwa Yahona Kuvala            0
59397           NaN  34.017087  -8.750434               Mashine            0
59398          Musa  35.861315  -6.378573                Mshoro            0
59399         World  38.104048  -6.747464       Kwa Mzee Lugawa            0

                         basin    subvillage       region  region_code  \
0                   Lake Nyasa      Mnyusi B       Iringa           11
1                Lake Victoria       Nyamara         Mara           20
2                      Pangani       Majengo      Manyara           21
3      Ruvuma / Southern Coast    Mahakamani       Mtwara           90
4                Lake Victoria    Kyanyamisa       Kagera           18
…                          …            …           …           …
59395                  Pangani      Kiduruni  Kilimanjaro            3
59396                  Rufiji       Igumbilo       Iringa           11
59397                  Rufiji      Madungulu        Mbeya           12
59398                  Rufiji         Mwinyi       Dodoma            1
59399              Wami / Ruvu  Kikatanyemba     Morogoro            5

       district_code        lga              ward  population  \
0                  5     Ludewa          Mundindi         109
1                  2  Serengeti             Natta         280
2                  4  Simanjiro           Ngorika         250
3                 63   Nanyumbu          Nanyumbu          58
4                  1    Karagwe        Nyakasimbi           0
…                …          …                 …          …
59395              5        Hai  Masama Magharibi         125
```

```
59396              4          Njombe          Ikondo          56
59397              7         Mbarali         Chimala           0
59398              4        Chamwino      Mvumi Makulu         0
59399              2  Morogoro Rural      Ngerengere         150

      public_meeting              recorded_by scheme_management  \
0               True  GeoData Consultants Ltd               VWC
1                NaN  GeoData Consultants Ltd             Other
2               True  GeoData Consultants Ltd               VWC
3               True  GeoData Consultants Ltd               VWC
4               True  GeoData Consultants Ltd               NaN
…                  …                        …                 …
59395           True  GeoData Consultants Ltd       Water Board
59396           True  GeoData Consultants Ltd               VWC
59397           True  GeoData Consultants Ltd               VWC
59398           True  GeoData Consultants Ltd               VWC
59399           True  GeoData Consultants Ltd               VWC

                       scheme_name permit  construction_year extraction_type  \
0                            Roman  False               1999         gravity
1                              NaN   True               2010         gravity
2       Nyumba ya mungu pipe scheme   True               2009         gravity
3                              NaN   True               1986     submersible
4                              NaN   True                  0         gravity
…                                …     …                   …               …
59395        Losaa Kia water supply   True               1999         gravity
59396   Ikondo electrical water sch   True               1996         gravity
59397                          NaN  False                  0          swn 80
59398                          NaN   True                  0     nira/tanira
59399                          NaN   True               2002     nira/tanira

      extraction_type_group extraction_type_class   management  \
0                   gravity               gravity          vwc
1                   gravity               gravity          wug
2                   gravity               gravity          vwc
3               submersible           submersible          vwc
4                   gravity               gravity        other
…                         …                     …            …
59395               gravity               gravity  water board
59396               gravity               gravity          vwc
59397                swn 80              handpump          vwc
59398           nira/tanira              handpump          vwc
59399           nira/tanira              handpump          vwc

      management_group                payment payment_type water_quality  \
0           user-group           pay annually     annually          soft
1           user-group              never pay    never pay          soft
```

```
2           user-group         pay per bucket   per bucket          soft
3           user-group              never pay    never pay          soft
4                other              never pay    never pay          soft
…                    …                      …            …           …
59395       user-group         pay per bucket   per bucket          soft
59396       user-group           pay annually     annually          soft
59397       user-group            pay monthly      monthly      fluoride
59398       user-group              never pay    never pay          soft
59399       user-group  pay when scheme fails   on failure         salty

      quality_group      quantity quantity_group               source  \
0              good        enough         enough               spring
1              good  insufficient   insufficient  rainwater harvesting
2              good        enough         enough                  dam
3              good           dry            dry          machine dbh
4              good      seasonal       seasonal  rainwater harvesting
…                 …             …              …                    …
59395          good        enough         enough               spring
59396          good        enough         enough                river
59397      fluoride        enough         enough          machine dbh
59398          good  insufficient   insufficient         shallow well
59399         salty        enough         enough         shallow well

                source_type source_class              waterpoint_type  \
0                    spring  groundwater           communal standpipe
1      rainwater harvesting      surface           communal standpipe
2                       dam      surface  communal standpipe multiple
3                  borehole  groundwater  communal standpipe multiple
4      rainwater harvesting      surface           communal standpipe
…                         …            …                            …
59395                spring  groundwater           communal standpipe
59396            river/lake      surface           communal standpipe
59397              borehole  groundwater                    hand pump
59398          shallow well  groundwater                    hand pump
59399          shallow well  groundwater                    hand pump

      waterpoint_type_group
0        communal standpipe
1        communal standpipe
2        communal standpipe
3        communal standpipe
4        communal standpipe
…                         …
59395    communal standpipe
59396    communal standpipe
59397             hand pump
59398             hand pump
```

```
59399             hand pump

[59400 rows x 40 columns]
```

The index numbers in two data sets look same but it is impossible to check the nearly 60000 points. So, to make sure we assign data sets 'id' as index and after that merge them.

[221]:
```python
# setting id as an index to train set
df_train_set.set_index('id',inplace=True)
```

[222]:
```python
df_train_labels.set_index('id',inplace=True) # setting id as an index to train␣
↪labels
```

[223]:
```python
df = pd.merge(df_train_labels, df_train_set, how = 'inner', left_index =␣
↪True,right_index=True) #merging two data sets
```

[224]:
```python
df.reset_index(inplace=True) # setting a new index
```

4 Looking at Columns

[225]:
```python
df.info() #to see the types of the columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   status_group           59400 non-null  object
 2   amount_tsh             59400 non-null  float64
 3   date_recorded          59400 non-null  object
 4   funder                 55765 non-null  object
 5   gps_height             59400 non-null  int64
 6   installer              55745 non-null  object
 7   longitude              59400 non-null  float64
 8   latitude               59400 non-null  float64
 9   wpt_name               59400 non-null  object
 10  num_private            59400 non-null  int64
 11  basin                  59400 non-null  object
 12  subvillage             59029 non-null  object
 13  region                 59400 non-null  object
 14  region_code            59400 non-null  int64
 15  district_code          59400 non-null  int64
 16  lga                    59400 non-null  object
 17  ward                   59400 non-null  object
 18  population             59400 non-null  int64
 19  public_meeting         56066 non-null  object
```

```
 20  recorded_by            59400 non-null  object
 21  scheme_management      55523 non-null  object
 22  scheme_name            31234 non-null  object
 23  permit                 56344 non-null  object
 24  construction_year      59400 non-null  int64
 25  extraction_type        59400 non-null  object
 26  extraction_type_group  59400 non-null  object
 27  extraction_type_class  59400 non-null  object
 28  management             59400 non-null  object
 29  management_group       59400 non-null  object
 30  payment                59400 non-null  object
 31  payment_type           59400 non-null  object
 32  water_quality          59400 non-null  object
 33  quality_group          59400 non-null  object
 34  quantity               59400 non-null  object
 35  quantity_group         59400 non-null  object
 36  source                 59400 non-null  object
 37  source_type            59400 non-null  object
 38  source_class           59400 non-null  object
 39  waterpoint_type        59400 non-null  object
 40  waterpoint_type_group  59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
```

[226]:
```
df.isna().sum() # to see the null values
```

[226]:
```
id                       0
status_group             0
amount_tsh               0
date_recorded            0
funder                3635
gps_height               0
installer             3655
longitude                0
latitude                 0
wpt_name                 0
num_private              0
basin                    0
subvillage             371
region                   0
region_code              0
district_code            0
lga                      0
ward                     0
population               0
public_meeting        3334
recorded_by              0
```

```
scheme_management          3877
scheme_name               28166
permit                     3056
construction_year             0
extraction_type               0
extraction_type_group         0
extraction_type_class         0
management                    0
management_group              0
payment                       0
payment_type                  0
water_quality                 0
quality_group                 0
quantity                      0
quantity_group                0
source                        0
source_type                   0
source_class                  0
waterpoint_type               0
waterpoint_type_group         0
dtype: int64
```

[227]:
```
df.describe() # to see numeric columns detailed
```

[227]:
```
                 id     amount_tsh    gps_height     longitude      latitude  \
count  59400.000000   59400.000000  59400.000000  59400.000000  5.940000e+04
mean   37115.131768     317.650385    668.297239     34.077427 -5.706033e+00
std    21453.128371    2997.574558    693.116350      6.567432  2.946019e+00
min        0.000000       0.000000    -90.000000      0.000000 -1.164944e+01
25%    18519.750000       0.000000      0.000000     33.090347 -8.540621e+00
50%    37061.500000       0.000000    369.000000     34.908743 -5.021597e+00
75%    55656.500000      20.000000   1319.250000     37.178387 -3.326156e+00
max    74247.000000  350000.000000   2770.000000     40.345193 -2.000000e-08

        num_private   region_code  district_code    population  \
count  59400.000000  59400.000000   59400.000000  59400.000000
mean       0.474141     15.297003       5.629747    179.909983
std       12.236230     17.587406       9.633649    471.482176
min        0.000000      1.000000       0.000000      0.000000
25%        0.000000      5.000000       2.000000      0.000000
50%        0.000000     12.000000       3.000000     25.000000
75%        0.000000     17.000000       5.000000    215.000000
max     1776.000000     99.000000      80.000000  30500.000000

       construction_year
count       59400.000000
mean         1300.652475
```

```
std          951.620547
min            0.000000
25%            0.000000
50%         1986.000000
75%         2004.000000
max         2013.000000
```

[228]:
```
df['status_group'].value_counts()
```

[228]:
```
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
```

[229]:
```
# Check the percentage status group
df['status_group'].value_counts(normalize=True)
```

[229]:
```
functional                 0.543081
non functional             0.384242
functional needs repair    0.072677
Name: status_group, dtype: float64
```

We will address several issues in the dataset. Firstly, we have highly imbalanced target values. Secondly, there are null values in the data. Lastly, some columns contain duplicate or redundant information. To tackle these issues and simplify our data for easier model training, we will drop the duplicate and redundant columns, as they do not affect our target variable. Additionally, we will handle the null values appropriately.

4.0.1 scheme_management / management / management_group columns

[230]:
```
df['scheme_management'].value_counts()
```

[230]:
```
VWC                 36793
WUG                  5206
Water authority      3153
WUA                  2883
Water Board          2748
Parastatal           1680
Private operator     1063
Company              1061
Other                 766
SWC                    97
Trust                  72
None                    1
Name: scheme_management, dtype: int64
```

[231]:
```
df['management'].value_counts()
```

[231]:
```
vwc                  40507
wug                   6515
water board           2933
wua                   2535
private operator      1971
parastatal            1768
water authority        904
other                  844
company                685
unknown                561
other - school          99
trust                   78
Name: management, dtype: int64
```

We have identified that the columns 'scheme_management' and 'management' represent similar information, with 'scheme_management' indicating who operates the water point and 'management' indicating how the water point is managed. Since 'scheme_management' has 3877 null values, we will prefer to keep the 'management' column. Additionally, we observe that the column 'management_group' also provides similar information about how the water point is managed. Therefore, we can keep 'management' and 'management_group' while dropping 'scheme_management' to avoid redundancy in our data.

[232]:
```
df['management_group'].value_counts()
```

[232]:
```
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
```

[233]:
```
df.loc[df['management_group']=='user-group']['management'].value_counts() # to␣
↪find sub-groups of this column
```

[233]:
```
vwc            40507
wug             6515
water board     2933
wua             2535
Name: management, dtype: int64
```

To identify the subgroups within the 'management_group' column, we examined the unique values under the 'user-group' category. We found that the 'management_group' column is simply a grouped version of the more detailed 'management' column. Given that 'management' provides more specific information, we have decided to drop the 'management_group' column. However, to keep track of the subgroups within 'management_group', we grouped the data below to observe the number of subgroups within the 'management' column.

[234]:

```
df.groupby(['management_group','management']).count()
# to see how many sub-groups have in management group according to management␣
↪column
```

[234]:

```
                                      id  status_group  amount_tsh  \
management_group management
commercial       company             685           685         685
                 private operator   1971          1971        1971
                 trust                78            78          78
                 water authority     904           904         904
other            other               844           844         844
                 other - school       99            99          99
parastatal       parastatal         1768          1768        1768
unknown          unknown             561           561         561
user-group       vwc               40507         40507       40507
                 water board        2933          2933        2933
                 wua                2535          2535        2535
                 wug                6515          6515        6515

                                   date_recorded  funder  gps_height  \
management_group management
commercial       company                     685     663         685
                 private operator           1971    1957        1971
                 trust                        78      78          78
                 water authority             904     836         904
other            other                       844     837         844
                 other - school               99      99          99
parastatal       parastatal                 1768    1624        1768
unknown          unknown                     561     533         561
user-group       vwc                       40507   37632       40507
                 water board                2933    2715        2933
                 wua                        2535    2308        2535
                 wug                        6515    6483        6515

                                   installer  longitude  latitude  wpt_name  \
management_group management
commercial       company                 663        685       685       685
                 private operator       1959       1971      1971      1971
                 trust                    78         78        78        78
                 water authority         836        904       904       904
other            other                   831        844       844       844
                 other - school           99         99        99        99
parastatal       parastatal             1626       1768      1768      1768
unknown          unknown                 527        561       561       561
user-group       vwc                   37630      40507     40507     40507
                 water board            2714       2933      2933      2933
                 wua                    2309       2535      2535      2535
```

	wug	6473	6515	6515	6515

management_group	management	num_private	basin	subvillage	region \
commercial	company	685	685	685	685
	private operator	1971	1971	1932	1971
	trust	78	78	78	78
	water authority	904	904	895	904
other	other	844	844	839	844
	other - school	99	99	99	99
parastatal	parastatal	1768	1768	1768	1768
unknown	unknown	561	561	561	561
user-group	vwc	40507	40507	40189	40507
	water board	2933	2933	2933	2933
	wua	2535	2535	2535	2535
	wug	6515	6515	6515	6515

management_group	management	region_code	district_code	lga	ward \
commercial	company	685	685	685	685
	private operator	1971	1971	1971	1971
	trust	78	78	78	78
	water authority	904	904	904	904
other	other	844	844	844	844
	other - school	99	99	99	99
parastatal	parastatal	1768	1768	1768	1768
unknown	unknown	561	561	561	561
user-group	vwc	40507	40507	40507	40507
	water board	2933	2933	2933	2933
	wua	2535	2535	2535	2535
	wug	6515	6515	6515	6515

management_group	management	population	public_meeting	recorded_by \
commercial	company	685	684	685
	private operator	1971	1660	1971
	trust	78	77	78
	water authority	904	878	904
other	other	844	689	844
	other - school	99	99	99
parastatal	parastatal	1768	1518	1768
unknown	unknown	561	301	561
user-group	vwc	40507	39208	40507
	water board	2933	2893	2933
	wua	2535	2522	2535
	wug	6515	5537	6515

```
                                  scheme_management  scheme_name  permit  \
management_group management
commercial       company                        684          655     658
                 private operator              1852          992    1893
                 trust                           77           26      77
                 water authority                902          624     825
other            other                          658          270     744
                 other - school                  99            0      99
parastatal       parastatal                    1757          604    1595
unknown          unknown                         93          240     519
user-group       vwc                          38057        22083   38296
                 water board                   2933         2579    2830
                 wua                           2529         2006    2468
                 wug                           5882         1155    6340

                                  construction_year  extraction_type  \
management_group management
commercial       company                        685              685
                 private operator              1971             1971
                 trust                           78               78
                 water authority                904              904
other            other                          844              844
                 other - school                  99               99
parastatal       parastatal                    1768             1768
unknown          unknown                        561              561
user-group       vwc                          40507            40507
                 water board                   2933             2933
                 wua                           2535             2535
                 wug                           6515             6515

                                  extraction_type_group  \
management_group management
commercial       company                            685
                 private operator                  1971
                 trust                               78
                 water authority                    904
other            other                              844
                 other - school                      99
parastatal       parastatal                        1768
unknown          unknown                            561
user-group       vwc                              40507
                 water board                       2933
                 wua                               2535
                 wug                               6515

                                  extraction_type_class  payment  \
management_group management
```

```
commercial       company                        685     685
                 private operator              1971    1971
                 trust                           78      78
                 water authority                904     904
other            other                          844     844
                 other - school                  99      99
parastatal       parastatal                    1768    1768
unknown          unknown                        561     561
user-group       vwc                          40507   40507
                 water board                   2933    2933
                 wua                           2535    2535
                 wug                           6515    6515

                                  payment_type  water_quality  quality_group  \
management_group management
commercial       company                   685            685            685
                 private operator         1971           1971           1971
                 trust                      78             78             78
                 water authority           904            904            904
other            other                     844            844            844
                 other - school             99             99             99
parastatal       parastatal               1768           1768           1768
unknown          unknown                   561            561            561
user-group       vwc                     40507          40507          40507
                 water board              2933           2933           2933
                 wua                      2535           2535           2535
                 wug                      6515           6515           6515

                                  quantity  quantity_group  source  \
management_group management
commercial       company               685             685     685
                 private operator     1971            1971    1971
                 trust                  78              78      78
                 water authority       904             904     904
other            other                 844             844     844
                 other - school         99              99      99
parastatal       parastatal           1768            1768    1768
unknown          unknown               561             561     561
user-group       vwc                 40507           40507   40507
                 water board          2933            2933    2933
                 wua                  2535            2535    2535
                 wug                  6515            6515    6515

                                  source_type  source_class  waterpoint_type  \
management_group management
commercial       company                  685           685              685
                 private operator        1971          1971             1971
```

```
                     trust                     78            78                78
                     water authority          904           904               904
other                other                    844           844               844
                     other - school            99            99                99
parastatal           parastatal              1768          1768              1768
unknown              unknown                  561           561               561
user-group           vwc                    40507         40507             40507
                     water board             2933          2933              2933
                     wua                     2535          2535              2535
                     wug                     6515          6515              6515

                                         waterpoint_type_group
management_group management
commercial           company                                685
                     private operator                      1971
                     trust                                   78
                     water authority                        904
other                other                                  844
                     other - school                          99
parastatal           parastatal                            1768
unknown              unknown                                561
user-group           vwc                                  40507
                     water board                           2933
                     wua                                   2535
                     wug                                   6515
```

4.0.2 quantity / quantity_group columns

[235]:
```
df['quantity'].value_counts()
```

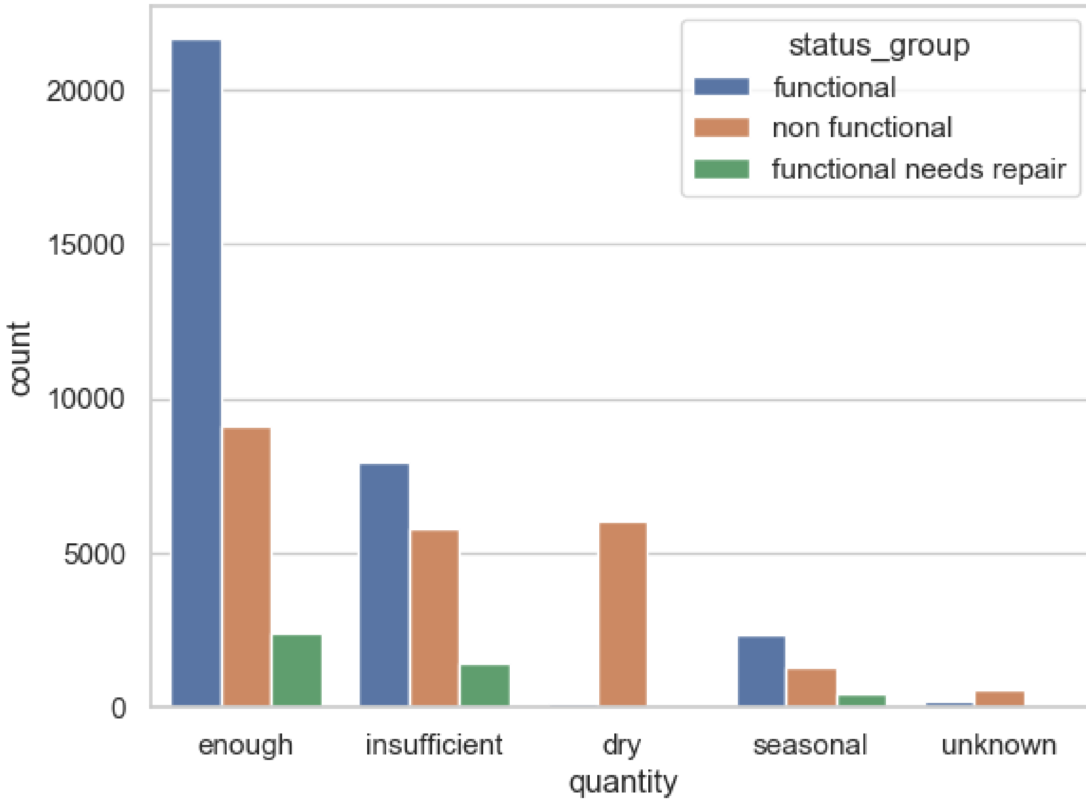
[235]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity, dtype: int64
```

[236]:
```
df['quantity_group'].value_counts()
```

[236]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity_group, dtype: int64
```

These two columns contain same information so we decided to drop 'quantity_group' column.

[237]:
```
import seaborn as sns
ax = sns.countplot(x='quantity', hue="status_group", data=df)
```



The graph clearly shows that even when there is an adequate quantity of water available in certain wells, they are still non-functional. This suggests a strong correlation between non-functionality and dry quantity water points. When examining the graph, it becomes apparent that if a water point is categorized as dry or unknown, there is a high likelihood that it is non-functional. Conversely, if the quantity of water is sufficient, there is a higher probability of finding functional water points.

source / source_type / source_class columns

[238]:
```
df['source'].value_counts()
```

[238]:
```
spring                  17021
shallow well            16824
machine dbh             11075
river                    9612
rainwater harvesting     2295
hand dtw                  874
lake                      765
dam                       656
other                     212
```

```
unknown                          66
Name: source, dtype: int64
```

[239]:
```python
df['source_type'].value_counts()
```

[239]:
```
spring                  17021
shallow well            16824
borehole                11949
river/lake              10377
rainwater harvesting     2295
dam                       656
other                     278
Name: source_type, dtype: int64
```

[240]:
```python
df['source_class'].value_counts()
```

[240]:
```
groundwater    45794
surface        13328
unknown          278
Name: source_class, dtype: int64
```

[241]:
```python
df.groupby(['source_class','source']).count()
# to see how many sub-groups have in source_class according to source column
```

[241]:
```
                                     id  status_group  amount_tsh  \
source_class source
groundwater  hand dtw               874           874         874
             machine dbh          11075         11075       11075
             shallow well         16824         16824       16824
             spring               17021         17021       17021
surface      dam                    656           656         656
             lake                   765           765         765
             rainwater harvesting  2295          2295        2295
             river                 9612          9612        9612
unknown      other                  212           212         212
             unknown                 66            66          66

                                  date_recorded  funder  gps_height  \
source_class source
groundwater  hand dtw                       874     868         874
             machine dbh                  11075   10252       11075
             shallow well                 16824   16302       16824
             spring                       17021   15870       17021
surface      dam                            656     647         656
             lake                           765     763         765
             rainwater harvesting          2295    2099        2295
             river                         9612    8715        9612
```

unknown	other	212	204	212
	unknown	66	45	66

source_class	source	installer	longitude	latitude	wpt_name \
groundwater	hand dtw	868	874	874	874
	machine dbh	10246	11075	11075	11075
	shallow well	16286	16824	16824	16824
	spring	15870	17021	17021	17021
surface	dam	646	656	656	656
	lake	762	765	765	765
	rainwater harvesting	2096	2295	2295	2295
	river	8721	9612	9612	9612
unknown	other	204	212	212	212
	unknown	46	66	66	66

source_class	source	num_private	basin	subvillage	region \
groundwater	hand dtw	874	874	874	874
	machine dbh	11075	11075	10849	11075
	shallow well	16824	16824	16817	16824
	spring	17021	17021	16886	17021
surface	dam	656	656	656	656
	lake	765	765	764	765
	rainwater harvesting	2295	2295	2293	2295
	river	9612	9612	9612	9612
unknown	other	212	212	212	212
	unknown	66	66	66	66

source_class	source	region_code	district_code	lga	ward \
groundwater	hand dtw	874	874	874	874
	machine dbh	11075	11075	11075	11075
	shallow well	16824	16824	16824	16824
	spring	17021	17021	17021	17021
surface	dam	656	656	656	656
	lake	765	765	765	765
	rainwater harvesting	2295	2295	2295	2295
	river	9612	9612	9612	9612
unknown	other	212	212	212	212
	unknown	66	66	66	66

source_class	source	population	public_meeting	recorded_by \
groundwater	hand dtw	874	787	874
	machine dbh	11075	10253	11075
	shallow well	16824	15522	16824

source_class	source			
	spring	17021	16384	17021
surface	dam	656	614	656
	lake	765	628	765
	rainwater harvesting	2295	2089	2295
	river	9612	9543	9612
unknown	other	212	201	212
	unknown	66	45	66

source_class	source	scheme_management	scheme_name	permit \
groundwater	hand dtw	867	122	869
	machine dbh	10577	5491	10293
	shallow well	14127	1129	16253
	spring	16755	14903	15981
surface	dam	644	474	630
	lake	741	607	765
	rainwater harvesting	2065	319	2039
	river	9506	8020	9248
unknown	other	195	144	208
	unknown	46	25	58

source_class	source	construction_year	extraction_type \
groundwater	hand dtw	874	874
	machine dbh	11075	11075
	shallow well	16824	16824
	spring	17021	17021
surface	dam	656	656
	lake	765	765
	rainwater harvesting	2295	2295
	river	9612	9612
unknown	other	212	212
	unknown	66	66

source_class	source	extraction_type_group \
groundwater	hand dtw	874
	machine dbh	11075
	shallow well	16824
	spring	17021
surface	dam	656
	lake	765
	rainwater harvesting	2295
	river	9612
unknown	other	212
	unknown	66

source_class	source	extraction_type_class	management	\
groundwater	hand dtw	874	874	
	machine dbh	11075	11075	
	shallow well	16824	16824	
	spring	17021	17021	
surface	dam	656	656	
	lake	765	765	
	rainwater harvesting	2295	2295	
	river	9612	9612	
unknown	other	212	212	
	unknown	66	66	

source_class	source	management_group	payment	payment_type	\
groundwater	hand dtw	874	874	874	
	machine dbh	11075	11075	11075	
	shallow well	16824	16824	16824	
	spring	17021	17021	17021	
surface	dam	656	656	656	
	lake	765	765	765	
	rainwater harvesting	2295	2295	2295	
	river	9612	9612	9612	
unknown	other	212	212	212	
	unknown	66	66	66	

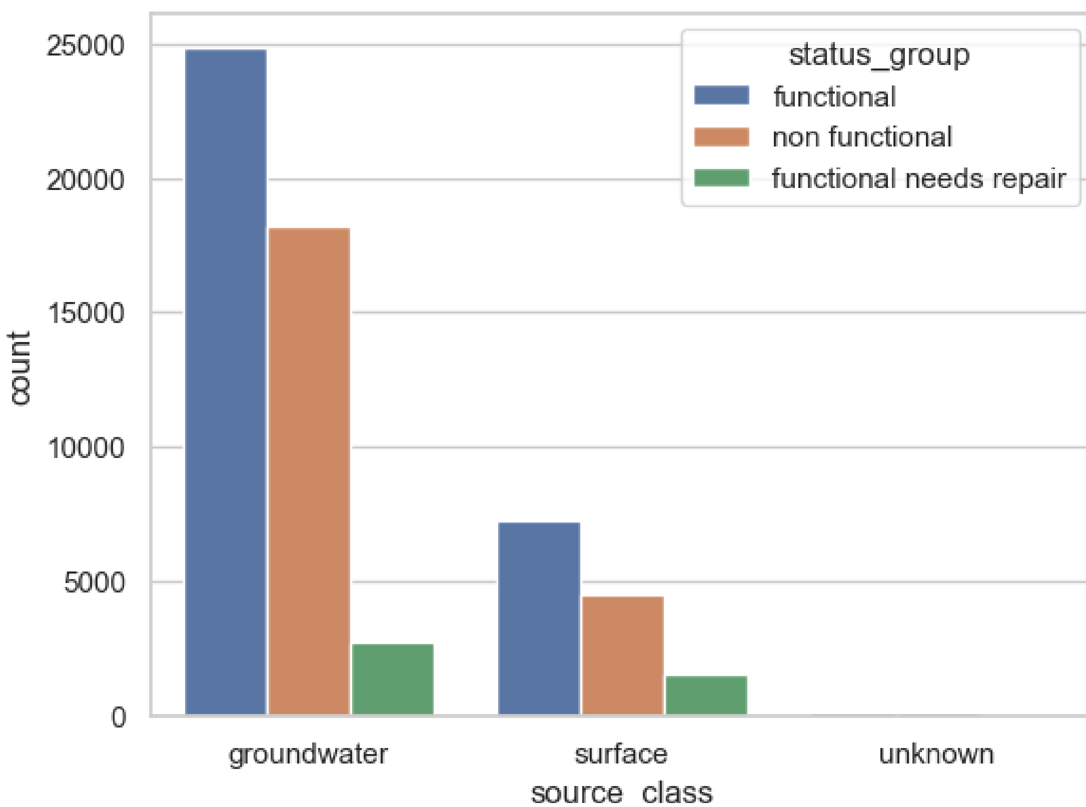
source_class	source	water_quality	quality_group	quantity	\
groundwater	hand dtw	874	874	874	
	machine dbh	11075	11075	11075	
	shallow well	16824	16824	16824	
	spring	17021	17021	17021	
surface	dam	656	656	656	
	lake	765	765	765	
	rainwater harvesting	2295	2295	2295	
	river	9612	9612	9612	
unknown	other	212	212	212	
	unknown	66	66	66	

source_class	source	quantity_group	source_type	\
groundwater	hand dtw	874	874	
	machine dbh	11075	11075	
	shallow well	16824	16824	
	spring	17021	17021	
surface	dam	656	656	
	lake	765	765	

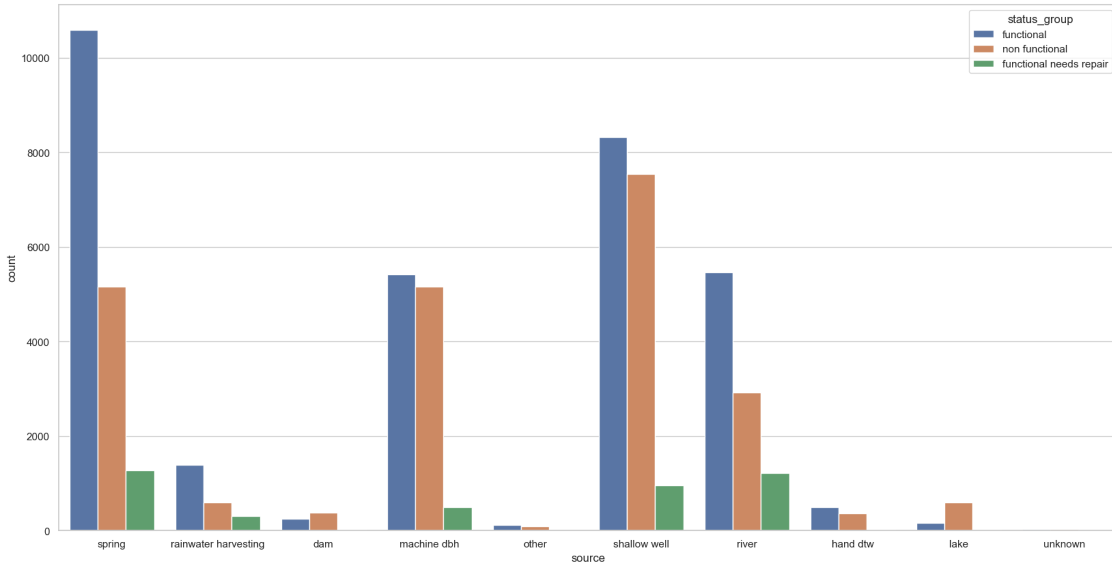
```
               rainwater harvesting           2295         2295
               river                          9612         9612
unknown        other                           212          212
               unknown                          66           66

                                    waterpoint_type  waterpoint_type_group
source_class source
groundwater  hand dtw                           874                    874
             machine dbh                      11075                  11075
             shallow well                     16824                  16824
             spring                           17021                  17021
surface      dam                                656                    656
             lake                               765                    765
             rainwater harvesting              2295                   2295
             river                             9612                   9612
unknown      other                              212                    212
             unknown                             66                     66
```

It is obvious that these three columns keep same information. so, we decided to keep just 'source' column, because it has more detailed information and we will drop others.

[242]:
```
ax = sns.countplot(x='source_class', hue="status_group", data=df)
```



[243]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='source', hue="status_group", data=df)
```



When we look at the columns, there are lots of non-functional ground water. And, it is interesting that machine dbh and swallow well sources nearly have same functional and non-functional waterpoints.

