Introduction

Access to clean and functional water sources is a fundamental necessity, yet many regions in Tanzania struggle to provide reliable water points for their population of over 67 million. Despite numerous water points being established across the country, a significant number are either non-functional or in need of repair. This situation hampers access to clean water, leading to health challenges, time lost in fetching water, and increased burdens on communities, particularly women and children.

This project seeks to address this issue by building a machine learning model to classify the operational status of water points. By analyzing data related to water point features such as pump type, installation details, and geographic characteristics, the project aims to predict whether a water point is functional, functional but requiring repair, or non-functional. Such insights can empower stakeholders to take targeted and proactive actions to improve water access.

+ Code + Text

Problem Statement

In Tanzania, many water points fail to provide reliable access to clean water, impacting millions of people and burdening rural communities. As a data scientist, my goal is to develop a machine learning model to predict the operational status of water points—functional, in need of repair, or non-functional. This will enable stakeholders to prioritize maintenance, allocate resources effectively, and address systemic issues, ensuring sustainable access to clean water for the population.

Objectives

General Objectives

To create a predictive model that identifies the operational status of water points in Tanzania to enhance water access and support efficient resource allocation.

Specific Objectives

> Predict Water Point Functionality: Develop a machine learning models to classify water points as functional, functional but in need of repair, or non-functional.

> Evaluate Model Performance: Assess the accuracy, precision, recall, and overall effectiveness of the models to ensure reliable predictions.

> Identify Failure Patterns: Analyze the data to uncover factors and trends contributing to water point failures.

> Optimize Resource Allocation: Provide actionable insights for stakeholders to prioritize maintenance and repair efforts effectively.

Data Understanding and Loading

The dataset originates from Taarifa and the Tanzanian Ministry of Water and was downloaded from DrivenData https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/23/. The following are set of information about the waterpoints:

amount_tsh - Total static head (amount water available to waterpoint)

date_recorded - The date the row was entered

funder - Who funded the well

gps_height - Altitude of the well

installer - Organization that installed the well

longitude - GPS coordinate

latitude - GPS coordinate

wpt_name - Name of the waterpoint if there is one

basin - Geographic water basin

subvillage - Geographic location

region - Geographic location

region_code - Geographic location (coded)

district_code - Geographic location (coded)

lga - Geographic location

ward - Geographic location

population - Population around the well

public_meeting - True/False

recorded_by - Group entering this row of data

scheme_management - Who operates the waterpoint

scheme_name - Who operates the waterpoint permit - If the waterpoint is permitted

construction_year - Year the waterpoint was constructed

extraction_type - The kind of extraction the waterpoint uses

extraction_type_group - The kind of extraction the waterpoint uses

extraction_type_class - The kind of extraction the waterpoint uses

management - How the waterpoint is managed

management_group - How the waterpoint is managed

payment - What the water costs

payment_type - What the water costs

water_quality - The quality of the water

quality_group - The quality of the water

quantity - The quantity of water

quantity_group - The quantity of water

source - The source of the water

source_type - The source of the water

source_class - The source of the water

waterpoint_type - The kind of waterpoint

waterpoint_type_group - The kind of waterpoint

```
#Important Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import FunctionTransformer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, PolynomialFeatures
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
```

```
train_values = pd.read_csv("Train_values.csv")
train_values.head()
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitud
0	69572	6000.0	3/14/2011	Roman	1390	Roman	34.938093	-9.85632
1	8776	0.0	3/6/2013	Grumeti	1399	GRUMETI	34.698766	-2.14746
2	34310	25.0	2/25/2013	Lottery Club	686	World vision	37.460664	-3.82132
3	67743	0.0	1/28/2013	Unicef	263	UNICEF	38.486161	-11.15529
4	19728	0.0	7/13/2011	Action In A	0	Artisan	31.130847	-1.82535

5 rows × 40 columns

```
train_labels = pd.read_csv("Train_labels.csv")
train_labels.head()
```

	id	status_group
0	69572	functional
1	8776	functional
2	34310	functional
3	67743	non functional
4	19728	functional

```
test_values = pd.read_csv("Test_values.csv")
test_values.head()
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lati
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.05
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.30
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.00
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.41
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.95

