Tanzania_water_wells_project / Data cleaning.ipynb

Kamaukaguru pdf, markdowns updates 7ff08ea · 4 hours ago

3711 lines (3711 loc) · 334 KB

3	45559	0.0	22/01/2013	Finn Water	267	WATER	38.058046	-
4	49871	500.0	27/03/2013	Bruder	1260	BRUDER	35.006123	-1

5 rows × 40 columns

The dataset has 14,850 rows and 40 columns.

In [80]:
```
#check the data types of DataFrame columns in our training set values.
data_type_counts = check_data_types(test_data)
print("Count of columns for each data type category:")
print(data_type_counts)
```

```
Count of columns for each data type category:
{'string': 30, dtype('int64'): 7, dtype('float64'): 3}
```

The dataset is divided into three data types categories:

1. String(object type) which has 30 columns
2. Integer type which has 7 columns
3. Float type which has 3 columns

1.4 Merging the training set values and training set labels

In [81]:
```
# merging the training set values and training set labels on the 'id' column
train_data = pd.merge(df1, df2, on='id')
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   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
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
```

In [82]:
```
#Check the distribution of the target variable(status_group)
train_data['status_group'].value_counts()
```

Out[82]:
```
status_group
functional                 32259
non functional             22824
functional needs repair     4317
Name: count, dtype: int64
```

Data Cleaning

In this, both my training data and test data will be cleaned in the same way, e.g.,the number of columns dropped in the training data will equal the number of columns dropped in the test data.

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Preview Code Blame Raw

In [83]:
```
train_data['num_private'].value_counts()
```

Out[83]:
```
num_private
0       58643
6          81
1          73
5          46
8          46
         ...
42          1
23          1
136         1
698         1
1402        1
```

```
Name: count, Length: 65, dtype: int64
```

Over 99% of the data = 0. I choose to drop the column entirely.

In [84]:
```
#drop the column 'num_private'
train_data.drop(columns=['num_private'],inplace=True)
```

I will drop the recorded by column.

In [85]:
```
#drop the column 'recorded_by'
train_data.drop(columns=['recorded_by'], inplace=True)
```

Next I explore columns with similar column names and descriptions. This will help me establish whether its the same information.

In [86]:
```
#Explore columns with similar column names and descriptions to see if there is
def explore_similar_columns(df, col1, col2):
    """
    Explore columns with similar names in the DataFrame and return the value c

    Parameters:
    - df (DataFrame): The DataFrame containing the columns.
    - col1 (str): The name of the first column.
    - col2 (str): The name of the second column.

    Returns:
    - col1_value_counts (Series): Value counts of the first column.
    - col2_value_counts (Series): Value counts of the second column.
    """
    # Ensure the specified columns exist in the DataFrame
    if col1 not in df.columns or col2 not in df.columns:
        raise ValueError(f"One or both of the columns '{col1}' and '{col2}' do

    # Get value counts for both columns
    col1_value_counts = df[col1].value_counts()
    col2_value_counts = df[col2].value_counts()

    return col1_value_counts, col2_value_counts
```

1. Payment and Payment_type

In [87]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'pa
print(col1_value_counts)

print(col2_value_counts)
```

```
payment
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
```

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

The two columns have similar information in the dataset. I will drop the payment type.

In [88]:
```
train_data.drop(columns=['payment_type'], inplace=True)
```

2. Quantity and quantity group

In [89]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'qu
print(col1_value_counts)

print(col2_value_counts)
```

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

The column 'quantity' and 'quantity_group' have similar names and descriptions, so I can drop one of them.

In [90]:
```
train_data.drop(columns=['quantity_group'], inplace=True)
```

3. Waterpoint_type and waterpoint_type group

In [91]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'wa
print(col1_value_counts)

print(col2_value_counts)
```

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

Similar names and descriptions. I will keep the columns because one of the keys - communal standpipe has different values.

4. Source ,source_type and source_type_group

In [92]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'so
print(col1_value_counts)

print(col2_value_counts)
```

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

In [93]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'so
print(col1_value_counts)

print(col2_value_counts)
```

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

I drop the source_type and source_class columns since they contain similar information to the source column, which is more detailed.

In [94]:
```
train_data.drop(columns=['source_type', 'source_class'], inplace=True)
```

5. Extraction_type, extraction_typ_group,extraction_type_name

In [95]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'ex
print(col1_value_counts)

print(col2_value_counts)
```

```
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
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
```

In [96]:

```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'ex
print(col1_value_counts)

print(col2_value_counts)
```

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

I will keep the extraction_type and extraction_type_name columns. I will go ahead and drop the extraction_type_group column.