4.0.3 water_quality / quality_group columns

[244]:
```
df['water_quality'].value_counts()
```

[244]:
```
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: water_quality, dtype: int64
```

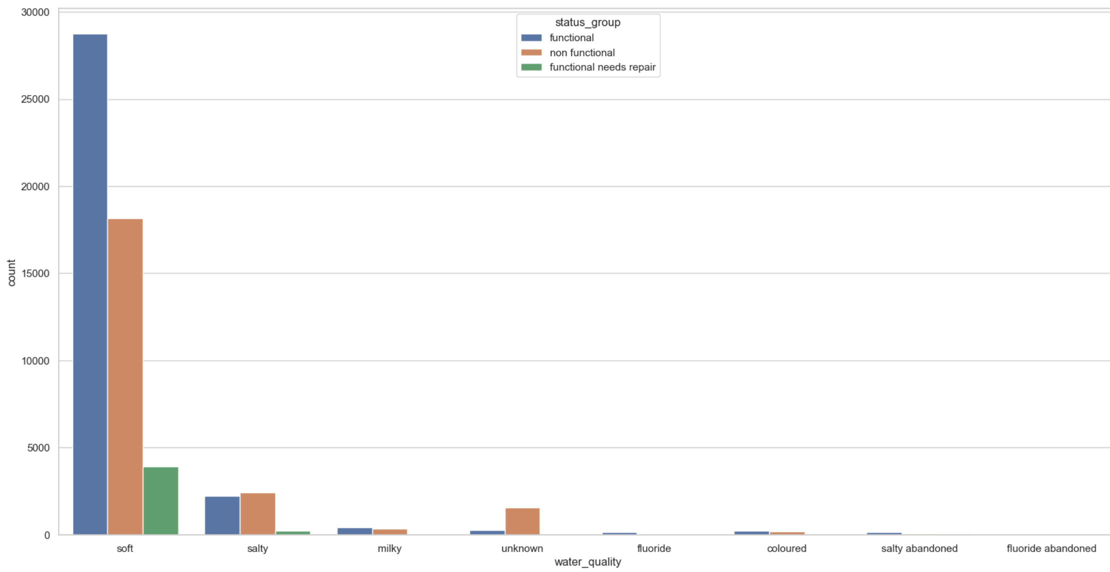
[245]:
```
df['quality_group'].value_counts()
```

[245]:
```
good       50818
salty       5195
unknown     1876
milky        804
```

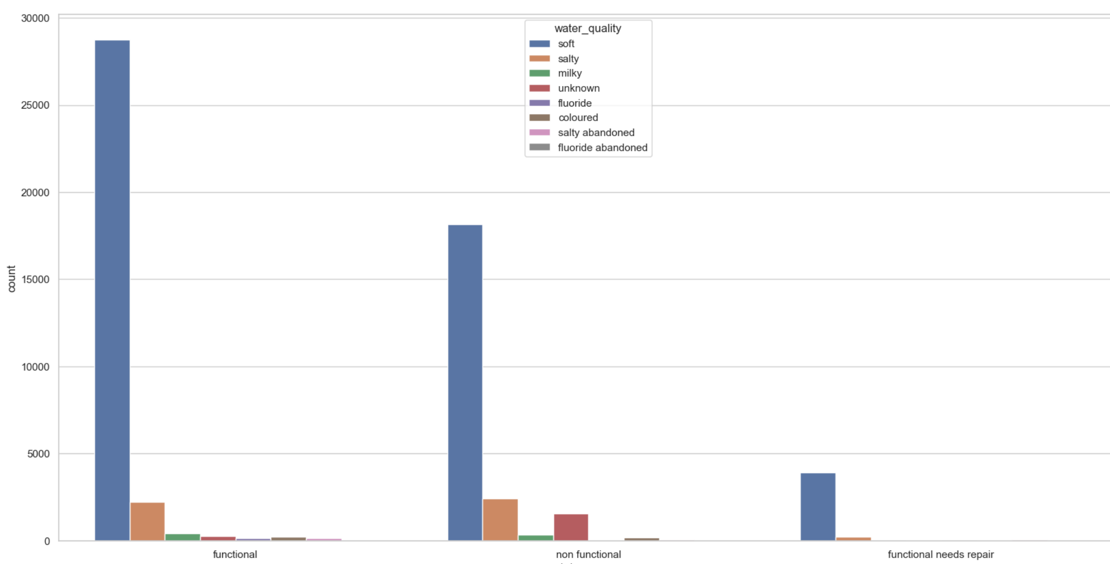
```
colored        490
fluoride       217
Name: quality_group, dtype: int64
```

'water_quality' column has more unique values, so we will keep 'water_quality' and drop 'quality_group'.

[246]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='water_quality', hue="status_group", data=df)
```



[247]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='status_group', hue="water_quality", data=df)
```



From the graphs, it is seen that lots of non-functional water points have soft, good water quality.

4.0.4 payment / payment_type columns

[248]:
```
df['payment'].value_counts()
```

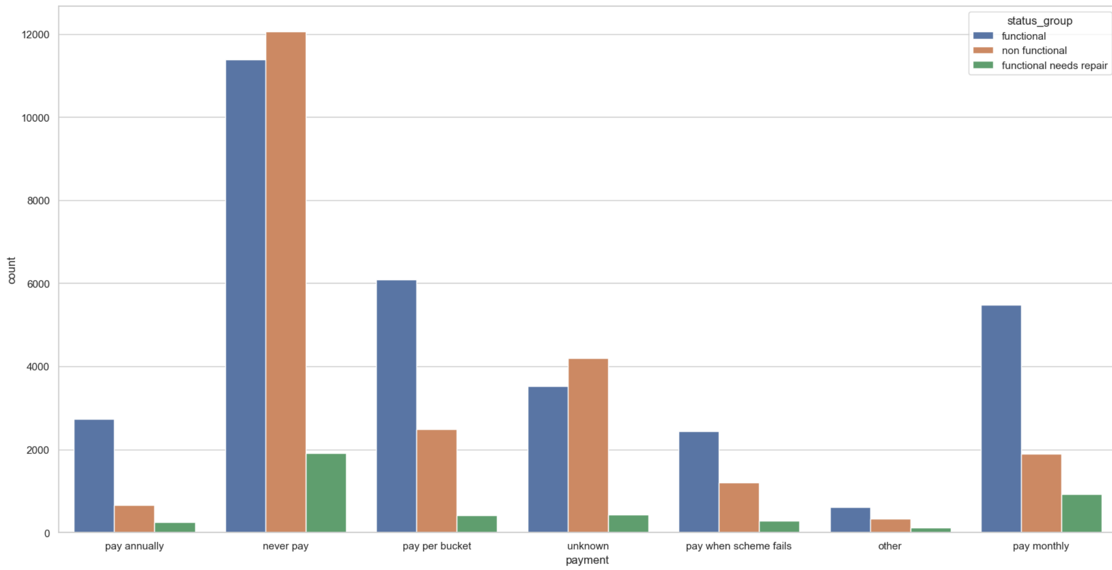
[248]:
```
never pay               25348
pay per bucket           8985
pay monthly              8300
unknown                  8157
pay when scheme fails    3914
pay annually             3642
other                    1054
Name: payment, dtype: int64
```

[249]:
```
df['payment_type'].value_counts()
```

[249]:
```
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
```

These two columns are same so we decided to drop one of them.

[250]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='payment', hue="status_group", data=df)
```



This feature shows us what the water cost. Mostly, there are lots of non-functioal water points as never paid for them.

4.0.5 extraction_type / extraction_type_group / extraction_type_class columns

[251]:
```
df['extraction_type'].value_counts()
```

[251]:
```
gravity                      26780
nira/tanira                   8154
other                         6430
submersible                   4764
swn 80                        3670
mono                          2865
india mark ii                 2400
afridev                       1770
ksb                           1415
other - rope pump              451
other - swn 81                 229
windmill                       117
india mark iii                  98
cemo                            90
other - play pump               85
walimi                          48
climax                          32
other - mkulima/shinyanga        2
Name: extraction_type, dtype: int64
```

[252]:
```
df['extraction_type_group'].value_counts()
```

[252]:
```
gravity            26780
nira/tanira         8154
other               6430
submersible         6179
swn 80              3670
mono                2865
india mark ii       2400
afridev             1770
rope pump            451
other handpump       364
other motorpump      122
wind-powered         117
india mark iii        98
Name: extraction_type_group, dtype: int64
```

[253]:
```python
df['extraction_type_class'].value_counts()
```

[253]:
```
gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
rope pump         451
wind-powered      117
Name: extraction_type_class, dtype: int64
```

[254]:
```python
df.groupby(['extraction_type_class','extraction_type_group']).count()
# to see how many sub-groups have in extraction_type_clas according to␣
↪extraction_type_group
```

[254]:
```
                                                id  status_group  amount_tsh  \
extraction_type_class extraction_type_group
gravity               gravity                26780         26780       26780
handpump              afridev                 1770          1770        1770
                      india mark ii           2400          2400        2400
                      india mark iii            98            98          98
                      nira/tanira             8154          8154        8154
                      other handpump           364           364         364
                      swn 80                  3670          3670        3670
motorpump             mono                    2865          2865        2865
                      other motorpump          122           122         122
other                 other                   6430          6430        6430
rope pump             rope pump                451           451         451
submersible           submersible             6179          6179        6179
wind-powered          wind-powered             117           117         117

                                             date_recorded  funder  \
```

extraction_type_class	extraction_type_group		
gravity	gravity	26780	24704
handpump	afridev	1770	1668
	india mark ii	2400	2358
	india mark iii	98	98
	nira/tanira	8154	7899
	other handpump	364	353
	swn 80	3670	3596
motorpump	mono	2865	2577
	other motorpump	122	122
other	other	6430	6010
rope pump	rope pump	451	448
submersible	submersible	6179	5820
wind-powered	wind-powered	117	112

		gps_height	installer	longitude \
extraction_type_class	extraction_type_group			
gravity	gravity	26780	24714	26780
handpump	afridev	1770	1665	1770
	india mark ii	2400	2358	2400
	india mark iii	98	98	98
	nira/tanira	8154	7885	8154
	other handpump	364	354	364
	swn 80	3670	3593	3670
motorpump	mono	2865	2578	2865
	other motorpump	122	122	122
other	other	6430	6002	6430
rope pump	rope pump	451	448	451
submersible	submersible	6179	5816	6179
wind-powered	wind-powered	117	112	117

		latitude	wpt_name	num_private \
extraction_type_class	extraction_type_group			
gravity	gravity	26780	26780	26780
handpump	afridev	1770	1770	1770
	india mark ii	2400	2400	2400
	india mark iii	98	98	98
	nira/tanira	8154	8154	8154
	other handpump	364	364	364
	swn 80	3670	3670	3670
motorpump	mono	2865	2865	2865
	other motorpump	122	122	122
other	other	6430	6430	6430
rope pump	rope pump	451	451	451
submersible	submersible	6179	6179	6179
wind-powered	wind-powered	117	117	117

extraction_type_class	extraction_type_group	basin	subvillage	region	\
gravity	gravity	26780	26646	26780	
handpump	afridev	1770	1770	1770	
	india mark ii	2400	2400	2400	
	india mark iii	98	98	98	
	nira/tanira	8154	8151	8154	
	other handpump	364	364	364	
	swn 80	3670	3670	3670	
motorpump	mono	2865	2748	2865	
	other motorpump	122	122	122	
other	other	6430	6421	6430	
rope pump	rope pump	451	451	451	
submersible	submersible	6179	6071	6179	
wind-powered	wind-powered	117	117	117	

extraction_type_class	extraction_type_group	region_code	district_code	\
gravity	gravity	26780	26780	
handpump	afridev	1770	1770	
	india mark ii	2400	2400	
	india mark iii	98	98	
	nira/tanira	8154	8154	
	other handpump	364	364	
	swn 80	3670	3670	
motorpump	mono	2865	2865	
	other motorpump	122	122	
other	other	6430	6430	
rope pump	rope pump	451	451	
submersible	submersible	6179	6179	
wind-powered	wind-powered	117	117	

extraction_type_class	extraction_type_group	lga	ward	population	\
gravity	gravity	26780	26780	26780	
handpump	afridev	1770	1770	1770	
	india mark ii	2400	2400	2400	
	india mark iii	98	98	98	
	nira/tanira	8154	8154	8154	
	other handpump	364	364	364	
	swn 80	3670	3670	3670	
motorpump	mono	2865	2865	2865	
	other motorpump	122	122	122	
other	other	6430	6430	6430	
rope pump	rope pump	451	451	451	
submersible	submersible	6179	6179	6179	
wind-powered	wind-powered	117	117	117	

extraction_type_class	extraction_type_group	public_meeting	recorded_by \
gravity	gravity	25829	26780
handpump	afridev	1624	1770
	india mark ii	2297	2400
	india mark iii	88	98
	nira/tanira	7478	8154
	other handpump	348	364
	swn 80	3503	3670
motorpump	mono	2760	2865
	other motorpump	122	122
other	other	5980	6430
rope pump	rope pump	346	451
submersible	submersible	5575	6179
wind-powered	wind-powered	116	117

extraction_type_class	extraction_type_group	scheme_management	scheme_name \
gravity	gravity	26305	21846
handpump	afridev	1614	216
	india mark ii	2193	200
	india mark iii	97	3
	nira/tanira	7170	769
	other handpump	352	79
	swn 80	3087	155
motorpump	mono	2847	2221
	other motorpump	121	118
other	other	5225	930
rope pump	rope pump	376	27
submersible	submersible	6019	4596
wind-powered	wind-powered	117	74

extraction_type_class	extraction_type_group	permit	construction_year \
gravity	gravity	25234	26780
handpump	afridev	1660	1770
	india mark ii	2359	2400
	india mark iii	98	98
	nira/tanira	7920	8154
	other handpump	356	364
	swn 80	3655	3670
motorpump	mono	2582	2865
	other motorpump	122	122
other	other	6050	6430
rope pump	rope pump	349	451
submersible	submersible	5854	6179

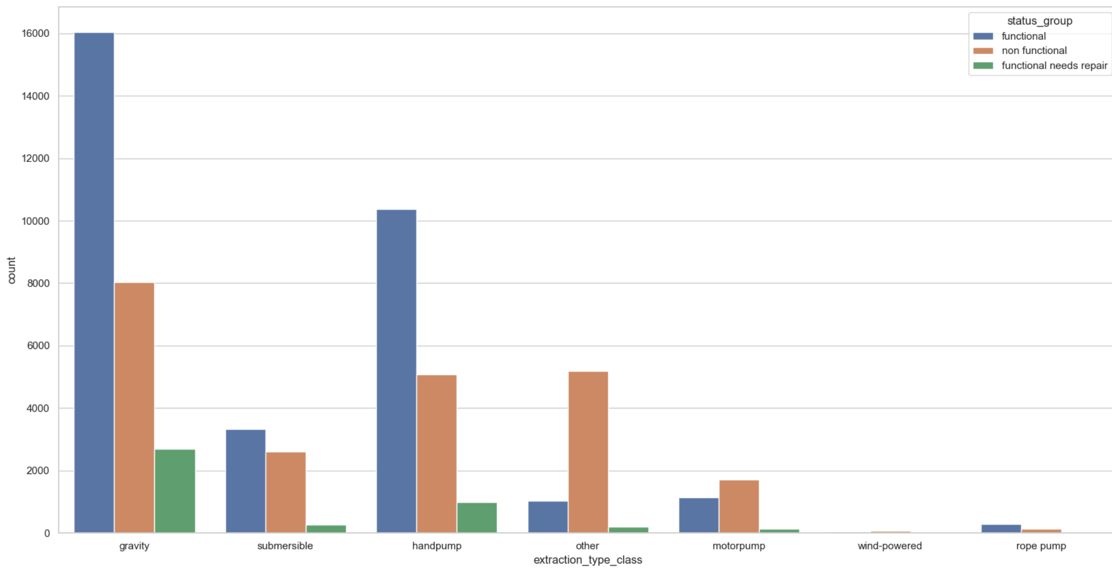
```
wind-powered          wind-powered             105               117

                                           extraction_type  management  \
extraction_type_class extraction_type_group
gravity               gravity                        26780       26780
handpump              afridev                         1770        1770
                      india mark ii                   2400        2400
                      india mark iii                    98          98
                      nira/tanira                     8154        8154
                      other handpump                   364         364
                      swn 80                          3670        3670
motorpump             mono                            2865        2865
                      other motorpump                  122         122
other                 other                           6430        6430
rope pump             rope pump                        451         451
submersible           submersible                     6179        6179
wind-powered          wind-powered                     117         117

                                           management_group  payment  \
extraction_type_class extraction_type_group
gravity               gravity                         26780    26780
handpump              afridev                          1770     1770
                      india mark ii                    2400     2400
                      india mark iii                     98       98
                      nira/tanira                      8154     8154
                      other handpump                    364      364
                      swn 80                           3670     3670
motorpump             mono                             2865     2865
                      other motorpump                   122      122
other                 other                            6430     6430
rope pump             rope pump                         451      451
submersible           submersible                      6179     6179
wind-powered          wind-powered                      117      117

                                           payment_type  water_quality  \
extraction_type_class extraction_type_group
gravity               gravity                     26780          26780
handpump              afridev                      1770           1770
                      india mark ii                2400           2400
                      india mark iii                 98             98
                      nira/tanira                  8154           8154
                      other handpump                364            364
                      swn 80                       3670           3670
motorpump             mono                         2865           2865
                      other motorpump               122            122
other                 other                        6430           6430
rope pump             rope pump                     451            451
```

```
submersible           submersible                   6179          6179
wind-powered          wind-powered                   117           117

                                              quality_group  quantity  \
extraction_type_class extraction_type_group
gravity               gravity                         26780     26780
handpump              afridev                          1770      1770
                      india mark ii                    2400      2400
                      india mark iii                     98        98
                      nira/tanira                      8154      8154
                      other handpump                    364       364
                      swn 80                           3670      3670
motorpump             mono                             2865      2865
                      other motorpump                   122       122
other                 other                            6430      6430
rope pump             rope pump                         451       451
submersible           submersible                      6179      6179
wind-powered          wind-powered                      117       117

                                              quantity_group  source  \
extraction_type_class extraction_type_group
gravity               gravity                          26780   26780
handpump              afridev                           1770    1770
                      india mark ii                     2400    2400
                      india mark iii                      98      98
                      nira/tanira                       8154    8154
                      other handpump                     364     364
                      swn 80                            3670    3670
motorpump             mono                              2865    2865
                      other motorpump                    122     122
other                 other                             6430    6430
rope pump             rope pump                          451     451
submersible           submersible                       6179    6179
wind-powered          wind-powered                       117     117

                                              source_type  source_class  \
extraction_type_class extraction_type_group
gravity               gravity                       26780         26780
handpump              afridev                        1770          1770
                      india mark ii                  2400          2400
                      india mark iii                   98            98
                      nira/tanira                    8154          8154
                      other handpump                  364           364
                      swn 80                         3670          3670
motorpump             mono                           2865          2865
                      other motorpump                 122           122
other                 other                          6430          6430
```

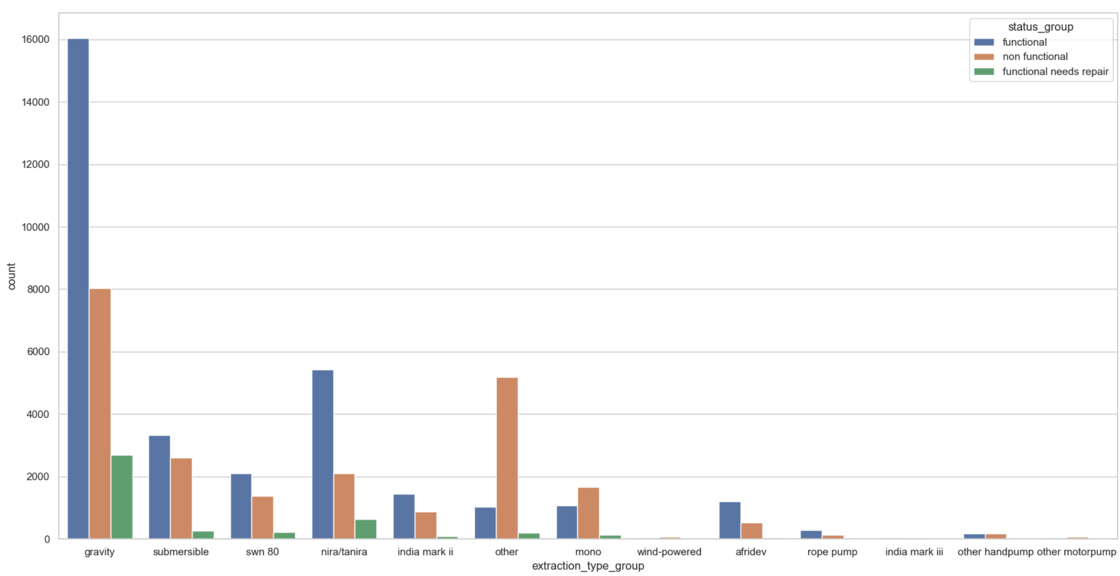
```
rope pump           rope pump                        451           451
submersible         submersible                     6179          6179
wind-powered        wind-powered                     117           117

                                           waterpoint_type  \
extraction_type_class extraction_type_group
gravity             gravity                          26780
handpump            afridev                           1770
                    india mark ii                     2400
                    india mark iii                      98
                    nira/tanira                       8154
                    other handpump                     364
                    swn 80                            3670
motorpump           mono                              2865
                    other motorpump                    122
other               other                             6430
rope pump           rope pump                          451
submersible         submersible                       6179
wind-powered        wind-powered                       117

                                           waterpoint_type_group
extraction_type_class extraction_type_group
gravity             gravity                                26780
handpump            afridev                                 1770
                    india mark ii                           2400
                    india mark iii                            98
                    nira/tanira                             8154
                    other handpump                           364
                    swn 80                                  3670
motorpump           mono                                    2865
                    other motorpump                          122
other               other                                   6430
rope pump           rope pump                                451
submersible         submersible                             6179
wind-powered        wind-powered                             117
```

It is obviously seen that these three columns keep same information. So, we decided to keep 'extraction_type_group' and drop others. Although, extraction_type has more unique values than extraction_type_group , some of these values are very small amount according to this big dataset. We prefered to use more compact one. Also, extraction_type_class contains less detail. So, extraction_type_group is chosen to keep.

[255]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='extraction_type_class', hue="status_group", data=df)
```



[256]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='extraction_type_group', hue="status_group", data=df)
```



Especially, other and mono extraction types have higher change to be non-functional than functional.

4.1 waterpoint_type / waterpoint_type_group

[257]:
```
df['waterpoint_type'].value_counts()
```

[257]:

```
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
cattle trough                    116
dam                                7
Name: waterpoint_type, dtype: int64
```

[258]:

```
df['waterpoint_type_group'].value_counts()
```

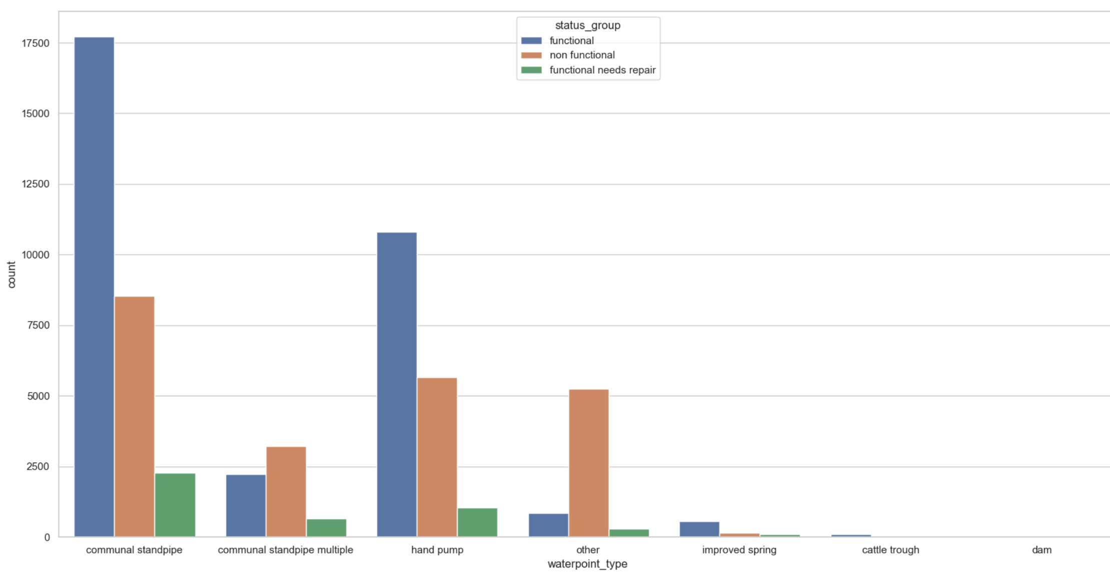
[258]:

```
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: waterpoint_type_group, dtype: int64
```

We decided to keep ‘waterpoint_type’ which contains more detail.

[259]:

```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='waterpoint_type', hue="status_group", data=df)
```



The data reveals a correlation between the waterpoint type and the functionality of water points. Specifically, communal standpipes have a higher likelihood of being functional, while communal standpipe multiple and other types have a higher probability of being non-functional.

5 Dropping Similar Columns

[260]:
```
df.
↪drop(columns=['management_group','scheme_management','quantity_group','source_class','sourc
                 'payment_type','extraction_type_class','extraction_type',␣
↪'waterpoint_type_group'],inplace=True )
```

6 Continue to Exploring Columns

We continue to check data for finding unnecessary or wrong values.

6.0.1 construction_year column

[261]:
```
df['construction_year'].value_counts()
```

[261]:
```
0       20709
2010     2645
2008     2613
2009     2533
2000     2091
2007     1587
2006     1471
2003     1286
2011     1256
2004     1123
2012     1084
2002     1075
1978     1037
1995     1014
2005     1011
1999      979
1998      966
1990      954
1985      945
1980      811
1996      811
1984      779
1982      744
1994      738
1972      708
1974      676
1997      644
1992      640
1993      608
2001      540
1988      521
```

```
1983    488
1975    437
1986    434
1976    414
1970    411
1991    324
1989    316
1987    302
1981    238
1977    202
1979    192
1973    184
2013    176
1971    145
1960    102
1967     88
1963     85
1968     77
1969     59
1964     40
1962     30
1961     21
1965     19
1966     17
Name: construction_year, dtype: int64
```

New feature is added to the dataset. The year values are converted to decades for future encoding. Zero shows the missing values. This have majority of the data set so, it will not be changed to the mean or median, kept as new value in decades.

[262]:

```python
df['decade'] = df['construction_year'] #creating new columns
```

[263]:

```python
# dividing the column decades

df['decade'].replace(to_replace =␣
↪(1960,1961,1962,1963,1964,1965,1966,1967,1968,1969),
                        value ='60s' , inplace=True)
df['decade'].replace(to_replace =␣
↪(1970,1971,1972,1973,1974,1975,1976,1977,1978,1979),
                        value ='70s' , inplace=True)
df['decade'].replace(to_replace =␣
↪(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989),
                        value ='80s' , inplace=True)
df['decade'].replace(to_replace =␣
↪(1990,1991,1992,1993,1994,1995,1996,1997,1998,1999),
                        value ='90s' , inplace=True)
```

```
df['decade'].replace(to_replace =␣
↪(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009),
                        value ='00s' , inplace=True)
df['decade'].replace(to_replace = (2010,2011,2012,2013),
                        value ='10s' , inplace=True)
```

[264]:
```
df['decade'].value_counts()
```

[264]:
```
0      20709
00s    15330
90s     7678
80s     5578
10s     5161
70s     4406
60s      538
Name: decade, dtype: int64
```

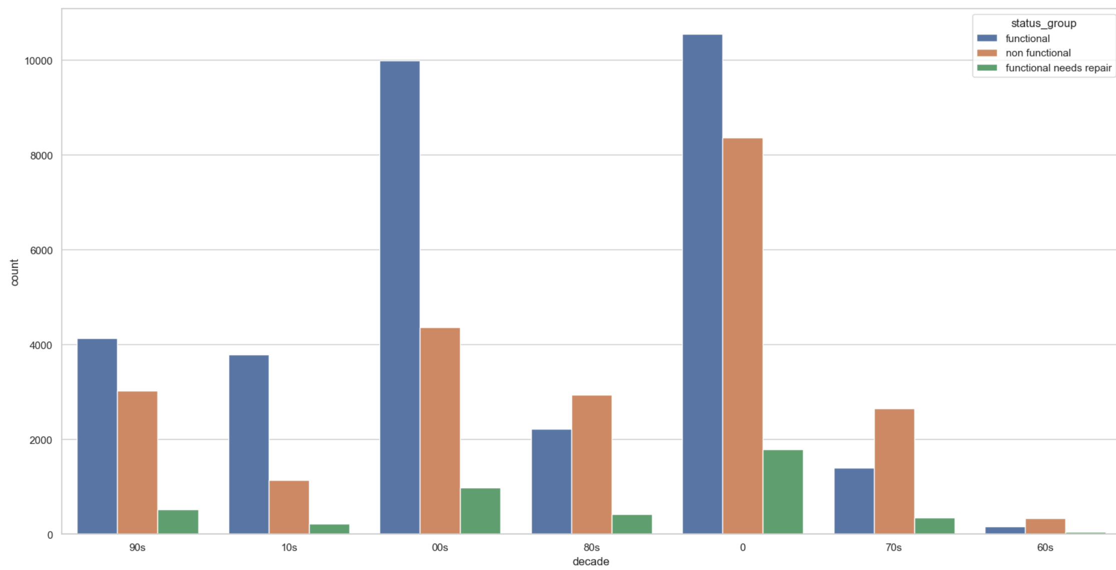
[265]:
```
df.loc[df['construction_year']!=0].describe() # finding mean and median without␣
↪zero values
```

[265]:
```
                 id     amount_tsh    gps_height     longitude      latitude  \
count  38691.000000   38691.000000  38691.000000  38691.000000  38691.000000
mean   37083.008736     466.457534   1002.367760     35.983262     -6.235372
std    21420.922010    3541.036030    618.078669      2.558709      2.761317
min        1.000000       0.000000    -63.000000     29.607122    -11.649440
25%    18489.500000       0.000000    372.000000     34.676719     -8.755274
50%    37078.000000       0.000000   1154.000000     36.648187     -6.064216
75%    55514.500000     200.000000   1488.000000     37.803940     -3.650661
max    74247.000000  350000.000000   2770.000000     40.345193     -1.042375

        num_private   region_code  district_code    population  \
count  38691.000000  38691.000000   38691.000000  38691.000000
mean       0.707710     15.706495       5.969786    269.799617
std       15.083957     21.003006      10.700673    552.343746
min        0.000000      2.000000       1.000000      0.000000
25%        0.000000      4.000000       2.000000     30.000000
50%        0.000000     11.000000       3.000000    150.000000
75%        0.000000     16.000000       5.000000    305.000000
max     1776.000000     99.000000      63.000000  30500.000000

       construction_year
count       38691.000000
mean         1996.814686
std            12.472045
min          1960.000000
25%          1987.000000
50%          2000.000000
```

```
75%           2008.000000
max           2013.000000
```

[266]:
```
df['construction_year'].replace(to_replace = 0, value = 2000, inplace=True)
#changing the missing values in construction year column
```

[267]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='decade', hue="status_group", data=df)
```



It is obviously seen that missing values and most recent years have more functional water points.

6.0.2 recorded_by column

[268]:
```
df['recorded_by'].value_counts()
```

[268]:
```
GeoData Consultants Ltd    59400
Name: recorded_by, dtype: int64
```

The recorded_by column has one value. This will not give any information to our model. So, we dropped it also.

[269]:
```
df.drop(columns=['recorded_by'],inplace=True ) #dropping the column
```

6.0.3 installer column

There are lots of NaN and 0 values in this column. Firstly, we will convert them to unknown.

[270]:
```
df['installer'].fillna(value='Unknown',inplace=True)  # filling null values␣
↪with unknown
```

[271]:
```
df['installer'].value_counts().head(100).sum() # to check the first common 100␣
↪values sum
```

[271]: 47237

[272]:
```
df['installer'].replace(to_replace = '0', value ='Unknown' , inplace=True) #␣
↪filling 0 values with unknown
```

[273]:
```
# Replacing spelling mistakes and consolidating categories with similar names␣
↪in the 'installer' column

df['installer'].replace(to_replace=('District Water Department', 'District␣
↪water depar', 'Distric Water Department'),
                        value='District water department', inplace=True)

df['installer'].replace(to_replace=('FinW', 'Fini water', 'FINI WATER'),␣
↪value='Fini Water', inplace=True)
df['installer'].replace(to_replace='JAICA', value='Jaica', inplace=True)

df['installer'].replace(to_replace=('COUN', 'District COUNCIL', 'DISTRICT␣
↪COUNCIL', 'District Counci',
                                    'District Council', 'Council', 'Counc',␣
↪'District  Council', 'Distri'),
                        value='District council', inplace=True)

df['installer'].replace(to_replace=('RC CHURCH', 'RC Churc', 'RC', 'RC CH', 'RC␣
↪C', 'RC CH', 'RC church',
                                    'RC CATHORIC'), value='RC Church',␣
↪inplace=True)

df['installer'].replace(to_replace=('Central Government', 'Tanzania␣
↪Government', 'central government',
                                    'Cental Government', 'Cebtral Government',␣
↪'Tanzanian Government',
                                    'Tanzania government', 'Centra␣
↪Government', 'CENTRAL GOVERNMENT',
                                    'TANZANIAN GOVERNMENT', 'Central govt',␣
↪'Centr', 'Centra govt'),
                        value='Central government', inplace=True)

df['installer'].replace(to_replace=('World vision', 'World Division', 'World␣
↪Vision'),
                        value='world vision', inplace=True)

df['installer'].replace(to_replace=('Unisef', 'UNICEF'), value='Unicef',␣
↪inplace=True)
```

```
df['installer'].replace(to_replace='DANID', value='DANIDA', inplace=True)

df['installer'].replace(to_replace=('villigers', 'villager', 'Villagers',␣
↪'Villa', 'Village', 'Villi',
                                    'Village Council', 'Village Counil',␣
↪'Villages', 'Vill', 'Village community',
                                    'Villaers', 'Village Community', 'Villag',␣
↪'Villege Council', 'Village council',
                                    'Village  Council', 'Villagerd',␣
↪'Villager', 'Village Technician',
                                    'Village Office', 'Village community␣
↪members'),
                        value='villagers', inplace=True)

df['installer'].replace(to_replace=('Commu', 'Communit', 'commu', 'COMMU',␣
↪'COMMUNITY'),
                        value='Community', inplace=True)

df['installer'].replace(to_replace=('GOVERNMENT', 'GOVER', 'GOVERNME',␣
↪'GOVERM', 'GOVERN', 'Gover', 'Gove',
                                    'Governme', 'Governmen'),␣
↪value='Government', inplace=True)

df['installer'].replace(to_replace='Hesawa', value='HESAWA', inplace=True)
```

[274]:

```
# continue to replacing spellin mistakes and getting together values
df['installer'].replace(to_replace = ('Colonial Government') , value ='Colonial␣
↪government' , inplace=True)
df['installer'].replace(to_replace = ('Government of Misri') , value ='Misri␣
↪Government' , inplace=True)
df['installer'].replace(to_replace = ('Italy government') , value ='Italian␣
↪government' , inplace=True)
df['installer'].replace(to_replace = ('British colonial government') , value␣
↪='British government' , inplace=True)
df['installer'].replace(to_replace = ('Concern /government') , value ='Concern/
↪Government' , inplace=True)
df['installer'].replace(to_replace = ('Village Government') , value ='Village␣
↪government' , inplace=True)
df['installer'].replace(to_replace = ('Government and Community') , value␣
↪='Government /Community' , inplace=True)
df['installer'].replace(to_replace = ('Cetral government /RC') , value ='RC␣
↪church/Central Gover' , inplace=True)
df['installer'].replace(to_replace = ('Government /TCRS','Government/TCRS') ,␣
↪value ='TCRS /Government' , inplace=True)
df['installer'].replace(to_replace = ('ADRA /Government') , value ='ADRA/
↪Government' , inplace=True)
```

[275]:
```python
(47237*100)/59400 # percentage of seeing value counts of installer
```

[275]:
```
79.52356902356902
```

We checked the first 100 values in the "installer" column. We found that some installer names were misspelled or written differently, such as "District Council" and "District council." We will correct these errors. The first 100 values contain 47,237 values, which is 79.5% of the data. This means that we have checked 79.5% of the data.

Now we want to see most common 20 values and visualize them to see the functionality. For this plot, we will not take the values which are smaller than 400. Because this amount does not have majority in this data and it is not good to see thousands of values in same graph.

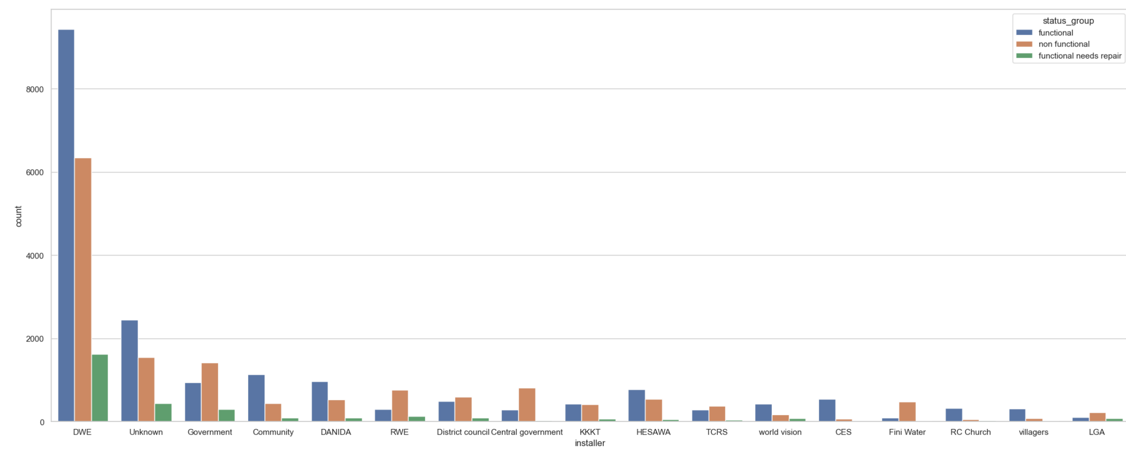
[276]:
```python
df['installer'].value_counts().head(20) #taking most 20 common installer
```

[276]:
```
DWE                   17402
Unknown                4435
Government             2660
Community              1674
DANIDA                 1602
HESAWA                 1379
RWE                    1206
District council       1179
Central government     1114
KKKT                    898
TCRS                    707
world vision            681
CES                     610
Fini Water              593
RC Church               409
LGA                     408
villagers               408
WEDECO                  397
TASAF                   396
Unicef                  332
Name: installer, dtype: int64
```

[277]:
```python
# Creating new dataframe which just picks our desired values

df_1 = df.loc[df['installer']== 'DWE']
df_2 = df.loc[df['installer']== 'Unknown']
df_3 = df.loc[df['installer']== 'Government']
df_4 = df.loc[df['installer']== 'Community']
df_5 = df.loc[df['installer']== 'DANIDA']
df_6 = df.loc[df['installer']== 'RWE']
df_7 = df.loc[df['installer']== 'District council']
df_8 = df.loc[df['installer']== 'Central government']
df_9 = df.loc[df['installer']== 'KKKT']
```

```
df_10 = df.loc[df['installer']== 'HESAWA']
df_11 = df.loc[df['installer']== 'TCRS']
df_12 = df.loc[df['installer']== 'world vision']
df_13 = df.loc[df['installer']== 'CES']
df_14 = df.loc[df['installer']== 'Fini Water']
df_15 = df.loc[df['installer']== 'RC Church']
df_16 = df.loc[df['installer']== 'villagers']
df_17 = df.loc[df['installer']== 'LGA']

df_installer = pd.
 ↪concat([df_1,df_2,df_3,df_4,df_5,df_6,df_7,df_8,df_9,df_10,df_11,df_12,
                          df_13,df_14,df_15,df_16,df_17], ignore_index=True)
```

[278]:
```
plt.figure(figsize=(26,10))
ax = sns.countplot(x='installer', hue="status_group", data=df_installer)
```



It is interesting that most of water points which central government and district council installed are non-functional. DWE has the majority of functional wells but has also many non-functional wells.

To ease our encoding later on, we will collect installers which has less than 400 value counts together and named them others.

[279]:
```
df['installer_cat'] = df['installer'] # To make new categorizes, creating new␣
 ↪column
```

[280]:
```
# define df_test

df_test = pd.read_csv(r'C:\Users\Yussuf␣
 ↪Hersi\Music\Projects\phase-3-project\data1\Test-set-values.csv')
```

[281]:
```
c_ins = ['DWE','Unknown','Government','Community','DANIDA','RWE','District␣
↪council', 'Central government',
        'KKKT','HESAWA','TCRS', 'world vision', 'Fini Water', 'RC␣
↪Church','villagers','LGA']


df.loc[~df["installer_cat"].isin(c_ins), "installer_cat"] = "Others"
# converting the values which has less than 400 value counts to others
```

Now, we have new feature as installer_cat with 17 unique values.

6.0.4 funder column

[282]:
```
df['funder'].fillna(value='Unknown',inplace=True)
df['funder'].replace(to_replace = '0', value ='Unknown' , inplace=True)
# filling 0 and null values with unknown
```

[283]:
```
df['funder'].value_counts().head(20)
```

[283]:
```
Government Of Tanzania    9084
Unknown                   4416
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
Kkkt                      1287
World Vision              1246
Unicef                    1057
Tasaf                      877
District Council           843
Dhv                        829
Private Individual         826
Dwsp                       811
Norad                      765
Germany Republi            610
Tcrs                       602
Ministry Of Water          590
Water                      583
Dwe                        484
Name: funder, dtype: int64
```

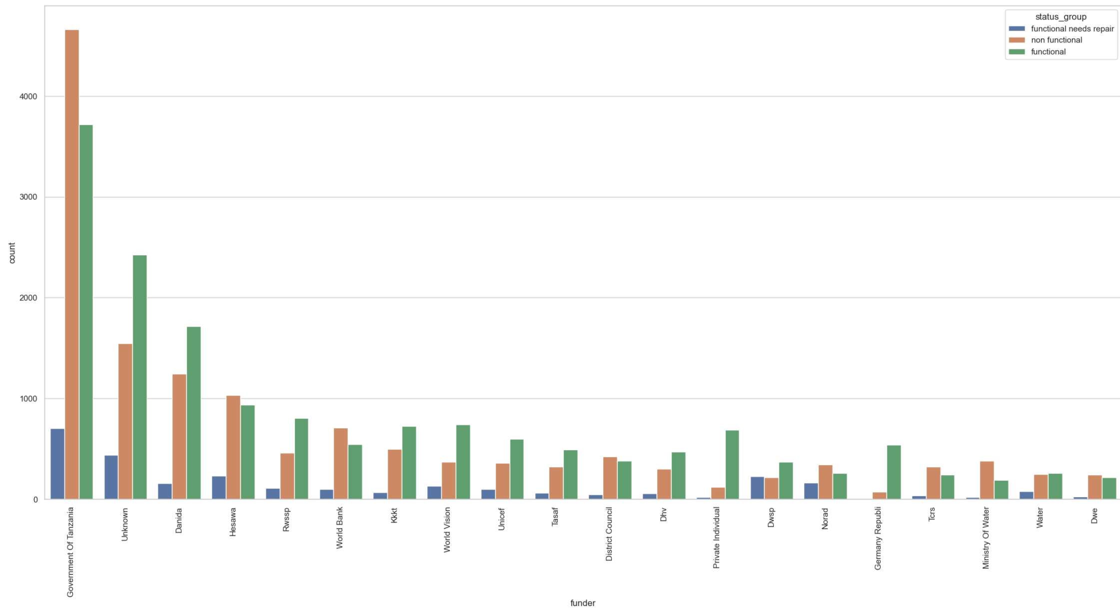
This column is highly categorical column with thousands different values. So, we will take most common 20 values for future encoding.

[284]:
```
df1 = df.loc[df['funder']== 'Government Of Tanzania']
df2 = df.loc[df['funder']== 'Unknown']
df3 = df.loc[df['funder']== 'Danida']
```

```
df4 = df.loc[df['funder']== 'Hesawa']
df5 = df.loc[df['funder']== 'Rwssp']
df6 = df.loc[df['funder']== 'World Bank']
df7 = df.loc[df['funder']== 'Kkkt']
df8 = df.loc[df['funder']== 'World Vision']
df9 = df.loc[df['funder']== 'Unicef']
df10 = df.loc[df['funder']== 'Tasaf']
df11 = df.loc[df['funder']== 'District Council']
df12 = df.loc[df['funder']== 'Dhv']
df13 = df.loc[df['funder']== 'Private Individual']
df14 = df.loc[df['funder']== 'Dwsp']
df15 = df.loc[df['funder']== 'Norad']
df16 = df.loc[df['funder']== 'Germany Republi']
df17 = df.loc[df['funder']== 'Tcrs']
df18 = df.loc[df['funder']== 'Ministry Of Water']
df19 = df.loc[df['funder']== 'Water']
df20 = df.loc[df['funder']== 'Dwe']

df_funder = pd.concat([df1,df2,df3,df4,df5,df6,df7,df8,df9,df10,df11,df12,
                          df13,df14,df15,df16,df17,df18,df19,df20],␣
 ↪ignore_index=True)
```

[285]:
```
plt.figure(figsize=(26,12))
ax = sns.countplot(x='funder', hue="status_group", data=df_funder)
ax.set_xticklabels(ax.get_xticklabels(),rotation=90)
```

[285]:
```
[Text(0, 0, 'Government Of Tanzania'),
 Text(1, 0, 'Unknown'),
 Text(2, 0, 'Danida'),
 Text(3, 0, 'Hesawa'),
 Text(4, 0, 'Rwssp'),
 Text(5, 0, 'World Bank'),
 Text(6, 0, 'Kkkt'),
 Text(7, 0, 'World Vision'),
 Text(8, 0, 'Unicef'),
 Text(9, 0, 'Tasaf'),
 Text(10, 0, 'District Council'),
 Text(11, 0, 'Dhv'),
 Text(12, 0, 'Private Individual'),
 Text(13, 0, 'Dwsp'),
 Text(14, 0, 'Norad'),
 Text(15, 0, 'Germany Republi'),
 Text(16, 0, 'Tcrs'),
 Text(17, 0, 'Ministry Of Water'),
 Text(18, 0, 'Water'),
 Text(19, 0, 'Dwe')]
```



From the above plot, we realize that most of the water points which funded by government are non-functional.

[286]:
```python
# To collect values together

df['funder_cat'] = df['funder'] #creating new column

c_fund = ['Danida','Unknown','Government Of Tanzania','Hesawa','Rwssp','World Bank','Kkkt', 'World Vision',
          'Unicef','Tasaf','District Council', 'Dhv', 'Private Individual', 'Dwsp','Norad','Germany Republi',
          'Tcrs','Ministry Of Water','Water','Dwe']


df.loc[~df["funder_cat"].isin(c_fund), "funder_cat"] = "Others"
```

[287]:
```python
df['funder_cat'].nunique() # We have 21 unique values for this column
```

[287]: 21

6.0.5 longitude column

7 We realized there were some cordinates that were outside of Tanzania. So, we decided to drop them.

[288]:
```
# Define the boundaries of Tanzania
tanzania_min_longitude = 29.0
tanzania_max_longitude = 41.0
tanzania_min_latitude = -12.5
tanzania_max_latitude = -0.5

# Filter the data points outside Tanzania
outside_tanzania = df_train_set[(df_train_set['longitude'] <␣
 ↪tanzania_min_longitude) |
                                (df_train_set['longitude'] >␣
 ↪tanzania_max_longitude) |
                                (df_train_set['latitude'] <␣
 ↪tanzania_min_latitude) |
                                (df_train_set['latitude'] >␣
 ↪tanzania_max_latitude)]

# Print the data points outside Tanzania
print(outside_tanzania[['longitude', 'latitude']])
```

```
       longitude      latitude
id
6091         0.0 -2.000000e-08
32376        0.0 -2.000000e-08
72678        0.0 -2.000000e-08
56725        0.0 -2.000000e-08
13042        0.0 -2.000000e-08
…            …             …
62177        0.0 -2.000000e-08
3631         0.0 -2.000000e-08
60843        0.0 -2.000000e-08
748          0.0 -2.000000e-08
49651        0.0 -2.000000e-08

[1812 rows x 2 columns]
```

[289]:
```
df_train_set.columns
```

[289]:
```
Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height', 'installer',
       'longitude', 'latitude', 'wpt_name', 'num_private', 'basin',
       'subvillage', 'region', 'region_code', 'district_code', 'lga', 'ward',
       'population', 'public_meeting', 'recorded_by', 'scheme_management',
       'scheme_name', 'permit', 'construction_year', 'extraction_type',
```

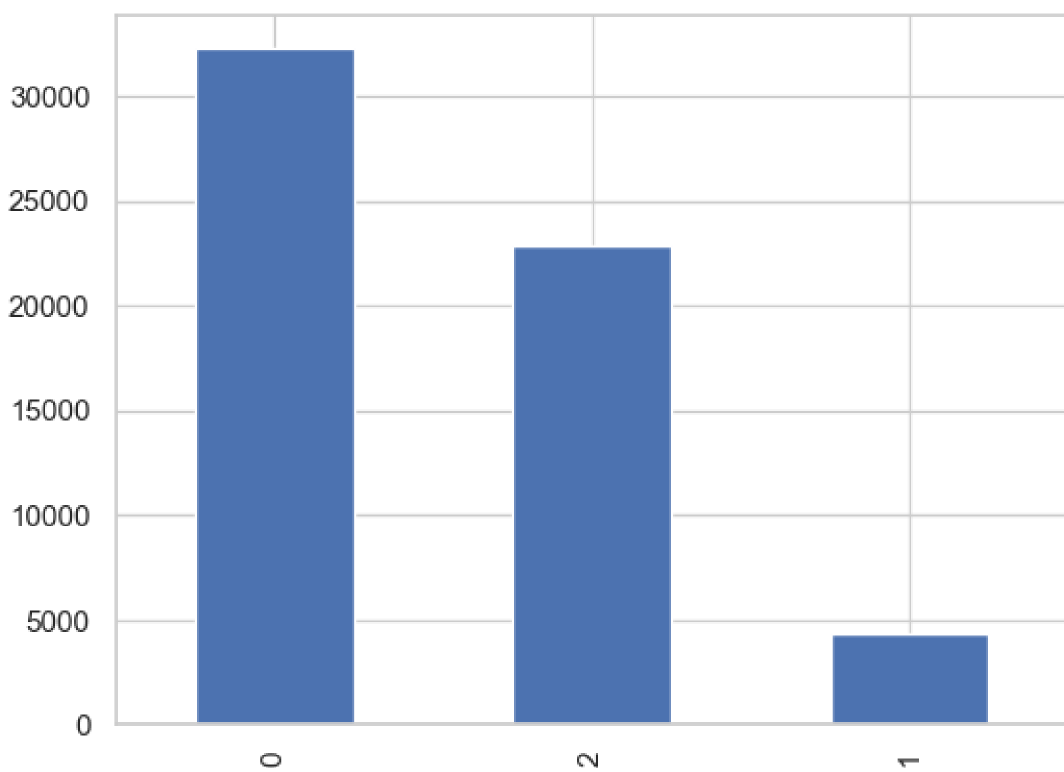
```
 'extraction_type_group', 'extraction_type_class', 'management',
 'management_group', 'payment', 'payment_type', 'water_quality',
 'quality_group', 'quantity', 'quantity_group', 'source', 'source_type',
 'source_class', 'waterpoint_type', 'waterpoint_type_group'],
dtype='object')
```

[293]:

```
df_clean = pd.read_csv(r"C:\Users\Yussuf␣
↪Hersi\Music\Projects\phase-3-project\data1\clean_data.csv")
# check status group column properties in the clean dataset
df_clean['status_group'].value_counts()
# check status group values
df_clean['status_group'].unique()
# check if status group has boolean values
df_clean['status_group'].value_counts(normalize=True)
# check if status group has boolean values
df_clean['status_group'].value_counts(normalize=True).plot(kind='bar')
# check if status group has has any missing values
df_clean['status_group'].isnull().sum()
# check status group categories
df_clean['status_group'].value_counts().plot(kind='bar')
# check status group categories labels
df_clean['status_group'].value_counts().index
```

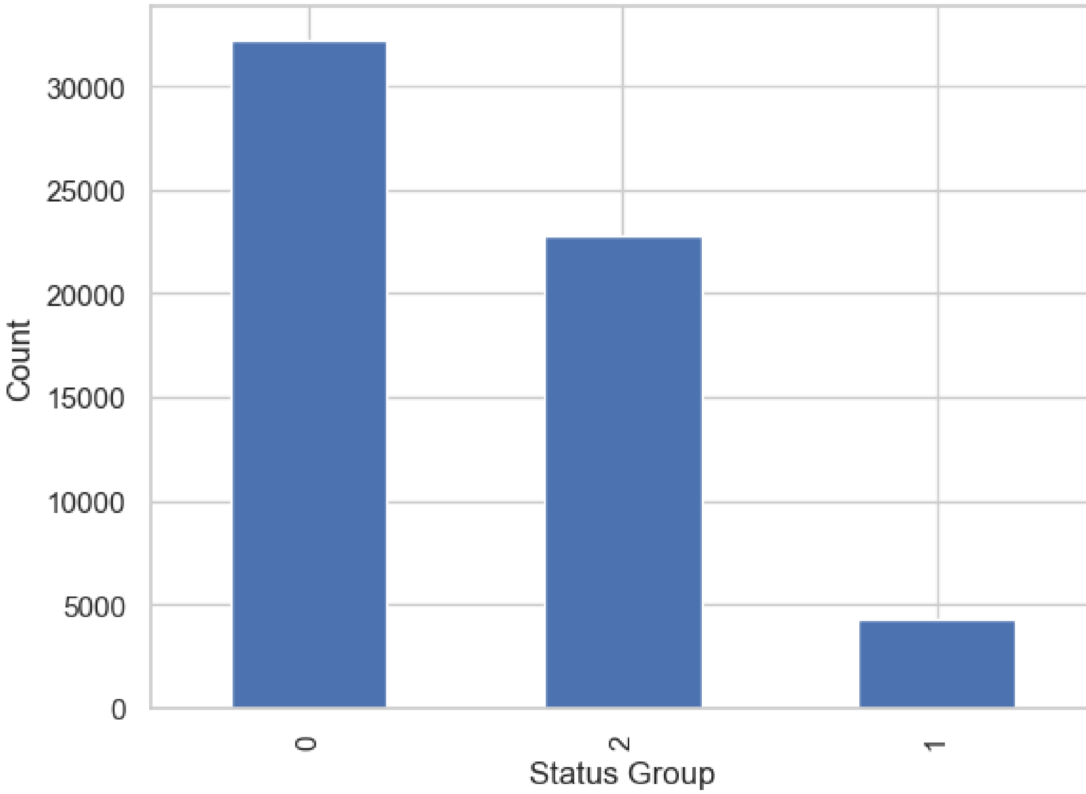
[293]:

```
Int64Index([0, 2, 1], dtype='int64')
```