5 rows × 40 columns

```
train_df = train_values.merge(train_labels, on= 'id')
train_df.head(10)
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latituc
0	69572	6000.0	3/14/2011	Roman	1390	Roman	34.938093	-9.85632
1	8776	0.0	3/6/2013	Grumeti	1399	GRUMETI	34.698766	-2.14746
2	34310	25.0	2/25/2013	Lottery Club	686	World vision	37.460664	-3.82132
3	67743	0.0	1/28/2013	Unicef	263	UNICEF	38.486161	-11.15529
4	19728	0.0	7/13/2011	Action In A	0	Artisan	31.130847	-1.82535
5	9944	20.0	3/13/2011	Mkinga Distric Coun	0	DWE	39.172796	-4.76558
6	19816	0.0	10/1/2012	Dwsp	0	DWSP	33.362410	-3.76636
7	54551	0.0	10/9/2012	Rwssp	0	DWE	32.620617	-4.22619
8	53934	0.0	11/3/2012	Wateraid	0	Water Aid	32.711100	-5.14671
9	46144	0.0	8/3/2011	Isingiro Ho	0	Artisan	30.626991	-1.25705

10 rows × 41 columns

id, wpt_name, recorded_by and num_private

```
train_df.columns
```

```
Index(['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'],
      dtype='object')
```

```
train_df.shape
```

```
(59400, 41)
```

```
train_df.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
```

```
train_df.describe().T
```

	count	mean	std	min	25%	5(
id	59400.0	37115.131768	21453.128371	0.00000	18519.750000	37061.5000(
amount_tsh	59400.0	317.650385	2997.574558	0.00000	0.000000	0.0000(
gps_height	59400.0	668.297239	693.116350	-90.00000	0.000000	369.0000(
longitude	59400.0	34.077427	6.567432	0.00000	33.090347	34.90874
latitude	59400.0	-5.706033	2.946019	-11.64944	-8.540621	-5.0215(
num_private	59400.0	0.474141	12.236230	0.00000	0.000000	0.0000(
region_code	59400.0	15.297003	17.587406	1.00000	5.000000	12.0000(
district_code	59400.0	5.629747	9.633649	0.00000	2.000000	3.0000(
population	59400.0	179.909983	471.482176	0.00000	0.000000	25.0000(

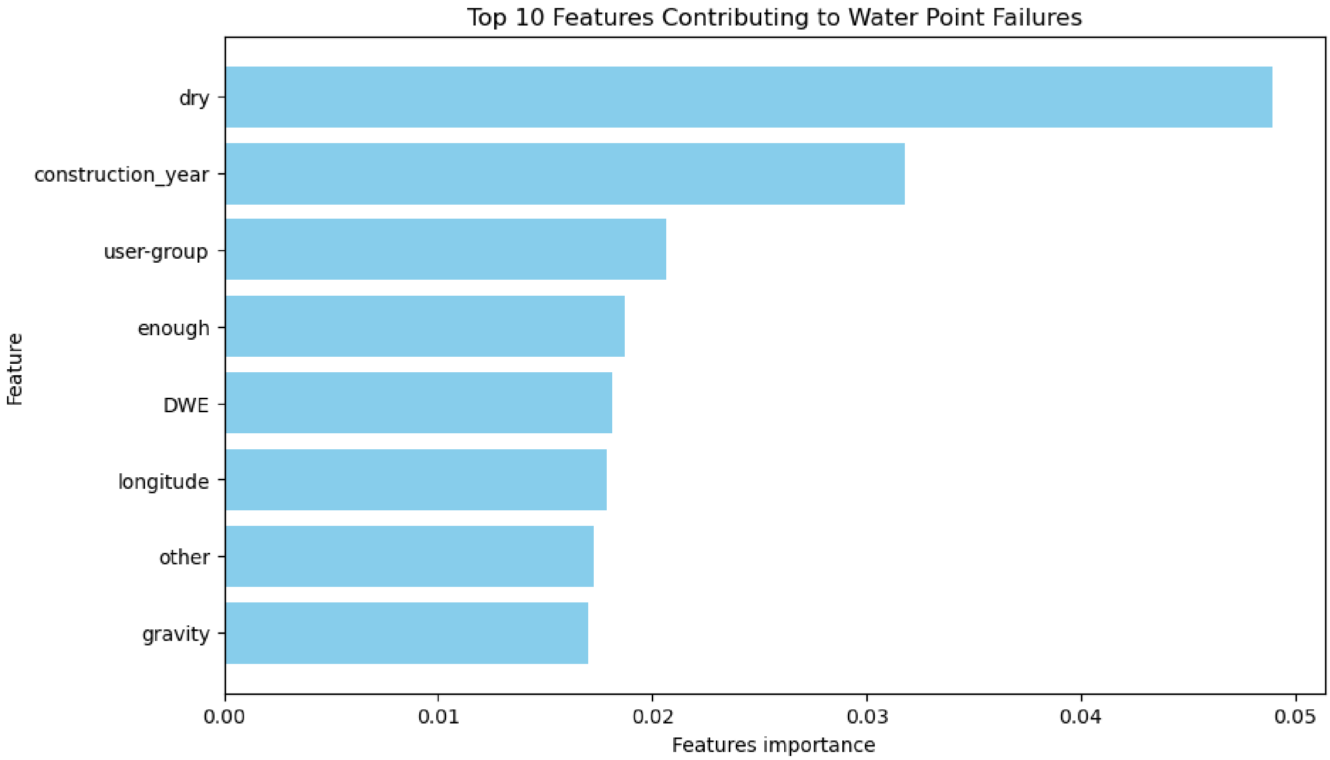
Preprocessing