In [97]:

```
train_data.drop(columns=['extraction_type_group'], inplace=True)
```

6. Waterpoint_type and waterpoint_type_group

In [98]:
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'wa
print(col1_value_counts)

print(col2_value_counts)
```

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

I will drop the water_type_group column

In [99]:
```
#drop the column 'waterpoint_type_group'
train_data.drop(columns=['waterpoint_type_group'], inplace=True)
```

7. Quality and Water_quality

In [100…
```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'qu
print(col1_value_counts)

print(col2_value_counts)
```

```
quality_group
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: count, dtype: int64
water_quality
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: count, dtype: int64
```

I will drop the column 'quality_group' as it has the same values as the column 'water_quality'

In [101…

```
#drop the column 'quality_group'
train_data.drop(columns=['quality_group'], inplace=True)
```

Next, we explore null values and decide how to clean nulls.

In [102…

```
def check_nulls_and_duplicates(df):
    # Calculate the number of null values in each column
    null_counts = df.isnull().sum()

    # Calculate the total number of rows
    total_rows = len(df)

    # Calculate the percentage of null values in each column
    null_percentage = (null_counts / total_rows) * 100

    # Display message about columns with null values
    columns_with_null = null_counts[null_counts > 0]
    if not columns_with_null.empty:
        print("Columns with null values and their count/percentage:")
        for column, count in columns_with_null.items():
            percentage = null_percentage[column]
            print(f"{column}: {count} ({percentage:.2f}%)")
    else:
        print("No null values")

    # Calculate the number of duplicate rows
    num_duplicates = df.duplicated().sum()

    # Display the number of duplicate rows
    print(f"Number of duplicate rows: {num_duplicates}")

    return num_duplicates
```

In [103…

```
# Check for null values and duplicates
check_nulls_and_duplicates(train_data)
```

```
Columns with null values and their count/percentage:
funder: 3637 (6.12%)
installer: 3655 (6.15%)
wpt_name: 2 (0.00%)
subvillage: 371 (0.62%)
public_meeting: 3334 (5.61%)
scheme_management: 3878 (6.53%)
scheme_name: 28810 (48.50%)
permit: 3056 (5.14%)
Number of duplicate rows: 0
```

Out[103… 0

From the above output, i will explore the scheme_management and scheme_names further by checking the value counts of each.

In [104…

```
col1_value_counts, col2_value_counts = explore_similar_columns(train_data, 'sc
print(col1_value_counts)

print(col2_value_counts)
```

```
scheme_name
K                        682
Borehole                 546
Chalinze wate            405
M                        400
DANIDA                   379
                        ...
Mradi wa maji Vijini       1
Villagers                  1
Magundi water supply       1
Saadani Chumv              1
Mtawanya                   1
Name: count, Length: 2695, dtype: int64
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
```

I will drop scheme name since scheme management captures similar data more cleanly with fewer nulls.

In [105…

```
train_data.drop(columns=['scheme_name'], inplace=True)
```

I will go ahead and replace the null values in the coulmns with about 5% or 6% of null values with "unknown"

In [106…

```
columns_to_fill = ['funder', 'installer', 'public_meeting', 'scheme_management

for column in columns_to_fill:
    train_data[column] = train_data[column].fillna(value='Unknown')
```

I will also drop the null values in the wpt_name and subvillage columns.

In [107…

```
train_data.dropna(subset=['wpt_name', 'subvillage'], inplace=True)
```

Finally, i will check the values in the permit column.

In [108…
```
train_data['permit'].value_counts()
```

Out[108…
```
permit
True     38791
False    17180
Name: count, dtype: int64
```

I will replace the null values with the mode.

In [109…
```
train_data['permit'] = train_data['permit'].fillna(value=True)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_16868\1024742864.py:1: FutureWarning:
Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated and wil
l change in a future version. Call result.infer_objects(copy=False) instead. To
opt-in to the future behavior, set `pd.set_option('future.no_silent_downcastin
g', True)`
  train_data['permit'] = train_data['permit'].fillna(value=True)
```

In [110…
```
check_nulls_and_duplicates(train_data)
```