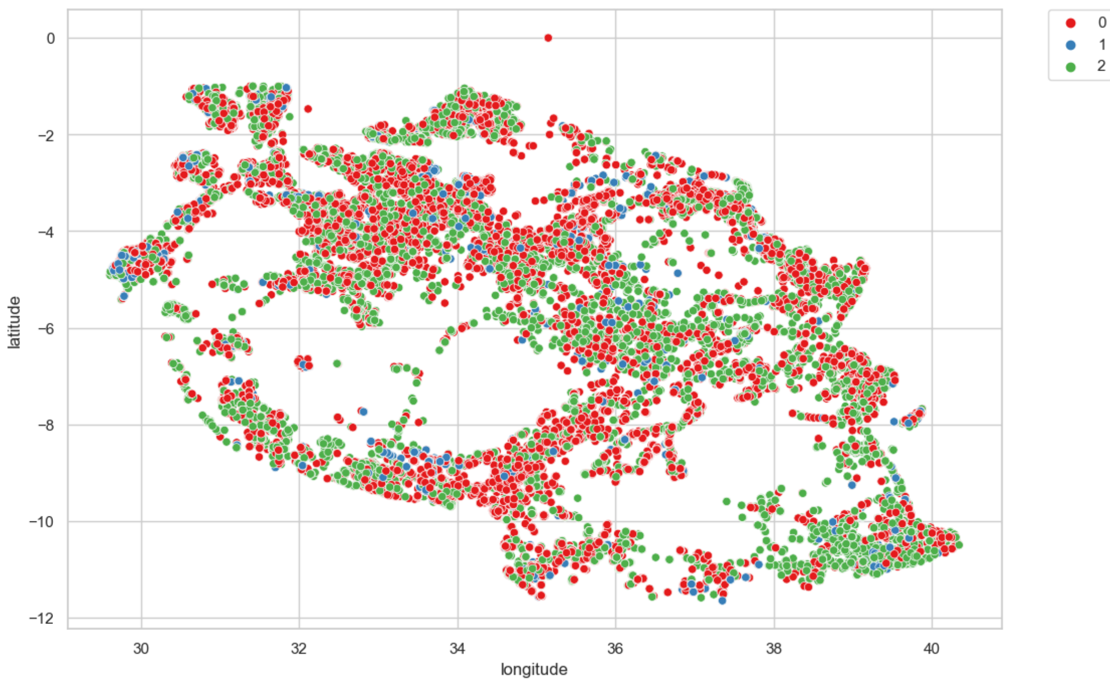


[294]:

```
import pandas as pd
import matplotlib.pyplot as plt

# Read the clean dataset
df_clean = pd.read_csv(r"C:\Users\Yussuf␣
↪Hersi\Music\Projects\phase-3-project\data1\clean_data.csv")


# Check status group column properties in the clean dataset
status_group_counts = df_clean['status_group'].value_counts()

# Display status group values
status_group_values = df_clean['status_group'].unique()

# Check the normalized value counts of status group
status_group_normalized = df_clean['status_group'].value_counts(normalize=True)

# Plot the bar chart of status group
status_group_normalized.plot(kind='bar')
plt.xlabel('Status Group')
plt.ylabel('Normalized Count')

# Check if status group has any missing values
status_group_missing_values = df_clean['status_group'].isnull().sum()

# Plot the bar chart of status group categories
status_group_counts.plot(kind='bar')
plt.xlabel('Status Group')
plt.ylabel('Count')

# Get the labels of status group categories
status_group_labels = df_clean['status_group'].value_counts().index
```

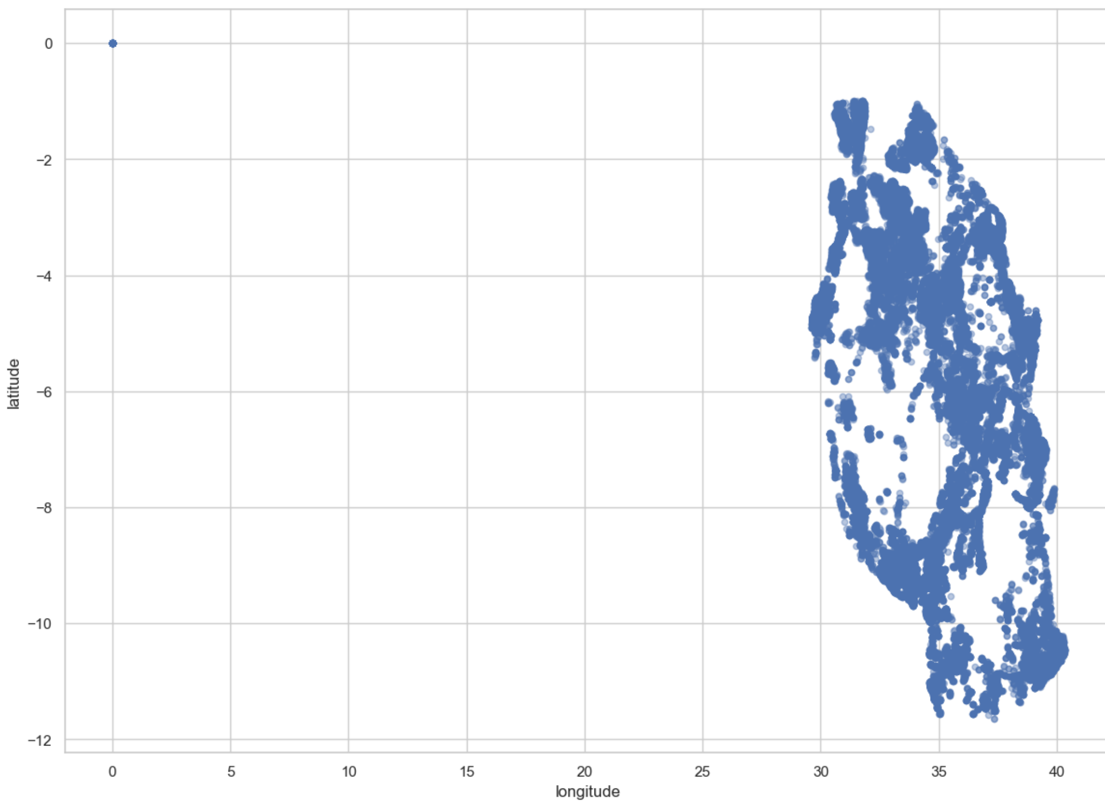


[295]:
```
status_cat = [0, 1, 2]
df_clean["status_cat"] = df_clean["status_group"].astype("category")

# Plotting the map of Tanzania with well locations and status represented by␣
↪color
plt.figure(figsize=(12, 8))

# Using seaborn's scatterplot to visualize the wells
sns.scatterplot(x='longitude', y='latitude', hue='status_cat', data=df_clean,␣
↪palette='Set1')

# Adding a legend to indicate the status categories
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)

# Displaying the plot
plt.show()
```



[296]:
```
# To see the outliers
df_train_set.plot(kind='scatter', x="longitude", y="latitude", alpha=0.4,␣
 ↪figsize=(14,10),sharex=False);
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a
single row if you intend to specify the same RGB or RGBA value for all points.
```



[297]:
```
df.loc[df['longitude']==0] # to check outside of Tanzania
```

[297]:
```
          id              status_group  amount_tsh date_recorded  \
21      6091                functional         0.0    2013-02-10
53     32376            non functional         0.0    2011-08-01
168    72678                functional         0.0    2013-01-30
177    56725            non functional         0.0    2013-01-17
253    13042   functional needs repair         0.0    2012-10-29
…        …                         …          …            …
59189  62177   functional needs repair         0.0    2011-07-18
59208   3631                functional         0.0    2013-01-22
59295  60843   functional needs repair         0.0    2011-07-19
59324    748                functional         0.0    2013-01-22
59374  49651                functional         0.0    2012-10-29

                       funder  gps_height     installer  longitude  \
21                       Dwsp           0           DWE        0.0
53     Government Of Tanzania           0    Government        0.0
168                       Wvt           0           WVT        0.0
177               Netherlands           0           DWE        0.0
253                    Hesawa           0           DWE        0.0
…                         …          …             …         …
```

```
59189                  Dwsp           0          DWE       0.0
59208                  Dwsp           0          DWE       0.0
59295                 Rwssp           0          DWE       0.0
59324          World Vision           0  world vision       0.0
59374                 Rwssp           0          DWE       0.0

          latitude                wpt_name  num_private          basin  \
21    -2.000000e-08                Muungano            0  Lake Victoria
53    -2.000000e-08                  Polisi            0  Lake Victoria
168   -2.000000e-08            Wvt Tanzania            0  Lake Victoria
177   -2.000000e-08  Kikundi Cha Wakina Mama            0  Lake Victoria
253   -2.000000e-08               Kwakisusi            0  Lake Victoria
…              …                       …          …             …
59189 -2.000000e-08                  Wazazo            0  Lake Victoria
59208 -2.000000e-08                 Mtakuja            0  Lake Victoria
59295 -2.000000e-08               Maendeleo            0  Lake Victoria
59324 -2.000000e-08                Mwazwilo            0  Lake Victoria
59374 -2.000000e-08              Nguvu Kazi            0  Lake Victoria

       subvillage     region  region_code  district_code      lga  \
21     Ibabachegu  Shinyanga           17              1  Bariadi
53         Center     Mwanza           19              6    Geita
168         Ilula  Shinyanga           17              1  Bariadi
177        Mahaha  Shinyanga           17              1  Bariadi
253     Nyamatala     Mwanza           19              2     Magu
…             …          …           …            …       …
59189   Mwamabuli  Shinyanga           17              1  Bariadi
59208       Mbiti  Shinyanga           17              1  Bariadi
59295  Mwamalizi  Shinyanga           17              1  Bariadi
59324       Mbita  Shinyanga           17              1  Bariadi
59374  Mwamtani A  Shinyanga           17              1  Bariadi

                  ward  population public_meeting  scheme_name permit  \
21     Ikungulyabashashi           0            NaN          NaN  False
53           Nyang'hwale           0           True  Nyang'hwale   True
168            Chinamili           0          False          NaN  False
177            Bunamhala           0            NaN          NaN  False
253               Malili           0           True          NaN   True
…                    …          …              …           …    …
59189             Mhunze           0           True          NaN  False
59208        Kinang'weli           0            NaN          NaN  False
59295          Chinamili           0           True          NaN  False
59324              Mbita           0            NaN          NaN  False
59374             Sagata           0           True          NaN  False

       construction_year extraction_type_group  management    payment  \
21                  2000                swn 80         wug    unknown
```

```
53                    2000           submersible         vwc    unknown
168                   2000               gravity  parastatal      other
177                   2000                 other         wug    unknown
253                   2000           nira/tanira         vwc  never pay
…                    …                   …          …         …
59189                 2000           nira/tanira         wug      other
59208                 2000           nira/tanira         wug    unknown
59295                 2000           nira/tanira         wug  never pay
59324                 2000           nira/tanira         wug    unknown
59374                 2000           nira/tanira         wug      other

      water_quality      quantity                source  \
21          unknown       unknown          shallow well
53          unknown           dry           machine dbh
168            soft      seasonal  rainwater harvesting
177            soft        enough          shallow well
253            soft  insufficient          shallow well
…             …            …                   …
59189          soft        enough          shallow well
59208          soft        enough          shallow well
59295          soft        enough          shallow well
59324          soft        enough          shallow well
59374          soft        enough          shallow well

                  waterpoint_type decade installer_cat  \
21                      hand pump      0           DWE
53     communal standpipe multiple      0    Government
168            communal standpipe      0        Others
177                         other      0           DWE
253                     hand pump      0           DWE
…                            …     …            …
59189                   hand pump      0           DWE
59208                   hand pump      0           DWE
59295                   hand pump      0           DWE
59324                   hand pump      0  world vision
59374                   hand pump      0           DWE

                  funder_cat
21                      Dwsp
53     Government Of Tanzania
168                   Others
177                   Others
253                   Hesawa
…                       …
59189                   Dwsp
59208                   Dwsp
59295                  Rwssp
```

```
59324              World Vision
59374                     Rwssp

[1812 rows x 33 columns]
```

[298]:
```python
df.loc[df['longitude']!=0].describe() # to find the non-zero values mean
```

[298]:
```
                id     amount_tsh    gps_height     longitude      latitude  \
count  57588.00000   57588.000000  57588.000000  57588.000000  57588.000000
mean   37106.48807     327.645219    689.325137     35.149669     -5.885572
std    21454.51421    3043.831403    693.564188      2.607428      2.809876
min        0.00000       0.000000    -90.000000     29.607122    -11.649440
25%    18522.75000       0.000000      0.000000     33.285100     -8.643841
50%    37054.50000       0.000000    426.000000     35.005943     -5.172704
75%    55667.25000      30.000000   1332.000000     37.233712     -3.372824
max    74247.00000  350000.000000   2770.000000     40.345193     -0.998464

        num_private   region_code  district_code    population  \
count  57588.000000  57588.000000   57588.000000  57588.000000
mean       0.489060     15.217615       5.728311    185.570831
std       12.426954     17.855254       9.760254    477.744239
min        0.000000      1.000000       0.000000      0.000000
25%        0.000000      5.000000       2.000000      0.000000
50%        0.000000     12.000000       3.000000     35.000000
75%        0.000000     17.000000       5.000000    230.000000
max     1776.000000     99.000000      80.000000  30500.000000

       construction_year
count       57588.000000
mean         1997.859919
std            10.331744
min          1960.000000
25%          1995.000000
50%          2000.000000
75%          2004.000000
max          2013.000000
```

It is obviously seen that it is written as 0 when the longtitude is unknown. Because, the zero points can seen easily in the graph above outliers and outside of Tanzania. So, we changed them to mean where median is the almost same value.

[299]:
```python
df['longitude'].replace(to_replace = 0 , value =35.15, inplace=True) # changing␣
↪0 values to mean
```

7.0.1 wpt_name / scheme_name / id/ region/ region_code columns

[300]:
```
df['wpt_name'].value_counts()
```

[300]:
```
none                           3563
Shuleni                        1748
Zahanati                        830
Msikitini                       535
Kanisani                        323
                               ...
Kwa Medadi                        1
Kwa Kubembeni                     1
Shule Ya Msingi Milanzi           1
Funua                             1
Kwa Mzee Lugawa                   1
Name: wpt_name, Length: 37400, dtype: int64
```

[301]:
```
df['scheme_name'].value_counts()
```

[301]:
```
K                           682
None                        644
Borehole                    546
Chalinze wate               405
M                           400
                           ...
Mradi wa maji Vijini          1
Villagers                     1
Magundi water supply          1
Saadani Chumv                 1
Mtawanya                      1
Name: scheme_name, Length: 2696, dtype: int64
```

[302]:
```
df.duplicated(subset='id', keep='first').sum() # to check the dublicates of id
```

[302]:
```
0
```

[303]:
```
df.drop(columns=['wpt_name','scheme_name','id','region_code'],inplace=True )
```

When we checked the wpt_name, scheme_name and id columns, they do not have any information about functionality. So, we decide to drop them. We dropped also region_code column because region column gives more information about the region. Also, before dropping columns we check the dublicated values in dataframe.

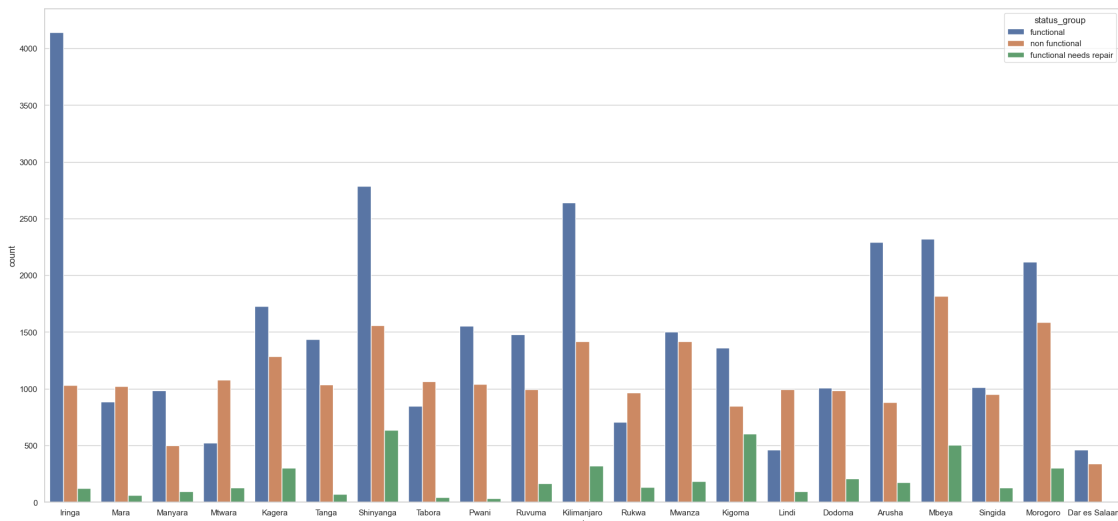
[304]:
```
df['region'].value_counts()
```

[304]:
```
Iringa            5294
Shinyanga         4982
Mbeya             4639
```

```
Kilimanjaro      4379
Morogoro         4006
Arusha           3350
Kagera           3316
Mwanza           3102
Kigoma           2816
Ruvuma           2640
Pwani            2635
Tanga            2547
Dodoma           2201
Singida          2093
Mara             1969
Tabora           1959
Rukwa            1808
Mtwara           1730
Manyara          1583
Lindi            1546
Dar es Salaam     805
Name: region, dtype: int64
```

[305]:

```
plt.figure(figsize=(26,12))
ax = sns.countplot(x='region', hue="status_group", data=df)
```



Some regions has higher probability of functional water well. Klimanjaro and Arusha have Pangani basin which has higher water point between basins. It is also seen that they have higher portions for functional wells.

[306]:

```
df_iringa =df.loc[df['region']=='Iringa'] #to see the Iringa area
```

[307]:

```
df_iringa.groupby(['water_quality','status_group']).count()
```

[307]:

```
                                          amount_tsh  date_recorded  funder  \
water_quality status_group
coloured      functional                           1              1       1
              non functional                       1              1       1
salty         functional                          19             19      19
              non functional                       8              8       8
soft          functional                        4120           4120    4120
              functional needs repair            123            123     123
              non functional                     983            983     983
unknown       functional                           1              1       1
              non functional                      38             38      38

                                          gps_height  installer  longitude  \
water_quality status_group
coloured      functional                           1          1          1
              non functional                       1          1          1
salty         functional                          19         19         19
              non functional                       8          8          8
soft          functional                        4120       4120       4120
              functional needs repair            123        123        123
              non functional                     983        983        983
unknown       functional                           1          1          1
              non functional                      38         38         38

                                          latitude  num_private  basin  \
water_quality status_group
coloured      functional                         1            1      1
              non functional                     1            1      1
salty         functional                        19           19     19
              non functional                     8            8      8
soft          functional                      4120         4120   4120
              functional needs repair          123          123    123
              non functional                   983          983    983
unknown       functional                         1            1      1
              non functional                    38           38     38

                                          subvillage  region  district_code  \
water_quality status_group
coloured      functional                           1       1              1
              non functional                       1       1              1
salty         functional                          19      19             19
              non functional                       8       8              8
soft          functional                        4120    4120           4120
              functional needs repair            123     123            123
              non functional                     983     983            983
unknown       functional                           1       1              1
              non functional                      38      38             38
```

water_quality	status_group	lga	ward	population	public_meeting	\
coloured	functional	1	1	1	1	
	non functional	1	1	1	1	
salty	functional	19	19	19	19	
	non functional	8	8	8	8	
soft	functional	4120	4120	4120	4118	
	functional needs repair	123	123	123	123	
	non functional	983	983	983	983	
unknown	functional	1	1	1	1	
	non functional	38	38	38	38	

water_quality	status_group	permit	construction_year	\
coloured	functional	1	1	
	non functional	1	1	
salty	functional	19	19	
	non functional	8	8	
soft	functional	4117	4120	
	functional needs repair	123	123	
	non functional	983	983	
unknown	functional	1	1	
	non functional	38	38	

water_quality	status_group	extraction_type_group	management	\
coloured	functional	1	1	
	non functional	1	1	
salty	functional	19	19	
	non functional	8	8	
soft	functional	4120	4120	
	functional needs repair	123	123	
	non functional	983	983	
unknown	functional	1	1	
	non functional	38	38	

water_quality	status_group	payment	quantity	source	\
coloured	functional	1	1	1	
	non functional	1	1	1	
salty	functional	19	19	19	
	non functional	8	8	8	
soft	functional	4120	4120	4120	
	functional needs repair	123	123	123	
	non functional	983	983	983	
unknown	functional	1	1	1	

```
                   non functional                 38         38       38

                                          waterpoint_type  decade  installer_cat  \
water_quality status_group
coloured      functional                                1       1              1
              non functional                            1       1              1
salty         functional                               19      19             19
              non functional                            8       8              8
soft          functional                             4120    4120           4120
              functional needs repair                 123     123            123
              non functional                          983     983            983
unknown       functional                                1       1              1
              non functional                           38      38             38

                                          funder_cat
water_quality status_group
coloured      functional                           1
              non functional                       1
salty         functional                          19
              non functional                       8
soft          functional                        4120
              functional needs repair            123
              non functional                     983
unknown       functional                           1
              non functional                      38
```

When we looked at the Iringa area which has higher water points. There are also 983 wells which has soft, good water but non-functional.

[308]:
```
df_daressalaam =df.loc[df['region']=='Dar es Salaam'] #to see the Dar es Salaam␣
↪area
```

[309]:
```
df_daressalaam.groupby(['water_quality','status_group']).count()
```

[309]:
```
                                                amount_tsh  date_recorded  funder  \
water_quality      status_group
fluoride abandoned non functional                        2              2       2
milky              functional                            1              1       1
                   non functional                        1              1       1
salty              functional                           41             41      41
                   non functional                      100            100     100
salty abandoned    functional                           63             63      63
                   non functional                       37             37      37
soft               functional                          352            352     352
                   functional needs repair               3              3       3
                   non functional                      186            186     186
unknown            functional                            4              4       4
```

```
                    non functional                    15            15       15

                                              gps_height  installer  longitude  \
water_quality      status_group
fluoride abandoned non functional                      2          2          2
milky              functional                          1          1          1
                   non functional                      1          1          1
salty              functional                         41         41         41
                   non functional                    100        100        100
salty abandoned    functional                         63         63         63
                   non functional                     37         37         37
soft               functional                        352        352        352
                   functional needs repair             3          3          3
                   non functional                    186        186        186
unknown            functional                          4          4          4
                   non functional                     15         15         15

                                              latitude  num_private  basin  \
water_quality      status_group
fluoride abandoned non functional                    2            2      2
milky              functional                        1            1      1
                   non functional                    1            1      1
salty              functional                       41           41     41
                   non functional                  100          100    100
salty abandoned    functional                       63           63     63
                   non functional                   37           37     37
soft               functional                      352          352    352
                   functional needs repair           3            3      3
                   non functional                  186          186    186
unknown            functional                        4            4      4
                   non functional                   15           15     15

                                              subvillage  region  district_code  \
water_quality      status_group
fluoride abandoned non functional                      2       2              2
milky              functional                          1       1              1
                   non functional                      1       1              1
salty              functional                         41      41             41
                   non functional                    100     100            100
salty abandoned    functional                         63      63             63
                   non functional                     37      37             37
soft               functional                        352     352            352
                   functional needs repair             3       3              3
                   non functional                    186     186            186
unknown            functional                          4       4              4
                   non functional                     15      15             15
```

```
                                            lga  ward  population  \
water_quality      status_group
fluoride abandoned non functional             2     2           2
milky              functional                 1     1           1
                   non functional             1     1           1
salty              functional                41    41          41
                   non functional           100   100         100
salty abandoned    functional                63    63          63
                   non functional            37    37          37
soft               functional               352   352         352
                   functional needs repair    3     3           3
                   non functional           186   186         186
unknown            functional                 4     4           4
                   non functional            15    15          15

                                            public_meeting  permit  \
water_quality      status_group
fluoride abandoned non functional                        2       2
milky              functional                            0       1
                   non functional                        0       1
salty              functional                           34      41
                   non functional                       95     100
salty abandoned    functional                            2      56
                   non functional                        9      36
soft               functional                          101     343
                   functional needs repair               3       3
                   non functional                       95     176
unknown            functional                            1       4
                   non functional                        3      14

                                            construction_year  \
water_quality      status_group
fluoride abandoned non functional                           2
milky              functional                               1
                   non functional                           1
salty              functional                              41
                   non functional                         100
salty abandoned    functional                              63
                   non functional                          37
soft               functional                             352
                   functional needs repair                  3
                   non functional                         186
unknown            functional                               4
                   non functional                          15

                                            extraction_type_group  management  \
water_quality      status_group
```

```
fluoride abandoned non functional                               2           2
milky              functional                                   1           1
                   non functional                               1           1
salty              functional                                  41          41
                   non functional                             100         100
salty abandoned    functional                                  63          63
                   non functional                              37          37
soft               functional                                 352         352
                   functional needs repair                      3           3
                   non functional                             186         186
unknown            functional                                   4           4
                   non functional                              15          15

                                            payment  quantity  source  \
water_quality      status_group
fluoride abandoned non functional                 2         2       2
milky              functional                     1         1       1
                   non functional                 1         1       1
salty              functional                    41        41      41
                   non functional               100       100     100
salty abandoned    functional                    63        63      63
                   non functional                37        37      37
soft               functional                   352       352     352
                   functional needs repair        3         3       3
                   non functional               186       186     186
unknown            functional                     4         4       4
                   non functional                15        15      15

                                            waterpoint_type  decade  \
water_quality      status_group
fluoride abandoned non functional                         2       2
milky              functional                             1       1
                   non functional                         1       1
salty              functional                            41      41
                   non functional                       100     100
salty abandoned    functional                            63      63
                   non functional                        37      37
soft               functional                           352     352
                   functional needs repair                3       3
                   non functional                       186     186
unknown            functional                             4       4
                   non functional                        15      15

                                            installer_cat  funder_cat
water_quality      status_group
fluoride abandoned non functional                       2           2
milky              functional                           1           1
```

```
                     non functional                  1            1
salty                functional                     41           41
                     non functional                100          100
salty abandoned      functional                     63           63
                     non functional                 37           37
soft                 functional                    352          352
                     functional needs repair         3            3
                     non functional                186          186
unknown              functional                      4            4
                     non functional                 15           15
```

It is very sad that Dar us Salaam is most populated area in Tanzania with its rural areas around, but water points are not enough. Even, 35% of the soft water wells are non-functional.

7.0.2 amount_tsh column

Total static head shows us the height of the flow from the surface. Mostly there are zero values in our dataset. But for zero values no need for pump , because it means we are already in surface.

[310]:
```
df['amount_tsh'].value_counts()
```

[310]:
```
0.0         41639
500.0        3102
50.0         2472
1000.0       1488
20.0         1463
            …
6300.0          1
120000.0        1
138000.0        1
350000.0        1
59.0            1
Name: amount_tsh, Length: 98, dtype: int64
```

[311]:
```
df.loc[df['amount_tsh']==0].groupby('status_group').count()
```

[311]:
```
                         amount_tsh  date_recorded  funder  gps_height  \
status_group
functional                    19706          19706   19706       19706
functional needs repair        3048           3048    3048        3048
non functional                18885          18885   18885       18885

                         installer  longitude  latitude  num_private  basin  \
status_group
functional                   19706      19706     19706        19706  19706
functional needs repair       3048       3048      3048         3048   3048
non functional               18885      18885     18885        18885  18885
```

```
                           subvillage  region  district_code    lga   ward  \
status_group
functional                      19501   19706          19706  19706  19706
functional needs repair          3047    3048           3048   3048   3048
non functional                  18720   18885          18885  18885  18885

                           population  public_meeting  permit  \
status_group
functional                      19706           18444   18374
functional needs repair          3048            2906    2775
non functional                  18885           17475   17862

                           construction_year  extraction_type_group  management  \
status_group
functional                             19706                  19706       19706
functional needs repair                 3048                   3048        3048
non functional                         18885                  18885       18885

                           payment  water_quality  quantity  source  \
status_group
functional                   19706          19706     19706   19706
functional needs repair       3048           3048      3048    3048
non functional               18885          18885     18885   18885

                           waterpoint_type  decade  installer_cat  funder_cat
status_group
functional                           19706   19706          19706       19706
functional needs repair               3048    3048           3048        3048
non functional                       18885   18885          18885       18885
```

[312]:

```
df['amount_tsh'].value_counts()/df['amount_tsh'].count()
```

[312]:

```
0.0         0.700993
500.0       0.052222
50.0        0.041616
1000.0      0.025051
20.0        0.024630
              …
6300.0      0.000017
120000.0    0.000017
138000.0    0.000017
350000.0    0.000017
59.0        0.000017
Name: amount_tsh, Length: 98, dtype: float64
```

We decided to drop this column because 70% of the column has no informative values. So, this column will not give idea to our model and we will drop it.

[313]:
```
df.drop(columns=['amount_tsh'],inplace=True )
```

7.0.3 gps_height column

[314]:
```
df.groupby('status_group')[['gps_height']].mean()
```

[314]:
```
                        gps_height
status_group
functional              740.131188
functional needs repair 627.607135
non functional          574.464774
```

[315]:
```
df['gps_height'].value_counts()
```

[315]:
```
 0      20438
-15        60
-16        55
-13        55
 1290      52
        …
 2378       1
-54         1
 2057       1
 2332       1
 2366       1
Name: gps_height, Length: 2428, dtype: int64
```

[316]:
```
df['gps_height'].value_counts()/df['gps_height'].count()
```

[316]:
```
 0      0.344074
-15     0.001010
-16     0.000926
-13     0.000926
 1290   0.000875
          …
 2378   0.000017
-54     0.000017
 2057   0.000017
 2332   0.000017
 2366   0.000017
Name: gps_height, Length: 2428, dtype: float64
```

Gps height shows the level of the water point from sea level. There are 34% zero values but maybe 34% of the water points are at the sea level so we do not change this column now.