```
#### Feature Importance analysis
feature_importances = model_rfc.feature_importances_
feature_names = X_train_df.columns

# Create a DataFrame for feature importance
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

# Display the top 10 features
top_features = importance_df.head(10)
#print("Top 10 Features Contributing to Water Point Failures:")
#print(top_features)

# Plot the top 10 features
plt.figure(figsize=(10, 6))
plt.barh(top_features['Feature'], top_features['Importance'], color='skyblue')
plt.xlabel('Features importance')
plt.ylabel('Feature')
plt.title('Top 10 Features Contributing to Water Point Failures')
plt.gca().invert_yaxis()
plt.show()
```



Insights

dry:This appears to be the most influential feature in predicting water point failures. It could indicate whether the water source has dried up. Prioritize investigating and restoring water points marked as "dry."

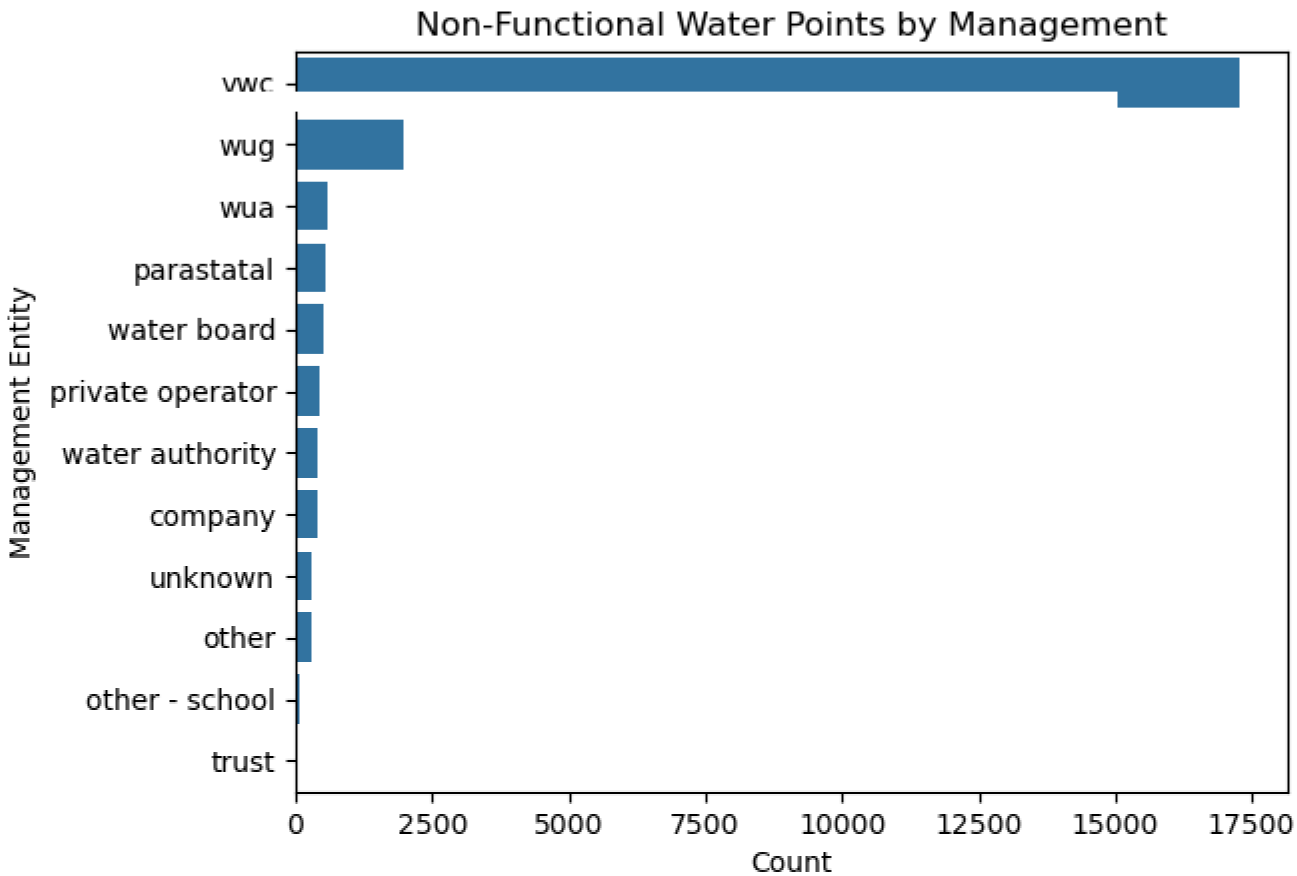
construction_year: Older water points might be more prone to failure.Focus maintenance on older water points or consider replacement for very old installations.

user-group: This might reflect how the water point is managed or shared among users.Assess the impact of user-group dynamics on functionality and repair needs.

