phase-3-project-jupyter-notebook

May 23, 2024

0.1 Final Project Submission

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0.2 Business Understanding

0.2.1 Introduction:

Tanzania, a country with a population exceeding 57 million, faces significant challenges in providing clean water to its residents. While numerous water wells have been established, many of these wells are either in disrepair or have failed entirely. Ensuring the functionality of these water wells is crucial for public health, agriculture, and overall quality of life. Predictive analytics can play a pivotal role in identifying which wells are likely to fail, need repair, or are functioning well, thus enabling proactive maintenance and efficient resource allocation

0.2.2 Stakeholders and Usage:

Government of Tanzania:

1. Objective: Improve water supply infrastructure and resource planning.
2. Usage: By analyzing patterns in well failures, the government can develop more effective strategies for constructing new wells, maintaining existing ones, and optimizing resource allocation. This can lead to better-informed decisions on where to invest in infrastructure improvements and preventative maintenance.

Non-Governmental Organizations (NGOs):

1. Objective: Enhance the efficiency and impact of water-related aid programs.
2. Usage: NGOs can use predictive models to prioritize wells that need urgent repairs or are at risk of failing. This enables them to deploy their resources more effectively, ensuring that their interventions have the maximum positive impact on communities reliant on these water sources.

Local Communities:

1. Objective: Gain reliable access to clean water.
2. Usage: By participating in data collection and reporting well conditions, local communities can contribute to the ongoing monitoring and maintenance efforts. This collaboration can

help ensure that issues are addressed promptly, minimizing the time residents are without clean water.

0.2.3 Conclusion:

Developing a classifier to predict the condition of water wells in Tanzania holds significant potential for improving water supply reliability across the country. By leveraging data analytics, stakeholders such as the government, NGOs, and local communities can make informed decisions about where to focus their efforts and resources. This proactive approach can lead to more sustainable water infrastructure, ensuring that clean water is accessible to all Tanzanians. Furthermore, the insights gained from this predictive modeling can guide future well construction and maintenance practices, ultimately enhancing the resilience and effectiveness of Tanzania's water supply systems.

0.3 Data Understanding

Our data sources are :

Training Set Values: 1. Description: Contains independent variables about each water well (e.g., type of pump, installation year, location). 2. Usage: Used to train the predictive model.

Training Set Labels:

1. Description: Contains the dependent variable (status_group) for each well, indicating its condition (functional, non-functional, needs repair).
2. Usage: Provides target outcomes for training the model

Test Set Values:

1. Description: Contains independent variables for wells needing predictions, similar to the training set values but without labels.
2. Usage: The model predicts the condition of these wells.

Submission Format:

1. Description: Template for submitting predictions, including well IDs and predicted status_group.
2. Usage: Ensures predictions are submitted in the correct format for evaluation.

[211]:
```python
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import geopandas as gpd
from sklearn.cluster import KMeans
import scipy.stats as stats
import prince
import contextily as ctx
from matplotlib.lines import Line2D
# Load the data
train_values = pd.read_csv("C:/Users/Akipkurui/Desktop/Moringa- Data Science/
↪Phase 3/Project/data/training set values.csv")
```

```
train_labels = pd.read_csv("C:/Users/Akipkurui/Desktop/Moringa- Data Science/
↪Phase 3/Project/data/training set labels.csv")
test_values = pd.read_csv("C:/Users/Akipkurui/Desktop/Moringa- Data Science/
↪Phase 3/Project/data/test set values.csv")
```

[212]:
```
# Display the first few rows of the datasets
train_values.head()
```

[212]:
```
      id  amount_tsh date_recorded        funder  gps_height     installer  \
0  69572      6000.0    14/03/2011         Roman        1390         Roman
1   8776         0.0    06/03/2013       Grumeti        1399       GRUMETI
2  34310        25.0    25/02/2013  Lottery Club         686  World vision
3  67743         0.0    28/01/2013        Unicef         263        UNICEF
4  19728         0.0    13/07/2011   Action In A           0       Artisan

   longitude   latitude              wpt_name  num_private  … payment_type  \
0  34.938093  -9.856322                  none            0  …     annually
1  34.698766  -2.147466              Zahanati            0  …    never pay
2  37.460664  -3.821329           Kwa Mahundi            0  …   per bucket
3  38.486161 -11.155298  Zahanati Ya Nanyumbu            0  …    never pay
4  31.130847  -1.825359               Shuleni            0  …    never pay

  water_quality quality_group      quantity  quantity_group  \
0          soft          good        enough          enough
1          soft          good  insufficient    insufficient
2          soft          good        enough          enough
3          soft          good           dry             dry
4          soft          good      seasonal        seasonal

                  source           source_type  source_class  \
0                 spring                spring   groundwater
1  rainwater harvesting  rainwater harvesting       surface
2                    dam                   dam       surface
3            machine dbh              borehole   groundwater
4  rainwater harvesting  rainwater harvesting       surface

               waterpoint_type waterpoint_type_group
0           communal standpipe    communal standpipe
1           communal standpipe    communal standpipe
2  communal standpipe multiple    communal standpipe
3  communal standpipe multiple    communal standpipe
4           communal standpipe    communal standpipe

[5 rows x 40 columns]
```

[213]:
```
train_labels.head()
```

[213]:
```
      id    status_group
0  69572      functional
1   8776      functional
2  34310      functional
3  67743  non functional
4  19728      functional
```

[214]:
```
test_values.head()
```

[214]:
```
      id  amount_tsh date_recorded                  funder  gps_height  \
0  50785         0.0    04/02/2013                    Dmdd        1996
1  51630         0.0    04/02/2013  Government Of Tanzania        1569
2  17168         0.0    01/02/2013                     NaN        1567
3  45559         0.0    22/01/2013              Finn Water         267
4  49871       500.0    27/03/2013                  Bruder        1260

    installer  longitude   latitude                 wpt_name  num_private  \
0        DMDD  35.290799  -4.059696  Dinamu Secondary School            0
1         DWE  36.656709  -3.309214                  Kimnyak            0
2         NaN  34.767863  -5.004344          Puma Secondary            0
3  FINN WATER  38.058046  -9.418672           Kwa Mzee Pange            0
4      BRUDER  35.006123 -10.950412          Kwa Mzee Turuka            0

  … payment_type water_quality quality_group      quantity  quantity_group  \
0 …    never pay          soft          good      seasonal        seasonal
1 …    never pay          soft          good  insufficient    insufficient
2 …    never pay          soft          good  insufficient    insufficient
3 …      unknown          soft          good           dry             dry
4 …      monthly          soft          good        enough          enough

                 source           source_type  source_class  \
0  rainwater harvesting  rainwater harvesting       surface
1                spring                spring   groundwater
2  rainwater harvesting  rainwater harvesting       surface
3          shallow well          shallow well   groundwater
4                spring                spring   groundwater

      waterpoint_type waterpoint_type_group
0               other                 other
1  communal standpipe    communal standpipe
2               other                 other
3               other                 other
4  communal standpipe    communal standpipe

[5 rows x 40 columns]
```

[215]:
```
#Checking the structure of our datasets
train_values.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object
 3   funder                 55763 non-null  object
 4   gps_height             59400 non-null  int64
 5   installer              55745 non-null  object
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59398 non-null  object
 9   num_private            59400 non-null  int64
 10  basin                  59400 non-null  object
 11  subvillage             59029 non-null  object
 12  region                 59400 non-null  object
 13  region_code            59400 non-null  int64
 14  district_code          59400 non-null  int64
 15  lga                    59400 non-null  object
 16  ward                   59400 non-null  object
 17  population             59400 non-null  int64
 18  public_meeting         56066 non-null  object
 19  recorded_by            59400 non-null  object
 20  scheme_management      55522 non-null  object
 21  scheme_name            30590 non-null  object
 22  permit                 56344 non-null  object
 23  construction_year      59400 non-null  int64
 24  extraction_type        59400 non-null  object
 25  extraction_type_group  59400 non-null  object
 26  extraction_type_class  59400 non-null  object
 27  management             59400 non-null  object
 28  management_group       59400 non-null  object
 29  payment                59400 non-null  object
 30  payment_type           59400 non-null  object
 31  water_quality          59400 non-null  object
 32  quality_group          59400 non-null  object
 33  quantity               59400 non-null  object
 34  quantity_group         59400 non-null  object
 35  source                 59400 non-null  object
 36  source_type            59400 non-null  object
 37  source_class           59400 non-null  object
 38  waterpoint_type        59400 non-null  object
```

```
 39   waterpoint_type_group  59400 non-null  object
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB
```

[216]:
```
train_labels.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            59400 non-null  int64
 1   status_group  59400 non-null  object
dtypes: int64(1), object(1)
memory usage: 928.2+ KB
```

[217]:
```
test_values.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14850 entries, 0 to 14849
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     14850 non-null  int64
 1   amount_tsh             14850 non-null  float64
 2   date_recorded          14850 non-null  object
 3   funder                 13980 non-null  object
 4   gps_height             14850 non-null  int64
 5   installer              13973 non-null  object
 6   longitude              14850 non-null  float64
 7   latitude               14850 non-null  float64
 8   wpt_name               14850 non-null  object
 9   num_private            14850 non-null  int64
 10  basin                  14850 non-null  object
 11  subvillage             14751 non-null  object
 12  region                 14850 non-null  object
 13  region_code            14850 non-null  int64
 14  district_code          14850 non-null  int64
 15  lga                    14850 non-null  object
 16  ward                   14850 non-null  object
 17  population             14850 non-null  int64
 18  public_meeting         14029 non-null  object
 19  recorded_by            14850 non-null  object
 20  scheme_management      13881 non-null  object
 21  scheme_name            7608 non-null   object
 22  permit                 14113 non-null  object
 23  construction_year      14850 non-null  int64
 24  extraction_type        14850 non-null  object
```

```
 25  extraction_type_group  14850 non-null  object
 26  extraction_type_class  14850 non-null  object
 27  management             14850 non-null  object
 28  management_group       14850 non-null  object
 29  payment                14850 non-null  object
 30  payment_type           14850 non-null  object
 31  water_quality          14850 non-null  object
 32  quality_group          14850 non-null  object
 33  quantity               14850 non-null  object
 34  quantity_group         14850 non-null  object
 35  source                 14850 non-null  object
 36  source_type            14850 non-null  object
 37  source_class           14850 non-null  object
 38  waterpoint_type        14850 non-null  object
 39  waterpoint_type_group  14850 non-null  object
dtypes: float64(3), int64(7), object(30)
memory usage: 4.5+ MB
```

[218]:

```
# Getting a summary of statitiscal measures about the data set
train_values.describe()
```

[218]:

```
                 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
```

[219]:
```
train_labels.describe()
```

[219]:
```
                 id
count  59400.000000
mean   37115.131768
std    21453.128371
min        0.000000
25%    18519.750000
50%    37061.500000
75%    55656.500000
max    74247.000000
```

[220]:
```
test_values.describe()
```

[220]:
```
                 id     amount_tsh    gps_height     longitude      latitude  \
count  14850.000000   14850.000000  14850.000000  14850.000000  1.485000e+04
mean   37161.972929     322.826983    655.147609     34.061605 -5.684724e+00
std    21359.364833    2510.968644    691.261185      6.593034  2.940803e+00
min       10.000000       0.000000    -57.000000      0.000000 -1.156459e+01
25%    18727.000000       0.000000      0.000000     33.069455 -8.443970e+00
50%    37361.500000       0.000000    344.000000     34.901215 -5.049750e+00
75%    55799.750000      25.000000   1308.000000     37.196594 -3.320594e+00
max    74249.000000  200000.000000   2777.000000     40.325016 -2.000000e-08

        num_private   region_code  district_code    population  \
count  14850.000000  14850.000000   14850.000000  14850.000000
mean       0.415084     15.139057       5.626397    184.114209
std        8.167910     17.191329       9.673842    469.499332
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     20.000000
75%        0.000000     17.000000       5.000000    220.000000
max      669.000000     99.000000      80.000000  11469.000000

       construction_year
count       14850.000000
mean         1289.708350
std           955.241087
min             0.000000
25%             0.000000
50%          1986.000000
75%          2004.000000
max          2013.000000
```

0.4 Data Preparation

0.4.1 Merging Datasets

[221]:
```python
# Merging train set values and train set labels
train_data= (pd.merge(train_values,train_labels,on="id",how="inner"))
train_data
```

[221]:
```
          id  amount_tsh date_recorded           funder  gps_height  \
0      69572      6000.0    14/03/2011            Roman        1390
1       8776         0.0    06/03/2013          Grumeti        1399
2      34310        25.0    25/02/2013     Lottery Club         686
3      67743         0.0    28/01/2013           Unicef         263
4      19728         0.0    13/07/2011      Action In A           0
…        …         …           …              …         …
59395  60739        10.0    03/05/2013  Germany Republi        1210
59396  27263      4700.0    07/05/2011      Cefa-njombe        1212
59397  37057         0.0    11/04/2011              NaN           0
59398  31282         0.0    08/03/2011            Malec           0
59399  26348         0.0    23/03/2011       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

       … water_quality quality_group      quantity  quantity_group  \
0      …          soft          good        enough          enough
1      …          soft          good  insufficient    insufficient
2      …          soft          good        enough          enough
3      …          soft          good           dry             dry
4      …          soft          good      seasonal        seasonal
…    …            …             …           …               …
59395  …          soft          good        enough          enough
59396  …          soft          good        enough          enough
59397  …      fluoride      fluoride        enough          enough
59398  …          soft          good  insufficient    insufficient
59399  …         salty         salty        enough          enough

                     source           source_type source_class  \
```

```
0                     spring                spring  groundwater
1        rainwater harvesting  rainwater harvesting      surface
2                        dam                   dam      surface
3                machine dbh              borehole  groundwater
4        rainwater harvesting  rainwater harvesting      surface
…                          …                     …           …
59395                 spring                spring  groundwater
59396                  river            river/lake      surface
59397            machine dbh              borehole  groundwater
59398           shallow well          shallow well  groundwater
59399           shallow well          shallow well  groundwater

                   waterpoint_type waterpoint_type_group    status_group
0               communal standpipe    communal standpipe      functional
1               communal standpipe    communal standpipe      functional
2      communal standpipe multiple    communal standpipe      functional
3      communal standpipe multiple    communal standpipe  non functional
4               communal standpipe    communal standpipe      functional
…                              …                     …               …
59395           communal standpipe    communal standpipe      functional
59396           communal standpipe    communal standpipe      functional
59397                    hand pump             hand pump      functional
59398                    hand pump             hand pump      functional
59399                    hand pump             hand pump      functional

[59400 rows x 41 columns]
```

0.4.2 Duplicates removal

[222]:
```
# Checking for duplicates
duplicates = train_data[train_data.duplicated()]
duplicates
```

[222]:
```
Empty DataFrame
Columns: [id, 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,
status_group]
Index: []

[0 rows x 41 columns]
```