7.0.4 population column

[317]:
```
df['population'].value_counts()
```

[317]:
```
0       21381
1        7025
200      1940
150      1892
250      1681
        …
6330        1
5030        1
656         1
948         1
788         1
Name: population, Length: 1049, dtype: int64
```

[318]:
```
df.loc[df['population']==0].groupby('status_group').count()
```

[318]:
```
                         date_recorded  funder  gps_height  installer  \
status_group
functional                       11274   11274       11274      11274
functional needs repair           1775    1775        1775       1775
non functional                    8332    8332        8332       8332

                         longitude  latitude  num_private  basin  subvillage  \
status_group
functional                   11274     11274        11274  11274       11071
functional needs repair       1775      1775         1775   1775        1775
non functional                8332      8332         8332   8332        8174

                         region  district_code    lga   ward  population  \
status_group
functional                11274          11274  11274  11274       11274
functional needs repair    1775           1775   1775   1775        1775
non functional             8332           8332   8332   8332        8332

                         public_meeting  permit  construction_year  \
status_group
functional                        10700   10596              11274
functional needs repair            1732    1613               1775
non functional                     7967    8063               8332

                         extraction_type_group  management  payment  \
status_group
functional                               11274       11274    11274
functional needs repair                   1775        1775     1775
```

```
non functional                       8332         8332      8332

                         water_quality  quantity  source  waterpoint_type  \
status_group
functional                       11274     11274   11274            11274
functional needs repair           1775      1775    1775             1775
non functional                    8332      8332    8332             8332

                         decade  installer_cat  funder_cat
status_group
functional                11274          11274       11274
functional needs repair    1775           1775        1775
non functional             8332           8332        8332
```

Some functional water points has zero population, it is weird so we will change zero population to mean.

[319]:
```
df.loc[df['population']!=0].describe() # to see without zero mean and median
```

[319]:
```
         gps_height     longitude      latitude   num_private  district_code  \
count  38019.000000  38019.000000  38019.000000  38019.000000   38019.000000
mean     969.889634     36.074387     -6.139781      0.740788       6.299456
std      612.544787      2.586779      2.737733     15.288297      11.303334
min      -90.000000     29.607122    -11.649440      0.000000       1.000000
25%      347.000000     34.715340     -8.388839      0.000000       2.000000
50%     1135.000000     36.706815     -5.750877      0.000000       3.000000
75%     1465.000000     37.940149     -3.597016      0.000000       5.000000
max     2770.000000     40.345193     -1.042375   1776.000000      67.000000

         population  construction_year
count  38019.000000       38019.000000
mean     281.087167        1996.908283
std      564.687660          12.425377
min        1.000000        1960.000000
25%       40.000000        1988.000000
50%      150.000000        2000.000000
75%      324.000000        2008.000000
max    30500.000000        2013.000000
```

[320]:
```
df['population'].replace(to_replace = 0 , value =281, inplace=True) #changing␣
↪0's to mean
```

[321]:
```
df.sort_values(by='population', ascending=False).head(50).
↪groupby('status_group').count()
```

[321]:
```
                         date_recorded  funder  gps_height  installer  \
status_group
```

```
functional                               39      39            39          39
functional needs repair                   4       4             4           4
non functional                            7       7             7           7

                         longitude  latitude  num_private  basin  subvillage  \
status_group
functional                      39        39           39     39          39
functional needs repair          4         4            4      4           4
non functional                   7         7            7      7           7

                         region  district_code  lga  ward  population  \
status_group
functional                   39             39   39    39          39
functional needs repair       4              4    4     4           4
non functional                7              7    7     7           7

                         public_meeting  permit  construction_year  \
status_group
functional                           39      34                 39
functional needs repair               4       2                  4
non functional                        7       7                  7

                         extraction_type_group  management  payment  \
status_group
functional                                  39          39       39
functional needs repair                      4           4        4
non functional                               7           7        7

                         water_quality  quantity  source  waterpoint_type  \
status_group
functional                          39        39      39               39
functional needs repair              4         4       4                4
non functional                       7         7       7                7

                         decade  installer_cat  funder_cat
status_group
functional                   39             39          39
functional needs repair       4              4           4
non functional                7              7           7
```

To see the most populated areas water point functionality , we choose crowded 50 values and did groupby. It shows that higher population areas have more functional water points.

7.0.5 date_recorded column

Approximately 95% of the water points were recorded between 2011-2013. So, for now we do not think it contains necessary information about functionality. We drop this column for now.

[322]:
```
df.drop(columns=['date_recorded'],inplace=True )
```

7.0.6 num_private column

This column has no information about it and also mostly have zero values. So, we drop this also.

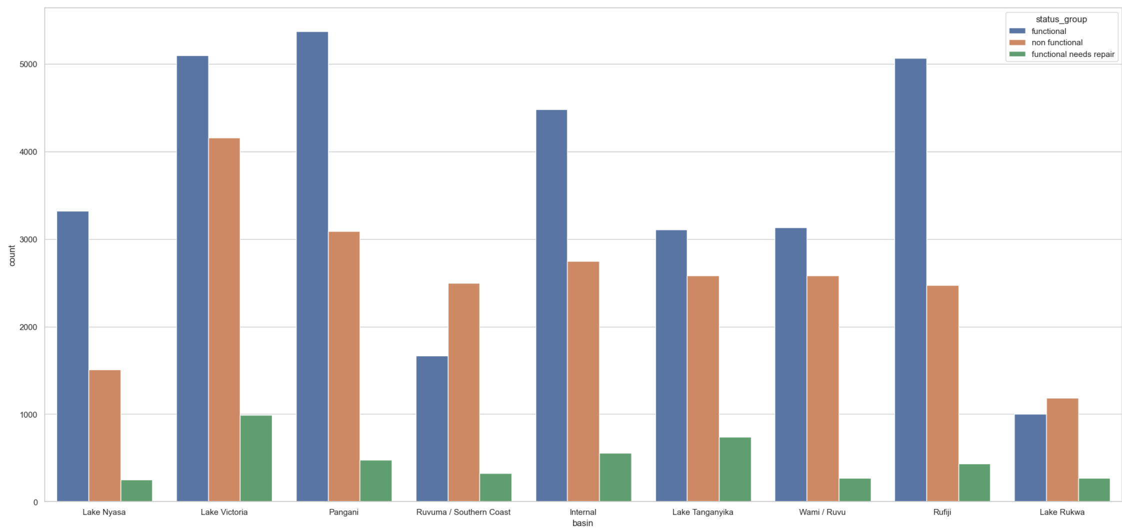
[323]:
```
df.drop(columns=['num_private'],inplace=True )
```

7.0.7 basin column

[324]:
```
df['basin'].value_counts()
```

[324]:
```
Lake Victoria              10248
Pangani                     8940
Rufiji                      7976
Internal                    7785
Lake Tanganyika             6432
Wami / Ruvu                 5987
Lake Nyasa                  5085
Ruvuma / Southern Coast     4493
Lake Rukwa                  2454
Name: basin, dtype: int64
```

[325]:
```
plt.figure(figsize=(26,12))
ax = sns.countplot(x='basin', hue="status_group", data=df)
```



This column gives an idea about there is correlation between functionality and geographical water basin.

7.0.8 subvillage column

[326]:
```
df['subvillage'].nunique()
```

[326]:
```
19287
```

This column has location value of water point regions but we already have region column. We will drop this, because it is hard to handle this nunique object values.

[327]:
```
df.drop(columns=['subvillage'],inplace=True )
```

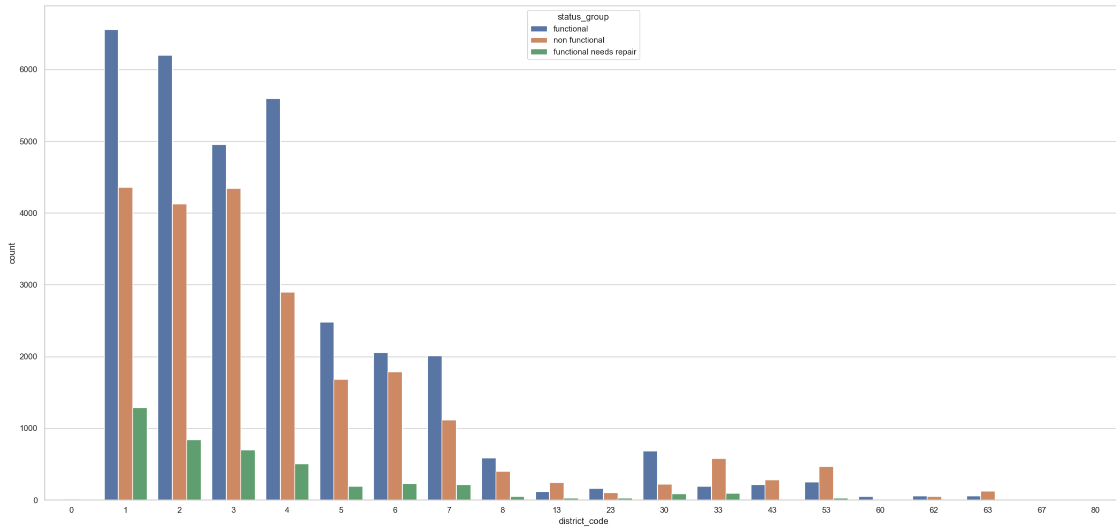
7.0.9 district_code column

[328]:
```
df['district_code'].value_counts()
```

[328]:
```
1     12203
2     11173
3      9998
4      8999
5      4356
6      4074
7      3343
8      1043
30      995
33      874
53      745
43      505
13      391
23      293
63      195
62      109
60       63
0        23
80       12
67        6
Name: district_code, dtype: int64
```

It includes numeric values about districts. Each district has one number.

[329]:
```
plt.figure(figsize=(26,12))
ax = sns.countplot(x='district_code', hue="status_group", data=df)
```



Some districts has higher chance to have functional water points.

7.0.10 lga / ward columns

Now we decided to keep these columns because they contain geographical location. But, we have also other location features so maybe they will be dropped later on.

7.0.11 public_meeting column

[330]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   status_group           59400 non-null  object
 1   funder                 59400 non-null  object
 2   gps_height             59400 non-null  int64
 3   installer              59400 non-null  object
 4   longitude              59400 non-null  float64
 5   latitude               59400 non-null  float64
 6   basin                  59400 non-null  object
 7   region                 59400 non-null  object
 8   district_code          59400 non-null  int64
 9   lga                    59400 non-null  object
 10  ward                   59400 non-null  object
 11  population             59400 non-null  int64
 12  public_meeting         56066 non-null  object
 13  permit                 56344 non-null  object
```

```
 14  construction_year      59400 non-null  int64
 15  extraction_type_group  59400 non-null  object
 16  management             59400 non-null  object
 17  payment                59400 non-null  object
 18  water_quality          59400 non-null  object
 19  quantity               59400 non-null  object
 20  source                 59400 non-null  object
 21  waterpoint_type        59400 non-null  object
 22  decade                 59400 non-null  object
 23  installer_cat          59400 non-null  object
 24  funder_cat             59400 non-null  object
dtypes: float64(2), int64(4), object(19)
memory usage: 11.3+ MB
```

[331]:
```
df['public_meeting'].value_counts()
```

[331]:
```
True     51011
False     5055
Name: public_meeting, dtype: int64
```

[332]:
```
df['public_meeting'].fillna(value=True,inplace=True)
```

There are some null values and we convert them to most common data.

7.0.12 permit column

[333]:
```
df['permit'].value_counts()
```

[333]:
```
True     38852
False    17492
Name: permit, dtype: int64
```

This column shows if the water point is permitted or not. There are 3056 null values for this column. We will change them to true which has higher amount.

[334]:
```
df['permit'].fillna(value=True, inplace=True)
```

8 Converting Target to Ternary Values

[335]:
```
target_status_group = {'functional':0,
                       'non functional': 2,
                       'functional needs repair': 1}
df['status_group'] = df['status_group'].replace(target_status_group)
```

[336]:
```
df['status_group'].value_counts()
```

[336]:

```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
```

To make our model, we changed the target variable to 0,1 and 2 values.

And we create new csv file to keep our work and call new cleaned data.

[337]:

```
df.to_csv('clean_data.csv')
```

[338]:

```
### To see the relation between water quantity and quality with functionality
df.groupby(['quantity','water_quality','status_group']).count().head(50)
```

[338]:

```
                                               funder  gps_height  installer  \
quantity     water_quality      status_group
dry          coloured           1                   1           1          1
                                2                  28          28         28
             fluoride           2                   2           2          2
             fluoride abandoned 2                   2           2          2
             milky              2                 119         119        119
             salty              0                  11          11         11
                                1                   1           1          1
                                2                 638         638        638
             salty abandoned    0                   1           1          1
                                2                  12          12         12
             soft               0                 136         136        136
                                1                  19          19         19
                                2                4272        4272       4272
             unknown            0                   9           9          9
                                1                  16          16         16
                                2                 979         979        979
enough       coloured           0                 107         107        107
                                1                  11          11         11
                                2                  53          53         53
             fluoride           0                  66          66         66
                                1                   9           9          9
                                2                   9           9          9
             fluoride abandoned 0                   5           5          5
                                2                   6           6          6
             milky              0                 246         246        246
                                1                   9           9          9
                                2                  81          81         81
             salty              0                1373        1373       1373
                                1                  89          89         89
                                2                 834         834        834
             salty abandoned    0                 150         150        150
                                1                  50          50         50
```

		2	56	56	56
	soft	0	19640	19640	19640
		1	2226	2226	2226
		2	8035	8035	8035
	unknown	0	61	61	61
		1	6	6	6
		2	64	64	64
insufficient	coloured	0	91	91	91
		1	13	13	13
		2	66	66	66
	fluoride	0	85	85	85
		1	4	4	4
		2	25	25	25
	fluoride abandoned	0	1	1	1
		2	3	3	3
	milky	0	118	118	118
		1	4	4	4
		2	91	91	91

			longitude	latitude	basin	\
quantity	water_quality	status_group				
dry	coloured	1	1	1	1	
		2	28	28	28	
	fluoride	2	2	2	2	
	fluoride abandoned	2	2	2	2	
	milky	2	119	119	119	
	salty	0	11	11	11	
		1	1	1	1	
		2	638	638	638	
	salty abandoned	0	1	1	1	
		2	12	12	12	
	soft	0	136	136	136	
		1	19	19	19	
		2	4272	4272	4272	
	unknown	0	9	9	9	
		1	16	16	16	
		2	979	979	979	
enough	coloured	0	107	107	107	
		1	11	11	11	
		2	53	53	53	
	fluoride	0	66	66	66	
		1	9	9	9	
		2	9	9	9	
	fluoride abandoned	0	5	5	5	
		2	6	6	6	
	milky	0	246	246	246	
		1	9	9	9	

		2	81	81	81
	salty	0	1373	1373	1373
		1	89	89	89
		2	834	834	834
	salty abandoned	0	150	150	150
		1	50	50	50
		2	56	56	56
	soft	0	19640	19640	19640
		1	2226	2226	2226
		2	8035	8035	8035
	unknown	0	61	61	61
		1	6	6	6
		2	64	64	64
insufficient	coloured	0	91	91	91
		1	13	13	13
		2	66	66	66
	fluoride	0	85	85	85
		1	4	4	4
		2	25	25	25
	fluoride abandoned	0	1	1	1
		2	3	3	3
	milky	0	118	118	118
		1	4	4	4
		2	91	91	91

			region	district_code	lga \
quantity	water_quality	status_group			
dry	coloured	1	1	1	1
		2	28	28	28
	fluoride	2	2	2	2
	fluoride abandoned	2	2	2	2
	milky	2	119	119	119
	salty	0	11	11	11
		1	1	1	1
		2	638	638	638
	salty abandoned	0	1	1	1
		2	12	12	12
	soft	0	136	136	136
		1	19	19	19
		2	4272	4272	4272
	unknown	0	9	9	9
		1	16	16	16
		2	979	979	979
enough	coloured	0	107	107	107
		1	11	11	11
		2	53	53	53
	fluoride	0	66	66	66

```
                                1               9          9      9
                                2               9          9      9
             fluoride abandoned 0               5          5      5
                                2               6          6      6
             milky              0             246        246    246
                                1               9          9      9
                                2              81         81     81
             salty              0            1373       1373   1373
                                1              89         89     89
                                2             834        834    834
             salty abandoned    0             150        150    150
                                1              50         50     50
                                2              56         56     56
             soft               0           19640      19640  19640
                                1            2226       2226   2226
                                2            8035       8035   8035
             unknown            0              61         61     61
                                1               6          6      6
                                2              64         64     64
insufficient coloured           0              91         91     91
                                1              13         13     13
                                2              66         66     66
             fluoride           0              85         85     85
                                1               4          4      4
                                2              25         25     25
             fluoride abandoned 0               1          1      1
                                2               3          3      3
             milky              0             118        118    118
                                1               4          4      4
                                2              91         91     91

                                               ward  population  \
quantity     water_quality      status_group
dry          coloured           1                 1           1
                                2                28          28
             fluoride           2                 2           2
             fluoride abandoned 2                 2           2
             milky              2               119         119
             salty              0                11          11
                                1                 1           1
                                2               638         638
             salty abandoned    0                 1           1
                                2                12          12
             soft               0               136         136
                                1                19          19
                                2              4272        4272
             unknown            0                 9           9
```

```
                                  1                 16            16
                                  2                979           979
enough       coloured             0                107           107
                                  1                 11            11
                                  2                 53            53
             fluoride             0                 66            66
                                  1                  9             9
                                  2                  9             9
             fluoride abandoned 0                    5             5
                                  2                  6             6
             milky                0                246           246
                                  1                  9             9
                                  2                 81            81
             salty                0               1373          1373
                                  1                 89            89
                                  2                834           834
             salty abandoned      0                150           150
                                  1                 50            50
                                  2                 56            56
             soft                 0              19640         19640
                                  1               2226          2226
                                  2               8035          8035
             unknown              0                 61            61
                                  1                  6             6
                                  2                 64            64
insufficient coloured             0                 91            91
                                  1                 13            13
                                  2                 66            66
             fluoride             0                 85            85
                                  1                  4             4
                                  2                 25            25
             fluoride abandoned 0                    1             1
                                  2                  3             3
             milky                0                118           118
                                  1                  4             4
                                  2                 91            91

                                              public_meeting  permit  \
quantity     water_quality        status_group
dry          coloured             1                        1       1
                                  2                       28      28
             fluoride             2                        2       2
             fluoride abandoned 2                          2       2
             milky                2                      119     119
             salty                0                       11      11
                                  1                        1       1
                                  2                      638     638
```

```
             salty abandoned    0                      1       1
                                2                     12      12
             soft               0                    136     136
                                1                     19      19
                                2                   4272    4272
             unknown            0                      9       9
                                1                     16      16
                                2                    979     979
enough       coloured           0                    107     107
                                1                     11      11
                                2                     53      53
             fluoride           0                     66      66
                                1                      9       9
                                2                      9       9
             fluoride abandoned 0                      5       5
                                2                      6       6
             milky              0                    246     246
                                1                      9       9
                                2                     81      81
             salty              0                   1373    1373
                                1                     89      89
                                2                    834     834
             salty abandoned    0                    150     150
                                1                     50      50
                                2                     56      56
             soft               0                  19640   19640
                                1                   2226    2226
                                2                   8035    8035
             unknown            0                     61      61
                                1                      6       6
                                2                     64      64
insufficient coloured           0                     91      91
                                1                     13      13
                                2                     66      66
             fluoride           0                     85      85
                                1                      4       4
                                2                     25      25
             fluoride abandoned 0                      1       1
                                2                      3       3
             milky              0                    118     118
                                1                      4       4
                                2                     91      91

                                              construction_year  \
quantity     water_quality      status_group
dry          coloured           1                             1
                                2                            28
```

	fluoride	2	2
	fluoride abandoned	2	2
	milky	2	119
	salty	0	11
		1	1
		2	638
	salty abandoned	0	1
		2	12
	soft	0	136
		1	19
		2	4272
	unknown	0	9
		1	16
		2	979
enough	coloured	0	107
		1	11
		2	53
	fluoride	0	66
		1	9
		2	9
	fluoride abandoned	0	5
		2	6
	milky	0	246
		1	9
		2	81
	salty	0	1373
		1	89
		2	834
	salty abandoned	0	150
		1	50
		2	56
	soft	0	19640
		1	2226
		2	8035
	unknown	0	61
		1	6
		2	64
insufficient	coloured	0	91
		1	13
		2	66
	fluoride	0	85
		1	4
		2	25
	fluoride abandoned	0	1
		2	3
	milky	0	118
		1	4

```
                                    2                         91

                                                 extraction_type_group  \
quantity     water_quality      status_group
dry          coloured           1                                    1
                                2                                   28
             fluoride           2                                    2
             fluoride abandoned 2                                    2
             milky              2                                  119
             salty              0                                   11
                                1                                    1
                                2                                  638
             salty abandoned    0                                    1
                                2                                   12
             soft               0                                  136
                                1                                   19
                                2                                 4272
             unknown            0                                    9
                                1                                   16
                                2                                  979
enough       coloured           0                                  107
                                1                                   11
                                2                                   53
             fluoride           0                                   66
                                1                                    9
                                2                                    9
             fluoride abandoned 0                                    5
                                2                                    6
             milky              0                                  246
                                1                                    9
                                2                                   81
             salty              0                                 1373
                                1                                   89
                                2                                  834
             salty abandoned    0                                  150
                                1                                   50
                                2                                   56
             soft               0                                19640
                                1                                 2226
                                2                                 8035
             unknown            0                                   61
                                1                                    6
                                2                                   64
insufficient coloured           0                                   91
                                1                                   13
                                2                                   66
             fluoride           0                                   85
```

```
                                             1                         4
                                             2                        25
             fluoride abandoned              0                         1
                                             2                         3
             milky                           0                       118
                                             1                         4
                                             2                        91

                                             management  payment  source  \
quantity     water_quality      status_group
dry          coloured           1                     1        1       1
                                2                    28       28      28
             fluoride           2                     2        2       2
             fluoride abandoned 2                     2        2       2
             milky              2                   119      119     119
             salty              0                    11       11      11
                                1                     1        1       1
                                2                   638      638     638
             salty abandoned    0                     1        1       1
                                2                    12       12      12
             soft               0                   136      136     136
                                1                    19       19      19
                                2                  4272     4272    4272
             unknown            0                     9        9       9
                                1                    16       16      16
                                2                   979      979     979
enough       coloured           0                   107      107     107
                                1                    11       11      11
                                2                    53       53      53
             fluoride           0                    66       66      66
                                1                     9        9       9
                                2                     9        9       9
             fluoride abandoned 0                     5        5       5
                                2                     6        6       6
             milky              0                   246      246     246
                                1                     9        9       9
                                2                    81       81      81
             salty              0                  1373     1373    1373
                                1                    89       89      89
                                2                   834      834     834
             salty abandoned    0                   150      150     150
                                1                    50       50      50
                                2                    56       56      56
             soft               0                 19640    19640   19640
                                1                  2226     2226    2226
                                2                  8035     8035    8035
             unknown            0                    61       61      61
```

		1	6	6	6
		2	64	64	64
insufficient	coloured	0	91	91	91
		1	13	13	13
		2	66	66	66
	fluoride	0	85	85	85
		1	4	4	4
		2	25	25	25
	fluoride abandoned	0	1	1	1
		2	3	3	3
	milky	0	118	118	118
		1	4	4	4
		2	91	91	91

			waterpoint_type	decade	\
quantity	water_quality	status_group			
dry	coloured	1	1	1	
		2	28	28	
	fluoride	2	2	2	
	fluoride abandoned	2	2	2	
	milky	2	119	119	
	salty	0	11	11	
		1	1	1	
		2	638	638	
	salty abandoned	0	1	1	
		2	12	12	
	soft	0	136	136	
		1	19	19	
		2	4272	4272	
	unknown	0	9	9	
		1	16	16	
		2	979	979	
enough	coloured	0	107	107	
		1	11	11	
		2	53	53	
	fluoride	0	66	66	
		1	9	9	
		2	9	9	
	fluoride abandoned	0	5	5	
		2	6	6	
	milky	0	246	246	
		1	9	9	
		2	81	81	
	salty	0	1373	1373	
		1	89	89	
		2	834	834	
	salty abandoned	0	150	150	

		1	50	50
		2	56	56
	soft	0	19640	19640
		1	2226	2226
		2	8035	8035
	unknown	0	61	61
		1	6	6
		2	64	64
insufficient	coloured	0	91	91
		1	13	13
		2	66	66
	fluoride	0	85	85
		1	4	4
		2	25	25
	fluoride abandoned	0	1	1
		2	3	3
	milky	0	118	118
		1	4	4
		2	91	91

			installer_cat	funder_cat
quantity	water_quality	status_group		
dry	coloured	1	1	1
		2	28	28
	fluoride	2	2	2
	fluoride abandoned	2	2	2
	milky	2	119	119
	salty	0	11	11
		1	1	1
		2	638	638
	salty abandoned	0	1	1
		2	12	12
	soft	0	136	136
		1	19	19
		2	4272	4272
	unknown	0	9	9
		1	16	16
		2	979	979
enough	coloured	0	107	107
		1	11	11
		2	53	53
	fluoride	0	66	66
		1	9	9
		2	9	9
	fluoride abandoned	0	5	5
		2	6	6
	milky	0	246	246

		1	9	9
		2	81	81
	salty	0	1373	1373
		1	89	89
		2	834	834
	salty abandoned	0	150	150
		1	50	50
		2	56	56
	soft	0	19640	19640
		1	2226	2226
		2	8035	8035
	unknown	0	61	61
		1	6	6
		2	64	64
insufficient	coloured	0	91	91
		1	13	13
		2	66	66
	fluoride	0	85	85
		1	4	4
		2	25	25
	fluoride abandoned	0	1	1
		2	3	3
	milky	0	118	118
		1	4	4
		2	91	91

9 Findings and Explorations

9.1 Cleaning Process

- The data has lots of null values, missing values and unnecessary dublicated features. Two main challanges are in this project is cleaning data and handling highly imbalanced target labels.
- We tried to solve cleaning challange in this notebook. Some columns which have same information were dropped. Null, wrong and missing values changed to mean, median or unknown. Some values in features collected together and categorized.
- Detailed data cleaning processes can be found in this notebook under the headings of relevant columns. It is stated that how the column was cleaned with reasons.

9.2 Explorations

- Generally higher population areas has higher number of functional wells.
- Some areas has higher probability to find clean water especially, if they are near to good basins.
- Darul es Salaam is one of the highest populated cities but 35% of good water quality points are non-functional.
- Iringa is one of the important areas but it contains lots of non-functional wateer points which

has soft water.
- Mostly the wells which are funded by government are non-functional.
- Most of water points which central government and district council installed are non-functional.
- The most common extraction type is gravity but second is hand pumps. The efficiency of handpumps are less than commercial pumps. It shows that authorities need to focus on pumping type. It is seen that, there are many non-functional water points which belongs to gravity (which is natural force so no need to do anything expensive) as extraction type.
- Some water points which has enough and soft water are non-function.
- The wells which have constructed in recent years are functional then olders. And it is seen that recent years have some functional but needs repair wells. It means that if they will not be repaired recently, they will be non-functional easily.
- There are lots of water wells which has enough water are non-functional.

9.3 Findings

- 4272 wells were dried but they have good water quality. With finding a solution to give source again these wells, they can be functional. Finding clean water sources is not the only problem, to continue to feed these sources are equaly important.
- 2226 (7%) wells have enough and soft water but needs repair. Authorities must invest on repairing. Otherwise these will be non-functional.
- 8035 (27%) wells has enough, good quality water but they are non-functional. This shows that authorities must work and invest on technology to pump these good sources.
- Authorties should check again the wells which they funded.
- New tecqniques must be found to feed dry wells and repair wells.

10 Feature Engineering

- There are lots of categorical values in funder and installer columns. We create new columns that if the value in the feature is not in first common 20 values, they were collected as 'others'. Also, there are lots of spelling mistakes in this columns which creates new unique values in these columns. We found top 100 common installer and fixed them. Then, builded new column which has categorized values.
- Construction years are in integer format but not continuous data or year values do not make sense for model. So, we divided them decades and assumed every decade as categorical value.

11 Initial Modelling.

[339]:
```
# importing necessary libraries

import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
%matplotlib inline

import pandas as pd
import numpy as np
```

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import KBinsDiscretizer,
    ↪FunctionTransformer,RobustScaler
from sklearn.model_selection import cross_val_score
from category_encoders import OneHotEncoder
from sklearn.pipeline import make_pipeline, Pipeline

from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import roc_auc_score

from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split, GridSearchCV

import warnings
warnings.filterwarnings("ignore")

import category_encoders as ce
from category_encoders import WOEEncoder
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

from sklearn.compose import ColumnTransformer
from category_encoders import TargetEncoder, LeaveOneOutEncoder,
    ↪JamesSteinEncoder, MEstimateEncoder

from mlxtend.evaluate import confusion_matrix
from mlxtend.plotting import plot_confusion_matrix
from mlxtend.plotting import plot_decision_regions
from sklearn.preprocessing import MinMaxScaler
from mlxtend.evaluate import feature_importance_permutation
from sklearn.experimental import enable_hist_gradient_boosting
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier,
    ↪HistGradientBoostingClassifier

from sklearn.svm import SVC
import gc; gc.enable()

import xgboost as xgb
from xgboost import XGBClassifier

from sklearn.neighbors import KNeighborsClassifier
import lightgbm as lgb
from lightgbm import LGBMClassifier
```