```
non_functional = train_df[train_df['status_group'] == 'non functional']
needs_repair = train_df[train_df['status_group'] == 'functional needs repair']


sns.countplot(data=non_functional, y='management', order=non_functional['management'].value_
plt.title('Non-Functional Water Points by Management')
plt.xlabel('Count')
```

```
plt.ylabel('Management Entity')
plt.show()
```



Observations

VWC (Village Water Committees): This entity accounts for the majority of non-functional water points, indicating potential challenges in maintenance or resource allocation.Investigate the capacity, training, and resources available to VWC. Provide targeted training or support to improve their management effectiveness.

WUG (Water User Groups):The second-highest number of non-functional water points is managed by WUG.Evaluate their management processes and identify gaps that lead to failure.

Data cleaning

```
train_df_copied = train_df.copy()
```

```
train_df.duplicated().sum()
```

```
0
```

```
# Encode the target variable
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(train_df['status_group'])
```

```
# Define Features (X) and Target (y)
X = train_df.drop(columns=['status_group', 'id'])  # Drop target and ID columns
y = y_encoded  # Target variable
# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
X_train.duplicated().sum()
```

```
26
```

```
X_train = X_train[~X_train.duplicated()].reset_index(drop=True)
y_train = y_train[X_train.index.to_numpy()]  # Align y_train with the updated X_train indice
```

```
X_train.duplicated().sum()
```

```
0
```

```
X_test.duplicated().sum()
```

```
1
```

```
X_test = X_test[~X_test.duplicated()].reset_index(drop=True)
y_test = y_test[X_test.index.to_numpy()]  # Align y_test with the updated X_test indices
```