```
No null values
Number of duplicate rows: 0
```

Out[110…
```
0
```

Next step is to check the year of construction

In [111…
```
train_data['construction_year'].value_counts()
```

Out[111…
```
construction_year
0       20347
2010     2644
2008     2613
2009     2533
2000     2091
2007     1586
2006     1471
2003     1286
2011     1254
2004     1123
2012     1083
2002     1075
1978     1037
1995     1013
2005     1009
1999      978
1998      966
1990      954
1985      945
1980      811
1996      811
1984      779
1982      744
1994      738
1972      707
1974      676
1997      644
```

```
1992      640
1993      608
2001      539
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
```

From the above output I can see that the construction year is 0 for 20347 rows. This is a huge perentage of our data. Next is to get the median of the column without the 20347 rows.

In [112…

```
# Create an object to hold column construction_year with year 0
train_data1 = train_data['construction_year']
train_data1.describe()
```

Out[112…

```
count    59027.000000
mean      1308.498297
std        949.092135
min          0.000000
25%          0.000000
50%       1986.000000
75%       2004.000000
max       2013.000000
Name: construction_year, dtype: float64
```

In [113…

```
# check the column construction_year without year 0
train_data1 = train_data1[train_data1 != 0]
train_data1.describe()
```

Out[113…

```
count    38680.000000
mean      1996.813056
std         12.472071
min       1960.000000
25%       1987.000000
50%       2000.000000
```

```
75%       2008.000000
max       2013.000000
Name: construction_year, dtype: float64
```

In [114…

```
#Change the data type of construction_year to int
train_data['construction_year'] = train_data['construction_year'].astype(int)
# Replace 0 with 2000,
train_data['construction_year'] = train_data['construction_year'].replace(0, 2
```

In [115…

```
#check the column construction_year after cleaning the data
train_data['construction_year'].value_counts()
```

Out[115…

```
construction_year
2000    22438
2010     2644
2008     2613
2009     2533
2007     1586
2006     1471
2003     1286
2011     1254
2004     1123
2012     1083
2002     1075
1978     1037
1995     1013
2005     1009
1999      978
1998      966
1990      954
1985      945
1996      811
1980      811
1984      779
1982      744
1994      738
1972      707
1974      676
1997      644
1992      640
1993      608
2001      539
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
```

Create an age column. Drop the contruction year column

In [116…

```
# create column age
train_data['age'] = 2024 - train_data['construction_year']

# drop column construction_year
train_data.drop(columns=['construction_year'], inplace=True)
train_data.head()
```

Out[116…

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lat
0	69572	6000.0	14/03/2011	Roman	1390	Roman	34.938093	-9.8
1	8776	0.0	06/03/2013	Grumeti	1399	GRUMETI	34.698766	-2.1
2	34310	25.0	25/02/2013	Lottery Club	686	World vision	37.460664	-3.8
3	67743	0.0	28/01/2013	Unicef	263	UNICEF	38.486161	-11.1
4	19728	0.0	13/07/2011	Action In A	0	Artisan	31.130847	-1.8

5 rows × 31 columns

In [117…

```
#We will check the region_code column
train_data['region_code'].value_counts()
```

Out[117…

```
region_code
11    5300
17    5010
12    4639
3     4378
5     4040
18    3324
19    3037
2     3024
16    2816
```

```
10    2640
4     2513
13    2093
14    1979
20    1969
1     1840
15    1808
6     1609
21    1583
80    1238
60    1025
90     917
7      805
99     423
9      390
24     326
8      300
40       1
Name: count, dtype: int64
```

In [118…

```
# Drop the row with value as 40 since it will be hard to split the value
train_data = train_data[train_data['region_code'] != 40]
```

I will drop the following columns: iga, ward, region,id, management_group, source.

In [119…

```
columns_to_drop = ['lga', 'ward', 'region','date_recorded', 'longitude','latit

# Drop specified columns
train_data.drop(columns=columns_to_drop, inplace=True)

#change the permit column to object
```

We will check the funders and installer columns in details.

In [120…

```
#check the column funder, 50 most frequent values
train_data.funder.value_counts()[:50]
```

Out[120…

```
funder
Government Of Tanzania           9014
Unknown                          3641
Danida                           3114
Hesawa                           2200
Rwssp                            1374
Kkkt                             1286
World Vision                     1246
World Bank                       1244
Unicef                           1057
Tasaf                             876
District Council                  843
Dhv                               829
Private Individual                825
Dwsp                              811
0                                 777
Norad                             765
Germany Republi                   610
```