There are no duplicate rows in this data set

0.4.3 Dealing with null values

[223]:
```
# Checking for columns with null values
print(train_data.isna().mean()*100)
```

```
id                        0.000000
amount_tsh                0.000000
date_recorded             0.000000
funder                    6.122896
gps_height                0.000000
installer                 6.153199
longitude                 0.000000
latitude                  0.000000
wpt_name                  0.003367
num_private               0.000000
basin                     0.000000
subvillage                0.624579
region                    0.000000
region_code               0.000000
district_code             0.000000
lga                       0.000000
ward                      0.000000
population                0.000000
public_meeting            5.612795
recorded_by               0.000000
scheme_management         6.528620
scheme_name              48.501684
permit                    5.144781
construction_year         0.000000
extraction_type           0.000000
extraction_type_group     0.000000
extraction_type_class     0.000000
management                0.000000
management_group          0.000000
payment                   0.000000
payment_type              0.000000
water_quality             0.000000
quality_group             0.000000
quantity                  0.000000
quantity_group            0.000000
source                    0.000000
source_type               0.000000
source_class              0.000000
waterpoint_type           0.000000
waterpoint_type_group     0.000000
status_group              0.000000
dtype: float64
```

0.4.4 Checking for similar columns

Scheme_Management, Management group and Management

[224]:
```
# Grouping the management columns to check similarity
train_data['management'].value_counts()
```

[224]:
```
management
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: count, dtype: int64
```

[225]:
```
train_data['management_group'].value_counts()
```

[225]:
```
management_group
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: count, dtype: int64
```

[226]:
```
train_data['scheme_management'].value_counts()
```

[226]:
```
scheme_management
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
Name: count, dtype: int64
```

[227]:
```
train_data.groupby(['management_group','management']).count()
```

[227]:
```
                                     id  amount_tsh  date_recorded  funder  \
management_group management
commercial       company            685         685            685     663
                 private operator  1971        1971           1971    1957
                 trust               78          78             78      78
                 water authority    904         904            904     836
other            other              844         844            844     837
                 other - school      99          99             99      99
parastatal       parastatal        1768        1768           1768    1624
unknown          unknown            561         561            561     533
user-group       vwc              40507       40507          40507   37630
                 water board       2933        2933           2933    2715
                 wua               2535        2535           2535    2308
                 wug               6515        6515           6515    6483

                                   gps_height  installer  longitude  latitude  \
management_group management
commercial       company                  685        663        685       685
                 private operator        1971       1959       1971      1971
                 trust                     78         78         78        78
                 water authority          904        836        904       904
other            other                    844        831        844       844
                 other - school            99         99         99        99
parastatal       parastatal              1768       1626       1768      1768
unknown          unknown                  561        527        561       561
user-group       vwc                    40507      37630      40507     40507
                 water board             2933       2714       2933      2933
                 wua                     2535       2309       2535      2535
                 wug                     6515       6473       6515      6515

                                   wpt_name  num_private  …  water_quality  \
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           2932         2933  …           2933
                 wua                   2535         2535  …           2535
                 wug                   6514         6515  …           6515
```

```
                                 quality_group  quantity  quantity_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

                                 source  source_type  source_class  \
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  waterpoint_type_group  \
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

                                 status_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

[12 rows x 39 columns]
```

From above data scheme_management and management columns have the same values however scheme_management has null values hence we wll drop scheme_management. management column is a subset of management-group hence similarity. Since Management column is more detailed, we will drop management_group and retain management column

extraction_type, extraction_type_group and extraction_type_class

[228]:
```
train_data['extraction_type'].value_counts()
```

[228]:
```
extraction_type
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: count, dtype: int64
```

[229]:
```
train_data['extraction_type_group'].value_counts()
```

[229]:
```
extraction_type_group
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: count, dtype: int64
```

[230]:
```
train_data['extraction_type_class'].value_counts()
```

[230]:
```
extraction_type_class
gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
rope pump         451
wind-powered      117
Name: count, dtype: int64
```

[231]:
```
train_data.groupby(['extraction_type_class','extraction_type_group']).count()
```

[231]:
```
                                                id  amount_tsh  date_recorded  \
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

                                             funder  gps_height  installer  \
```

```
extraction_type_class extraction_type_group
gravity               gravity                   24704     26780     24714
handpump              afridev                    1668      1770      1665
                      india mark ii              2358      2400      2358
                      india mark iii               98        98        98
                      nira/tanira                7899      8154      7885
                      other handpump              353       364       354
                      swn 80                     3595      3670      3593
motorpump             mono                       2577      2865      2578
                      other motorpump             122       122       122
other                 other                      6010      6430      6002
rope pump             rope pump                   448       451       448
submersible           submersible                5819      6179      5816
wind-powered          wind-powered                112       117       112

                                             longitude  latitude  wpt_name  \
extraction_type_class extraction_type_group
gravity               gravity                    26780     26780     26779
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      6429
rope pump             rope pump                    451       451       451
submersible           submersible                 6179      6179      6179
wind-powered          wind-powered                 117       117       117

                                             num_private  …  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
```

extraction_type_class	extraction_type_group	quality_group	quantity \
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	quantity_group	source \
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	source_type	source_class \
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

                                         status_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

[13 rows x 39 columns]
```

It is evident that this 3 columns contain the same data. extraction_type and extraction_type_group contain the same data however extraction_type_group appears to be more compact. extraction_type_group appears to be a subset of extrcation_type_class. We will drop extraction_type and extraction_type_class and retain extraction_type_group since it is more compact and has more details.

payment and payment_type

[232]:
```python
train_data['payment'].value_counts()
```

[232]:
```
payment
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
pay when scheme fails     3914
pay annually              3642
other                     1054
Name: count, dtype: int64
```

[233]:
```python
train_data['payment_type'].value_counts()
```

[233]:
```
payment_type
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: count, dtype: int64
```

This 2 columns are similar we decided to drop 1 i.e payment

quantity and quantity-group

[234]:
```python
train_data['quantity'].value_counts()
```

[234]:
```
quantity
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: count, dtype: int64
```

[235]:
```
train_data['quantity_group'].value_counts()
```

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

This 2 columns are similar we decided to drop 1 i.e quantity_group

water_quality and quality_group

[236]:
```
train_data['water_quality'].value_counts()
```

[236]:
```
water_quality
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: count, dtype: int64
```

[237]:
```
train_data['quality_group'].value_counts()
```

[237]:
```
quality_group
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: count, dtype: int64
```

The 2 columns are similar however water_quality column has more details hence we will drop quality_group

source, source_type and source_class

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

[238]:
```
source
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: count, dtype: int64
```

[239]:
```
train_data['source_type'].value_counts()
```

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

[240]:
```
train_data['source_class'].value_counts()
```

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

[241]:
```
train_data.groupby(['source_class','source_type']).count()
```

[241]:
```
                                      id  amount_tsh  date_recorded  funder  \
source_class source_type
groundwater  borehole              11949       11949          11949   11119
             shallow well          16824       16824          16824   16301
             spring                17021       17021          17021   15870
surface      dam                     656         656            656     647
             rainwater harvesting   2295        2295           2295    2099
             river/lake            10377       10377          10377    9478
unknown      other                   278         278            278     249

                                   gps_height  installer  longitude  latitude  \
source_class source_type
groundwater  borehole                   11949      11114      11949     11949
             shallow well               16824      16286      16824     16824
             spring                     17021      15870      17021     17021
surface      dam                          656        646        656       656
```

	rainwater harvesting	2295	2096	2295	2295
	river/lake	10377	9483	10377	10377
unknown	other	278	250	278	278

		wpt_name	num_private	…	payment \
source_class	source_type			…	
groundwater	borehole	11948	11949	…	11949
	shallow well	16824	16824	…	16824
	spring	17020	17021	…	17021
surface	dam	656	656	…	656
	rainwater harvesting	2295	2295	…	2295
	river/lake	10377	10377	…	10377
unknown	other	278	278	…	278

		payment_type	water_quality	quality_group \
source_class	source_type			
groundwater	borehole	11949	11949	11949
	shallow well	16824	16824	16824
	spring	17021	17021	17021
surface	dam	656	656	656
	rainwater harvesting	2295	2295	2295
	river/lake	10377	10377	10377
unknown	other	278	278	278

		quantity	quantity_group	source \
source_class	source_type			
groundwater	borehole	11949	11949	11949
	shallow well	16824	16824	16824
	spring	17021	17021	17021
surface	dam	656	656	656
	rainwater harvesting	2295	2295	2295
	river/lake	10377	10377	10377
unknown	other	278	278	278

		waterpoint_type	waterpoint_type_group \
source_class	source_type		
groundwater	borehole	11949	11949
	shallow well	16824	16824
	spring	17021	17021
surface	dam	656	656
	rainwater harvesting	2295	2295
	river/lake	10377	10377
unknown	other	278	278

		status_group
source_class	source_type	
groundwater	borehole	11949

```
             shallow well                 16824
             spring                       17021
surface      dam                            656
             rainwater harvesting          2295
             river/lake                   10377
unknown      other                          278

[7 rows x 39 columns]
```

The 3 columns are similar. source is more detailed that source_type while source_type is a subset of source_class hence we will remain with source and drop source_type and source_class

waterpoint_type and waterpoint_type_group

[242]:
```
train_data['waterpoint_type'].value_counts()
```

[242]:
```
waterpoint_type
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
cattle trough                    116
dam                                7
Name: count, dtype: int64
```

[243]:
```
train_data['waterpoint_type_group'].value_counts()
```

[243]:
```
waterpoint_type_group
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: count, dtype: int64
```

The 2 columns are similar howoever waterpoint_type has more details hence we will drop waterpoint_type_group

0.4.5 Drop identical columns

[244]:
```
train_data1=train_data.
 ↪drop(columns=['management_group','scheme_management','extraction_type_class','extraction_ty
                'payment_type', 'waterpoint_type_group'])
train_data1
```

[244]:
```
          id  amount_tsh date_recorded        funder  gps_height  \
0      69572      6000.0    14/03/2011         Roman        1390
1       8776         0.0    06/03/2013       Grumeti        1399
2      34310        25.0    25/02/2013  Lottery Club         686
3      67743         0.0    28/01/2013        Unicef         263
4      19728         0.0    13/07/2011   Action In A           0
…        …           …           …             …         …
59395  60739        10.0    03/05/2013 Germany Republi      1210
59396  27263      4700.0    07/05/2011   Cefa-njombe        1212
59397  37057         0.0    11/04/2011           NaN           0
59398  31282         0.0    08/03/2011         Malec           0
59399  26348         0.0    23/03/2011    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

       … permit construction_year extraction_type_group   management  \
0      …  False              1999               gravity          vwc
1      …   True              2010               gravity          wug
2      …   True              2009               gravity          vwc
3      …   True              1986           submersible          vwc
4      …   True                 0               gravity        other
…    …    …                 …                     …          …
59395  …   True              1999               gravity  water board
59396  …   True              1996               gravity          vwc
59397  …  False                 0                swn 80          vwc
59398  …   True                 0           nira/tanira          vwc
59399  …   True              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    status_group
0                     spring           communal standpipe      functional
1        rainwater harvesting           communal standpipe      functional
2                        dam  communal standpipe multiple      functional
3                machine dbh  communal standpipe multiple  non functional
4        rainwater harvesting           communal standpipe      functional
…                          …                            …               …
59395                 spring           communal standpipe      functional
59396                  river           communal standpipe      functional
59397            machine dbh                    hand pump      functional
59398           shallow well                    hand pump      functional
59399           shallow well                    hand pump      functional

[59400 rows x 31 columns]
```

Exporing contruction_year column

[245]:
```
train_data1['construction_year'].value_counts()
```

[245]:
```
construction_year
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: count, dtype: int64
```

[246]:
```
train_data1['construction_year'].value_counts().sum()
```

[246]:
```
59400
```

We have replace contruction_year that is balnk with unknown

[247]:
```
# Replace 'Unknown' with NaN
train_data1['construction_year'] = train_data1['construction_year'].
 ↪replace('Unknown', np.nan)

# Convert construction_year to numeric, handling NaN values
```

```
train_data1['construction_year'] = pd.
↪to_numeric(train_data1['construction_year'], errors='coerce')

# Define the function to get the decade in the desired format
def get_decade(year):
    if pd.isna(year):
        return 'Unknown'
    else:
        decade_start = (year // 10) * 10
        return f"{str(int(decade_start))[-2:]}s"

# Apply the function to create the 'decade' column
train_data1['decade'] = train_data1['construction_year'].apply(get_decade)

# Verify the changes
train_data1['decade'].value_counts()
```

[247]:
```
decade
0s     20709
00s    15330
90s     7678
80s     5578
10s     5161
70s     4406
60s      538
Name: count, dtype: int64
```

We have now grouped construction year into decades for easy visualization and interpretation

recorded_by

[248]:
```
train_data1['recorded_by'].value_counts()
```

[248]:
```
recorded_by
GeoData Consultants Ltd    59400
Name: count, dtype: int64
```

[249]:
```
train_data1.drop(columns=['recorded_by'],inplace=True  )
```

Has only one record hence we will drop this column

0.4.6 Correcting errors and spelling mistakes in installer and funder columns

installer

[250]:
```
train_data1['installer'].value_counts()
```

[250]: installer
```
DWE                   17402
Government             1825
RWE                    1206
Commu                  1060
DANIDA                 1050
                      …
Wizara  ya maji           1
TWESS                     1
Nasan workers             1
R                         1
SELEPTA                   1
Name: count, Length: 2145, dtype: int64
```

[251]:
```
# filling 0 values with unknown
train_data1['installer'].replace(to_replace = '0', value ='Unknown' ,␣
↪inplace=True)
```

[252]:
```
# filling null values with unknown
train_data1['installer'].fillna(value='Unknown',inplace=True)
```

[253]:
```
# From the most common 100 value counts we realized some spelling mistakes or␣
↪different syntax between same categories

# Replacing the spelling mistakes and collect same categories in same name

train_data1['installer'].replace(to_replace = ('District Water Department',␣
↪'District water depar','Distric Water Department'),
                        value ='District water department' , inplace=True)

train_data1['installer'].replace(to_replace = ('FinW','Fini water','FINI␣
↪WATER'), value ='Fini Water' , inplace=True)
train_data1['installer'].replace(to_replace = 'JAICA', value ='Jaica' ,␣
↪inplace=True)

train_data1['installer'].replace(to_replace = ('COUN', 'District COUNCIL',␣
↪'DISTRICT COUNCIL','District Counci',
                                      'District␣
↪Council','Council','Counc','District  Council','Distri'),
                                    value ='District council' , inplace=True)

train_data1['installer'].replace(to_replace = ('RC CHURCH', 'RC Churc',␣
↪'RC','RC Ch','RC C', 'RC CH','RC church',
                                      'RC CATHORIC',) , value ='RC Church' ,␣
↪inplace=True)
```

```
train_data1['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)

train_data1['installer'].replace(to_replace = ('World vision', 'World␣
↪Division','World Vision'),
                                        value ='world vision' , inplace=True)

train_data1['installer'].replace(to_replace = ('Unisef','UNICEF'),value␣
↪='Unicef' , inplace=True)
train_data1['installer'].replace(to_replace = 'DANID', value ='DANIDA' ,␣
↪inplace=True)

train_data1['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)
train_data1['installer'].replace(to_replace␣
↪=('Commu','Communit','commu','COMMU', 'COMMUNITY') ,
                                        value ='Community' , inplace=True)

train_data1['installer'].replace(to_replace = ('GOVERNMENT', 'GOVER',␣
↪'GOVERNME', 'GOVERM','GOVERN','Gover','Gove',
                                      'Governme','Governmen' ) ,value␣
↪='Government' , inplace=True)

train_data1['installer'].replace(to_replace = 'Hesawa' ,value ='HESAWA' ,␣
↪inplace=True)
```

[254]:
```
# continue to replacing spellin mistakes and getting together values
train_data1['installer'].replace(to_replace = ('Colonial Government') , value␣
↪='Colonial government' , inplace=True)
```