```
X_test.duplicated().sum()
```

```
0
```

X_Train Data

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47494 entries, 0 to 47493
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   amount_tsh             47494 non-null  float64
 1   date_recorded          47494 non-null  object
 2   funder                 44617 non-null  object
```

```
 3   gps_height             47494 non-null  int64
 4   installer              44605 non-null  object
 5   longitude              47494 non-null  float64
 6   latitude               47494 non-null  float64
 7   wpt_name               47493 non-null  object
 8   num_private            47494 non-null  int64
 9   basin                  47494 non-null  object
 10  subvillage             47198 non-null  object
 11  region                 47494 non-null  object
 12  region_code            47494 non-null  int64
 13  district_code          47494 non-null  int64
 14  lga                    47494 non-null  object
 15  ward                   47494 non-null  object
 16  population             47494 non-null  int64
 17  public_meeting         44819 non-null  object
 18  recorded_by            47494 non-null  object
 19  scheme_management      44391 non-null  object
 20  scheme_name            24480 non-null  object
 21  permit                 45055 non-null  object
 22  construction_year      47494 non-null  int64
 23  extraction_type        47494 non-null  object
 24  extraction_type_group  47494 non-null  object
 25  extraction_type_class  47494 non-null  object
 26  management             47494 non-null  object
 27  management_group       47494 non-null  object
 28  payment                47494 non-null  object
 29  payment_type           47494 non-null  object
 30  water_quality          47494 non-null  object
 31  quality_group          47494 non-null  object
 32  quantity               47494 non-null  object
 33  quantity_group         47494 non-null  object
 34  source                 47494 non-null  object
 35  source_type            47494 non-null  object
 36  source_class           47494 non-null  object
 37  waterpoint_type        47494 non-null  object
 38  waterpoint_type_group  47494 non-null  object
dtypes: float64(3), int64(6), object(30)
memory usage: 14.1+ MB
```

```
X_train.isna().sum()
```

```
amount_tsh              0
date_recorded           0
funder               2877
gps_height              0
installer            2889
longitude               0
latitude                0
wpt_name                1
num_private             0
basin                   0
subvillage            296
region                  0
region_code             0
district_code           0
```

```
lga                          0
ward                         0
population                   0
public_meeting            2675
recorded_by                  0
scheme_management         3103
scheme_name              23014
permit                    2439
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
dtype: int64
```

```
#Checking the percentage of missing values in each column
missing_percentage = X_train.isnull().mean() * 100
missing_percentage[missing_percentage > 0]
```

```
funder                6.057607
installer             6.082874
wpt_name              0.002106
subvillage            0.623237
public_meeting        5.632290
scheme_management     6.533457
scheme_name          48.456647
permit                5.135386
dtype: float64
```

```
# dropping column Scheme_name , missing data is almost 50%
X_train = X_train.drop(columns= ['scheme_name'])
```

```
#filling all non-numerical columns values having null values with mode
X_train[X_train.select_dtypes(include=[object]).columns] = X_train.select_dtypes(include=[ob
```

```
C:\Users\Hp\AppData\Local\Temp\ipykernel_10552\765570030.py:2: FutureWarning: Downcastir
  X_train[X_train.select_dtypes(include=[object]).columns] = X_train.select_dtypes(inclu
```

```
X_train.duplicated().sum()
```

```
0
```

```
X_train.isna().sum().sum()
```

```
0
```

```
X_train.shape
```

```
(47494, 38)
```

```
X_train.columns
```

```
Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height', 'installer',
       'longitude', 'latitude', 'wpt_name', 'num_private', 'basin',
       'subvillage', 'region', 'region_code', 'district_code', 'lga', 'ward',
       'population', 'public_meeting', 'recorded_by', 'scheme_management',
       'permit', 'construction_year', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source', 'source_type',
       'source_class', 'waterpoint_type', 'waterpoint_type_group'],
      dtype='object')
```

```
# dropping columns which are not necessary in our model prediction
X_train = X_train.drop(columns= ['wpt_name', 'num_private','recorded_by', 'date_recorded', '
```

```
X_train.shape
```

```
(47494, 31)
```

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47494 entries, 0 to 47493
Data columns (total 31 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             47494 non-null  float64
 1   funder                 47494 non-null  object 
 2   gps_height             47494 non-null  int64  
 3   installer              47494 non-null  object 
 4   longitude              47494 non-null  float64
 5   latitude               47494 non-null  float64
 6   basin                  47494 non-null  object 
 7   region                 47494 non-null  object 
 8   region_code            47494 non-null  int64  
 9   district_code          47494 non-null  int64  
 10  population             47494 non-null  int64  
```

```
 11  public_meeting         47494 non-null  bool
 12  scheme_management      47494 non-null  object
 13  permit                 47494 non-null  bool
 14  construction_year      47494 non-null  int64
 15  extraction_type        47494 non-null  object
 16  extraction_type_group  47494 non-null  object
 17  extraction_type_class  47494 non-null  object
 18  management             47494 non-null  object
 19  management_group       47494 non-null  object
 20  payment                47494 non-null  object
 21  payment_type           47494 non-null  object
 22  water_quality          47494 non-null  object
 23  quality_group          47494 non-null  object
 24  quantity               47494 non-null  object
 25  quantity_group         47494 non-null  object
 26  source                 47494 non-null  object
 27  source_type            47494 non-null  object
 28  source_class           47494 non-null  object
 29  waterpoint_type        47494 non-null  object
 30  waterpoint_type_group  47494 non-null  object
dtypes: bool(2), float64(3), int64(5), object(21)
memory usage: 10.6+ MB
```

```
X_train.select_dtypes(exclude=["int64", "float64"]).columns
```

```
Index(['funder', 'installer', 'basin', 'region', 'public_meeting',
       'scheme_management', 'permit', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source', 'source_type',
       'source_class', 'waterpoint_type', 'waterpoint_type_group'],
      dtype='object')
```

Onehotencoding

```
X_train_categorical = X_train.select_dtypes(exclude=["int64", "float64"])
ohe = OneHotEncoder(handle_unknown="ignore", sparse_output=False)