```
Germany Republi                 610
Tcrs                            602
Ministry Of Water               590
Water                           510
Dwe                             484
Netherlands                     470
Hifab                           450
Adb                             447
Lga                             442
Amref                           425
Fini Water                      393
Oxfam                           359
Wateraid                        333
Rc Church                       321
Isf                             316
Rudep                           312
Mission                         301
Private                         294
Jaica                           280
Roman                           275
Rural Water Supply And Sanitat  270
Adra                            263
Ces(gmbh)                       260
Jica                            259
Shipo                           241
Wsdp                            233
Rc                              230
Finw                            219
Dh                              213
Ded                             198
Plan Int                        195
Kiliwater                       189
Dmdd                            186
Go                              181
Name: count, dtype: int64
```

In [121…

```
# Replace 0 with Unknown
train_data['funder'] = train_data['funder'].replace(to_replace='0', value='Unk
```

In [122…

```
#check the column installer, 50 most frequent values
train_data.installer.value_counts()[:50]
```

Out[122…

```
installer
DWE                     17361
Unknown                  3658
Government               1825
RWE                      1205
DANIDA                   1050
KKKT                      898
Commu                     894
Hesawa                    840
0                         777
TCRS                      707
Central government        622
CES                       610
Community                 553
DANID                     552
District Council          551
```

```
District Council          551
HESAWA                    539
LGA                       408
World vision              408
WEDECO                    397
TASAF                     396
District council          392
Gover                     352
AMREF                     329
TWESA                     316
WU                        301
Dmdd                      287
ACRA                      278
World Vision              270
SEMA                      249
DW                        246
OXFAM                     234
Da                        224
Gove                      222
Idara ya maji             222
UNICEF                    222
Sengerema Water Department  214
Kiliwater                 210
NORAD                     208
FinW                      208
DH                        202
Villagers                 199
DWSP                      192
Distri                    181
Lawatefuka water sup      179
Magadini-Makiwaru wa      175
RC                        174
FW                        173
KKKT _ Konde and DWE      166
Centr                     162
WVT                       158
Name: count, dtype: int64
```

In [123…

```
# Replace 0 with Unknown
train_data['installer'] = train_data['installer'].replace(to_replace='0', valu
```

In [124…

```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 59026 entries, 0 to 59399
Data columns (total 20 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             59026 non-null  float64
 1   funder                 59026 non-null  object 
 2   gps_height             59026 non-null  int64  
 3   installer              59026 non-null  object 
 4   basin                  59026 non-null  object 
 5   region_code            59026 non-null  int64  
 6   district_code          59026 non-null  int64  
 7   population             59026 non-null  int64  
 8   public_meeting         59026 non-null  object 
 9   scheme_management      59026 non-null  object 
```

```
 10  permit                 59026 non-null  bool
 11  extraction_type_class  59026 non-null  object
 12  management             59026 non-null  object
 13  payment                59026 non-null  object
 14  water_quality          59026 non-null  object
 15  quantity               59026 non-null  object
 16  source                 59026 non-null  object
 17  waterpoint_type        59026 non-null  object
 18  status_group           59026 non-null  object
 19  age                    59026 non-null  int32
dtypes: bool(1), float64(1), int32(1), int64(4), object(13)
memory usage: 8.8+ MB
```

Dealing with Outliers

In [125…