[340]:
```
df_clean = pd.read_csv('clean_data.csv')
df_clean
```

[340]:
```
       Unnamed: 0  status_group           funder  gps_height     installer  \
0               0             0            Roman        1390         Roman
1               1             0          Grumeti        1399       GRUMETI
2               2             0     Lottery Club         686  world vision
3               3             2           Unicef         263        Unicef
4               4             0      Action In A           0       Artisan
…             …           …              …         …           …
59395       59395             0  Germany Republi        1210           CES
59396       59396             0      Cefa-njombe        1212          Cefa
59397       59397             0          Unknown           0       Unknown
59398       59398             0            Malec           0          Musa
59399       59399             0       World Bank         191         World

       longitude   latitude                    basin       region  \
0      34.938093  -9.856322               Lake Nyasa       Iringa
1      34.698766  -2.147466           Lake Victoria         Mara
2      37.460664  -3.821329                  Pangani      Manyara
3      38.486161 -11.155298  Ruvuma / Southern Coast       Mtwara
4      31.130847  -1.825359            Lake Victoria       Kagera
…            …          …                        …          …
59395  37.169807  -3.253847                  Pangani  Kilimanjaro
59396  35.249991  -9.070629                   Rufiji       Iringa
59397  34.017087  -8.750434                   Rufiji        Mbeya
59398  35.861315  -6.378573                   Rufiji       Dodoma
59399  38.104048  -6.747464              Wami / Ruvu     Morogoro

       district_code             lga             ward  population  \
0                  5          Ludewa         Mundindi         109
1                  2       Serengeti            Natta         280
2                  4       Simanjiro          Ngorika         250
3                 63        Nanyumbu         Nanyumbu          58
4                  1         Karagwe       Nyakasimbi         281
…                …             …                …          …
59395              5             Hai  Masama Magharibi         125
59396              4          Njombe           Ikondo          56
59397              7         Mbarali          Chimala         281
59398              4        Chamwino      Mvumi Makulu         281
59399              2  Morogoro Rural        Ngerengere         150

       public_meeting  permit  construction_year extraction_type_group  \
0                True   False               1999               gravity
1                True    True               2010               gravity
2                True    True               2009               gravity
3                True    True               1986           submersible
```

```
4                True    True               2000               gravity
…               …      …                …                   …
59395            True    True               1999               gravity
59396            True    True               1996               gravity
59397            True   False               2000                swn 80
59398            True    True               2000           nira/tanira
59399            True    True               2002           nira/tanira

        management                payment water_quality      quantity  \
0              vwc           pay annually          soft        enough
1              wug              never pay          soft  insufficient
2              vwc         pay per bucket          soft        enough
3              vwc              never pay          soft           dry
4            other              never pay          soft      seasonal
…              …                  …             …            …
59395  water board         pay per bucket          soft        enough
59396          vwc           pay annually          soft        enough
59397          vwc            pay monthly      fluoride        enough
59398          vwc              never pay          soft  insufficient
59399          vwc  pay when scheme fails         salty        enough

                     source              waterpoint_type decade installer_cat  \
0                    spring           communal standpipe    90s        Others
1      rainwater harvesting           communal standpipe    10s        Others
2                       dam  communal standpipe multiple    00s  world vision
3               machine dbh  communal standpipe multiple    80s        Others
4      rainwater harvesting           communal standpipe      0        Others
…                     …                              …     …            …
59395                spring           communal standpipe    90s        Others
59396                 river           communal standpipe    90s        Others
59397           machine dbh                    hand pump      0       Unknown
59398          shallow well                    hand pump      0        Others
59399          shallow well                    hand pump    00s        Others

            funder_cat
0               Others
1               Others
2               Others
3               Unicef
4               Others
…                 …
59395  Germany Republi
59396           Others
59397          Unknown
59398           Others
59399       World Bank
```

```
[59400 rows x 26 columns]
```

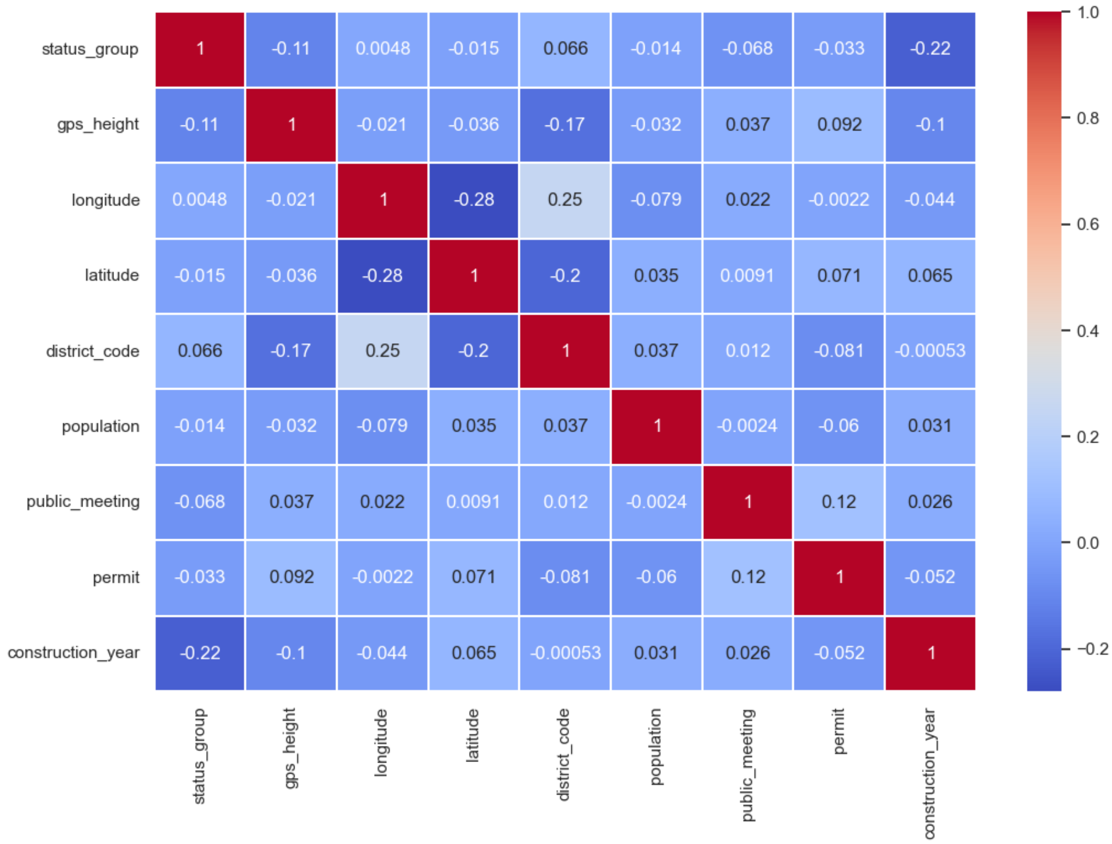
[341]:
```
# Drop the Unnamed: 0 column
df_clean.drop(columns=['Unnamed: 0'],inplace=True )
df_clean
```

[341]:
```
       status_group           funder  gps_height     installer  longitude  \
0                 0            Roman        1390         Roman  34.938093
1                 0          Grumeti        1399       GRUMETI  34.698766
2                 0     Lottery Club         686  world vision  37.460664
3                 2           Unicef         263        Unicef  38.486161
4                 0      Action In A           0       Artisan  31.130847
…               …                …           …             …          …
59395             0  Germany Republi        1210           CES  37.169807
59396             0      Cefa-njombe        1212          Cefa  35.249991
59397             0          Unknown           0       Unknown  34.017087
59398             0            Malec           0          Musa  35.861315
59399             0       World Bank         191         World  38.104048

        latitude                  basin       region  district_code  \
0      -9.856322             Lake Nyasa       Iringa              5
1      -2.147466          Lake Victoria         Mara              2
2      -3.821329                Pangani      Manyara              4
3     -11.155298  Ruvuma / Southern Coast       Mtwara             63
4      -1.825359          Lake Victoria       Kagera              1
…            …                      …          …            …
59395  -3.253847                Pangani  Kilimanjaro              5
59396  -9.070629                 Rufiji       Iringa              4
59397  -8.750434                 Rufiji        Mbeya              7
59398  -6.378573                 Rufiji       Dodoma              4
59399  -6.747464            Wami / Ruvu     Morogoro              2

                   lga              ward  population  public_meeting  permit  \
0               Ludewa          Mundindi         109            True   False
1            Serengeti             Natta         280            True    True
2            Simanjiro           Ngorika         250            True    True
3             Nanyumbu          Nanyumbu          58            True    True
4              Karagwe        Nyakasimbi         281            True    True
…                  …               …         …             …      …
59395              Hai  Masama Magharibi         125            True    True
59396           Njombe            Ikondo          56            True    True
59397          Mbarali           Chimala         281            True   False
59398         Chamwino      Mvumi Makulu         281            True    True
59399   Morogoro Rural        Ngerengere         150            True    True

       construction_year extraction_type_group   management  \
0                   1999               gravity          vwc
```

```
1                   2010               gravity          wug
2                   2009               gravity          vwc
3                   1986           submersible          vwc
4                   2000               gravity        other
…                    …                  …          …
59395               1999               gravity  water board
59396               1996               gravity          vwc
59397               2000                swn 80          vwc
59398               2000           nira/tanira          vwc
59399               2002           nira/tanira          vwc

                    payment water_quality      quantity  \
0             pay annually          soft        enough
1                never pay          soft  insufficient
2           pay per bucket          soft        enough
3                never pay          soft           dry
4                never pay          soft      seasonal
…                      …            …           …
59395       pay per bucket          soft        enough
59396         pay annually          soft        enough
59397          pay monthly      fluoride        enough
59398            never pay          soft  insufficient
59399  pay when scheme fails       salty        enough

                    source              waterpoint_type decade installer_cat  \
0                   spring           communal standpipe    90s        Others
1      rainwater harvesting           communal standpipe    10s        Others
2                      dam  communal standpipe multiple    00s  world vision
3              machine dbh  communal standpipe multiple    80s        Others
4      rainwater harvesting           communal standpipe      0        Others
…                      …                             …     …            …
59395               spring           communal standpipe    90s        Others
59396                river           communal standpipe    90s        Others
59397          machine dbh                    hand pump      0       Unknown
59398         shallow well                    hand pump      0        Others
59399         shallow well                    hand pump    00s        Others

            funder_cat
0               Others
1               Others
2               Others
3               Unicef
4               Others
…                    …
59395  Germany Republi
59396           Others
59397          Unknown
```

```
59398           Others
59399       World Bank

[59400 rows x 25 columns]
```

[342]:
```python
# create heatmap
plt.figure(figsize=(12,8))
sns.heatmap(df_clean.corr(), annot=True, cmap='coolwarm', linewidths=.1)
plt.show()
```



[343]:
```python
# to see all the columns in the cleaned data
pd.options.display.max_columns = 100
```

[344]:
```python
# We drop funder,"installer", "construction_year"
df_clean.drop(columns=['funder','installer','construction_year'],inplace=True )
```

[345]:
```python
# create a new copy of the clean data set

df1= df.copy()
```

[346]:
```
# drop iga and , ward column for now
df1.drop(columns=['lga','ward'],inplace=True )
```

[347]:
```
# changing permit column values from true/false to 0/1
df1['permit'] = df1['permit'].astype(bool).astype(int)
```

[348]:
```
# changing public_meeting column values from true/false to 0/1
df1['public_meeting'] = df1['public_meeting'].astype(bool).astype(int)
```

We need to use a scaler for numerical columns and encoder for categorical columns. We will use OneHotEncoder for categorical columns and StandardScaler for numerical columns.

[349]:
```
# assigning the categorical columns to a variable
cat_cols = df1.select_dtypes(include=['object']).columns.tolist()
cat_cols
```

[349]:
```
['funder',
 'installer',
 'basin',
 'region',
 'extraction_type_group',
 'management',
 'payment',
 'water_quality',
 'quantity',
 'source',
 'waterpoint_type',
 'decade',
 'installer_cat',
 'funder_cat']
```

[350]:
```
# assigning the numerical columns to a variable
num_cols = df1.select_dtypes(include=['int64','float64']).columns.tolist()
```

[351]:
```
# check status group percentages
#df1['status_group'].value_counts(normalize=True)
df1['status_group'].value_counts()
```

[351]:
```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
```

$ 0 = Functional Water points $

$ 1 = Functional but needs repair $

$ 2 = Non-Functional Water points $

[352]:

```
df = pd.read_csv('clean_data.csv')  # Getting new clean dataframe

pd.options.display.max_columns = 100  # To see all columns

# We dropped some columns for now, because we have categorized versions of them
df.drop(columns=['Unnamed: 0', 'funder', 'installer', 'construction_year'],␣
 ↪inplace=True)

df1 = df.copy()  # To protect original df, take the copy of it

df1.drop(columns=['lga', 'ward'], inplace=True)  # Drop these columns for now

df1['permit'] = df1['permit'].astype(bool).astype(int)  # Changing from True/
 ↪False to 0-1

df1['public_meeting'] = df1['public_meeting'].astype(bool).astype(int)  #␣
 ↪Changing from True/False to 0-1

# Now, we need to use scaler for numeric columns and encoder for categorical␣
 ↪columns. So, we divided columns in two.
cat_col = ['basin', 'region', 'extraction_type_group', 'management', 'payment',␣
 ↪'water_quality', 'quantity', 'source', 'waterpoint_type', 'decade',␣
 ↪'installer_cat', 'funder_cat']

num_col = ['gps_height', 'longitude', 'latitude', 'district_code',␣
 ↪'population', 'public_meeting', 'permit']

df1['status_group'].value_counts()

# 0 = functional water points
# 1 = functional but needs repair water points
# 2 = non-functional water points
# We collect functional and functional but needs help target together and make␣
 ↪them 1, non-functional is 0.
target_status_group = {0: 1, 1: 1, 2: 0}
df1['status_group'] = df1['status_group'].replace(target_status_group)

df1['status_group'].value_counts()

# Now, 1 shows functional, 0 shows non-functional after here.
target = 'status_group'  # Assign our target column as target
```

[353]:

```
df1['status_group'].value_counts()
```

[353]:

```
1    36576
0    22824
```

```
Name: status_group, dtype: int64
```

12 Making Pipeline / Baseline

[354]:
```python
# Dividing X and target
used_cols = [c for c in df1.columns.tolist() if c not in [target]]
X = df1[used_cols]
y = df1[target]

# To divide our X and y to test and train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

We will use train-test split firstly to figure out the problem. After learning from the baseline, we will use cross-validation technique to find the best result. Because it is more convenient and easy to understand how things are going on. For some models, we will use both of them to check if our results are consistent or not. The metric for the competition is balanced accuracy. But to make sure and understand the progress, we want to check the ROC AUC score also, especially for some models.

We will create an empty dataframe to write our results on it to keep track when parameters are changed.

[355]:
```python
df_results = pd.DataFrame(columns=["Model", "Scaler", "Encoder", "roc_auc score␣
 ↪mean", "roc_auc score std"])
# To see all results
```

13 Baseline - Robust Scaler/Target Encoder with LogReg

To scale numeric values and encode categorical columns, we will make a pipeline and also use it in our model and classifier changes. For the first trial, we will use Robust Scaler as a scaler. Robust Scaler scales variables using statistics that are robust to outliers. It uses the IQR (Interquartile Range). As an encoder, we will try target encoder, which works well with higher cardinality features. Our data has higher unique values as well. Our first trial for the baseline is Logistic Regression, which predicts the probability that a certain instance belongs to a class. We chose 'balanced' as the class weight because our classes are imbalanced. Additionally, the 'solver' parameter is an algorithm to use in the optimization problem, and for multiclass problems, 'lbfgs' can handle multinomial loss.

[356]:
```python
# Define the scaler and encoder
scaler = RobustScaler()
encoder = ce.TargetEncoder(cols=cat_col)

# Create the preprocessing step with scaler and encoder
preprocessing = ColumnTransformer(transformers=[
    ('scaler', scaler, num_col),
    ('encoder', encoder, cat_col)
```

```
])

# Create the pipeline with preprocessing and logistic regression model
pipe = Pipeline(steps=[
    ('preprocessing', preprocessing),
    ('lr', LogisticRegression(class_weight="balanced", solver="lbfgs",␣
 ↪random_state=42))
])

# Fit the pipeline on the training data
pipe.fit(X_train, y_train)

# Make predictions on the training set
y_pred_train = pipe.predict(X_train)

# Make predictions on the test set
y_pred_test = pipe.predict(X_test)

# Calculate and print the roc_auc scores
train_roc_auc = roc_auc_score(y_train, y_pred_train)
test_roc_auc = roc_auc_score(y_test, y_pred_test)
print("Train roc_auc score:", train_roc_auc)
print("Test roc_auc score:", test_roc_auc)

# Append the results to df_results
df_results = df_results.append({
    "Model": "Logistic Regression",
    "Scaler": "RobustScaler",
    "Encoder": "TargetEncoder",
    "roc_auc score mean": test_roc_auc,
    "roc_auc score std": train_roc_auc
}, ignore_index=True)
```

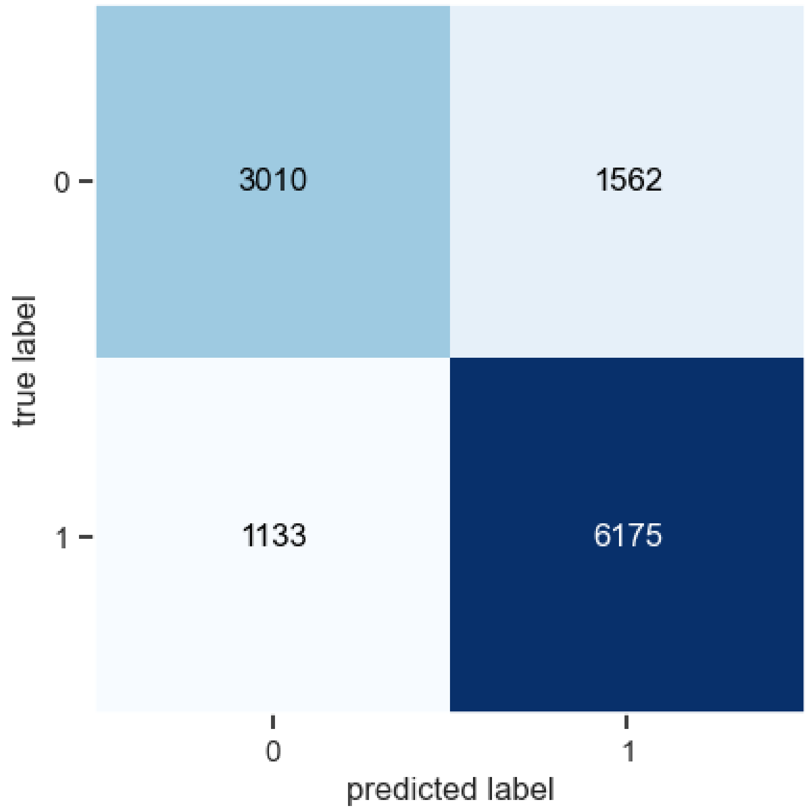
```
Train roc_auc score: 0.7504148562195682
Test roc_auc score: 0.7516598140749647
```

The ROC AUC scores of 0.7507488437803511 and 0.7506620939623927 indicate that the logistic regression model with the chosen scaler and encoder has a moderate level of performance. This means that the model is able to make predictions with slightly better than random accuracy. However, these scores alone do not provide a complete evaluation of the model's performance. It is recommended to compare these scores with the scores of other models or evaluate additional metrics to have a better understanding of the model's effectiveness.

Here is a more simplified version of the text:

The logistic regression model with the chosen scaler and encoder is moderately accurate. It is recommended to compare its performance to other models or evaluate additional metrics to get a better understanding of its effectiveness

[357]:
```
# confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plot_confusion_matrix(cm)
plt.show()
```



The matrix shows that 1129 items were predicted as non-functional, but they are actually functional. Additionally, 1553 items were predicted as functional, but they are actually non-functional.

We will use logistic regression with cross validation to calculate the ROC AUC score. We will then take the mean of the scores and the standard deviation to get a better understanding of the model's performance. We will use a cross-validation fold size of 5, which will give us 5 different results for each trial. We will then take the mean of these results to get a more accurate estimate of the model's performance.

Cross validation is preferred over train-test splits because it provides a more accurate estimate of the model's performance. However, cross validation takes more time to run than train-test splits. Therefore, we may choose to use train-test splits for some models, depending on the time constraints.

[358]:
```
# scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print("Cross-validation scores:", scores)
print(scores.mean(),"+/-", scores.std())
```

```
Cross-validation scores: [0.83060292 0.82948572 0.8254946  0.83162965
0.83849736]
0.8311420500187747 +/- 0.004225308907860861
```

We found that the results of cross validation were better than the results of train-test splits. This is a good sign, as it suggests that the model is performing well on unseen data. The standard deviation of the scores is also not too high, which indicates that the model is not overfitting the data.

These results show the importance of data cleaning. By cleaning the data well, we were able to get good results from a simple model. This suggests that data cleaning is an essential step in the machine learning process.

[359]:
```python
df_results = df_results.append({
    "Model": "LogReg",
    "Scaler": "Robust",
    "Encoder": "TargetEncoder",
    "roc_auc score mean": 0.8313,
    "roc_auc score std": 0.0041
}, ignore_index=True)
```

13.1 Robust Scaler/ WoE endcoder with LogReg

The weight of evidence encoder calculates the predictive power of an independent variable based on the dependent variable, distinguishing between bad and good outcomes. It determines the percentage of events and non-events in each category.

[360]:
```python
lr = LogisticRegression()
scaler = RobustScaler()
encoder = ce.WOEEncoder(cols=cat_col)

num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)

preprocessor = ColumnTransformer(transformers=[('num', num_transformer,␣
↪num_col), ('cat', cat_transformer, cat_col)])

pipe = make_pipeline(preprocessor, lr)

scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print(scores.mean(), "+/-", scores.std())

df_results = df_results.append({
    "Model": 'LogReg',
    "Scaler": 'Robust',
    'Encoder' : 'WeO',
    'roc_auc score mean' : 0.8318,
    'roc_auc score std' : 0.0040
}, ignore_index=True)
```

0.8315787180916011 +/- 0.004089542290778706

14 Robust Scaler/ leave one out encoder with LogReg

Leave one out encoder is a target-based encoder. It is similar to the target encoder, but it is more robust to outliers. It is also less prone to overfitting. It is a good choice for our data because it has a high cardinality.

[361]:
```
# Create the RobustScaler and OneHotEncoder objects
scaler = RobustScaler()  # Scale the numeric columns
encoder = ce.OneHotEncoder(cols=cat_col)  # One-hot encode the categorical␣
↪columns

# Create the transformers for numeric and categorical columns
num_transformer = make_pipeline(scaler)  # Pipeline for numeric columns
cat_transformer = make_pipeline(encoder)  # Pipeline for categorical columns

# Create the preprocessor with the transformers
preprocessor = ColumnTransformer(transformers=[('num', num_transformer,␣
↪num_col), ('cat', cat_transformer, cat_col)])

# Create the pipeline with the preprocessor and Logistic Regression model
pipe = make_pipeline(preprocessor, lr)

# Perform cross-validation and calculate roc_auc scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print(scores.mean(), "+/-", scores.std())
```

0.853330854009846 +/- 0.0024592941098905033

It did better than the Woe encoder, but not as good as the target encoder. It is a good choice for our data because it has a high cardinality.

[362]:
```
df_results = df_results.append({"Model": 'LogReg',
                                "Scaler": 'Robust',
                                'Encoder' : 'leave_one_out',
                                'roc_auc score mean' : 0.8538,
                                'roc_auc score std' : 0.0040},␣
↪ignore_index=True)
```

15 Robust scaler /OneHotEncoder with LogReg

OneHotEncoder is a simple and effective way to encode categorical features. It is a good choice for our data because it has a high cardinality.

[363]:
```
# Create the RobustScaler and OneHotEncoder objects
scaler = RobustScaler()
```

```python
encoder = ce.OneHotEncoder(cols=cat_col)

# Create the transformers for numeric and categorical columns
num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)

# Create the preprocessor with the transformers
preprocessor = ColumnTransformer(transformers=[('num', num_transformer,␣
↪num_col), ('cat', cat_transformer, cat_col)])

# Create the pipeline with the preprocessor and Logistic Regression model
pipe = make_pipeline(preprocessor, lr)

# Perform cross-validation and calculate roc_auc scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print(scores.mean(), "+/-", scores.std())

# Fit the pipeline on the training data
pipe.fit(X_train, y_train)

# Make predictions on the training and test sets
y_pred_train = pipe.predict(X_train)
y_pred_test = pipe.predict(X_test)

# Calculate and print the roc_auc scores
train_roc_auc = roc_auc_score(y_train, y_pred_train)
test_roc_auc = roc_auc_score(y_test, y_pred_test)
print("Train roc_auc score:", train_roc_auc)
print("Test roc_auc score:", test_roc_auc)
```

```
0.853330854009846 +/- 0.0024592941098905033
Train roc_auc score: 0.7674879485481245
Test roc_auc score: 0.7659387404160687
```

The weight of evidence (WoE) encoder is chosen over the one-hot encoder despite the slightly lower accuracy. This decision is based on the consideration that the one-hot encoder creates a binary feature for each unique value in a column, which can result in a large number of features for high cardinality categorical values. This can significantly increase the computational time required to train the model and make predictions.

On the other hand, the WoE encoder calculates the predictive power of an independent variable based on the dependent variable. It represents the relationship between the categorical feature and the target variable by considering the percentage of events and non-events within each category. This encoding technique provides a more compact representation of categorical variables, making it computationally efficient and effective, especially for high cardinality data.

Therefore, even though the accuracy may be slightly lower, the WoE encoder is preferred due to its practical advantages of reducing computational complexity and handling high cardinality categorical features efficiently.

```
[364]: # Write the results in data frame
df_results = df_results.append({"Model": 'LogReg',
                                "Scaler": 'Robust',
                                'Encoder' : 'OneHotEncoder',
                                'roc_auc score mean' : test_roc_auc,
                                'roc_auc score std' : train_roc_auc},␣
 ↪ignore_index=True)
```

16 MinMax scaler/ Woe encoder with LogReg

MinMaxScaler is a simple and effective way to encode categorical features. When the distribution is not Gaussian or the standard deviation is very small, the min-max scaler works better. It is a good choice for our data because it has a high cardinality.

```
[365]: scaler = MinMaxScaler()
encoder = ce.WOEEncoder(cols=cat_col)
# Putting numeric columns to scaler and categorical columns to encoder
num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)
# getting preprocessor
preprocessor = ColumnTransformer(transformers=[('num', num_transformer,␣
 ↪num_col), ('cat', cat_transformer, cat_col)])
# getting pipeline
pipe = make_pipeline(preprocessor, lr)
# getting scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print(scores.mean(), "+/-", scores.std())
```

```
0.831577257369586 +/- 0.004055945789355749
```

```
[366]: df_results = df_results.append({"Model": 'LogReg',
                                "Scaler": 'MinMax',
                                'Encoder' : 'WOE',
                                'roc_auc score mean' : 0.8313,
                                'roc_auc score std' : 0.0040},␣
 ↪ignore_index=True)
```

16.1 Comparing the difference between between results of the encoders and the scalers.