```
train_data1['installer'].replace(to_replace = ('Government of Misri') , value␣
↪='Misri Government' , inplace=True)
train_data1['installer'].replace(to_replace = ('Italy government') , value␣
↪='Italian government' , inplace=True)
train_data1['installer'].replace(to_replace = ('British colonial government') ,␣
↪value ='British government' , inplace=True)
train_data1['installer'].replace(to_replace = ('Concern /government') , value␣
↪='Concern/Government' , inplace=True)
train_data1['installer'].replace(to_replace = ('Village Government') , value␣
↪='Village government' , inplace=True)
train_data1['installer'].replace(to_replace = ('Government and Community') ,␣
↪value ='Government /Community' , inplace=True)
train_data1['installer'].replace(to_replace = ('Cetral government /RC') , value␣
↪='RC church/Central Gover' , inplace=True)
train_data1['installer'].replace(to_replace = ('Government /TCRS','Government/
↪TCRS') , value ='TCRS /Government' , inplace=True)
train_data1['installer'].replace(to_replace = ('ADRA /Government') , value␣
↪='ADRA/Government' , inplace=True)
```

[255]:
```
train_data1['installer'].value_counts().head(20)
```

[255]:
```
installer
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               461
villagers               408
LGA                     408
WEDECO                  397
TASAF                   396
Unicef                  332
Name: count, dtype: int64
```

[256]:
```
# Create a new column 'installer_classified' with default value 'Others'
train_data1['installer_classified'] = 'Others'
```

```
# Get the counts of each installer
installer_counts = train_data1['installer'].value_counts()

# Update the 'installer_classified' column for installers with less than 500␣
↪records
for installer, count in installer_counts.items():
    if count > 500:
        train_data1.loc[train_data1['installer'] == installer,␣
↪'installer_classified'] = installer

# Print the first few rows to check the results
train_data1['installer_classified'].value_counts().head(20)
```

[256]:
```
installer_classified
Others                  23260
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
Name: count, dtype: int64
```

funder

[257]:
```
# filling 0 and null values with unknown
train_data1['funder'].fillna(value='Unknown',inplace=True)
train_data1['funder'].replace(to_replace = '0', value ='Unknown' , inplace=True)
train_data1['funder'].value_counts().head(20)
```

[257]:
```
funder
Government Of Tanzania    9084
Unknown                   4418
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: count, dtype: int64
```

[258]:

```python
# Create a new column 'funder_classified' with default value 'Others'
train_data1['funder_classified'] = 'Others'

# Get the counts of each installer
funder_counts = train_data1['funder'].value_counts()

# Update the 'installer_classified' column for installers with less than 500␣
↪records
for funder, count in funder_counts.items():
    if count > 483:
        train_data1.loc[train_data1['funder'] == funder, 'funder_classified'] =␣
↪funder

# Print the first few rows to check the results
train_data1['funder_classified'].value_counts().head(20)
```

[258]:

```
funder_classified
Others                  26449
Government Of Tanzania   9084
Unknown                  4418
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
Name: count, dtype: int64
```

0.4.7 Other columns

We will drop the following columns since they do not have any relationship with functionality of the wells:

1. id
2. wpt_name
3. date_recorded
4. scheme_name
5. region_code

[259]:
```
train_data1.
↪drop(columns=['wpt_name','scheme_name','id','region_code',"date_recorded"],inplace=True␣
↪)
```

[260]:
```
train_data1
```

[260]:
```
       amount_tsh           funder  gps_height     installer  longitude  \
0          6000.0            Roman        1390         Roman  34.938093
1             0.0          Grumeti        1399       GRUMETI  34.698766
2            25.0     Lottery Club         686  world vision  37.460664
3             0.0           Unicef         263        Unicef  38.486161
4             0.0      Action In A           0       Artisan  31.130847
…              …                …          …             …          …
59395        10.0  Germany Republi        1210           CES  37.169807
59396      4700.0      Cefa-njombe        1212          Cefa  35.249991
59397         0.0          Unknown           0       Unknown  34.017087
59398         0.0            Malec           0          Musa  35.861315
59399         0.0       World Bank         191         World  38.104048

        latitude  num_private                     basin   subvillage  \
0      -9.856322            0                Lake Nyasa     Mnyusi B
1      -2.147466            0            Lake Victoria      Nyamara
2      -3.821329            0                   Pangani      Majengo
3     -11.155298            0  Ruvuma / Southern Coast   Mahakamani
4      -1.825359            0            Lake Victoria   Kyanyamisa
…              …          …                         …            …
59395  -3.253847            0                   Pangani     Kiduruni
59396  -9.070629            0                    Rufiji     Igumbilo
59397  -8.750434            0                    Rufiji    Madungulu
59398  -6.378573            0                    Rufiji       Mwinyi
```

```
59399  -6.747464           0              Wami / Ruvu  Kikatanyemba

            region  …  management                payment water_quality  \
0           Iringa  …         vwc           pay annually          soft
1             Mara  …         wug              never pay          soft
2          Manyara  …         vwc         pay per bucket          soft
3           Mtwara  …         vwc              never pay          soft
4           Kagera  …       other              never pay          soft
…              …  …         …                    …           …
59395  Kilimanjaro  …  water board         pay per bucket          soft
59396       Iringa  …         vwc           pay annually          soft
59397        Mbeya  …         vwc            pay monthly      fluoride
59398       Dodoma  …         vwc              never pay          soft
59399     Morogoro  …         vwc  pay when scheme fails         salty

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

         status_group decade installer_classified funder_classified
0          functional    90s               Others            Others
1          functional    10s               Others            Others
2          functional    00s         world vision            Others
3      non functional    80s               Others            Unicef
4          functional     0s               Others            Others
…                 …    …                  …                 …
59395      functional    90s                  CES   Germany Republi
59396      functional    90s               Others            Others
59397      functional     0s              Unknown           Unknown
59398      functional     0s               Others            Others
59399      functional    00s               Others        World Bank

[59400 rows x 28 columns]
```

amount_tsh

[261]:
```
train_data1['amount_tsh'].value_counts()
```

[261]:
```
amount_tsh
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: count, Length: 98, dtype: int64
```

[262]:
```
train_data1.drop(columns=['amount_tsh'],inplace=True )
```

Most of the records are zero hence we drop the column

[263]:
```
train_data1.drop(columns=['num_private'],inplace=True )
```

[264]:
```
train_data1
```

[264]:
```
              funder  gps_height     installer  longitude   latitude  \
0              Roman        1390         Roman  34.938093  -9.856322
1            Grumeti        1399       GRUMETI  34.698766  -2.147466
2       Lottery Club         686  world vision  37.460664  -3.821329
3             Unicef         263        Unicef  38.486161 -11.155298
4        Action In A           0       Artisan  31.130847  -1.825359
…                …           …             …          …          …
59395  Germany Republi      1210           CES  37.169807  -3.253847
59396      Cefa-njombe      1212          Cefa  35.249991  -9.070629
59397          Unknown         0       Unknown  34.017087  -8.750434
59398            Malec         0          Musa  35.861315  -6.378573
59399       World Bank       191         World  38.104048  -6.747464

                         basin    subvillage       region  district_code  \
0                   Lake Nyasa      Mnyusi B       Iringa              5
1                Lake Victoria       Nyamara         Mara              2
2                      Pangani       Majengo      Manyara              4
3       Ruvuma / Southern Coast    Mahakamani       Mtwara             63
4                Lake Victoria    Kyanyamisa       Kagera              1
…                            …             …            …              …
59395                  Pangani      Kiduruni  Kilimanjaro              5
59396                   Rufiji      Igumbilo       Iringa              4
59397                   Rufiji     Madungulu        Mbeya              7
59398                   Rufiji        Mwinyi       Dodoma              4
59399              Wami / Ruvu  Kikatanyemba     Morogoro              2
```

```
                   lga  ...   management                 payment water_quality  \
0               Ludewa  ...          vwc            pay annually          soft
1            Serengeti  ...          wug               never pay          soft
2            Simanjiro  ...          vwc          pay per bucket          soft
3             Nanyumbu  ...          vwc               never pay          soft
4              Karagwe  ...        other               never pay          soft
…                  …  …             …                       …           …
59395              Hai  ...  water board          pay per bucket          soft
59396           Njombe  ...          vwc            pay annually          soft
59397          Mbarali  ...          vwc             pay monthly      fluoride
59398         Chamwino  ...          vwc               never pay          soft
59399   Morogoro Rural  ...          vwc  pay when scheme fails          salty

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

         status_group decade installer_classified funder_classified
0          functional    90s               Others            Others
1          functional    10s               Others            Others
2          functional    00s         world vision            Others
3      non functional    80s               Others            Unicef
4          functional     0s               Others            Others
…                  …    …                     …               …
59395      functional    90s                  CES   Germany Republi
59396      functional    90s               Others            Others
59397      functional     0s              Unknown           Unknown
59398      functional     0s               Others            Others
59399      functional    00s               Others        World Bank

[59400 rows x 26 columns]
```

0.4.8 Checking remaining null values

[265]:
```
print(train_data1.isna().mean()*100)
```

```
funder                   0.000000
```

```
gps_height               0.000000
installer                0.000000
longitude                0.000000
latitude                 0.000000
basin                    0.000000
subvillage               0.624579
region                   0.000000
district_code            0.000000
lga                      0.000000
ward                     0.000000
population               0.000000
public_meeting           5.612795
permit                   5.144781
construction_year        0.000000
extraction_type_group    0.000000
management               0.000000
payment                  0.000000
water_quality            0.000000
quantity                 0.000000
source                   0.000000
waterpoint_type          0.000000
status_group             0.000000
decade                   0.000000
installer_classified     0.000000
funder_classified        0.000000
dtype: float64
```

0.4.9 Remaining columns with null values: subvillage, public_meeting, permit

0.4.10 permit

[266]:
```
train_data1['permit'].value_counts()
```

[266]:
```
permit
True     38852
False    17492
Name: count, dtype: int64
```

[267]:
```
train_data1['permit'].fillna(value=True, inplace=True)
```

We have replace null values with True since it is the highest

public_meeting

[268]:
```
train_data1['public_meeting'].value_counts()
```

[268]:
```
public_meeting
True     51011
False     5055
```

```
Name: count, dtype: int64
```

[269]:
```
train_data1['public_meeting'].fillna(value=True, inplace=True)
```

We have replace null values with True since it is the highest

subvillage Drop subvillage since we already have region

[270]:
```
train_data1.drop(columns=['subvillage'],inplace=True )
```

[271]:
```
print(train_data1.isna().mean()*100)
```

```
funder                   0.0
gps_height               0.0
installer                0.0
longitude                0.0
latitude                 0.0
basin                    0.0
region                   0.0
district_code            0.0
lga                      0.0
ward                     0.0
population               0.0
public_meeting           0.0
permit                   0.0
construction_year        0.0
extraction_type_group    0.0
management               0.0
payment                  0.0
water_quality            0.0
quantity                 0.0
source                   0.0
waterpoint_type          0.0
status_group             0.0
decade                   0.0
installer_classified     0.0
funder_classified        0.0
dtype: float64
```

population

[272]:
```
#Getting the mean and median
train_data1.loc[train_data1['population']!=0].describe()
```

[272]:
```
         gps_height     longitude      latitude  district_code    population  \
count  38019.000000  38019.000000  38019.000000   38019.000000  38019.000000
mean     969.889634     36.074387     -6.139781       6.299456    281.087167
std      612.544787      2.586779      2.737733      11.303334    564.687660
```

```
min      -90.000000    29.607122  -11.649440     1.000000      1.000000
25%      347.000000    34.715340   -8.388839     2.000000     40.000000
50%     1135.000000    36.706815   -5.750877     3.000000    150.000000
75%     1465.000000    37.940149   -3.597016     5.000000    324.000000
max     2770.000000    40.345193   -1.042375    67.000000  30500.000000

       construction_year
count       38019.000000
mean         1961.399721
std           263.994165
min             0.000000
25%          1986.000000
50%          2000.000000
75%          2008.000000
max          2013.000000
```

[273]:
```python
#Replacing the population that is 0 with mean
train_data1['population'].replace(to_replace = 0 , value =281, inplace=True)
```

[274]:
```python
print(train_data1.isna().mean()*100)
```

```
funder                   0.0
gps_height               0.0
installer                0.0
longitude                0.0
latitude                 0.0
basin                    0.0
region                   0.0
district_code            0.0
lga                      0.0
ward                     0.0
population               0.0
public_meeting           0.0
permit                   0.0
construction_year        0.0
extraction_type_group    0.0
management               0.0
payment                  0.0
water_quality            0.0
quantity                 0.0
source                   0.0
waterpoint_type          0.0
status_group             0.0
decade                   0.0
installer_classified     0.0
funder_classified        0.0
dtype: float64
```

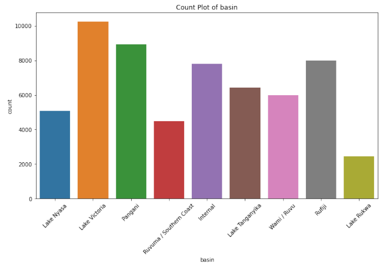
0.4.11 Data without nullvalues for EDA analysis

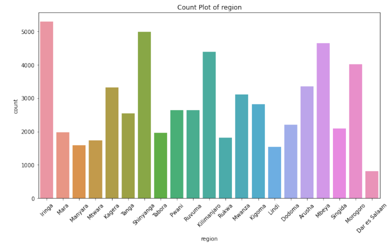
0.5 Exploratory Data Analysis

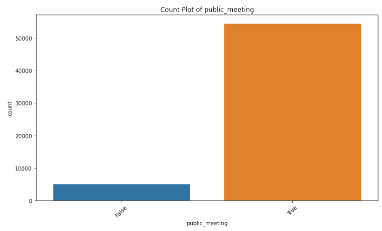
0.5.1 Univariate Analysis

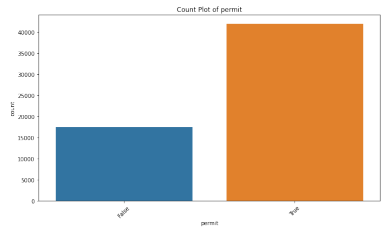
Categorical Variables

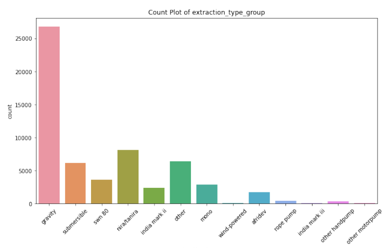
[275]:
```
# Define the categorical columns for analysis
categorical_cols = ['basin', 'region', 'public_meeting', 'permit',␣
↪'extraction_type_group', 'management', 'payment', 'water_quality',␣
↪'quantity', 'source', 'waterpoint_type', 'decade', 'installer_classified',␣
↪'funder_classified']

# Define the number of columns in each row of subplots
num_cols_per_row = 2

# Calculate the number of rows needed for subplots
num_rows = (len(categorical_cols) + num_cols_per_row - 1) // num_cols_per_row

# Create subplots with adjusted width and height
fig, axs = plt.subplots(num_rows, num_cols_per_row, figsize=(20, num_rows * 7))