```
# check the descriptive statistics
train_data.describe()
```

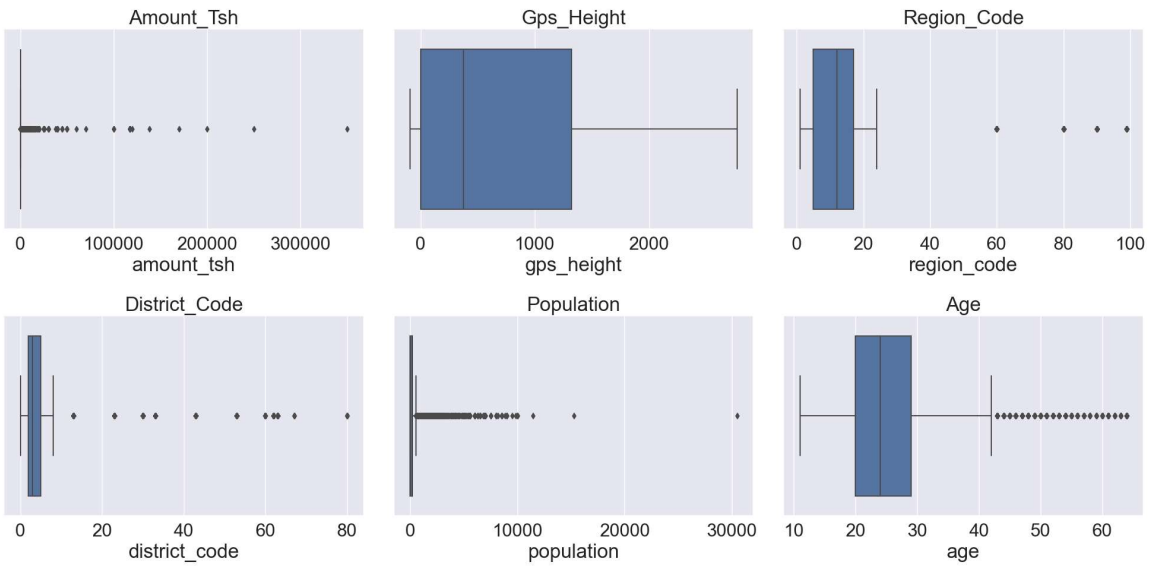
Out[125…

	amount_tsh	gps_height	region_code	district_code	population	
count	59026.000000	59026.000000	59026.000000	59026.000000	59026.000000	59026.0
mean	319.663078	672.307085	15.383577	5.645953	180.949260	26.0
std	3006.949342	693.279832	17.606927	9.660505	472.720492	10.2
min	0.000000	-90.000000	1.000000	0.000000	0.000000	11.0
25%	0.000000	0.000000	5.000000	2.000000	0.000000	20.0
50%	0.000000	377.000000	12.000000	3.000000	30.000000	24.0
75%	25.000000	1322.000000	17.000000	5.000000	220.000000	29.0
max	350000.000000	2770.000000	99.000000	80.000000	30500.000000	64.0

In [126…

```
# function to visualize outliers

def boxplot_outliers(df, cols):
    fig, axes = plt.subplots(2, 3, figsize=(20,10))
    axes = axes.ravel()
    sns.set(font_scale=2.0)
    for i, col in enumerate(cols):

        # convert the x-axis variable to a numeric data type

        df[col] = df[col].astype(float)
        sns.boxplot(x=df[col], ax=axes[i])

        axes[i].set_title(col.title())
    plt.tight_layout()

# specify the columns to plot

cols = ['amount_tsh', 'gps_height',     'region_code','district_code','populat

# call the plot_boxplots function
```

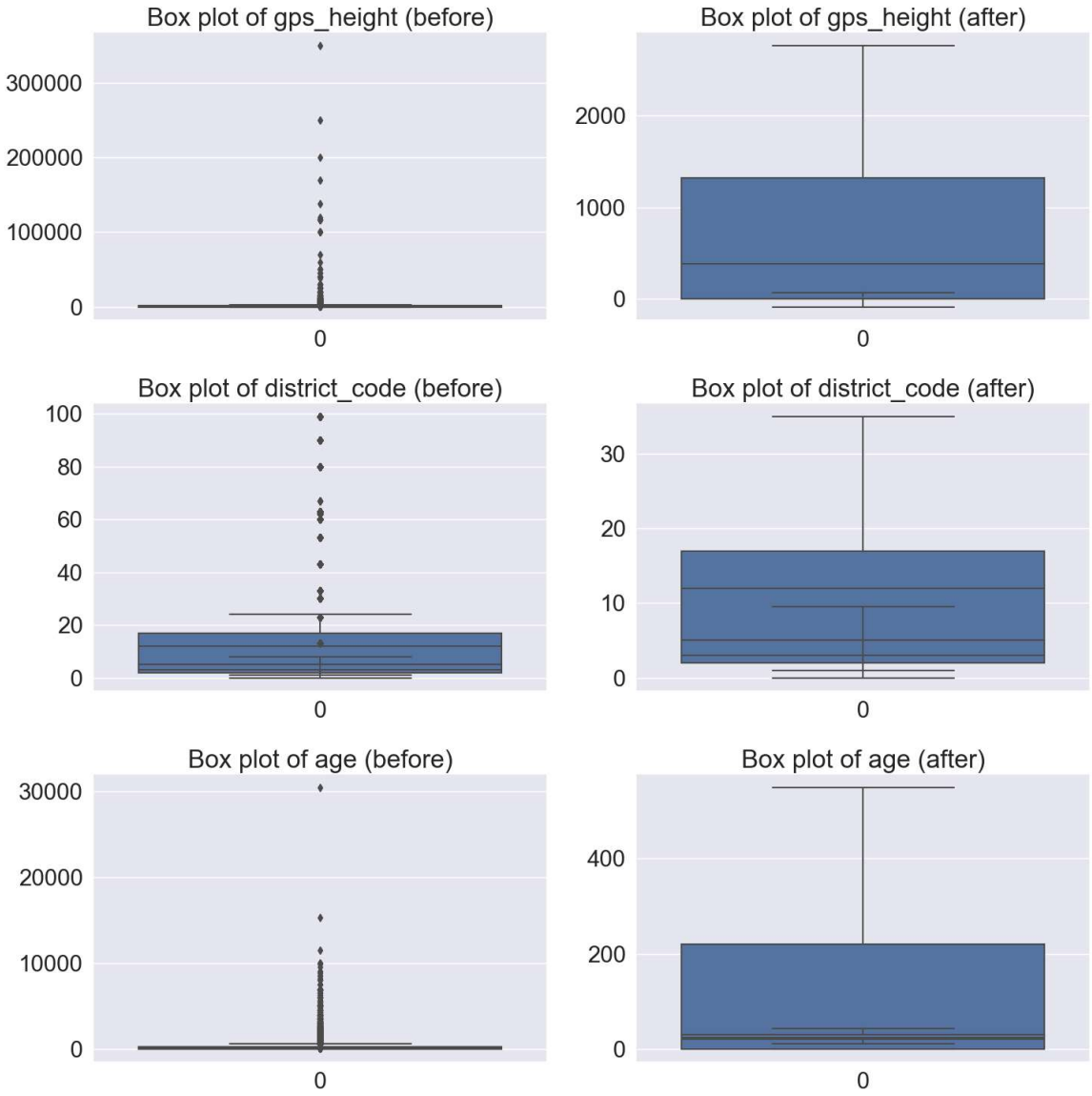
```
boxplot_outliers(train_data, cols)
```



In [127…