X_train_ohe = pd.DataFrame(
    ohe.fit_transform(X_train_categorical),
    #index is important to ensure we can concatenate with other columns
    index=X_train_categorical.index,
    # we are dummying multiple columns at once, so stack the names
    columns=np.hstack(ohe.categories_)
)
X_train_ohe
```

	0	A/co Germany	Aar	Abasia	Abc-ihushi Development Cent	Abd	Abdul	Abood	Abs	Aco/germany	...
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
47489	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
47490	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
47491	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
47492	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
47493	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

47494 rows × 3791 columns

Normalization

```
X_train_numerical = X_train.select_dtypes(include=["int64", "float64"])
scaler = MinMaxScaler()

X_train_scaled = pd.DataFrame(
    scaler.fit_transform(X_train_numerical),
    # index is important to ensure we can concatenate with other columns
    index=X_train_numerical.index,
    columns=X_train_numerical.columns
)
X_train_scaled
```

	amount_tsh	gps_height	longitude	latitude	region_code	district_code	populati
0	0.000143	0.760678	0.878073	0.637112	0.204082	0.0125	0.0052
1	0.000000	0.022238	0.880156	0.508598	0.000000	0.0750	0.0000
2	0.000000	0.022238	0.805545	0.220458	0.112245	0.0750	0.0000
3	0.000000	0.022238	0.844227	0.242006	0.112245	0.0875	0.0000
4	0.000857	0.383339	0.917896	0.481453	0.040816	0.0125	0.0039
...	...	...	...	...	...	...	
47489	0.002857	0.137663	0.901399	0.246765	0.040816	0.0500	0.0083
47490	0.002857	0.637487	0.855902	0.161367	0.102041	0.0625	0.0011
47491	0.000000	0.017649	0.966024	0.534671	0.030612	0.0625	0.0327
47492	0.000000	0.022238	0.850574	0.733278	0.163265	0.0750	0.0000
47493	0.000000	0.477586	0.932612	0.724325	0.020408	0.0125	0.0000

47494 rows × 8 columns

Concatenation

```
X_train_df = pd.concat([X_train_scaled, X_train_ohe], axis=1)
X_train_df
```

	amount_tsh	gps_height	longitude	latitude	region_code	district_code	populati
0	0.000143	0.760678	0.878073	0.637112	0.204082	0.0125	0.0052
1	0.000000	0.022238	0.880156	0.508598	0.000000	0.0750	0.0000
2	0.000000	0.022238	0.805545	0.220458	0.112245	0.0750	0.0000
3	0.000000	0.022238	0.844227	0.242006	0.112245	0.0875	0.0000
4	0.000857	0.383339	0.917896	0.481453	0.040816	0.0125	0.0039
...	...	...	...	...	...	...	
47489	0.002857	0.137663	0.901399	0.246765	0.040816	0.0500	0.0083
47490	0.002857	0.637487	0.855902	0.161367	0.102041	0.0625	0.0011
47491	0.000000	0.017649	0.966024	0.534671	0.030612	0.0625	0.0327
47492	0.000000	0.022238	0.850574	0.733278	0.163265	0.0750	0.0000
47493	0.000000	0.477586	0.932612	0.724325	0.020408	0.0125	0.0000

47494 rows × 3799 columns

```
X_train_df.duplicated().sum()
```

```
855
```

LOGISTIC REGRESSION MODEL

```
y_train.shape
```

```
(47494,)
```

```
print(y_train.dtype)  # Should be numeric or categorical (e.g., int, float)
print(pd.Series(y_train).isnull().sum())  # Check for null values
```

```
int32
0
```

```
print(pd.Series(y_train).unique())
```

```
[0 2 1]
```

```
print(X_train_df.shape)  # Should be (47520, n_features)
print(y_train.shape)     # Should be (47520,)
```

```
(47494, 3799)
(47494,)
```

```
X_train_df.columns = X_train_df.columns.astype(str)
```

```
print(X_train_df.dtypes.value_counts())
```

```
float64    3799
Name: count, dtype: int64
```

```
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')
model_log = logreg.fit(X_train_df, y_train)
model_log
```

```
C:\Users\Hp\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: L
  warnings.warn(
```

```
LogisticRegression
LogisticRegression(C=1000000000000.0, fit_intercept=False, solver='liblinear')
```

Model Evaluation