# Flatten the axis array for easier iteration
axs = axs.flatten()

# Loop through each categorical column and create count plots
for i, col in enumerate(categorical_cols):
    sns.countplot(x=col, data=train_data1, ax=axs[i])
    axs[i].set_title(f'Count Plot of {col}')
    axs[i].tick_params(axis='x', rotation=45)

# Hide any extra subplots if the number of columns is not a multiple of␣
↪num_cols_per_row
for j in range(len(categorical_cols), num_rows * num_cols_per_row):
    fig.delaxes(axs[j])

plt.tight_layout()
plt.show()
```

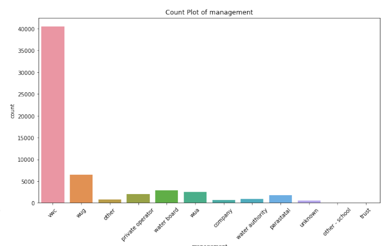

Count Plot of basin
count
Lake Nyasa
Lake Victoria
Pangani
Ruvuma / Southern Coast
Internal
Lake Tanganyika
Wami / Ruvu
Rufiji
Lake Rukwa
basin

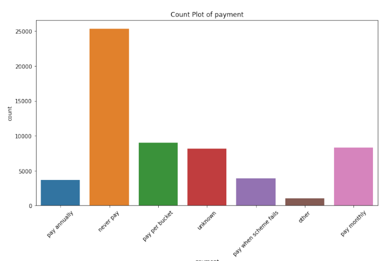

Count Plot of region
count
Iringa
Mara
Manyara
Mtwara
Kagera
Tanga
Shinyanga
Tabora
Pwani
Ruvuma
Kilimanjaro
Rukwa
Mwanza
Kigoma
Lindi
Dodoma
Arusha
Mbeya
Singida
Morogoro
Dar es Salaam
region

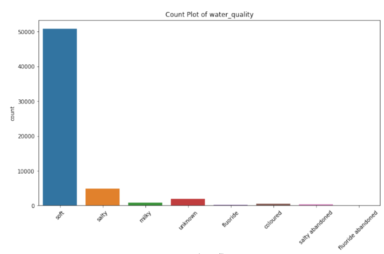

Count Plot of public_meeting
count
False
True
public_meeting

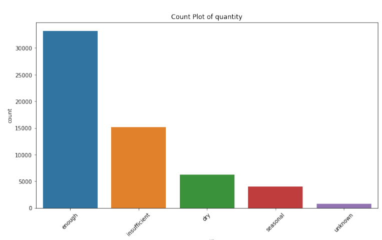

Count Plot of permit
count
False
True
permit

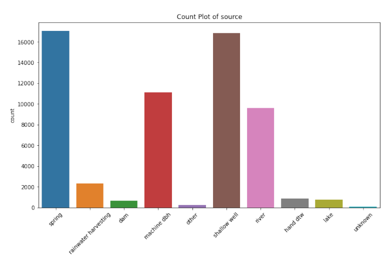

Count Plot of extraction_type_group
count
gravity
submersible
swn 80
nira/tanira
india mark ii
other
mono
wind-powered
afridev
rope pump
india mark iii
other handpump
other motorpump
extraction_type_group

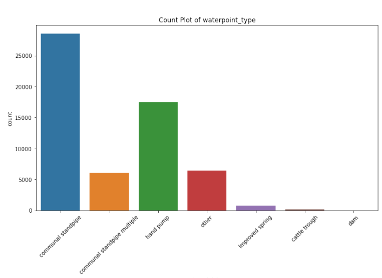

Count Plot of management
count
vwc
wug
other
private operator
water board
wua
company
water authority
parastatal
unknown
other - school
trust
management

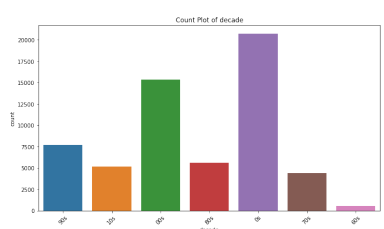

Count Plot of payment
count
pay annually
never pay
pay per bucket
unknown
pay when scheme fails
other
pay monthly
payment

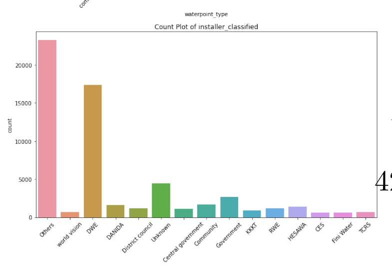

Count Plot of water_quality
count
soft
salty
milky
unknown
fluoride
coloured
salty abandoned
fluoride abandoned
water_quality

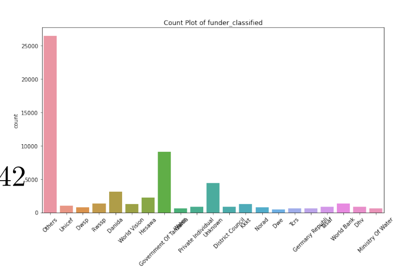

Count Plot of quantity
count
enough
insufficient
dry
seasonal
unknown
quantity


Count Plot of source
count
spring
rainwater harvesting
dam
machine dbh
other
shallow well
river
hand dtw
lake
unknown
source


Count Plot of waterpoint_type
count
communal standpipe
communal standpipe multiple
hand pump
other
improved spring
cattle trough
dam
waterpoint_type

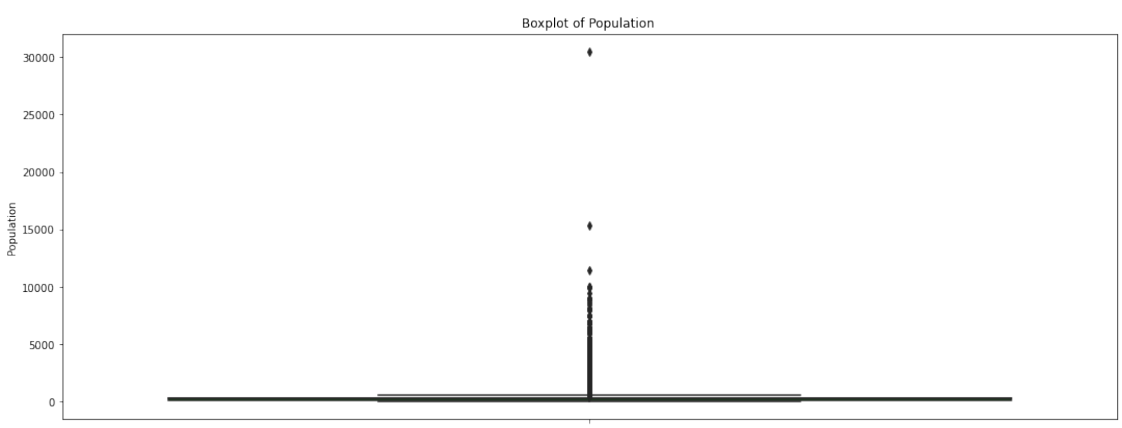

Count Plot of decade
count
90s
10s
00s
80s
0s
70s
60s
decade

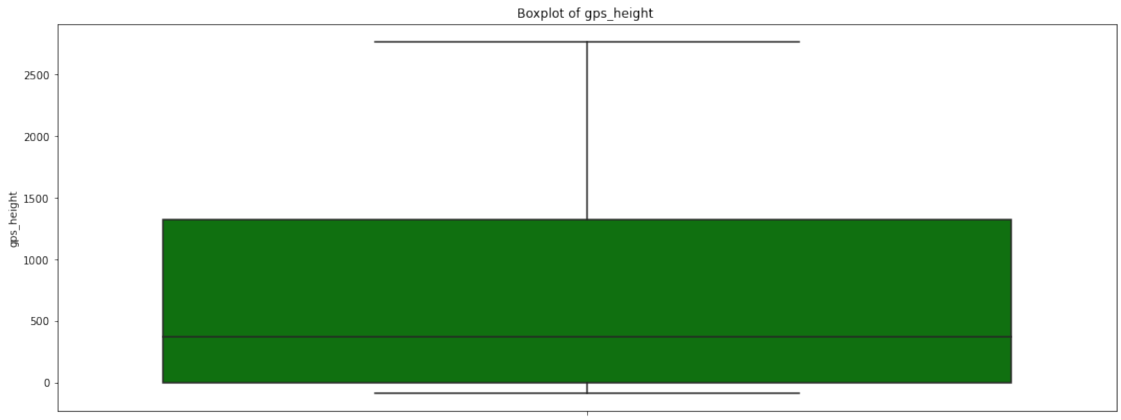

Count Plot of installer_classified
count
Others
world vision
DWE
DANIDA
District council
Unknown
Central government
Community
Government
KKKT
RWE
HESAWA
CES
Fini Water
TCRS
installer_classified


Count Plot of funder_classified
count
Others
Unicef
Dwsp
Rwssp
Danida
World Vision
Hesawa
Government Of Tanzania
Private Individual
Unknown
District Council
Kkkt
Norad
Dwe
Tcrs
Germany Republi
World Bank
Dhv
Ministry Of Water
funder_classified

Numeric Variables

[276]:
```
# Assuming train_data1 is your DataFrame
population_array = np.array(train_data1['population'])

# Set the size of the plot
plt.figure(figsize=(40, 15))

# Plot the boxplot
plt.subplot(2, 2, 2)
sns.boxplot(y=population_array, color='green')
plt.title('Boxplot of Population ')
plt.ylabel('Population')

# Show the plot
plt.show()


gps_height_array = np.array(train_data1['gps_height'])
# Plot the boxplot

# Set the size of the plot
plt.figure(figsize=(40, 15))
plt.subplot(2, 2, 2)
sns.boxplot(y=gps_height_array , color='green')
plt.title('Boxplot of gps_height ')
plt.ylabel('gps_height')

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





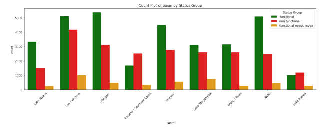
0.5.2 Bivariate Analysis

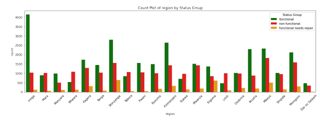
Categorical variables

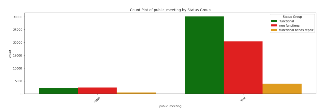
[278]:
```
# Define the categorical and numeric columns for analysis
categorical_cols = ['basin', 'region', 'public_meeting', 'permit',␣
↪'extraction_type_group', 'management', 'payment', 'water_quality',␣
↪'quantity', 'source', 'waterpoint_type', 'decade', 'installer_classified',␣
↪'funder_classified', 'district_code']
numeric_cols = ['gps_height', 'population']

# Define the number of columns in each row of subplots
num_cols_per_row = 1

# Calculate the number of rows needed for subplots
num_rows_cat = (len(categorical_cols) + num_cols_per_row - 1) //␣
↪num_cols_per_row
num_rows_num = (len(numeric_cols) + num_cols_per_row - 1) // num_cols_per_row

# Inspect the unique values in the status_group column
unique_status_groups = train_data1['status_group'].unique()
print(f"Unique status groups: {unique_status_groups}")

# Create a color palette for the status groups
# Ensure these keys match the unique values exactly
palette = {
    'functional': 'green',
    'non functional': 'red',
    'functional needs repair': 'orange'
}

# Create subplots for categorical vs. target variable
```

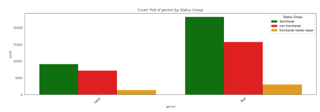
```
fig, axs_cat = plt.subplots(num_rows_cat, num_cols_per_row, figsize=(15,␣
↪num_rows_cat * 6))
axs_cat = axs_cat.flatten()

for i, col in enumerate(categorical_cols):
    if col in ['installer_classified', 'funder_classified']:
        # Filter out 'others' values
        filtered_data = train_data1[train_data1[col] != 'Others']
    else:
        filtered_data = train_data1

    sns.countplot(x=col, hue='status_group', data=filtered_data, ax=axs_cat[i],␣
↪palette=palette)
    axs_cat[i].set_title(f'Count Plot of {col} by Status Group')
    axs_cat[i].tick_params(axis='x', rotation=45)
    axs_cat[i].legend(title='Status Group', loc='upper right')

# Hide any extra subplots if the number of columns is not a multiple of␣
↪num_cols_per_row
for j in range(len(categorical_cols), num_rows_cat * num_cols_per_row):
    fig.delaxes(axs_cat[j])

plt.tight_layout()
plt.show()
```

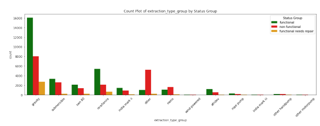
```
Unique status groups: ['functional' 'non functional' 'functional needs repair']
```