```
def detect_and_handle_outliers(df, method='remove'):
    # Select all numerical columns
    numerical_cols = df.select_dtypes(include=[np.number]).columns

    # Create subplots with a matrix layout
    num_plots = len(numerical_cols)
    num_rows = (num_plots + 1) // 2  # Ensure there are enough rows
    fig, axes = plt.subplots(num_rows, 2, figsize=(15, num_rows * 5))

    for i, col in enumerate(numerical_cols):
        # 1st quartile
        Q1 = np.percentile(df[col], 25)

        # 3rd quartile
        Q3 = np.percentile(df[col], 75)

        # IQR
        IQR = Q3 - Q1

        # Outlier step
        outlier_step = IQR * 1.5

        # Determine the indices of outliers
        outliers = df[(df[col] < Q1 - outlier_step) | (df[col] > Q3 + outlier_

        # Plot box plot before handling outliers
        sns.boxplot(df[col], ax=axes[i // 2, 0])
        axes[i // 2, 0].set_title(f'Box plot of {col} (before)')

        if method == 'remove':
            # Remove outliers
            df = df.drop(outliers)
        elif method == 'cap':
            # Cap outliers
            lower_cap = Q1 - outlier_step
            upper_cap = Q3 + outlier_step
            df[col] = np.where(df[col] < lower_cap, lower_cap, df[col])
            df[col] = np.where(df[col] > upper_cap, upper_cap, df[col])
```

```
            df[col] = np.where(df[col] > upper_cap, upper_cap, df[col])

        # Plot box plot after handling outliers
        sns.boxplot(df[col], ax=axes[i // 2, 1])
        axes[i // 2, 1].set_title(f'Box plot of {col} (after)')

    # Adjust layout
    plt.tight_layout()
    plt.show()

    return df

# Assuming you have your data in train_data
# train_data = pd.read_csv('path_to_your_dataset.csv')

# Detect and handle outliers
train_data_c = detect_and_handle_outliers(train_data, method='cap')
```



In [128…

```
# save the cleaned train data
train_data.to_csv('train_data_clean.csv', index=False)
```

In [144...

```
# check info about train_data_clean.csv
train_data_clean = pd.read_csv('Data/train_data_clean.csv')
train_data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59026 entries, 0 to 59025
Data columns (total 20 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             59026 non-null  float64
 1   funder                 59026 non-null  object 
 2   gps_height             59026 non-null  int64  
 3   installer              59026 non-null  object 
 4   basin                  59026 non-null  object 
 5   region_code            59026 non-null  int64  
 6   district_code          59026 non-null  int64  
 7   population             59026 non-null  int64  
 8   public_meeting         59026 non-null  object 
 9   scheme_management      59026 non-null  object 
```