```
y_hat_train = logreg.predict(X_train_df)

train_residuals = np.abs(y_train - y_hat_train)
print(pd.Series(train_residuals, name="Residuals (counts)").value_counts())
print()
print(pd.Series(train_residuals, name="Residuals (proportions)").value_counts(normalize=True
```

```
Residuals (counts)
0    28097
2    16044
1     3353
Name: count, dtype: int64

Residuals (proportions)
0    0.591591
2    0.337811
1    0.070598
Name: proportion, dtype: float64
```

X_Test Data

```
# dropping columns which are not necessary in our model prediction or has missing values abo
X_test = X_test.drop(columns= ['wpt_name', 'num_private','recorded_by', 'date_recorded', 'su
#filling all non-numerical columns values having null values with mode
X_test[X_test.select_dtypes(include=[object]).columns] = X_test.select_dtypes(include=[objec
#onehotencoding for categorical columns
X_test_categorical = X_test.select_dtypes(exclude=["int64", "float64"])


X_test_ohe = pd.DataFrame(
    ohe.transform(X_test_categorical),
    #index is important to ensure we can concatenate with other columns
    index=X_test_categorical.index,
    # we are dummying multiple columns at once, so stack the names
    columns=np.hstack(ohe.categories_)
)
#Normalization
X_test_numerical = X_test.select_dtypes(include=["int64", "float64"])
scaler = MinMaxScaler()

X_test_scaled = pd.DataFrame(
    scaler.fit_transform(X_test_numerical),
    # index is important to ensure we can concatenate with other columns
    index=X_test_numerical.index,
    columns=X_test_numerical.columns
)
#concatenation
X_test_df = pd.concat([X_test_scaled, X_test_ohe], axis=1)
X_test_df
```

```
C:\Users\Hp\AppData\Local\Temp\ipykernel_10552\1391562617.py:4: FutureWarning: Downcasti
  X_test[X_test.select_dtypes(include=[object]).columns] = X_test.select_dtypes(include=
```

	amount_tsh	gps_height	longitude	latitude	region_code	district_code	populati
0	0.000000	0.033174	0.793240	0.688925	0.163265	0.0625	0.00
1	0.000000	0.033174	0.814249	0.572276	0.132653	0.0750	0.00
2	0.000072	0.650571	0.880105	0.633074	0.204082	0.0125	0.01
3	0.000000	0.033174	0.821888	0.216387	0.112245	0.0750	0.00
4	0.000362	0.441946	0.848579	0.616771	0.122449	0.0125	0.02
...	...	...	...	...	...	...	
11874	0.001449	0.687431	0.857796	0.153262	0.102041	0.0625	0.05
11875	0.003623	0.715076	0.908797	0.718680	0.010204	0.0250	0.01
11876	0.000000	0.033174	0.757487	0.784715	0.173469	0.3750	0.00
11877	0.000000	0.269812	0.932341	0.475600	0.040816	0.0750	0.00
11878	0.000000	0.560265	0.949343	0.583469	0.030612	0.0125	0.00

11879 rows × 3799 columns

```
X_test_df.columns = X_test_df.columns.astype(str)
```

```
print(X_train_df.shape)  # Should be (n_samples_train, n_features)
print(X_test_df.shape)   # Should be (n_samples_test, n_features)
```

```
(47494, 3799)
(11879, 3799)
```

```
y_hat_test = logreg.predict(X_test_df)

test_residuals = np.abs(y_test - y_hat_test)
print(pd.Series(test_residuals, name="Residuals (counts)").value_counts())
print()
print(pd.Series(test_residuals, name="Residuals (proportions)").value_counts(normalize=True)
```

```
Residuals (counts)
0    7214
2    3789
1     876
Name: count, dtype: int64

Residuals (proportions)
0    0.607290
```

```
2    0.318966
1    0.073744
Name: proportion, dtype: float64
```

Evaluation Matrics

```
y_test.shape
```

```
(11879,)
```

```
y_hat_test.shape
```

```
(11879,)
```

```
# classification report
from sklearn.metrics import classification_report

report = classification_report(y_true=y_test,y_pred=y_hat_test)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.60      0.87      0.71      6456
           1       0.10      0.00      0.01       851
           2       0.63      0.35      0.45      4572

    accuracy                           0.61     11879
   macro avg       0.44      0.41      0.39     11879
weighted avg       0.58      0.61      0.56     11879
```

SMOTE