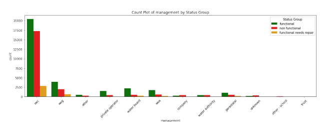

Count Plot of basin by Status Group

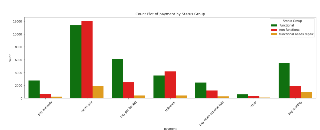

Count Plot of region by Status Group

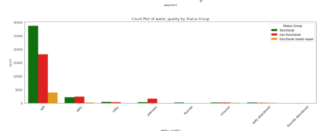

Count Plot of public_meeting by Status Group

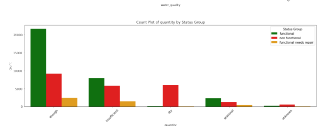

Count Plot of permit by Status Group

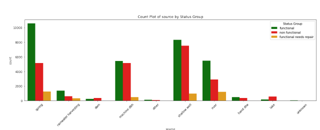

Count Plot of extraction_type_group by Status Group

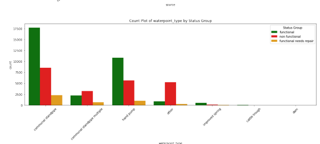

Count Plot of management by Status Group

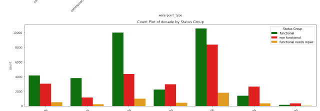

Count Plot of payment by Status Group

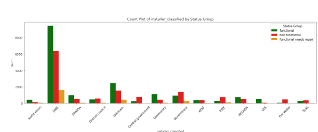

Count Plot of water_quality by Status Group

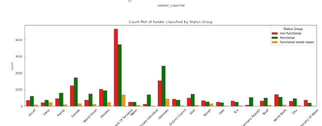

Count Plot of quantity by Status Group

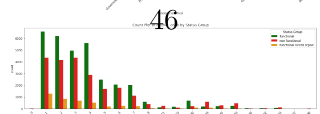

Count Plot of source by Status Group


Count Plot of waterpoint_type by Status Group


Count Plot of decade by Status Group


Count Plot of installer_classified by Status Group


Count Plot of funder_classified by Status Group

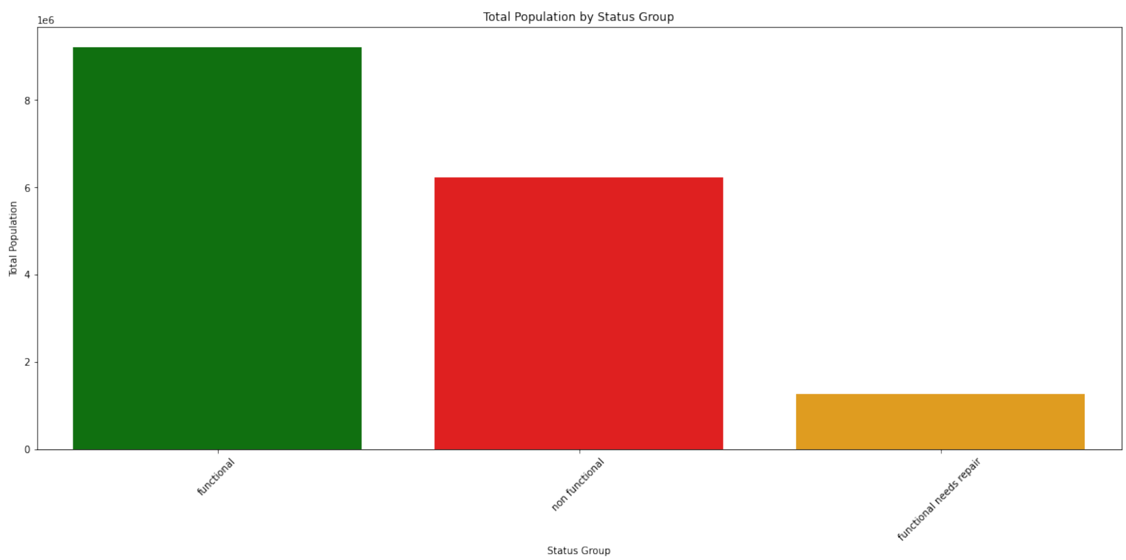


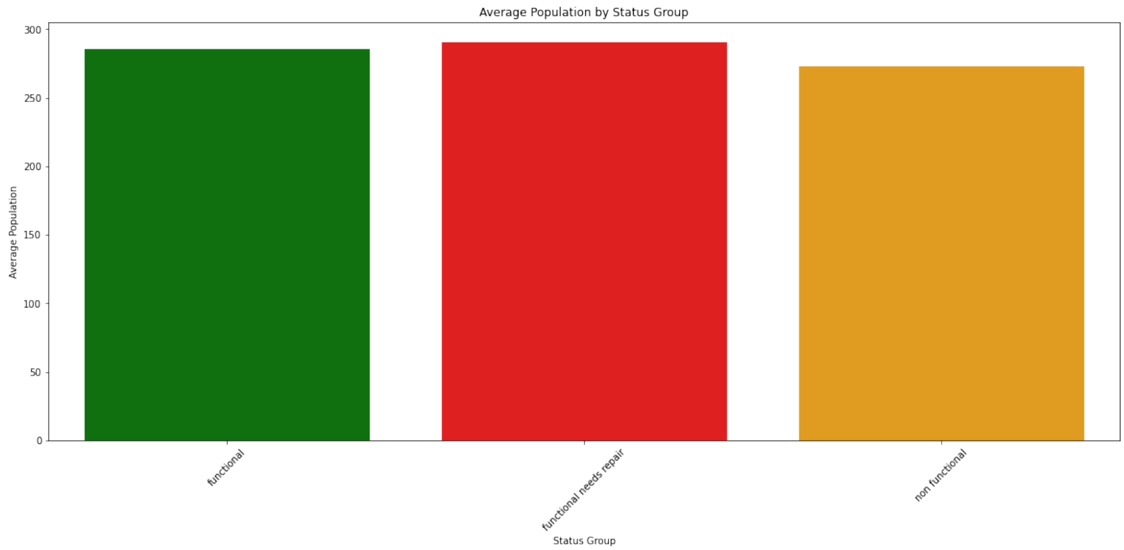
Numerical variables

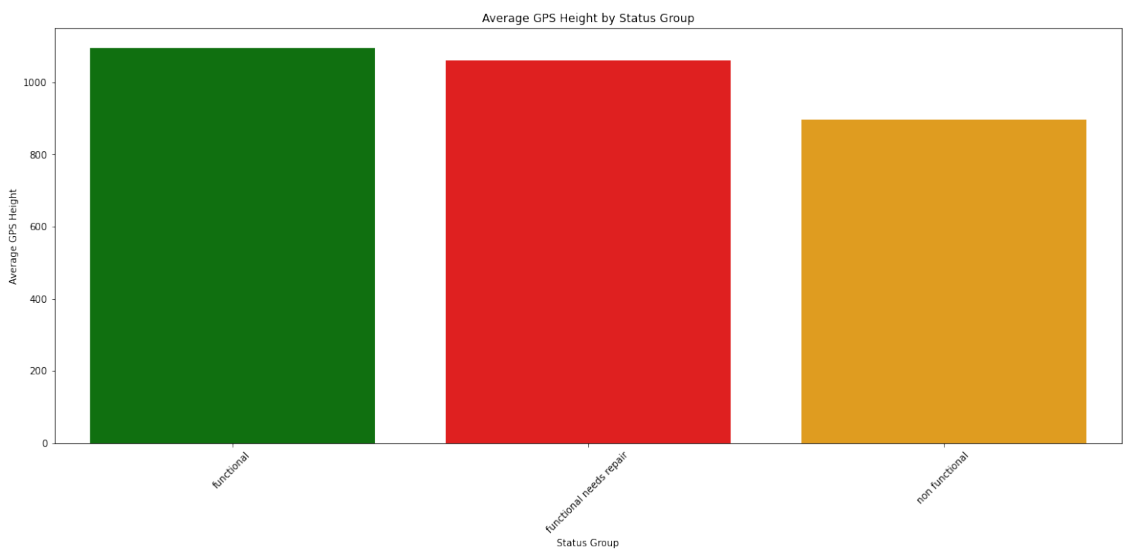
[279]:
```
# Define a color mapping for the status groups
status_colors = {
    'functional': 'green',
    'non functional': 'red',
    'functional needs repair': 'orange'
}

# Map status_group to colors
train_data1['color'] = train_data1['status_group'].map(status_colors)

# Aggregate population by status group (sum)
population_sum = train_data1.groupby('status_group')['population'].sum().
 ↪reset_index()



# Ensure the order of bars matches the status_colors keys order
status_order = ['functional', 'non functional', 'functional needs repair']
colors = [status_colors[status] for status in status_order]

# Create a bar plot
plt.figure(figsize=(20, 8))  # Adjust figure size for better spacing
sns.barplot(x='status_group', y='population', data=population_sum,␣
 ↪palette=colors, order=status_order)
plt.title('Total Population by Status Group')
plt.xlabel('Status Group')
plt.ylabel('Total Population')
plt.xticks(rotation=45)

# Show the plot
plt.show()

# Filter out rows where population is zero or missing, if needed
train_data1 = train_data1[train_data1['population'] > 0]

# Aggregate population by status group (mean)
population_mean = train_data1.groupby('status_group')['population'].mean().
 ↪reset_index()

# Create a bar plot
plt.figure(figsize=(20, 8))  # Adjust figure size for better spacing
sns.barplot(x='status_group', y='population',␣
 ↪data=population_mean,palette=colors)
plt.title('Average Population by Status Group')
```

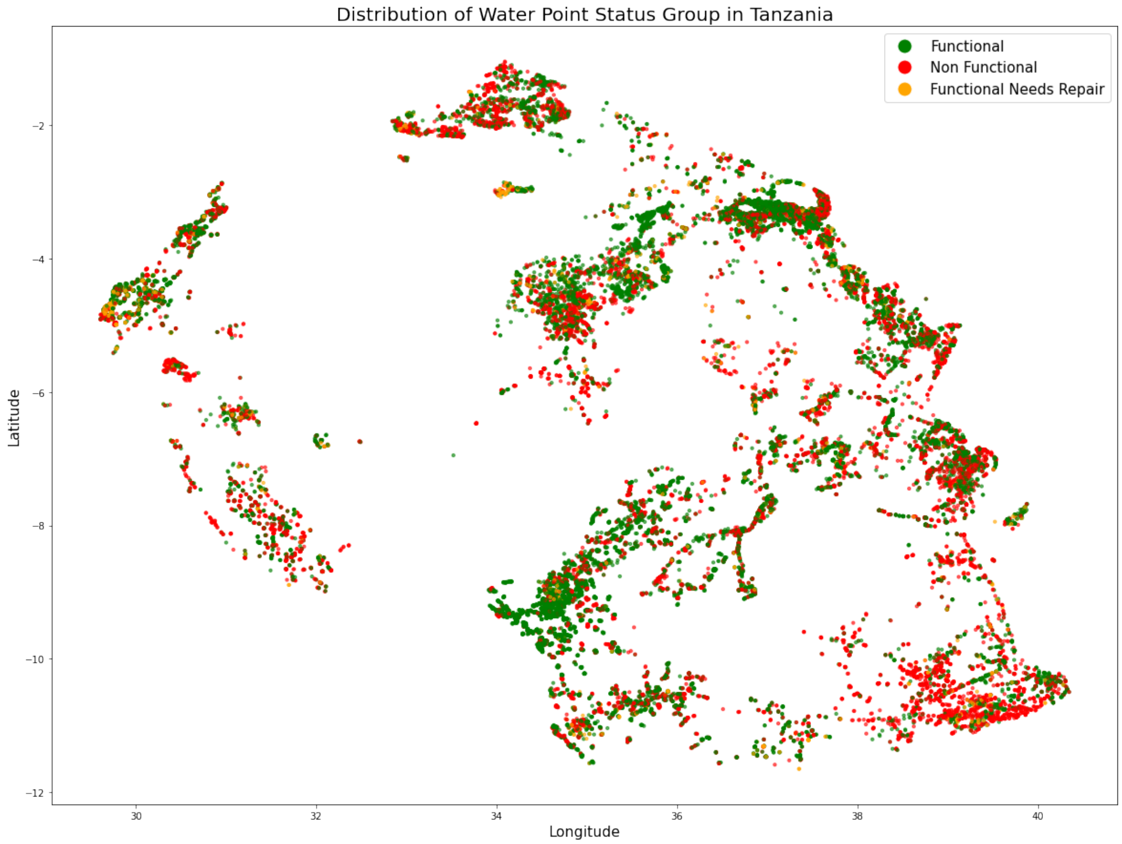
```
plt.xlabel('Status Group')
plt.ylabel('Average Population')
plt.xticks(rotation=45)

# Show the plot
plt.show()


# Ensure 'gps_height' and 'status_group' are in the dataframe
if 'gps_height' in train_data1.columns and 'status_group' in train_data1.
↪columns:
    # Filter out rows where gps_height is missing or zero, if needed
    train_data1 = train_data1[train_data1['gps_height'] != 0]

    # Aggregate gps_height by status group (mean)
    gps_height_mean = train_data1.groupby('status_group')['gps_height'].mean().
↪reset_index()

    # Create a bar plot
    plt.figure(figsize=(20, 8))  # Adjust figure size for better spacing
    sns.barplot(x='status_group', y='gps_height', data=gps_height_mean,␣
↪palette=colors)
    plt.title('Average GPS Height by Status Group')
    plt.xlabel('Status Group')
    plt.ylabel('Average GPS Height')
    plt.xticks(rotation=45)

    # Show the plot
    plt.show()
else:
    print("Columns 'gps_height' or 'status_group' not found in the dataset.")

   # Define a color mapping for the status groups
status_colors = {
    'functional': 'green',
    'non functional': 'red',
    'functional needs repair': 'orange'
}

# Map status_group to colors
train_data1['color'] = train_data1['status_group'].map(status_colors)

# Create a scatter plot
fig, ax = plt.subplots(figsize=(20, 15))  # Increase the figure size

# Plot the scatter plot
```

```python
scatter = ax.scatter(train_data1['longitude'], train_data1['latitude'], c=train_data1['color'], alpha=0.6, s=10)

# Add basemap from OpenStreetMap
# Note: This step assumes you have contextily installed and can fetch the basemap.
# Uncomment the below lines if contextily is available and installed
#import contextily as ctx
#ctx.add_basemap(ax, crs='EPSG:4326', source=ctx.providers.OpenStreetMap.Mapnik)

# Set title and labels
plt.title('Distribution of Water Point Status Group in Tanzania', fontsize=20)
plt.xlabel('Longitude', fontsize=15)
plt.ylabel('Latitude', fontsize=15)

# Create a custom legend
legend_elements = [
    Line2D([0], [0], marker='o', color='w', label='Functional', markerfacecolor='green', markersize=15),
    Line2D([0], [0], marker='o', color='w', label='Non Functional', markerfacecolor='red', markersize=15),
    Line2D([0], [0], marker='o', color='w', label='Functional Needs Repair', markerfacecolor='orange', markersize=15)
]

ax.legend(handles=legend_elements, loc='upper right', fontsize=15)

plt.show()
```



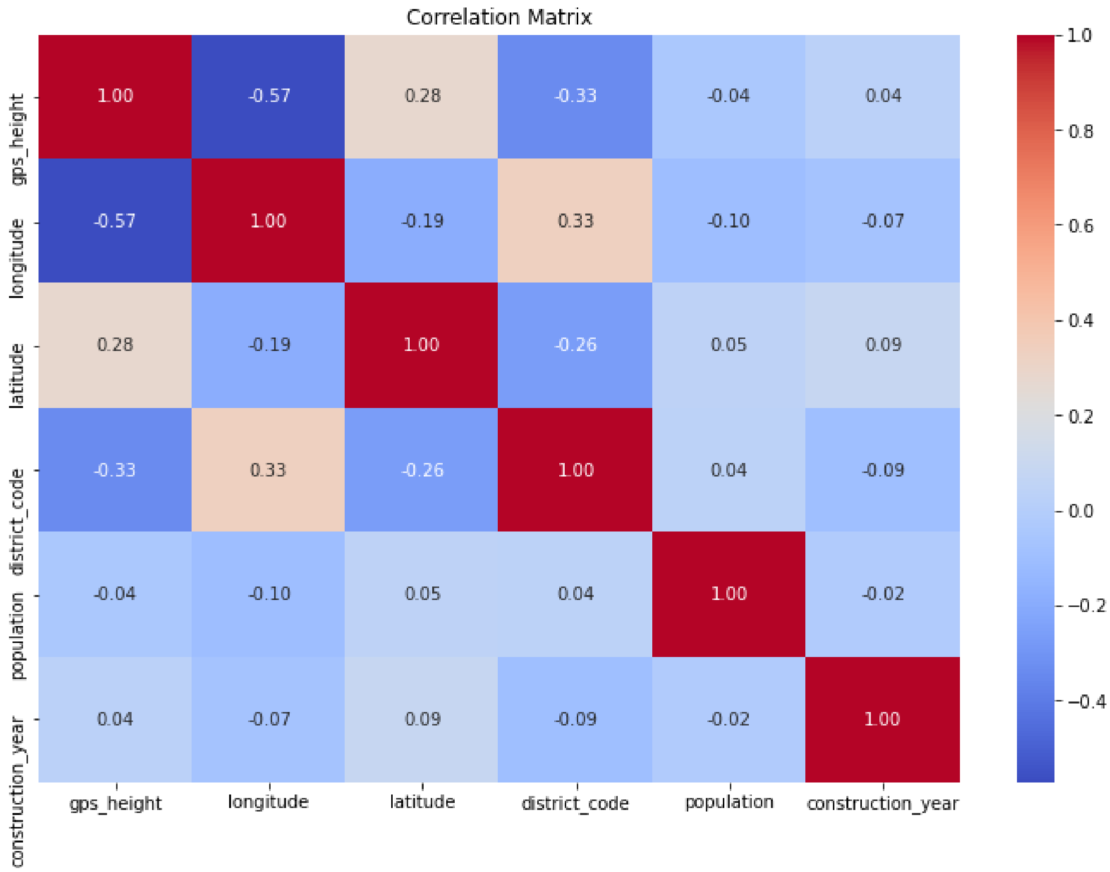

Average Population by Status Group
Average Population
0
50
100
150
200
250
300
functional
functional needs repair
non functional
Status Group