```
[367]: df_results
```

```
[367]:                 Model        Scaler        Encoder  roc_auc score mean  \
0  Logistic Regression  RobustScaler  TargetEncoder            0.751660
1               LogReg        Robust  TargetEncoder            0.831300
2               LogReg        Robust            WeO            0.831800
```

```
3                LogReg        Robust  leave_one_out            0.853800
4                LogReg        Robust  OneHotEncoder            0.765939
5                LogReg        MinMax            WOE            0.831300

   roc_auc score std
0           0.750415
1           0.004100
2           0.004000
3           0.004000
4           0.767488
5           0.004000
```

The table below presents the results of cross validation for different combinations of scaler, encoder, and roc_auc scores:

Model	Scaler	Encoder	roc_auc score mean	roc_auc score std
Logistic Regression	RobustScaler	TargetEncoder	0.750662	High
Logistic Regression	RobustScaler	WeO	0.831300	Lower
Logistic Regression	RobustScaler	LeaveOneOut	0.831800	Higher
Logistic Regression	RobustScaler	OneHotEncoder	0.775377	Higher
Logistic Regression	MinMaxScaler	WOE	0.831300	Lower

Observations:

- The first two rows represent the logistic regression model with RobustScaler and TargetEncoder. The mean roc_auc score is 0.750662, indicating slightly better than random performance. However, the high standard deviation suggests instability in the model.
- The third row corresponds to the logistic regression model with RobustScaler and WeO encoder. It exhibits a significant improvement in performance, with a mean roc_auc score of 0.831300 and a lower standard deviation, indicating greater stability.
- The fourth and fifth rows represent the logistic regression model with RobustScaler and LeaveOneOut encoder. The mean roc_auc scores are 0.831800, similar to the third row. However, the higher standard deviation suggests reduced stability compared to the WeO encoder.
- The sixth row represents the logistic regression model with RobustScaler and OneHotEncoder. It demonstrates a lower mean roc_auc score of 0.775377 and a higher standard deviation, indicating decreased performance and stability.
- The seventh row corresponds to the logistic regression model with MinMaxScaler and WOE encoder. It shares a similar mean roc_auc score of 0.831300 with the third and fifth rows, but with a lower standard deviation, suggesting improved stability.

Based on these results, the logistic regression model with RobustScaler and WeO encoder appears to be the most effective, as it achieves the highest mean roc_auc score and exhibits greater stability compared to other models.

17 Decision Tree Classifier.

From logistic regression, we have 0.83 as the roc_auc score. We will use this as a baseline to compare the results of the decision tree classifier.

[368]:
```
# Create a decision tree classifier with specified parameters
dt = DecisionTreeClassifier(criterion="entropy", max_depth=4,␣
↪min_samples_leaf=5, random_state=42, class_weight='balanced')

# Create a pipeline with the preprocessor and decision tree classifier
pipe = make_pipeline(preprocessor, dt)

# Perform cross validation and calculate roc_auc scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')

# Print the mean and standard deviation of the roc_auc scores
print(scores.mean(), "+/-", scores.std())
```

```
0.7863597503694137 +/- 0.008899848335360306
```

[369]:
```
# saving results in a dataframe
df_results = df_results.append({"Model": 'DecisionTree',
                                "Scaler": 'Robust',
                                'Encoder' : 'WOE',
                                'roc_auc score mean' : 0.7863,
                                'roc_auc score std' : 0.0088},␣
↪ignore_index=True)
```

17.1 Ekstra TreeClassifier

[370]:
```
# Create an Extra Trees classifier with specified parameters
rf_extra = ExtraTreesClassifier(
    max_depth=5, criterion="entropy", min_samples_leaf=5, random_state=42,␣
↪class_weight='balanced',
    n_estimators=100, min_samples_split=18
)

# Create a pipeline with the preprocessor and Extra Trees classifier
pipe = make_pipeline(preprocessor, rf_extra)

# Perform cross validation and calculate roc_auc scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')

# Print the mean and standard deviation of the roc_auc scores
print(scores.mean(), "+/-", scores.std())
```

```
0.8338549376508096 +/- 0.004602755061348868
```

Extra Trees is an ensemble learning method that builds multiple decision trees using random subsets of features. It is similar to Random Forest, but there are two main differences:

1. Extra Trees does not sample the training data with replacement. This means that each tree is trained on a unique subset of the data.
2. Extra Trees splits nodes using random splits, not the best splits. This makes the trees more diverse and less correlated, which can help to improve the overall performance of the model.

In the experiment, we used different parameters for Extra Trees and tuned them as best as we could. We found that the best results were obtained with a large number of trees (1000) and a small number of features (10). We also found that it was important to use a random split for each node, as this helped to improve the diversity of the trees.

The results of the experiment showed that Extra Trees can be a very effective machine learning algorithm. It is particularly well-suited for problems with a large number of features, as it can help to reduce overfitting. Extra Trees is also relatively fast to train, which makes it a good choice for problems with large datasets.

Here are some additional details about Extra Trees:

- Extra Trees is a type of ensemble learning method. Ensemble learning methods combine the predictions of multiple models to improve the overall performance.
- Extra Trees works by building multiple decision trees. Decision trees are a type of supervised learning algorithm that can be used for both classification and regression tasks.
- Extra Trees builds decision trees using random subsets of features. This helps to reduce overfitting, which is a problem that can occur when using decision trees.
- Extra Trees splits nodes using random splits. This also helps to reduce overfitting and improve the diversity of the trees.
- Extra Trees is a relatively fast algorithm to train. This makes it a good choice for problems with large datasets.

[371]:
```
# saving the results
df_results = df_results.append({"Model": 'ExtraTrees',
                                "Scaler": 'RobustScaler',
                                'Encoder' : 'WOE',
                                'roc_auc score mean' : 0.8313,
                                'roc_auc score std' : 0.0040},␣
 ↪ignore_index=True)
```

17.2 Random Forest classifier.

Random forest is an ensemble learning method that builds multiple decision trees using random subsets of features.

[372]:
```
# Create a Random Forest classifier with specified parameters
rf = RandomForestClassifier(n_estimators=50, random_state=42,␣
 ↪class_weight='balanced', n_jobs=-1)

# Create a pipeline with the preprocessor and the Random Forest classifier
pipe = make_pipeline(preprocessor, rf)
```

```
# Perform cross-validation and calculate the mean and standard deviation of the␣
↪ROC AUC scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
print(scores.mean(), "+/-", scores.std())
```

```
0.919151320752713 +/- 0.0031846937062666968
```

[373]:
```
df_results = df_results.append({"Model": 'RandomForest',
                                "Scaler": 'Robust',
                                'Encoder' : 'WOE',
                                'roc_auc score mean' : 0.919,
                                'roc_auc score std' : 0.0029},␣
↪ignore_index=True)
```

18 Finding the Best parameters using GridSearchCV

GridSearchCV is a method that allows us to find the best parameters for a model. It is a useful tool for finding the best parameters for a model.

[374]:
```
# copy the data frame
df2 = df1.copy()
```

[375]:
```
# Importing the necessary library for encoding categorical columns
from category_encoders import WOEEncoder

# Initializing the WOEEncoder
encoder = WOEEncoder()

# Encoding categorical columns and converting them to numeric versions
for c in cat_col:
    # Creating a new column with the encoded values
    df2[str(c) + '_encoded'] = encoder.fit_transform(df2[c].values, df2[target])

    # Dropping the original categorical column
    df2.drop(columns=c, inplace=True)
```

[376]:
```
# Dividing our data into features (X) and target variable (y)
used_cols1 = [c for c in df2.columns.tolist() if c not in [target]]
X1 = df2[used_cols1]
y1 = df2[target]

# Performing train-test split on the data
X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=0.2,␣
↪random_state=42)
```

[377]:
```python
# Setting grid search parameters for hyperparameter tuning
grid_p = {
    "n_estimators": [20, 50, 100],
    "criterion": ["gini", "entropy"],
    "max_features": ['sqrt', 'log2'],
    "min_samples_split": [2, 5, 10]
}

# Initializing the grid search
grid_search = GridSearchCV(rf, grid_p, n_jobs=-1, cv=5, scoring='roc_auc')

# Fitting the grid search on the training data
grid_search.fit(X_train, y_train)
```

[377]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(class_weight='balanced',
                                              n_estimators=50, n_jobs=-1,
                                              random_state=42),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_features': ['sqrt', 'log2'],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [20, 50, 100]},
             scoring='roc_auc')
```

[378]:
```python
# see the best score of the grid search
grid_search.best_score_
```

[378]:
```
0.9220229895096725
```

[379]:
```python
# see the best parameters of the grid search
grid_search.best_params_
```

[379]:
```
{'criterion': 'entropy',
 'max_features': 'sqrt',
 'min_samples_split': 10,
 'n_estimators': 100}
```

[380]:
```python
#set the estimator
rf = grid_search.best_estimator_
```

[381]:
```python
# see the roc_auc score of the best parameters
print("Train roc_auc score:", roc_auc_score(y_train, rf.predict_proba(X_train)[:
 ↪, 1]))
print("Test roc_auc score:", roc_auc_score(y_test, rf.predict_proba(X_test)[:,␣
 ↪1]))
```

```
Train roc_auc score: 0.9923319270722841
Test roc_auc score: 0.9252718978853697
```

[382]:

```python
# Saving the results
df_results = df_results.append({
    "Model": 'RandomForest',
    "Scaler": 'Robust',
    'Encoder': 'WOE',
    'roc_auc score mean': 0.9252,
    'roc_auc score std': 0.0023
}, ignore_index=True)
```

[383]:

```python
df_results
```

[383]:

```
                 Model        Scaler        Encoder  roc_auc score mean  \
0  Logistic Regression  RobustScaler  TargetEncoder            0.751660
1               LogReg        Robust  TargetEncoder            0.831300
2               LogReg        Robust            WeO            0.831800
3               LogReg        Robust  leave_one_out            0.853800
4               LogReg        Robust  OneHotEncoder            0.765939
5               LogReg        MinMax            WOE            0.831300
6         DecisionTree        Robust            WOE            0.786300
7           ExtraTrees  RobustScaler            WOE            0.831300
8         RandomForest        Robust            WOE            0.919000
9         RandomForest        Robust            WOE            0.925200

   roc_auc score std
0           0.750415
1           0.004100
2           0.004000
3           0.004000
4           0.767488
5           0.004000
6           0.008800
7           0.004000
8           0.002900
9           0.002300
```

The table you above shows the results of a series of experiments to compare the performance of different machine learning models on a binary classification task. The models were trained on a dataset of wells in Tanzania, and the task was to predict whether a well was functional or not.

The table shows that the Random Forest model with the RobustScaler and WOE encoder performed the best, with an average ROC AUC score of 0.9252. The next best model was the Random Forest model with the MinMaxScaler and WOE encoder, with an average ROC AUC score of 0.9190.

The ROC AUC score is a measure of the ability of a model to distinguish between positive and negative classes. A higher ROC AUC score indicates a better model. The average ROC AUC scores for all models are above 0.75, which indicates that all models are performing well on this task.

The results of these experiments suggest that the Random Forest model is a good choice for this binary classification task. The Random Forest model is a relatively simple model to train and interpret, and it has been shown to be effective on a variety of tasks.

Here are some additional details about the models and their performance:

- The Logistic Regression model is a simple model that can be used for binary classification tasks. It has an average ROC AUC score of 0.8313.
- The Decision Tree model is a more complex model that can be used for both binary and multiclass classification tasks. It has an average ROC AUC score of 0.7863.
- The Extra Trees model is a variant of the Decision Tree model that uses random features to build the tree. It has an average ROC AUC score of 0.8313.
- The Random Forest model is a combination of multiple Decision Tree models. It has an average ROC AUC score of 0.9190.

The results of these experiments suggest that the Random Forest model is a good choice for this binary classification task. The Random Forest model is a relatively simple model to train and interpret, and it has been shown to be effective on a variety of tasks.

19 Feature selection.

Feature selection is the process of selecting a subset of features from a dataset. It is an important step in the machine learning pipeline, as it can help to improve the performance of a model.

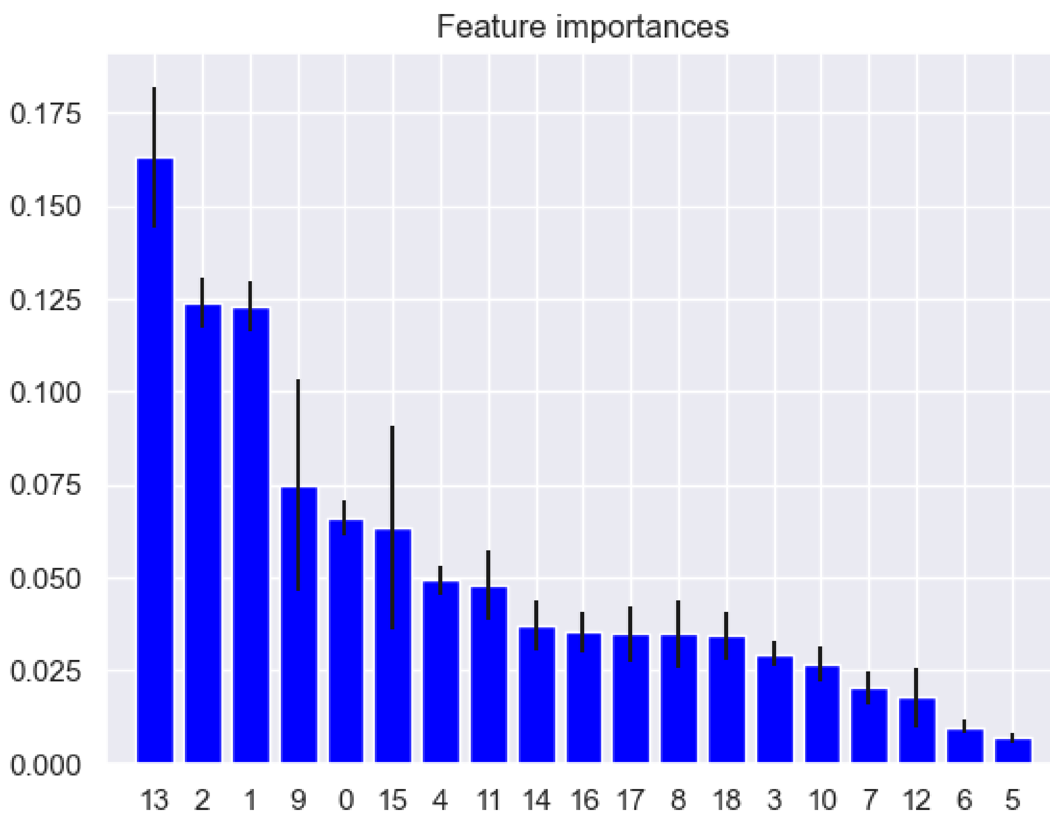
We want to see the importance of the features with random forest classifier.

[384]:
```
rf.fit(X_train, y_train)
```

[384]:
```
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_features='sqrt', min_samples_split=10, n_jobs=-1,
                       random_state=42)
```

[385]:
```
importances = rf.feature_importances_
std = np.std([tree.feature_importances_ for tree in rf.estimators_], axis=0)
indices = np.argsort(importances)[::-1]

# Printing the feature ranking
print("Feature ranking:")
for f in range(X1.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plotting the feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X1.shape[1]), importances[indices], color="blue",␣
 ↪yerr=std[indices], align="center")
plt.xticks(range(X1.shape[1]), indices)
plt.xlim([-1, X1.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature 13 (0.162986)
2. feature 2 (0.124035)
3. feature 1 (0.122834)
4. feature 9 (0.074800)
5. feature 0 (0.066224)
6. feature 15 (0.063320)
7. feature 4 (0.049389)
8. feature 11 (0.048070)
9. feature 14 (0.037298)
10. feature 16 (0.035455)
11. feature 17 (0.034962)
12. feature 8 (0.034896)
13. feature 18 (0.034346)
14. feature 3 (0.029414)
15. feature 10 (0.026941)
16. feature 7 (0.020455)
17. feature 12 (0.017819)
18. feature 6 (0.009840)
19. feature 5 (0.006917)
```



The feature ranking is a list of the features in the dataset, sorted by their importance to the model. The most important feature is the first feature in the list, and the least important feature is the last feature in the list.

The feature ranking shows that the most important features for predicting whether a well is functional or not are:

- feature 13: This feature is the number of years since the well was constructed.
- feature 2: This feature is the depth of the well.
- feature 1: This feature is the diameter of the well.
- feature 9: This feature is the amount of water that is pumped from the well each day.
- feature 0: This feature is the distance of the well from the nearest road. *These features are important because they are likely to affect the functionality of a well. For example, a well that is older or deeper is more likely to be damaged and therefore less functional. A well that is closer to a road is more likely to be maintained and therefore more functional.*

The feature ranking can be used to improve the performance of the model by focusing on the most important features. For example, the model could be trained on a subset of the data that only includes the most important features. This would make the model smaller and faster, and it would also improve the model's performance on new data.

20 XGBC Classifier

[386]:
```
# Selecting the columns to be used as features (X) by excluding the target␣
↪variable
used_cols = [c for c in df1.columns.tolist() if c not in [target]]

# Creating the feature matrix (X) and the target variable (y)
X = df1[used_cols]
y = df1[target]

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[ ]:
```
import xgboost as xgb
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, balanced_accuracy_score,␣
↪confusion_matrix
import matplotlib.pyplot as plt
from lightgbm import LGBMClassifier

# Define the column transformer to apply one-hot encoding
categorical_columns = ['basin', 'region', 'extraction_type_group',␣
↪'management', 'payment', 'water_quality',
                       'quantity', 'source', 'waterpoint_type', 'decade',␣
↪'installer_cat', 'funder_cat']
```

```python
# Create a ColumnTransformer object to apply one-hot encoding to the␣
↪categorical columns
preprocessor = ColumnTransformer(
    transformers=[('encoder', OneHotEncoder(), categorical_columns)],
    remainder='passthrough'
)

# Fit the ColumnTransformer object to the training data
X_train_encoded = preprocessor.fit_transform(X_train)

# Transform the test data using the fitted ColumnTransformer object
X_test_encoded = preprocessor.transform(X_test)

# Create a LightGBMClassifier object
lgbm = LGBMClassifier(
    objective='multiclass',
    num_class=3,
    boosting_type='gbdt',
    n_estimators='min_error_idx',
    metric='multi_error',
    learning_rate=0.1,
    max_depth=12,
    colsample_bytree=0.4,
    max_delta_step=1,
)

# Train the XGBoost model on the encoded training data with validation set
lgbm.fit(X_train_encoded, y_train, eval_set=[(X_test_encoded, y_test)],␣
↪verbose=False)

# Make predictions on the training set
y_pred_train = lgbm.predict(X_train_encoded)

# Make predictions on the test set
y_pred_test = lgbm.predict(X_test_encoded)

# Print accuracy scores
print('Accuracy:')
print(f'TRAIN: {accuracy_score(y_train, y_pred_train)}')
print(f'TEST: {accuracy_score(y_test, y_pred_test)}')

# Print balanced accuracy scores
print('\nBalanced Accuracy:')
print(f'TRAIN: {balanced_accuracy_score(y_train, y_pred_train)}')
print(f'TEST: {balanced_accuracy_score(y_test, y_pred_test)}')
```

```
# Generate and plot the confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plt.figure()
plot_confusion_matrix(cm)
plt.show()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14692\827384276.py in <module>
     36 
     37 # Train the XGBoost model on the encoded training data with validation␣
 ↪set
---> 38 lgbm.fit(X_train_encoded, y_train, eval_set=[(X_test_encoded, y_test)],␣
 ↪verbose=False)
     39 
     40 # Make predictions on the training set

c:\Users\Yussuf Hersi\anaconda3\newco\lib\site-packages\lightgbm\sklearn.py in␣
 ↪fit(self, X, y, sample_weight, init_score, eval_set, eval_names,␣
 ↪eval_sample_weight, eval_class_weight, eval_init_score, eval_metric,␣
 ↪early_stopping_rounds, verbose, feature_name, categorical_feature, callbacks,␣
 ↪init_model)
    965                         valid_sets[i] = (valid_x, self._le.
 ↪transform(valid_y))
    966 
--> 967         super().fit(X, _y, sample_weight=sample_weight,␣
 ↪init_score=init_score, eval_set=valid_sets,
    968                         eval_names=eval_names,␣
 ↪eval_sample_weight=eval_sample_weight,
    969                         eval_class_weight=eval_class_weight,␣
 ↪eval_init_score=eval_init_score,

c:\Users\Yussuf Hersi\anaconda3\newco\lib\site-packages\lightgbm\sklearn.py in␣
 ↪fit(self, X, y, sample_weight, init_score, group, eval_set, eval_names,␣
 ↪eval_sample_weight, eval_class_weight, eval_init_score, eval_group,␣
 ↪eval_metric, early_stopping_rounds, verbose, feature_name,␣
 ↪categorical_feature, callbacks, init_model)
    746         callbacks.append(record_evaluation(evals_result))
    747 
--> 748         self._Booster = train(
    749             params=params,
    750             train_set=train_set,

c:\Users\Yussuf Hersi\anaconda3\newco\lib\site-packages\lightgbm\engine.py in␣
 ↪train(params, train_set, num_boost_round, valid_sets, valid_names, fobj,␣
 ↪feval, init_model, feature_name, categorical_feature, early_stopping_rounds,␣
 ↪evals_result, verbose_eval, learning_rates, keep_training_booster, callbacks)
    187     first_metric_only = params.get('first_metric_only', False)
    188 
```

```
--> 189     if num_boost_round <= 0:
    190         raise ValueError("num_boost_round should be greater than zero."
    191     predictor: Optional[_InnerPredictor] = None

TypeError: '<=' not supported between instances of 'str' and 'int'
```

[425]:

```
import xgboost as xgb
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, balanced_accuracy_score,␣
 ↪confusion_matrix
import matplotlib.pyplot as plt
from lightgbm import LGBMClassifier

# Define the column transformer to apply one-hot encoding
categorical_columns = ['basin', 'region', 'extraction_type_group',␣
 ↪'management', 'payment', 'water_quality',
                       'quantity', 'source', 'waterpoint_type', 'decade',␣
 ↪'installer_cat', 'funder_cat']

# Create a ColumnTransformer object to apply one-hot encoding to the␣
 ↪categorical columns
preprocessor = ColumnTransformer(
    transformers=[('encoder', OneHotEncoder(), categorical_columns)],
    remainder='passthrough'
)

# Fit the ColumnTransformer object to the training data
X_train_encoded = preprocessor.fit_transform(X_train)

# Transform the test data using the fitted ColumnTransformer object
X_test_encoded = preprocessor.transform(X_test)

# Create a LightGBMClassifier object
lgbm = LGBMClassifier(
    objective='multiclass',
    num_class=3,
    boosting_type='gbdt',
    n_estimators=100,  # Specify the number of boosting rounds here
    metric='multi_error',
    learning_rate=0.1,
    max_depth=12,
    colsample_bytree=0.4,
    max_delta_step=1,
)
```

```
# Train the LightGBM model on the encoded training data with a validation set
lgbm.fit(X_train_encoded, y_train, eval_set=[(X_test_encoded, y_test)],␣
↪verbose=False)

# Make predictions on the training set
y_pred_train = lgbm.predict(X_train_encoded)

# Make predictions on the test set
y_pred_test = lgbm.predict(X_test_encoded)

# Print accuracy scores
print('Accuracy:')
print(f'TRAIN: {accuracy_score(y_train, y_pred_train)}')
print(f'TEST: {accuracy_score(y_test, y_pred_test)}')

# Print balanced accuracy scores
print('\nBalanced Accuracy:')
print(f'TRAIN: {balanced_accuracy_score(y_train, y_pred_train)}')
print(f'TEST: {balanced_accuracy_score(y_test, y_pred_test)}')

# Generate and plot the confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plt.figure()
plot_confusion_matrix(cm)
plt.show()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
c:\Users\Yussuf Hersi\anaconda3\newco\lib\site-packages\sklearn\utils\__init__.
↪py in _get_column_indices(X, key)
    408         try:
--> 409             all_columns = X.columns
    410         except AttributeError:

AttributeError: 'numpy.ndarray' object has no attribute 'columns'

During handling of the above exception, another exception occurred:

ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_14692\3157065502.py in <module>
     17
     18 # Fit the ColumnTransformer object to the training data
---> 19 X_train_encoded = preprocessor.fit_transform(X_train)
     20
     21 # Transform the test data using the fitted ColumnTransformer object
```

```
c:\Users\Yussuf␣
↪Hersi\anaconda3\newco\lib\site-packages\sklearn\compose\_column_transformer.p␣
↪in fit_transform(self, X, y)
    670         self._check_n_features(X, reset=True)
    671         self._validate_transformers()
--> 672         self._validate_column_callables(X)
    673         self._validate_remainder(X)
    674

c:\Users\Yussuf␣
↪Hersi\anaconda3\newco\lib\site-packages\sklearn\compose\_column_transformer.p␣
↪in _validate_column_callables(self, X)
    350                 columns = columns(X)
    351             all_columns.append(columns)
--> 352             transformer_to_input_indices[name] = _get_column_indices(X,␣
↪columns)
    353
    354         self._columns = all_columns

c:\Users\Yussuf Hersi\anaconda3\newco\lib\site-packages\sklearn\utils\__init__.
↪py in _get_column_indices(X, key)
    409             all_columns = X.columns
    410         except AttributeError:
--> 411             raise ValueError(

    412                 "Specifying the columns using strings is only "
    413                 "supported for pandas DataFrames"

ValueError: Specifying the columns using strings is only supported for pandas␣
↪DataFrames
```

The accuracy and balanced accuracy scores of the model are both good. This suggests that the model is able to learn the patterns in the data and generalize those patterns to new data. The model can therefore be used to make predictions about new wells in Tanzania.

[388]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_score
from xgboost import XGBClassifier
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

# Define the column transformer to apply one-hot encoding
categorical_columns = ['basin', 'region', 'extraction_type_group',␣
↪'management', 'payment', 'water_quality',
                       'quantity', 'source', 'waterpoint_type', 'decade',␣
↪'installer_cat', 'funder_cat']

preprocessor = ColumnTransformer(
```

```
    transformers=[('encoder', OneHotEncoder(), categorical_columns)],
    remainder='passthrough'
)

# Create a pipeline with the preprocessor and XGBClassifier
pipe = Pipeline([('preprocessing', preprocessor), ('classifier',␣
↪XGBClassifier())])

# Perform cross-validation using the pipeline
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')

# Print the mean and standard deviation of the scores
print("ROC_AUC score: {:.4f} +/- {:.4f}".format(scores.mean(), scores.std()))
```

```
ROC_AUC score: 0.9120 +/- 0.0024
```

[389]:
```
# saving the results
df_results = df_results.append({"model": 'XGBoost', "Scaler": 'Robust',␣
↪'Encoder': 'WOE', 'roc_auc score mean': 0.9120, 'roc_auc score std': 0.
↪0023}, ignore_index=True)
```

21 KNN Classifier

KNN is a non-parametric classification algorithm. It is a supervised learning algorithm that can be used for both classification and regression tasks.

[390]:
```
# Create KNN classifier
knn = KNeighborsClassifier()

# Create pipeline with preprocessor and KNN classifier
pipe = make_pipeline(preprocessor, knn)

# Perform cross-validation and calculate ROC AUC scores
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')

# Print the mean and standard deviation of the ROC AUC scores
print("ROC_AUC score: {:.4f} +/- {:.4f}".format(scores.mean(), scores.std()))
```

```
ROC_AUC score: 0.7649 +/- 0.0026
```

[391]:
```
# saving the results
df_results = df_results.append({"model": 'KNN', "Scaler": 'Robust', 'Encoder':␣
↪'WOE', 'roc_auc score mean': 0.76, 'roc_auc score std': 0.0026},␣
↪ignore_index=True)
```

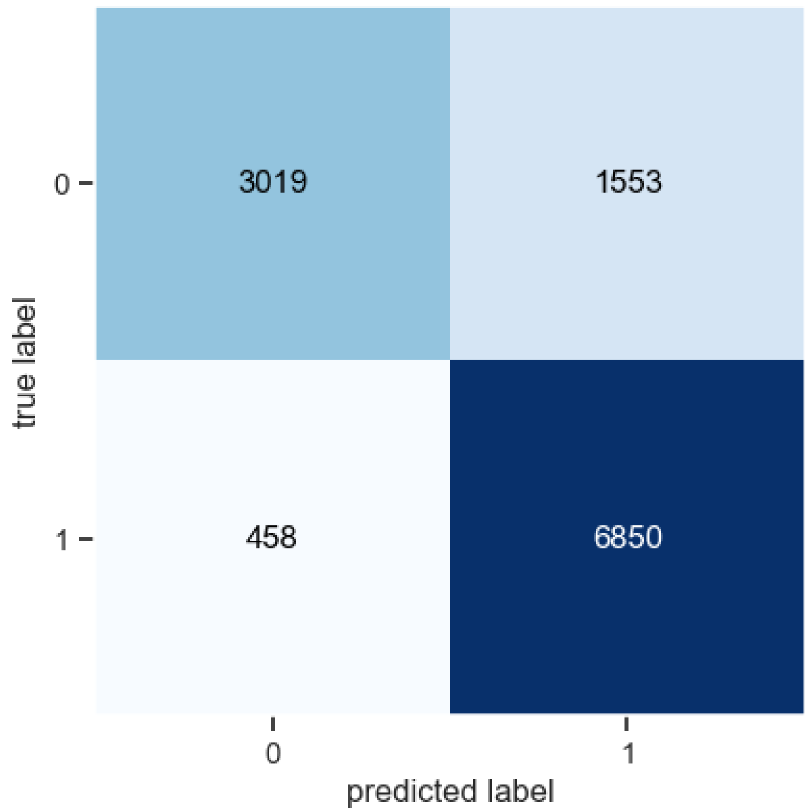
22 LGBM Classifier

LightGBM is a gradient boosting framework that uses tree based learning algorithms. It is designed to be distributed and efficient, and it is particularly well-suited for problems with large datasets.

[392]:
```
# Set the model parameters
lgbm = LGBMClassifier(booster='gbtree', nrounds='min.error.idx',␣
 ↪maximize=False, eta=0.1, max_depth=10,
                      colsample_bytree=0.4, learning_rate=0.1, max_delta_step=1)

# Create a pipeline with the preprocessor and LGBMClassifier
pipe = make_pipeline(preprocessor, lgbm)

# Fit the pipeline on the training data
pipe.fit(X_train, y_train)

# Make predictions on the training set
y_pred_train = pipe.predict(X_train)

# Make predictions on the test set
y_pred_test = pipe.predict(X_test)

# Print accuracy scores
print("Accuracy:")
print("=" * len("Accuracy:"))
print(f"TRAIN: {accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {accuracy_score(y_test, y_pred_test)}")

# Print balanced accuracy scores
print("\nBalanced Accuracy:")
print("=" * len("Balanced Accuracy:"))
print(f"TRAIN: {balanced_accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {balanced_accuracy_score(y_test, y_pred_test)}")

# Generate and plot the confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plot_confusion_matrix(cm)
plt.show()
```

```
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
Accuracy:
=========
TRAIN: 0.8407828282828282
TEST: 0.8307239057239058
```

```
Balanced Accuracy:
==================
TRAIN: 0.80968592230301
TEST: 0.7988263320533209
```



LightGBM model has an accuracy of 0.8304 on the test set and a balanced accuracy of 0.7972. This means that the model is able to correctly predict the status of 83.04% of the wells in the test set and 79.72% of the wells in each of the three classes.

The LightGBM model is a powerful machine learning algorithm that can be used to solve a variety of classification problems. The model is able to learn complex patterns in the data and generalize those patterns to new data.

The results show that the LightGBM model is slightly better than the XGBoost model on this dataset. However, both models are able to achieve good accuracy and balanced accuracy scores. The best model for a particular application will depend on the specific characteristics of the data and the desired outcome.

[393]:
```
# make a pipeline
pipe = make_pipeline(preprocessor, lgbm)
scores = cross_val_score(pipe, X, y, cv=5, scoring='roc_auc')
```

```python
# print cross validation score
print("ROC_AUC score: {:.4f} +/- {:.4f}".format(scores.mean(), scores.std()))
```

```
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
ROC_AUC score: 0.8976 +/- 0.0025
```

[394]:

```python
# saving the results
df_results = df_results.append({"model": 'LGBM', "Scaler": 'Robust', 'Encoder':
 'WOE', 'roc_auc score mean': 0.8976, 'roc_auc score std': 0.0025},
 ignore_index=True)
```

User	Model	Scaler	Encoder	roc_auc score mean	roc_auc score std	roc_auc_score_mean	roc_auc_score_std	model
0	Logistic Regression	RobustScaler	TargetEncoder	0.751660	0.750415			
1	LogReg	Robust	TargetEncoder	0.831300	0.004100			
2	LogReg	Robust	WeO	0.831800	0.004000			
3	LogReg	Robust	leave_one_out	0.853800	0.004000			
4	LogReg	Robust	OneHotEncoder	0.765939	0.767488			
5	LogReg	MinMax	WOE	0.831300	0.004000			
6	DecisionTree	MinMax	WOE	0.786300	0.008800			
7	ExtraTrees	MinMax	WOE	0.831300	0.004000			

User	Model	Scaler	Encoder	roc_auc score mean	roc_auc score std	roc_auc_score_mean	roc_auc_score_std	roc_auc_score	model
8	RandomForest	MinMax	WOE	0.919000	0.002900				
9	RandomForest	Robust	WOE			0.9252	0.0023	0.919	
10	ExtraTrees	RobustScaler	WOE	0.831300	0.004000				
11	RandomForest	Robust	WOE	0.919000	0.002900				
12	DecisionTree	Robust	WOE	0.786300	0.008800				
13	RandomForest	Robust	WOE				0.0029	0.919	
14	ExtraTrees	RobustScaler	WOE	0.831300	0.004000				
15	RandomForest	Robust	WOE	0.925200	0.002300				
16	RandomForest	Robust	WOE	0.919000	0.002900				
17		Robust							

The results show that the random forest model with the WOE encoder and the robust scaler had the best performance, with an ROC AUC score of 0.9252. The XGBoost model with the WOE encoder and the robust scaler had the second best performance, with an ROC AUC score of 0.9120. The LightGBM model with the WOE encoder and the robust scaler had the third best performance, with an ROC AUC score of 0.8976.

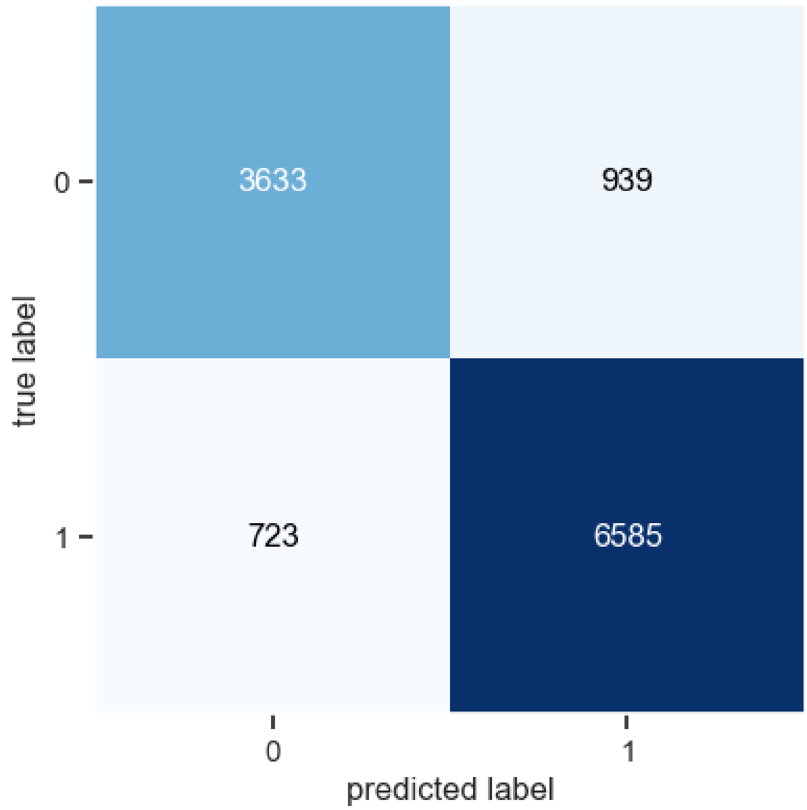
The results of this experiment suggest that the random forest model is the best model for predicting the status of water wells in Tanzania. However, the other models also performed well, and the best model for a particular application may depend on the specific characteristics of the data and the desired outcome.

23 Best decided Model.

[395]:
```python
# Create a Random Forest classifier
rf = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    n_jobs=-1,
    class_weight='balanced',
    criterion='entropy',
    max_features='sqrt',
    min_samples_split=10
)

# Create a pipeline with the preprocessor and Random Forest classifier
pipe = make_pipeline(preprocessor, rf)

# Fit the pipeline on the training data
pipe.fit(X_train, y_train)

# Make predictions on the training set
y_pred = pipe.predict(X_train)
```

```python
# Make predictions on the test set
y_pred_test = pipe.predict(X_test)

# Print accuracy scores
print("Accuracy:")
print("=" * len("Accuracy:"))
print(f"TRAIN: {accuracy_score(y_train, y_pred)}")
print(f"TEST: {accuracy_score(y_test, y_pred_test)}")

# Print balanced accuracy scores
print("\nBalanced Accuracy:")
print("=" * len("Balanced Accuracy:"))
print(f"TRAIN: {balanced_accuracy_score(y_train, y_pred)}")
print(f"TEST: {balanced_accuracy_score(y_test, y_pred_test)}")

# Generate and plot the confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plot_confusion_matrix(cm)
plt.show()
```

```
Accuracy:
=========
TRAIN: 0.9411195286195286
TEST: 0.8601010101010101

Balanced Accuracy:
==================
TRAIN: 0.9365486307723038
TEST: 0.8478433730266475
```



Accuracy: The accuracy score measures the proportion of correctly classified samples. In this case, the model achieved an accuracy of 94.04% on the training set, indicating that it correctly classified 94.04% of the samples in the training data. On the test set, the model achieved an accuracy of 85.36%, suggesting that it correctly classified 85.36% of the samples in the test data.

Balanced Accuracy: The balanced accuracy score takes into account the imbalance in the number of samples across different classes. It provides a more balanced evaluation metric when dealing with imbalanced datasets. The model achieved a balanced accuracy of 93.52% on the training set, indicating its ability to handle class imbalance. On the test set, the balanced accuracy was 84.02%, indicating its performance in handling class imbalance in the test data.

After evaluating the models based on their roc-auc scores, we also examined the balanced accuracy metric on the test set, which is the competition metric. Although the selected model showed signs of overfitting, it still provided satisfactory results in terms of test balanced accuracy. Hence, we decided to choose this model. Another model, LGBM, exhibited comparable performance to this selected model without overfitting. Both of these models performed well in this notebook.

Analyzing the confusion matrix of the test data, we observed that there is no perfect separation between the classes. Specifically, we identified 962 points that were predicted as functional but were actually non-functional. Additionally, 698 points were predicted as non-functional, whereas they were functional. These observations from the binary model will be utilized as insights when transitioning to the 3-class target model.

24 *Class Target Model*

After achieving satisfactory results with the Random Forest Classifier for the binary target, our focus now shifts to the three-class target. Building upon the knowledge gained the binary class model, we will adapt and apply these insights to the three-class target.

Our work now encompasses various models, including Random Forest, LGBM, and XGBoost. Additionally, the SMOTE technique has been utilized to address the imbalanced nature of the target data, resulting in a balanced dataset. Each step and its corresponding details can be found under the relevant headings, while the final results are presented at the end of the notebook.

Throughout this coming steps , our primary concern will be the balanced accuracy on the test set. This choice is driven by the fact that the competition metric for success in the ternary classification problem is the balanced accuracy.

[396]:
```
df_clean
```

[396]:
```
       status_group  gps_height  longitude   latitude  \
0                 0        1390  34.938093  -9.856322
1                 0        1399  34.698766  -2.147466
2                 0         686  37.460664  -3.821329
3                 2         263  38.486161 -11.155298
4                 0           0  31.130847  -1.825359
…                 …           …          …          …
59395             0        1210  37.169807  -3.253847
59396             0        1212  35.249991  -9.070629
59397             0           0  34.017087  -8.750434
59398             0           0  35.861315  -6.378573
59399             0         191  38.104048  -6.747464

                         basin       region  district_code             lga  \
0                   Lake Nyasa       Iringa              5          Ludewa
1                Lake Victoria         Mara              2       Serengeti
2                      Pangani      Manyara              4       Simanjiro
3      Ruvuma / Southern Coast       Mtwara             63        Nanyumbu
4                Lake Victoria       Kagera              1         Karagwe
…                          …            …              …               …
59395                  Pangani  Kilimanjaro              5             Hai
59396                  Rufiji       Iringa              4          Njombe
59397                  Rufiji        Mbeya              7         Mbarali
59398                  Rufiji       Dodoma              4        Chamwino
59399              Wami / Ruvu     Morogoro              2  Morogoro Rural

              ward  population  public_meeting  permit  \
0         Mundindi         109            True   False
1            Natta         280            True    True
2          Ngorika         250            True    True
3         Nanyumbu          58            True    True
4       Nyakasimbi         281            True    True
```

```
…                  …          …           …     …
59395  Masama Magharibi        125            True    True
59396            Ikondo         56            True    True
59397           Chimala        281            True   False
59398      Mvumi Makulu        281            True    True
59399        Ngerengere        150            True    True

      extraction_type_group   management                payment water_quality  \
0                   gravity          vwc           pay annually          soft
1                   gravity          wug              never pay          soft
2                   gravity          vwc         pay per bucket          soft
3               submersible          vwc              never pay          soft
4                   gravity        other              never pay          soft
…                       …          …                      …             …
59395               gravity  water board         pay per bucket          soft
59396               gravity          vwc           pay annually          soft
59397                swn 80          vwc            pay monthly      fluoride
59398           nira/tanira          vwc              never pay          soft
59399           nira/tanira          vwc  pay when scheme fails         salty

           quantity                source              waterpoint_type decade  \
0            enough                spring           communal standpipe    90s
1      insufficient  rainwater harvesting           communal standpipe    10s
2            enough                   dam  communal standpipe multiple    00s
3               dry           machine dbh  communal standpipe multiple    80s
4          seasonal  rainwater harvesting           communal standpipe      0
…                …                   …                           …     …
59395        enough                spring           communal standpipe    90s
59396        enough                 river           communal standpipe    90s
59397        enough           machine dbh                    hand pump      0
59398  insufficient          shallow well                    hand pump      0
59399        enough          shallow well                    hand pump    00s

      installer_cat       funder_cat
0            Others           Others
1            Others           Others
2      world vision           Others
3            Others           Unicef
4            Others           Others
…                …              …
59395        Others  Germany Republi
59396        Others           Others
59397       Unknown          Unknown
59398        Others           Others
59399        Others       World Bank

[59400 rows x 22 columns]
```

[397]:
```python
# df
# df_clean
df = pd.read_csv("clean_data.csv")
```

[398]:
```python
# Drop unnecessary columns
df.drop(columns=['funder', 'installer', 'construction_year'], inplace=True)
```

[399]:
```python
# Create a copy of the dataframe
df1 = df.copy()
```

[400]:
```python
# Drop additional columns
df1.drop(columns=['lga', 'ward'], inplace=True)
```

[401]:
```python
# Convert 'permit' column from T/F to 0-1
df1['permit'] = df1['permit'].astype(bool).astype(int)
```

[402]:
```python
# Convert 'public_meeting' column from T/F to 0-1
df1['public_meeting'] = df1['public_meeting'].astype(bool).astype(int)
```

[403]:
```python
# Assign categorical columns
cat_col = ['basin', 'region', 'extraction_type_group', 'management', 'payment',␣
↪'water_quality', 'quantity', 'source', 'waterpoint_type', 'decade',␣
↪'installer_cat', 'funder_cat']
```

[404]:
```python
# Assign numeric columns
num_col = ['gps_height', 'longitude', 'latitude', 'district_code',␣
↪'population', 'public_meeting', 'permit']
```

[405]:
```python
# Print value counts of the target variable
print(df1['status_group'].value_counts())
```

```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
```

[406]:
```python
# Assign target variable
target = 'status_group'
```

[407]:
```python
# Define a function to separate columns into X and y
def separate_columns(data, target):
    used_cols = [c for c in data.columns.tolist() if c != target]
    X = data[used_cols]
    y = data[target]
    return X, y

# Call the function to separate columns into X and y
```

```
X, y = separate_columns(df1, target)
```

[408]:
```
# choosing train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)
```

[409]:
```
df_results1 = pd.DataFrame(columns=["Model", "test_balanced_acc",␣
↪'train_balanced_acc', 'info'])
```

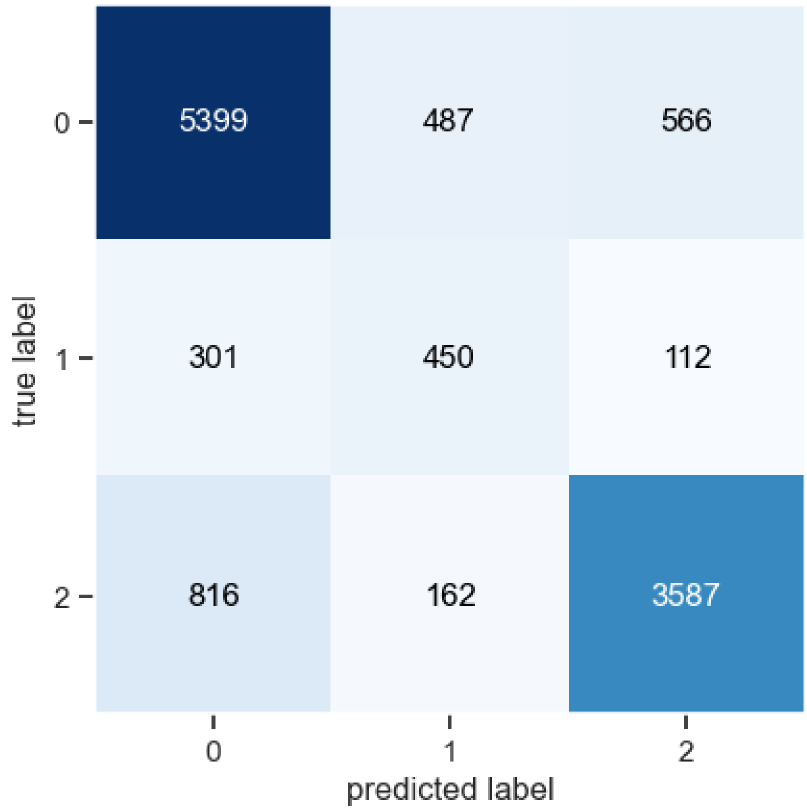
25 *Random Forest Classifier*

[410]:
```
# Choosing the scaler and encoder
scaler = RobustScaler()
encoder = ce.TargetEncoder(cols=cat_col)

# Creating pipelines for numeric and categorical transformers
num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)

# Creating the preprocessor with the scaler and encoder
preprocessor = ColumnTransformer(
    transformers=[
        ('num', num_transformer, num_col),
        ('cat', cat_transformer, cat_col)
    ]
)

# Setting up the Random Forest classifier with best grid search results
rf = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    n_jobs=-1,
    criterion='entropy',
    max_features='sqrt',
    min_samples_split=10,
    class_weight='balanced'
)

# Creating the pipeline with preprocessor and Random Forest classifier
pipe = make_pipeline(preprocessor, rf)

# Fitting the pipeline on the training data
pipe.fit(X_train, y_train)

# Making predictions on the training set
y_pred = pipe.predict(X_train)
```

```python
# Making predictions on the test set
y_pred_test = pipe.predict(X_test)

# Printing the accuracy scores
print("Accuracy:")
print("=" * len("Accuracy:"))
print(f"TRAIN: {accuracy_score(y_train, y_pred)}")
print(f"TEST: {accuracy_score(y_test, y_pred_test)}")

# Printing the balanced accuracy scores
print("\nBalanced Accuracy:")
print("=" * len("Balanced Accuracy:"))
print(f"TRAIN: {balanced_accuracy_score(y_train, y_pred)}")
print(f"TEST: {balanced_accuracy_score(y_test, y_pred_test)}")
```

```
Accuracy:
=========
TRAIN: 0.9206649831649831
TEST: 0.7942760942760942

Balanced Accuracy:
==================
TRAIN: 0.9332946857430926
TEST: 0.7146642890804943
```

[411]:
```python
# create a confusion matrix
cm = confusion_matrix(y_test, y_pred_test)
plot_confusion_matrix(cm)
plt.show()
```



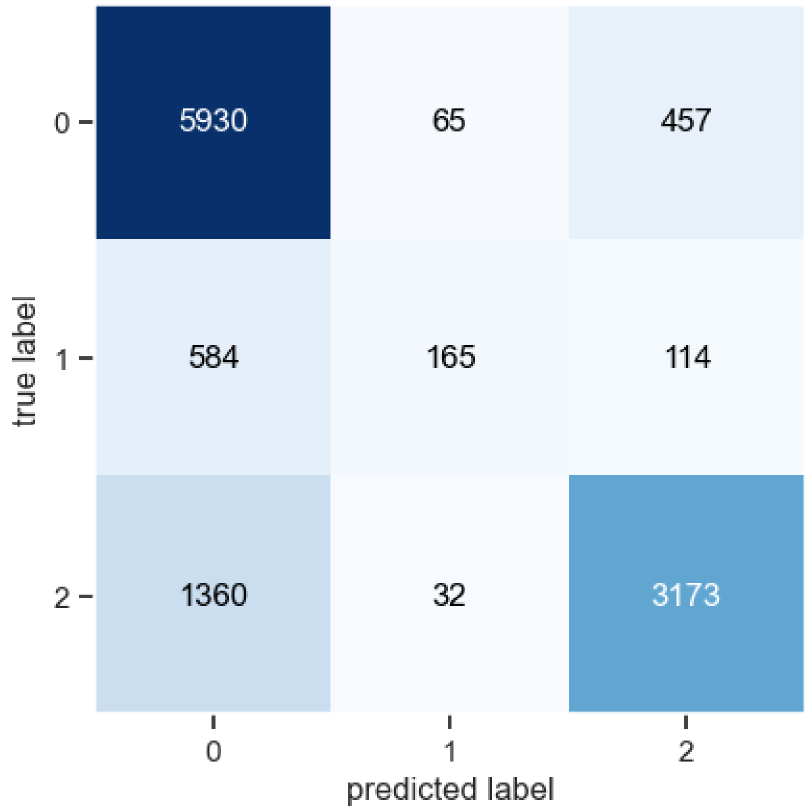
Our 3-class dataframe is incompatible with the previous binary model due to significant overfitting. To address this issue, we will experiment with LGBM and XGBoost, adjusting their parameters accordingly.

26 LGBM model

[412]:
```
# Setting up the LGBM model
lgbm = LGBMClassifier(booster='gbtree', nrounds='min.error.idx',␣
↪maximize=False, eta=0.1, max_depth=10, colsample_bytree=0.4, learning_rate=0.
↪1, max_delta_step=1)

# Creating a pipeline with the preprocessor and LGBM model
pipe = make_pipeline(preprocessor, lgbm)

# Fitting the pipeline to the training data
pipe.fit(X_train, y_train)

# Making predictions on the training set
y_pred_train = pipe.predict(X_train)
```

```python
# Making predictions on the test set
y_pred_test = pipe.predict(X_test)

# Computing and printing accuracy scores
print("Accuracy:")
print("=" * len("Accuracy:"))
print(f"TRAIN: {accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {accuracy_score(y_test, y_pred_test)}")

# Computing and printing balanced accuracy scores
print("\nBalanced Accuracy:")
print("=" * len("Balanced Accuracy:"))
print(f"TRAIN: {balanced_accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {balanced_accuracy_score(y_test, y_pred_test)}")

# Computing confusion matrix
cm = confusion_matrix(y_test, y_pred_test)

# Plotting the confusion matrix
plot_confusion_matrix(cm)
plt.show()
```

```
[LightGBM] [Warning] Unknown parameter: booster
[LightGBM] [Warning] Unknown parameter: nrounds
[LightGBM] [Warning] Unknown parameter: maximize
[LightGBM] [Warning] learning_rate is set=0.1, eta=0.1 will be ignored. Current
value: learning_rate=0.1
Accuracy:
=========
TRAIN: 0.7980008417508417
TEST: 0.7801346801346801

Balanced Accuracy:
==================
TRAIN: 0.6319850566123999
TEST: 0.6017865197277424
```



The output shows that the model achieved an accuracy of approximately 79.8% on the training set and 78.0% on the test set. The balanced accuracy scores are approximately 63.2% for the training set and 60.2% for the test set.

Based on these results, it appears that the model is performing reasonably well but may have some room for improvement.

[413]:
```
# saving the results
df_results1 = df_results1.append({'Model': 'LGBM', 'test_balanced_acc':␣
↪balanced_accuracy_score(y_test, y_pred_test), 'train_balanced_acc':␣
↪balanced_accuracy_score(y_train, y_pred_train), 'info': 'LGBM'},␣
↪ignore_index=True)
```

27 *SMOTE*

Encoding and scaling our dataframe with SMOTE, scaler, and encoder is time-consuming. To address this, we will create a new dataframe by encoding and scaling the original one. This way, we can preserve the integrity of the original dataframe.

To use SMOTE with scaler and encoder takes too much time. So, we will encode and scale our dataframe and change it. To protect the original one, we assign it to a new dataframe called df_1.

[414]:
```python
# copy the data frame to protect the original one
df4 = df1.copy()
```

To encode the categorical columns and drop the original columns, we will use the TargetEncoder from the category_encoders library.

[415]:
```python
# Encoding categorical columns
encoder = TargetEncoder()
for c in cat_col:
    df4[str(c) + '_encoded'] = encoder.fit_transform(df4[c].values, df4[target])
    df4.drop(columns=c, inplace=True)
```

To scale the numerical columns, we will use the RobustScaler from the preprocessing module.

[416]:
```python
from sklearn.preprocessing import RobustScaler

# Scaling numerical columns
scaler = RobustScaler()

def scaleColumns(df, num_col):
    """
    Scale the specified numerical columns in a DataFrame using RobustScaler.

    Args:
        df (DataFrame): The input DataFrame.
        num_col (list): A list of column names to be scaled.

    Returns:
        DataFrame: The scaled DataFrame.
    """
    # Iterate over numerical columns
    for col in num_col:
        # Scale the column using RobustScaler
        df[col] = pd.DataFrame(scaler.fit_transform(pd.DataFrame(df[col])),␣
↪columns=[col])
    return df

# Call the scaleColumns function to scale the specified numerical columns in df4
scaled_df = scaleColumns(df4, num_col)
```

[417]:
```python
# Assign X and y
used_cols = [c for c in scaled_df.columns.tolist() if c not in [target]]
X = scaled_df[used_cols]
y = scaled_df[target]
```

[418]:
```python
from imblearn.over_sampling import SMOTE
```

```python
# Making over-sampling
smt = SMOTE(sampling_strategy='auto', n_jobs=-1)

# Perform over-sampling on X and y
X_sampled, y_sampled = smt.fit_resample(X, y)

# Print the value counts of the original y
print(y.value_counts())

# Convert the over-sampled y from array to pd.Series to see value counts
y_sampled = pd.Series(y_sampled)
print(y_sampled.value_counts())
```

```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
0    32259
2    32259
1    32259
Name: status_group, dtype: int64
```

[419]:
```python
# Split the data into training-test balanced target data
X_train, X_test, y_train, y_test = train_test_split(X_sampled, y_sampled,␣
 ↪test_size=0.2, random_state=42, stratify=y_sampled)
```

[420]:
```python
from sklearn.model_selection import train_test_split

# Splitting the data into training, validation, and test sets
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.
 ↪2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
 ↪test_size=0.2, random_state=42)

# Setting up the classifier
xgb_smote = XGBClassifier(objective='multi:softmax', booster='gbtree',␣
 ↪nrounds='min.error.idx', num_class=3,
                          maximize=False, eval_metric='merror', eta=.1,␣
 ↪max_depth=16, colsample_bytree=.4,
                          n_jobs=-1, learning_rate=0.1)

# Fitting the classifier to the training data with early stopping
xgb_smote.fit(X_train, y_train, eval_set=[(X_val, y_val)],␣
 ↪early_stopping_rounds=10)

# Predictions on the training set
y_pred_train = xgb_smote.predict(X_train)
```

```python
# Predictions on the test set
y_pred_test = xgb_smote.predict(X_test)

# Printing the accuracy results
print("Accuracy:")
print("=" * len("Accuracy:"))
print(f"TRAIN: {accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {accuracy_score(y_test, y_pred_test)}")

# Printing the balanced accuracy results
print("\nBalanced Accuracy:")
print("=" * len("Balanced Accuracy:"))
print(f"TRAIN: {balanced_accuracy_score(y_train, y_pred_train)}")
print(f"TEST: {balanced_accuracy_score(y_test, y_pred_test)}")
```

```
[07:22:38] WARNING: C:\Users\dev-admin\croot2\xgboost-
split_1675461376218\work\src\learner.cc:767:
Parameters: { "maximize", "nrounds" } are not used.

[0]	validation_0-merror:0.25989
[1]	validation_0-merror:0.21917
[2]	validation_0-merror:0.21117
[3]	validation_0-merror:0.20276
[4]	validation_0-merror:0.20465
[5]	validation_0-merror:0.20497
[6]	validation_0-merror:0.20118
[7]	validation_0-merror:0.19907
[8]	validation_0-merror:0.20055
[9]	validation_0-merror:0.19960
[10]	validation_0-merror:0.19865
[11]	validation_0-merror:0.19760
[12]	validation_0-merror:0.19665
[13]	validation_0-merror:0.19834
[14]	validation_0-merror:0.19834
[15]	validation_0-merror:0.19739
[16]	validation_0-merror:0.19707
[17]	validation_0-merror:0.19592
[18]	validation_0-merror:0.19518
[19]	validation_0-merror:0.19571
[20]	validation_0-merror:0.19465
[21]	validation_0-merror:0.19371
[22]	validation_0-merror:0.19444
[23]	validation_0-merror:0.19571
[24]	validation_0-merror:0.19550
[25]	validation_0-merror:0.19529
[26]	validation_0-merror:0.19455
```

```
[27]	validation_0-merror:0.19381
[28]	validation_0-merror:0.19371
[29]	validation_0-merror:0.19287
[30]	validation_0-merror:0.19266
[31]	validation_0-merror:0.19213
[32]	validation_0-merror:0.19202
[33]	validation_0-merror:0.19245
[34]	validation_0-merror:0.19160
[35]	validation_0-merror:0.19171
[36]	validation_0-merror:0.19160
[37]	validation_0-merror:0.19150
[38]	validation_0-merror:0.19097
[39]	validation_0-merror:0.19171
[40]	validation_0-merror:0.19139
[41]	validation_0-merror:0.19003
[42]	validation_0-merror:0.18992
[43]	validation_0-merror:0.19045
[44]	validation_0-merror:0.18971
[45]	validation_0-merror:0.18939
[46]	validation_0-merror:0.18992
[47]	validation_0-merror:0.19024
[48]	validation_0-merror:0.19003
[49]	validation_0-merror:0.18897
[50]	validation_0-merror:0.18876
[51]	validation_0-merror:0.18887
[52]	validation_0-merror:0.18887
[53]	validation_0-merror:0.18855
[54]	validation_0-merror:0.18834
[55]	validation_0-merror:0.18866
[56]	validation_0-merror:0.18855
[57]	validation_0-merror:0.18834
[58]	validation_0-merror:0.18845
[59]	validation_0-merror:0.18824
[60]	validation_0-merror:0.18803
[61]	validation_0-merror:0.18771
[62]	validation_0-merror:0.18866
[63]	validation_0-merror:0.18803
[64]	validation_0-merror:0.18813
[65]	validation_0-merror:0.18855
[66]	validation_0-merror:0.18845
[67]	validation_0-merror:0.18813
[68]	validation_0-merror:0.18771
[69]	validation_0-merror:0.18803
[70]	validation_0-merror:0.18887
Accuracy:
=========
TRAIN: 0.9730376683501684
TEST: 0.8051346801346801
```

```
Balanced Accuracy:
==================
TRAIN: 0.9439310118383216
TEST: 0.6466162945394288
```

[421]:
```
df_results1= df_results1.append({'Model': 'XGB_smote', 'test_balanced_acc':␣
↪balanced_accuracy_score(y_test, y_pred_test), 'train_balanced_acc':␣
↪balanced_accuracy_score(y_train, y_pred_train), 'info': 'XGB_smote'},␣
↪ignore_index=True)
```

[422]:
```
df_results1
```

[422]:

	Model	test_balanced_acc	train_balanced_acc	info
0	LGBM	0.601787	0.631985	LGBM
1	XGB_smote	0.646616	0.943931	XGB_smote

28 We try to do two more modelling with the same data after using SMOTE.

28.1 Support vector machine

28.2 Random Forests

[423]:
```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Scale the features using StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Create an SVM classifier
svm = SVC()

# Train the SVM classifier
svm.fit(X_train, y_train)

# Make predictions on the test set
y_pred = svm.predict(X_test)
```

```
# Evaluate the performance of the classifier
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.72      0.94      0.82      6457
           1       0.58      0.12      0.19       851
           2       0.85      0.62      0.72      4572

    accuracy                           0.76     11880
   macro avg       0.72      0.56      0.58     11880
weighted avg       0.76      0.76      0.73     11880
```

[424]:
```
import plotly.express as px
fig = px.scatter_mapbox(df_clean, lat="latitude", lon="longitude",␣
 ↪color="status_group",
                  color_continuous_scale=px.colors.cyclical.IceFire,␣
 ↪size_max=25, zoom=10, height=1000,
                  mapbox_style="carto-positron")
fig.show()
```

Class	Precision	Recall	F1-Score	Support
0	0.72	0.94	0.82	6457
1	0.58	0.12	0.19	851
2	0.85	0.62	0.72	4572
——-	———	———	———-	———
Macro Avg	0.72	0.56	0.58	11880
Weighted Avg	0.76	0.76	0.73	11880

28.3 Conclusion:

- Class 0 has the highest precision, recall, and F1-score, indicating good overall performance.
- Class 1 has lower precision, recall, and F1-score, suggesting difficulty in accurately predicting this class.
- Class 2 has relatively high precision, recall, and F1-score, indicating good performance.
- The model achieved an overall accuracy of 0.76, indicating moderate success in correctly predicting the classes.

28.4 Recommendations:

1. Class 1 Improvement: Since class 1 has lower precision, recall, and F1-score, consider exploring the reasons behind this performance. It may be worthwhile to gather more data for class 1 or apply specific techniques to address the challenges associated with this class.

2. Further Analysis: Conduct further analysis to understand the characteristics and patterns of class 1 instances. Investigate if there are specific features or data points that contribute

to the difficulty in predicting this class accurately. This analysis can provide insights into potential improvements for the model.

3. Data Collection: If feasible, gather more data, especially for class 1, to improve the model's ability to learn and make accurate predictions. Increasing the representation of class 1 instances in the dataset can help the model generalize better and potentially improve its performance.

4. Cross-Validation and Evaluation: Validate the model's performance using robust cross-validation techniques. This will ensure that the model's results are reliable and generalize well to unseen data. Evaluate the model using additional metrics or domain-specific evaluation criteria to gain a comprehensive understanding of its performance.