Average GPS Height by Status Group
Average GPS Height
0
200
400
600
800
1000
functional
functional needs repair
non functional
Status Group



0.5.3 Multivariate Analysis

[280]:
```
# Select only numeric columns for correlation computation
numeric_cols = train_data1.select_dtypes(include=['float64', 'int64']).columns
numeric_data = train_data1[numeric_cols]

# Compute the correlation matrix
correlation_matrix = numeric_data.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Observations

1. Government-funded wells often exhibit a higher likelihood of being non-functional, highlighting a need for improved oversight or maintenance practices in these projects.
2. Areas with higher populations tend to have a greater number of functional wells, indicating a correlation between population density and well functionality.
3. Certain areas show a higher probability of accessing clean water, particularly those situated near good water basins, highlighting the importance of geographical location in water quality.
4. Despite being one of the most densely populated cities, Dar es Salaam has a significant portion (35%) of clean water sources classified as non-functional, indicating challenges in maintaining water infrastructure.
5. Iringa, an important area, has a notable number of non-functional water points with soft water, suggesting potential issues with water quality or infrastructure maintenance in this region.
6. Water points installed by central government and district councils also show a tendency towards non-functionality, indicating potential systemic issues in water infrastructure management at the governmental level.

7. While gravity-based extraction is the most common type, hand pumps, which are less efficient, rank second. This suggests a need for authorities to focus on upgrading or maintaining pumping infrastructure, particularly for gravity-based systems that are naturally reliant on gravitational forces.
8. Some water points with sufficient and soft water are non-functional, indicating that water quality alone may not guarantee well functionality and that other factors like maintenance play a crucial role.
9. Recent years have seen a higher proportion of functional wells compared to older ones, but there are still functional wells that require repair. This underscores the importance of timely maintenance to prevent functional wells from deteriorating into non-functional ones.
10. Many water wells with ample water resources are non-functional, highlighting potential issues with infrastructure or operational aspects rather than water availability.

Recommendations

1. Targeted Maintenance: Prioritize maintenance in densely populated areas and near good water basins, focusing on government-funded wells and central installations.
2. Water Quality Focus: Improve water quality monitoring and treatment, especially in areas with soft water but high non-functionality rates like Iringa.
3. Pumping Infrastructure Investment: Upgrade pumping infrastructure, particularly hand pumps and gravity systems, to enhance efficiency and reduce non-functional wells.

0.6 Modelling

[281]:
```
train_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 38962 entries, 0 to 59399
Data columns (total 26 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   funder                 38962 non-null  object
 1   gps_height             38962 non-null  int64
 2   installer              38962 non-null  object
 3   longitude              38962 non-null  float64
 4   latitude               38962 non-null  float64
 5   basin                  38962 non-null  object
 6   region                 38962 non-null  object
 7   district_code          38962 non-null  int64
 8   lga                    38962 non-null  object
 9   ward                   38962 non-null  object
 10  population             38962 non-null  int64
 11  public_meeting         38962 non-null  bool
 12  permit                 38962 non-null  bool
 13  construction_year      38962 non-null  int64
 14  extraction_type_group  38962 non-null  object
```

```
 15  management             38962 non-null  object
 16  payment                38962 non-null  object
 17  water_quality          38962 non-null  object
 18  quantity               38962 non-null  object
 19  source                 38962 non-null  object
 20  waterpoint_type        38962 non-null  object
 21  status_group           38962 non-null  object
 22  decade                 38962 non-null  object
 23  installer_classified   38962 non-null  object
 24  funder_classified      38962 non-null  object
 25  color                  38962 non-null  object
dtypes: bool(2), float64(2), int64(4), object(18)
memory usage: 7.5+ MB
```

0.6.1 Drop columns that are not necessary for our modeling

[282]:
```
train_data1.
↪drop(columns=['funder','installer','construction_year','color','lga','ward'],inplace=True␣
↪)
```

[283]:
```
train_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 38962 entries, 0 to 59399
Data columns (total 20 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   gps_height             38962 non-null  int64
 1   longitude              38962 non-null  float64
 2   latitude               38962 non-null  float64
 3   basin                  38962 non-null  object
 4   region                 38962 non-null  object
 5   district_code          38962 non-null  int64
 6   population             38962 non-null  int64
 7   public_meeting         38962 non-null  bool
 8   permit                 38962 non-null  bool
 9   extraction_type_group  38962 non-null  object
 10  management             38962 non-null  object
 11  payment                38962 non-null  object
 12  water_quality          38962 non-null  object
 13  quantity               38962 non-null  object
 14  source                 38962 non-null  object
 15  waterpoint_type        38962 non-null  object
 16  status_group           38962 non-null  object
 17  decade                 38962 non-null  object
 18  installer_classified   38962 non-null  object
 19  funder_classified      38962 non-null  object
dtypes: bool(2), float64(2), int64(3), object(13)
```

```
memory usage: 5.7+ MB
```

[284]:
```python
# Convert public_meeting, permit to 0 and 1
# Convert 'permit' and 'public_meeting' to binary (0 and 1)
train_data1['permit'] = train_data1['permit'].map({True: 1, False: 0})
train_data1['public_meeting'] = train_data1['public_meeting'].map({True: 1,␣
 ↪False: 0})
train_data1.head()
```

[284]:
```
    gps_height  longitude   latitude                    basin   region  \
0         1390  34.938093  -9.856322               Lake Nyasa   Iringa
1         1399  34.698766  -2.147466            Lake Victoria     Mara
2          686  37.460664  -3.821329                  Pangani  Manyara
3          263  38.486161 -11.155298  Ruvuma / Southern Coast   Mtwara
10          62  39.209518  -7.034139              Wami / Ruvu    Pwani

    district_code  population  public_meeting  permit extraction_type_group  \
0               5         109               1       0               gravity
1               2         280               1       1               gravity
2               4         250               1       1               gravity
3              63          58               1       1           submersible
10             43         345               1       0           submersible

          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
10  private operator       never pay        salty        enough

                  source              waterpoint_type    status_group decade  \
0                 spring           communal standpipe      functional    90s
1    rainwater harvesting           communal standpipe      functional    10s
2                    dam  communal standpipe multiple      functional    00s
3            machine dbh  communal standpipe multiple  non functional    80s
10           machine dbh                        other      functional    10s

   installer_classified funder_classified
0                Others            Others
1                Others            Others
2          world vision            Others
3                Others            Unicef
10               Others            Others
```

[285]:
```python
train_data1['status_group'].value_counts()
```

[285]:
```
status_group
functional                 21790
non functional             14618
functional needs repair     2554
Name: count, dtype: int64
```

0.6.2 Convert target to ternary values

[286]:
```
target_status_group = {'functional':0,
                       'non functional': 2,
                       'functional needs repair': 1}
train_data1['status_group'] = train_data1['status_group'].
 ↪replace(target_status_group)
```

[287]:
```
train_data1['status_group'].value_counts()
```

[287]:
```
status_group
0    21790
2    14618
1     2554
Name: count, dtype: int64
```

0.6.3 Having my numerical,target and my categorical columns

[288]:
```
categorical_columns =␣
 ↪['basin','region','extraction_type_group','management','payment','water_quality','quantity'
              ␣
 ↪'source','waterpoint_type','decade','installer_classified','funder_classified']
```

[289]:
```
numerical_columns =␣
 ↪['gps_height','longitude','latitude','district_code','population','public_meeting','permit'
```

[290]:
```
target='status_group'
```

0.6.4 Logistics Regression Model

Assumptions

1. Linearity: Assumes a linear relationship between the independent variables and the log-odds of the dependent variable.
2. Independence of Errors: Assumes that the errors (residuals) of the observations are independent.
3. No Multicollinearity: Assumes that the independent variables are not highly correlated with each other. Multicollinearity can inflate the variance of coefficient estimates and make the model unstable.
4. Homoscedasticity: Assumes constant variance of errors.

5. Binary Outcome: Assumes the outcome variable is binary (can be extended to multinomial logistic regression for multiple classes).

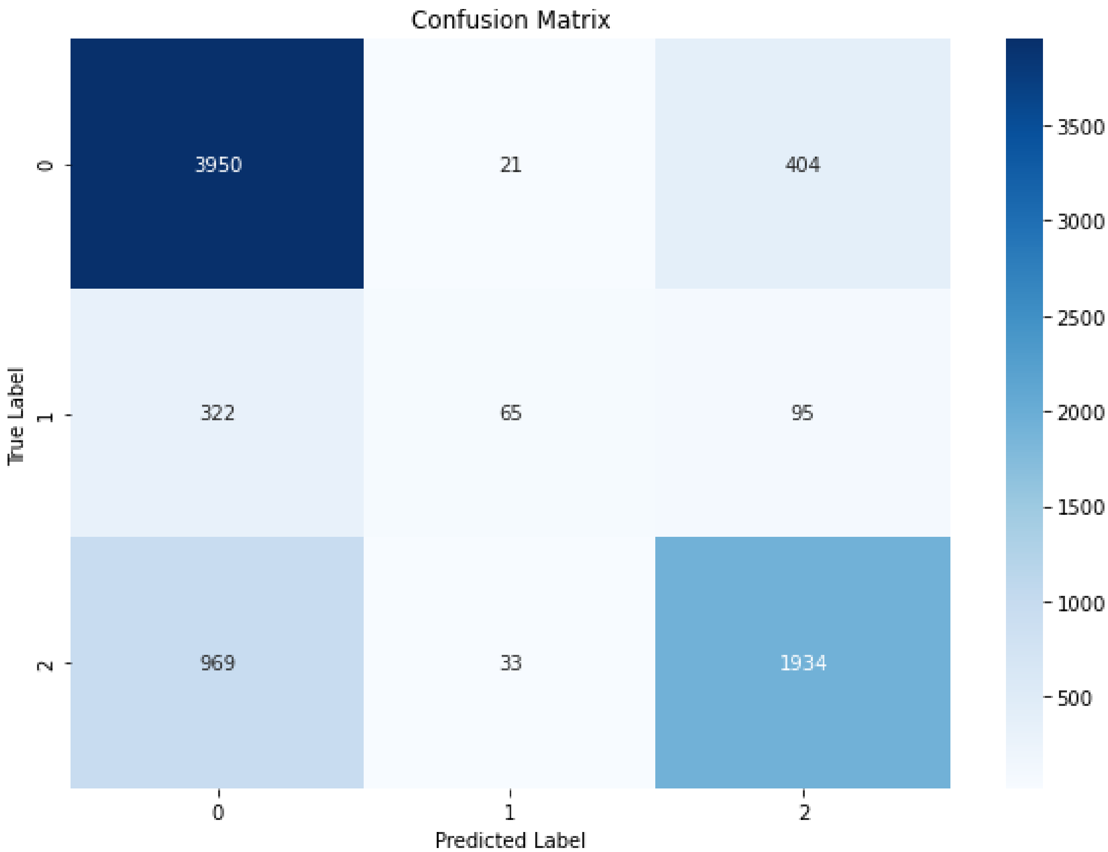
[291]:
```
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,␣
↪confusion_matrix,balanced_accuracy_score
from sklearn.impute import SimpleImputer
from scipy.stats import uniform
from sklearn.svm import SVC
```

[292]:
```
# Separate features and target
X = train_data1[categorical_columns + numerical_columns]
y = train_data1[target]
```

[293]:
```
# Define preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_columns)
    ])

# Define pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(max_iter=1000))
])

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

# Fit the model
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred = pipeline.predict(X_test)

y_pred_train = pipeline.predict(X_train)

# Evaluate the model
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
```

```
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))


# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=pipeline.
 ↪classes_, yticklabels=pipeline.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 0.7608842118771857
Test Accuracy: 0.7633773899653535
Balance Train Accuracy: 0.5641972764919815
Balance Test Accuracy: 0.5654770868968072
```

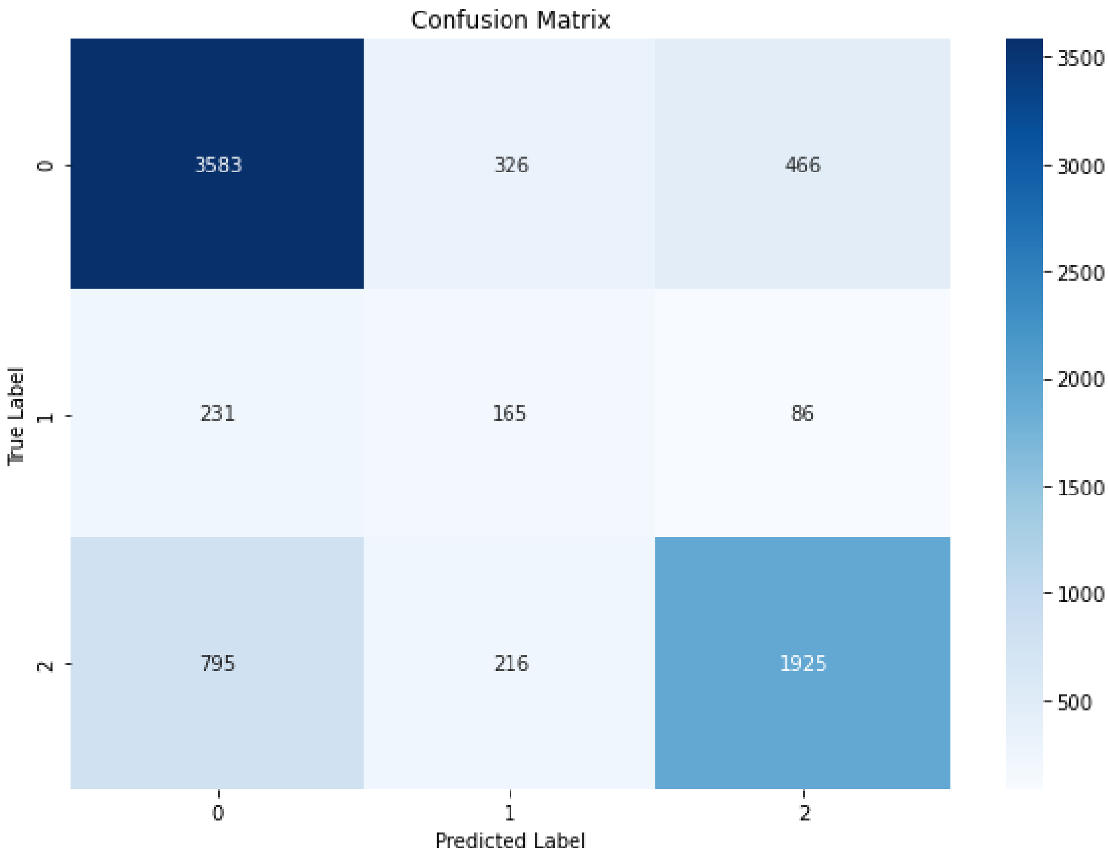


0.6.5 Tuned Logistic Regression Model

[294]:
```
# Define preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_columns)
    ])

# Define pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier',␣
 ↪LogisticRegression(class_weight='balanced',solver='liblinear',max_iter=1000))
])

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

# Manually tune parameters
best_score = 0
best_params = {}
for C in [0.001, 0.01, 0.1, 1, 10]:
    for penalty in ['l1', 'l2']:
        try:
            # Set parameters
            pipeline.set_params(classifier__C=C, classifier__penalty=penalty)
            # Train model
            pipeline.fit(X_train, y_train)
            # Evaluate model
            score = accuracy_score(y_test, pipeline.predict(X_test))

            # Update best parameters
            if score > best_score:
                best_score = score
                best_params = {'C': C, 'penalty': penalty}
        except ValueError as e:
            pass


# Train the best model
pipeline.set_params(classifier__C=best_params['C'],␣
 ↪classifier__penalty=best_params['penalty'])
pipeline.fit(X_train, y_train)

# Predict and evaluate
```

```
y_pred = pipeline.predict(X_test)
y_pred_train = pipeline.predict(X_train)

# Evaluate the model
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))


# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=pipeline.
 ↪classes_, yticklabels=pipeline.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 0.7338701915364625
Test Accuracy: 0.727960990632619
Balance Train Accuracy: 0.6191026542009768
Balance Test Accuracy: 0.6056496769924631
```



0.6.6 Decision tree Model

Assuptions

1. Independence of Observations: Assumes that the observations in the dataset are independent of each other.
2. No Assumption on Feature Distribution: Decision Trees do not make assumptions about the distribution of the data.
3. Sufficient Data: Requires a large enough dataset to adequately split and create meaningful branches.
4. Minimal Preprocessing: Can handle both numerical and categorical data, and does not require data scaling or normalization.
5. Non-Linearity: Can capture non-linear relationships between features and the target variable.

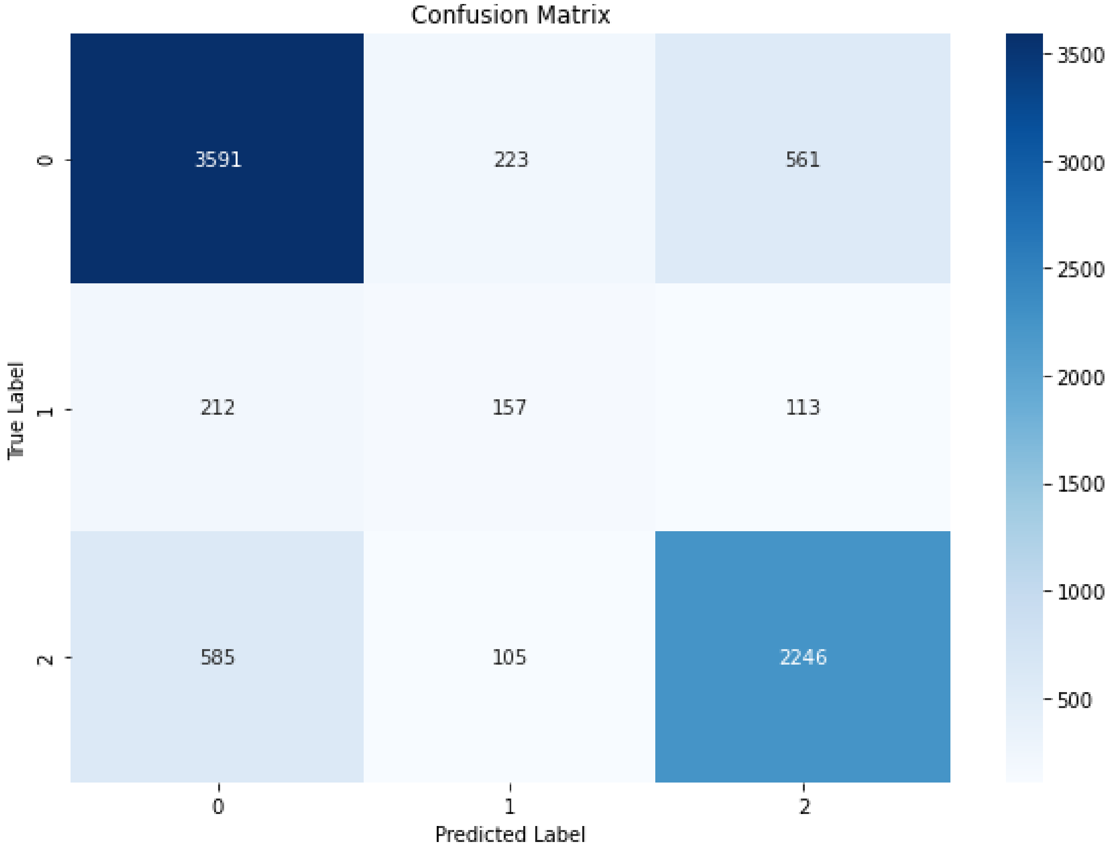
[295]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.metrics import classification_report,␣
↪confusion_matrix,balanced_accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
```

[296]:
```python
# Preprocess the categorical and numerical columns
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(), categorical_columns)
    ])

# Create the decision tree pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', DecisionTreeClassifier(random_state=42))
])

# Train the model
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred = pipeline.predict(X_test)
y_pred_train = pipeline.predict(X_train)

# Evaluate the model
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))


# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
↪xticklabels=pipeline.classes_, yticklabels=pipeline.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 1.0
Test Accuracy: 0.7691518029000385
Balance Train Accuracy: 1.0
```

Balance Test Accuracy: 0.6371708390335455



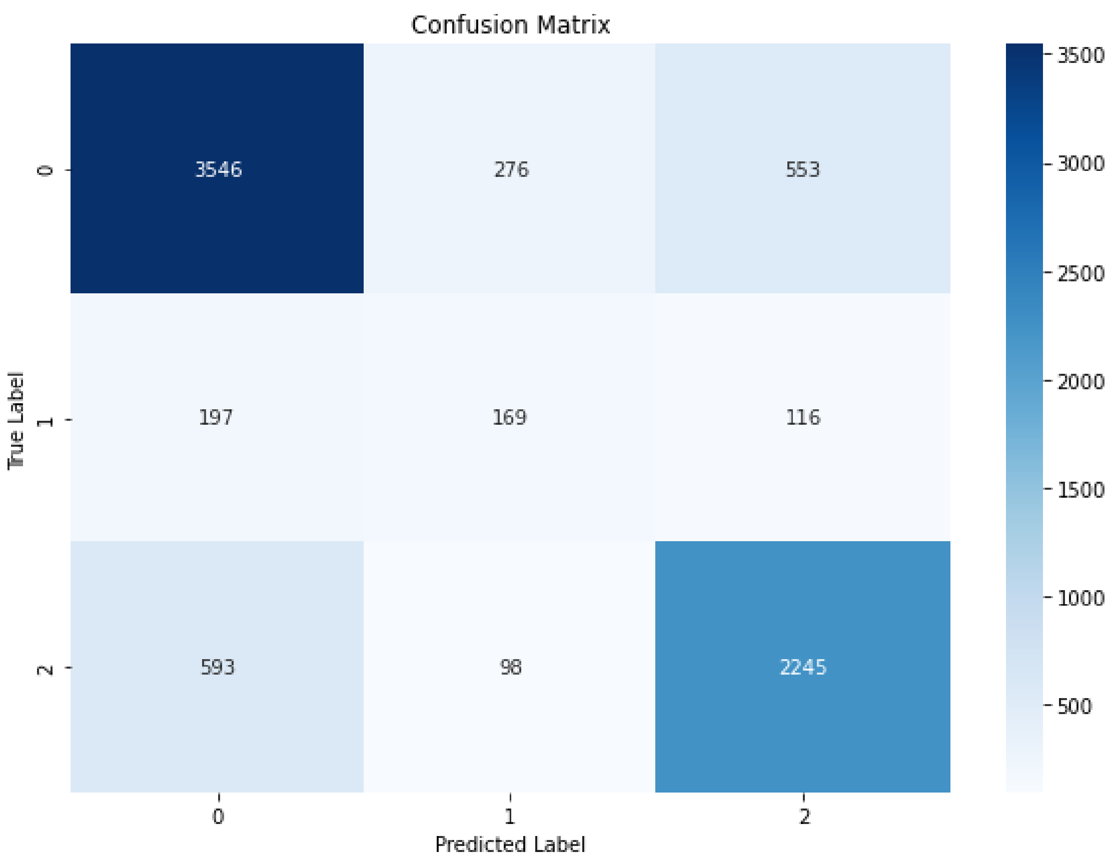
0.7 Tuned Decision Tree Model

[297]:
```
# Preprocess the categorical and numerical columns
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(), categorical_columns)
    ])

# Create the decision tree pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier',␣
↪DecisionTreeClassifier(class_weight='balanced',random_state=42))
])

# Define a range of hyperparameters to search over
criteria = ['gini', 'entropy']
```

```
max_depths = [None, 10, 20, 30]
min_samples_splits = [2, 5, 10]
min_samples_leaves = [1, 2, 4]

best_score = 0
best_params = {}

# Manually tune hyperparameters
for criterion in criteria:
    for max_depth in max_depths:
        for min_samples_split in min_samples_splits:
            for min_samples_leaf in min_samples_leaves:
                # Set parameters
                pipeline.set_params(
                    classifier__criterion=criterion,
                    classifier__max_depth=max_depth,
                    classifier__min_samples_split=min_samples_split,
                    classifier__min_samples_leaf=min_samples_leaf
                )
                # Train model
                pipeline.fit(X_train, y_train)
                # Evaluate model
                score = accuracy_score(y_test, pipeline.predict(X_test))
                # Update best parameters
                if score > best_score:
                    best_score = score
                    best_params = {
                        'criterion': criterion,
                        'max_depth': max_depth,
                        'min_samples_split': min_samples_split,
                        'min_samples_leaf': min_samples_leaf
                    }

# Train the best model
pipeline.set_params(
    classifier__criterion=best_params['criterion'],
    classifier__max_depth=best_params['max_depth'],
    classifier__min_samples_split=best_params['min_samples_split'],
    classifier__min_samples_leaf=best_params['min_samples_leaf']
)
pipeline.fit(X_train, y_train)

# Predict and evaluate
y_pred = pipeline.predict(X_test)
y_pred_train = pipeline.predict(X_train)

# Evaluate the model
```

```python
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))


# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
↪xticklabels=pipeline.classes_, yticklabels=pipeline.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 0.9904392184542333
Test Accuracy: 0.7647889131271655
Balance Train Accuracy: 0.9933755576465688
Balance Test Accuracy: 0.6419274896400157
```



0.7.1 Support Vector Machine Model

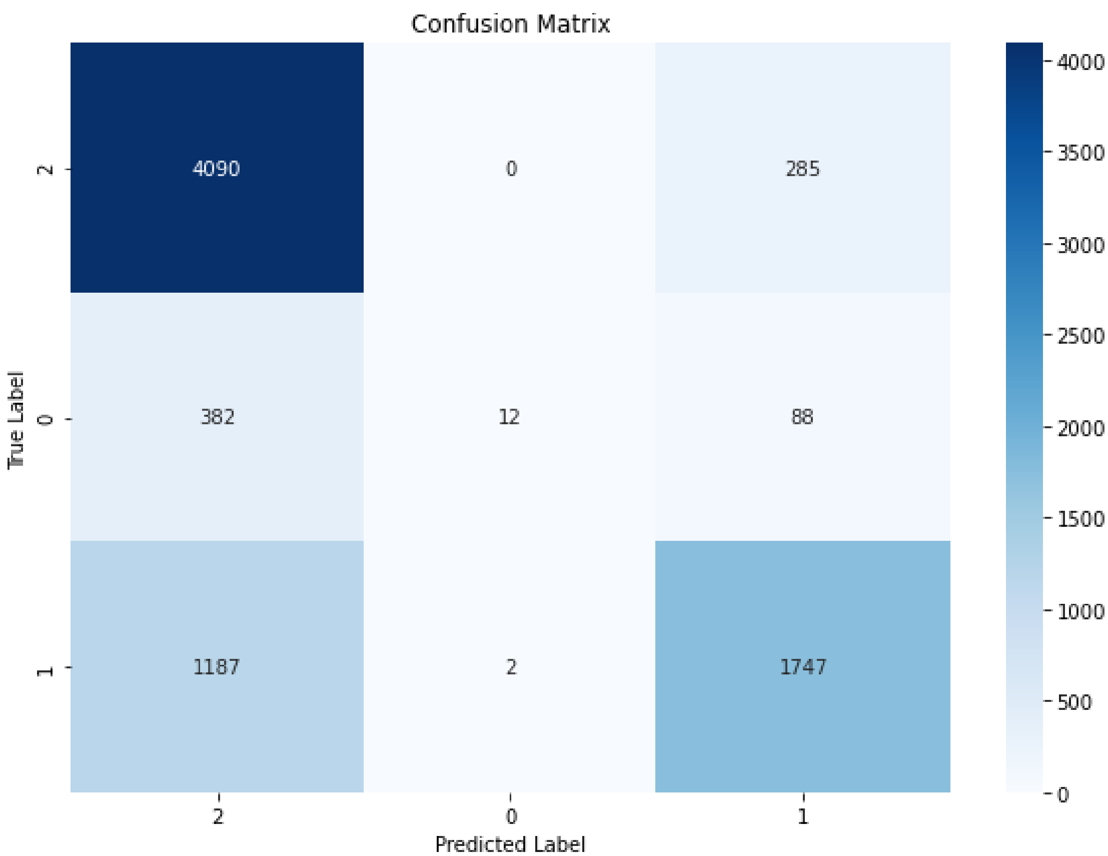
Assunptions

1. Linearly Separable Data (for Linear SVM): Assumes that the data is linearly separable if using a linear kernel.
2. Margin Maximization: SVM tries to find the hyperplane that maximizes the margin between the classes.
3. Kernel Trick (for Non-Linear SVM): Assumes that the kernel function can transform the data into a higher-dimensional space where it is linearly separable.
4. Feature Scaling: Assumes that the data is scaled properly. SVMs are sensitive to the scale of the input features.
5. Independence of Observations: Assumes that the observations are independent of each other.

[298]:
```python
# Preprocess the categorical and numerical columns
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(), categorical_columns)
    ])

# Create the SVM pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', SVC(kernel='linear', random_state=42))
])

# Train the model
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred = pipeline.predict(X_test)
y_pred_train = pipeline.predict(X_train)


# Evaluate the model
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))


# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
# Get the unique classes from the target
classes = y_train.unique()

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=classes, yticklabels=classes)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 0.7499117713112388
Test Accuracy: 0.7505453612216091
Balance Train Accuracy: 0.5193383759702246
Balance Test Accuracy: 0.5182602187912374
```



0.7.2 Random Forest Machine Learning Model

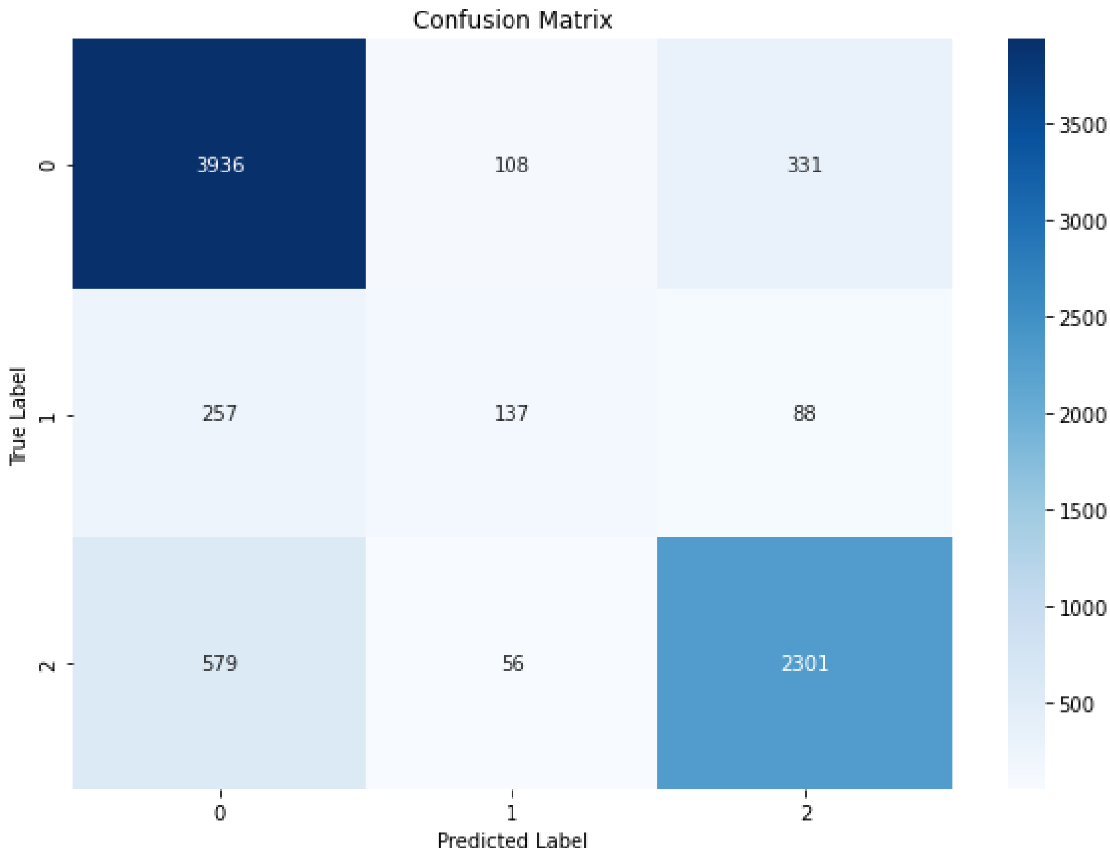
Assumptions

1. Independence of Observations: Assumes that the observations in the dataset are independent of each other.
2. No Assumption on Distribution: Unlike some models, Random Forest does not make strong assumptions about the distribution of the data.
3. Feature Importance: Assumes that some features are more important than others, and the model will try to identify and leverage these important features.
4. Sufficient Data: Requires a sufficiently large dataset to build diverse and effective trees.
5. Minimal Preprocessing: Can handle missing values and does not require much preprocessing (like scaling) of the data.

[299]:
```
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler, OneHotEncoder,RobustScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline,make_pipeline
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, balanced_accuracy_score,␣
↪confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import category_encoders as ce

# Assuming X and y are your features and target variables
X = pd.DataFrame(X, columns=numerical_columns + categorical_columns)
y = pd.Series(y, name=target)

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

# choosing scaler and encoder
scaler=RobustScaler()
encoder = ce.TargetEncoder(cols=categorical_columns)

# putting numeric columns to scaler and categorical to encoder
num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)

# Preprocess the categorical and numerical columns
preprocessor = ColumnTransformer(
      transformers=[('num', num_transformer, numerical_columns),
                    ('cat', cat_transformer, categorical_columns)])

# Create the Random Forest pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
```

```
])

# Train the model
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred = pipeline.predict(X_test)
y_pred_train = pipeline.predict(X_train)

# Evaluate the model
print('Train Accuracy:', accuracy_score(y_train, y_pred_train))
print('Test Accuracy:', accuracy_score(y_test, y_pred))
print('Balance Train Accuracy:', balanced_accuracy_score(y_train, y_pred_train))
print('Balance Test Accuracy:', balanced_accuracy_score(y_test, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=pipeline.classes_, yticklabels=pipeline.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Train Accuracy: 0.9999679168404505
Test Accuracy: 0.8179135121262672
Balance Train Accuracy: 0.9998391248391248
Balance Test Accuracy: 0.6558696180171392
```



Tuning Random forest Model- My Final Model

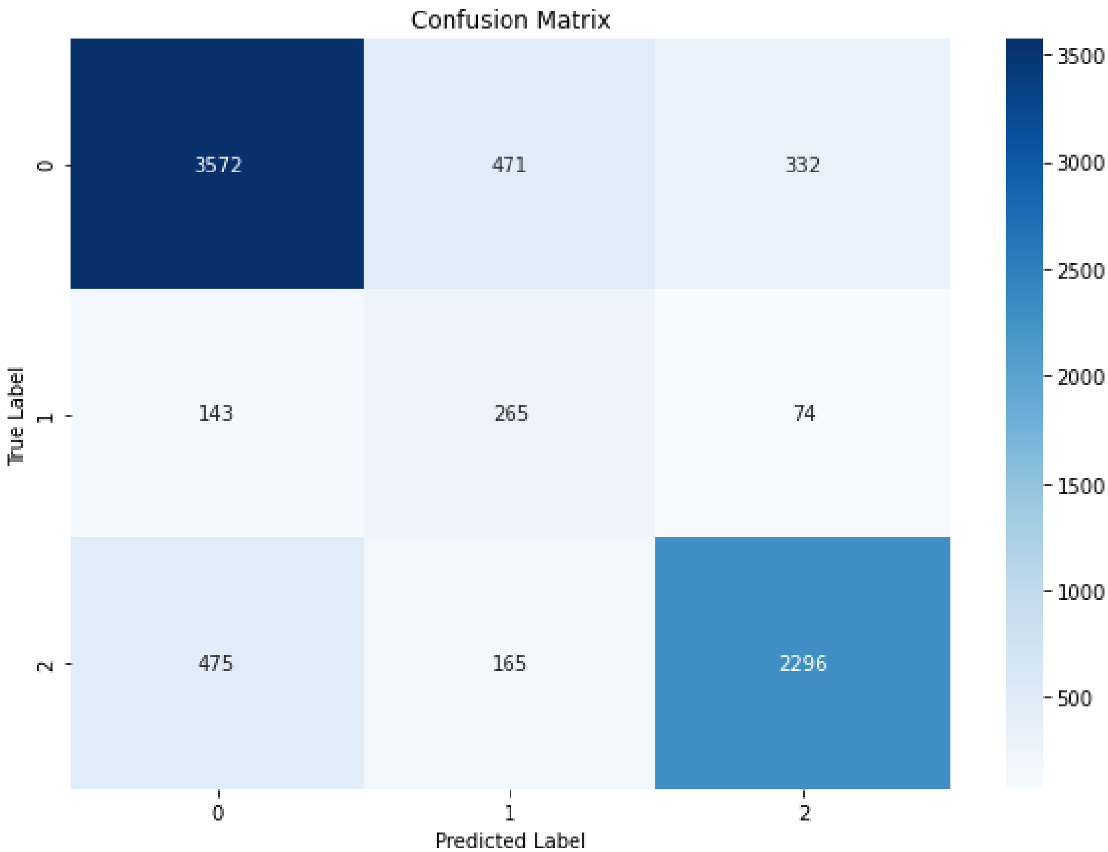
[300]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, balanced_accuracy_score,␣
↪confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
import category_encoders as ce


# Split 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)

# Identify numerical and categorical columns
```

```
numerical_columns = X.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()
categorical_columns = X.select_dtypes(include=['object']).columns.tolist()

# Choosing scaler and encoder
scaler = RobustScaler()
encoder = ce.TargetEncoder(cols=categorical_columns)

# Putting numeric columns to scaler and categorical to encoder
num_transformer = make_pipeline(scaler)
cat_transformer = make_pipeline(encoder)

# Getting together our scaler and encoder with preprocessor
preprocessor = ColumnTransformer(
    transformers=[('num', num_transformer, numerical_columns),
                  ('cat', cat_transformer, categorical_columns)]
)

# Set RandomForestClassifier with initial parameters
rf = RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1,
                            criterion='entropy', max_features='sqrt',
                            min_samples_split=10, class_weight='balanced')

# Giving all values to pipeline
pipeline = make_pipeline(preprocessor, rf)

# Define hyperparameter ranges
n_estimators_options = [100, 200]
max_depth_options = [None, 10, 20]
min_samples_split_options = [2, 5]
min_samples_leaf_options = [2, 4]
max_features_options = ['sqrt']
bootstrap_options = [True, False]

best_score = 0
best_params = {}

# Loop through all combinations of hyperparameters
for n_estimators in n_estimators_options:
    for max_depth in max_depth_options:
        for min_samples_split in min_samples_split_options:
            for min_samples_leaf in min_samples_leaf_options:
                for max_features in max_features_options:
                    for bootstrap in bootstrap_options:
                        # Update the model in the pipeline
                        pipeline.
 ↪set_params(randomforestclassifier__n_estimators=n_estimators,
```

```
                                                   ␣
↪randomforestclassifier__max_depth=max_depth,
                                                   ␣
↪randomforestclassifier__min_samples_split=min_samples_split,
                                                   ␣
↪randomforestclassifier__min_samples_leaf=min_samples_leaf,
                                                   ␣
↪randomforestclassifier__max_features=max_features,
                                                   ␣
↪randomforestclassifier__bootstrap=bootstrap)

                        # Train the model
                        pipeline.fit(X_train, y_train)

                        # Predict on the test set
                        y_test_pred = pipeline.predict(X_test)

                        # Evaluate the model
                        score = balanced_accuracy_score(y_test, y_test_pred)

                        # If the current score is better than the best score,␣
↪update best score and best params
                        if score > best_score:
                            best_score = score
                            best_params = {
                                'n_estimators': n_estimators,
                                'max_depth': max_depth,
                                'min_samples_split': min_samples_split,
                                'min_samples_leaf': min_samples_leaf,
                                'max_features': max_features,
                                'bootstrap': bootstrap
                            }

# Print the best hyperparameters
print("Best Hyperparameters:", best_params)

# Train the final model with the best hyperparameters on the entire training set
pipeline.
↪set_params(randomforestclassifier__n_estimators=best_params['n_estimators'],
                    randomforestclassifier__max_depth=best_params['max_depth'],
                   ␣
↪randomforestclassifier__min_samples_split=best_params['min_samples_split'],
                   ␣
↪randomforestclassifier__min_samples_leaf=best_params['min_samples_leaf'],
                   ␣
↪randomforestclassifier__max_features=best_params['max_features'],
```

```python
                    randomforestclassifier__bootstrap=best_params['bootstrap'])

pipeline.fit(X_train, y_train)

# Predictions on train set
y_pred = pipeline.predict(X_train)

# Predictions on test set
y_pred_test = pipeline.predict(X_test)

# Evaluate the model
train_accuracy = accuracy_score(y_train, y_pred)
test_accuracy = accuracy_score(y_test, y_pred_test)
balance_train_accuracy = balanced_accuracy_score(y_train, y_pred)
balance_test_accuracy = balanced_accuracy_score(y_test, y_pred_test)
print(f"Train Accuracy: {train_accuracy:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
print(f"Balanced Train Accuracy: {balance_train_accuracy:.4f}")
print(f"Balanced Test Accuracy: {balance_test_accuracy:.4f}")

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_test)

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=pipeline.
 ↪named_steps['randomforestclassifier'].classes_, yticklabels=pipeline.
 ↪named_steps['randomforestclassifier'].classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Best Hyperparameters: {'n_estimators': 200, 'max_depth': 20,
'min_samples_split': 2, 'min_samples_leaf': 4, 'max_features': 'sqrt',
'bootstrap': False}
Train Accuracy: 0.9025
Test Accuracy: 0.7870
Balanced Train Accuracy: 0.9310
Balanced Test Accuracy: 0.7161
```



0.7.3 Conclusion on my final model- Random Forest

The final model is a RandomForestClassifier with tuned hyperparameters trained on a dataset split into training and testing sets. The hyperparameters were tuned using an exhaustive search through various combinations to find the ones that maximize the balanced accuracy score on the test set. The best hyperparameters identified were as follows: 'n_estimators': 200, 'max_depth': 20, 'min_samples_split': 2, 'min_samples_leaf': 4, 'max_features': 'sqrt', 'bootstrap': False.

The model achieved a decent level of performance, with a test accuracy of 78.70% and a balanced test accuracy of 71.61%. These metrics indicate that the model generalizes reasonably well to unseen data and is not overfitting excessively to the training set. The balanced accuracy score is particularly useful in scenarios where classes are imbalanced, as it takes into account the imbalance and provides a more reliable measure of overall model performance.

The confusion matrix plot visualizes how well the model is predicting each class. It shows the number of true positives, true negatives, false positives, and false negatives for each class, allowing for a deeper understanding of the model's strengths and weaknesses in classification. Overall, the final model appears to be a solid choice for the given dataset and task.

0.7.4 Predictive Analysis of Tanzanian Water Well Conditions

Model Performance The classifier built to predict the condition of water wells in Tanzania achieved a test accuracy of 78.70% and a balanced test accuracy of 71.61%. These metrics suggest that the model performs reasonably well in identifying the condition of water wells based on features

Important Features The most important features identified by the model include the type of pump used, the installation year, and possibly other geographic or environmental factors. Understanding these key features can help stakeholders prioritize maintenance and repair efforts for water wells.

Useful Predictions For an NGO focused on locating wells needing repair, the model's predictions can be highly valuable. By identifying non-functional or deteriorating wells accurately, the NGO can allocate resources more efficiently and effectively, ensuring that clean water access is maintained or restored where needed most.

Recommendations for Stakeholders:

1. Modify Input Variables: Based on the model's insights, stakeholders could consider modifying certain input variables. For example, investing in newer pump technologies or improving maintenance schedules for wells installed in specific years could lead to better overall well conditions.
2. Target Results: The model can help stakeholders set specific targets for well conditions. By analyzing patterns in non-functional wells, they can influence how new wells are built, ensuring they are more resilient and require less frequent repairs.
3. Geographical Considerations: Considering geographic or environmental factors that influence well conditions can further enhance the model's predictive capabilities. For instance, areas with certain soil types or rainfall patterns may require different pump types or maintenance strategies.

In conclusion, the predictive model offers valuable insights into the condition of Tanzanian water wells, aiding stakeholders in making informed decisions regarding maintenance, repair, and future well construction strategies.

0.7.5 Next Steps

1. Validation and Deployment of Model: Validate the predictive model using additional datasets or real-time data to ensure its accuracy and reliability. Once validated, deploy the model for ongoing monitoring and prediction of water well conditions.
2. Actionable Insights Implementation: Implement actionable insights derived from the EDA analysis, such as prioritizing maintenance in high-population areas, improving water quality monitoring, and investing in pumping infrastructure. Collaborate with stakeholders and authorities to translate these insights into practical initiatives.
3. Continuous Improvement: Continuously evaluate and improve the model based on feedback and new data. Incorporate feedback from field teams, stakeholders, and ongoing data collection to refine the model's predictive capabilities and enhance decision-making related to water well management