```
y_train= pd.Series(y_train)
```

```
y_train.value_counts()
```

```
0    25783
2    18247
1     3464
Name: count, dtype: int64
```

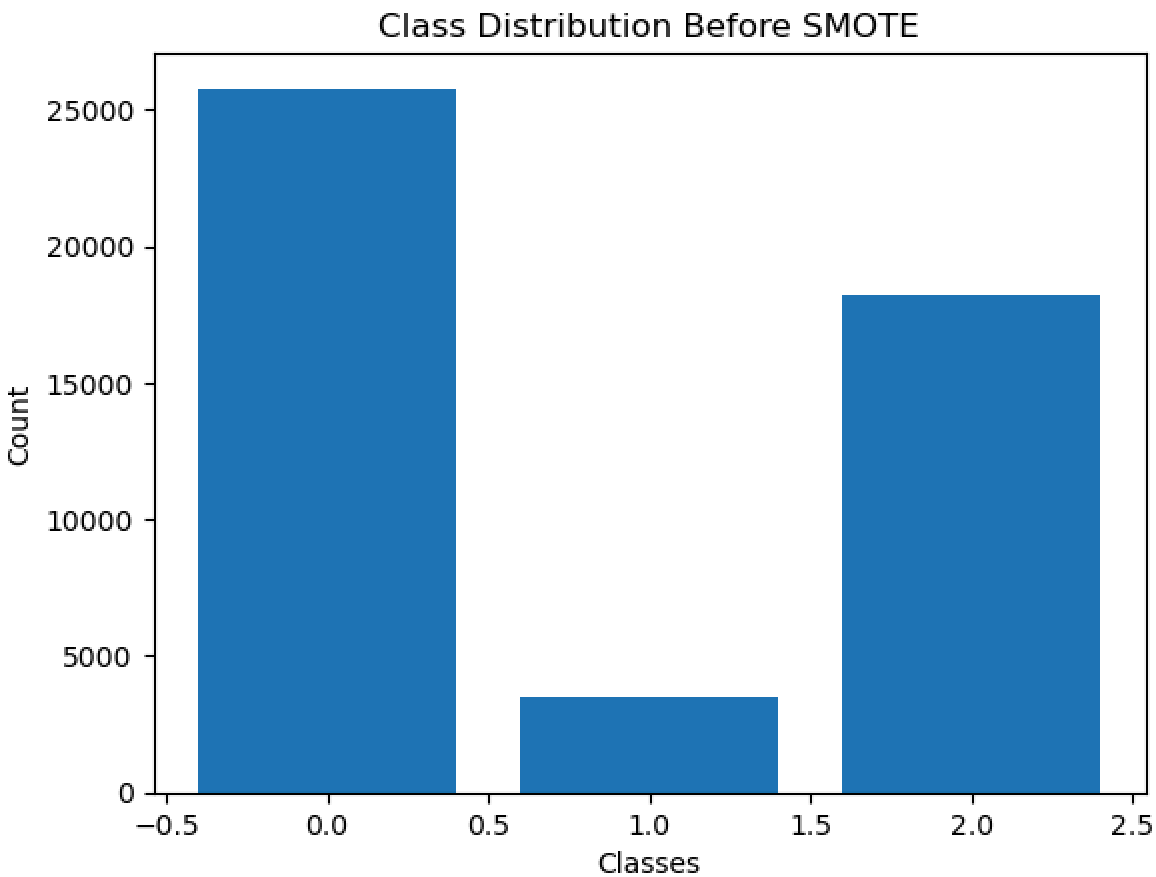
```
import matplotlib.pyplot as plt
from collections import Counter
```

```
# Assuming y_train is your target variable before SMOTE
# Calculate class distribution
class_distribution_before = Counter(y_train)

# Display the class distribution
print("Class distribution before SMOTE:", class_distribution_before)

# Visualize the class distribution
plt.bar(class_distribution_before.keys(), class_distribution_before.values())
plt.xlabel('Classes')
plt.ylabel('Count')
plt.title('Class Distribution Before SMOTE')
plt.show()
```

```
Class distribution before SMOTE: Counter({0: 25783, 2: 18247, 1: 3464})
```




```
from imblearn.over_sampling import SMOTE
```

```
y_train = pd.Series(y_train)
```

```
print("X_train_df type:", type(X_train_df))
print("y_train type:", type(y_train))
print("X_train_df shape:", X_train_df.shape)
print("y_train shape:", y_train.shape)
```

```
X_train_df type: <class 'pandas.core.frame.DataFrame'>
y_train type: <class 'pandas.core.series.Series'>
X_train_df shape: (47494, 3799)
y_train shape: (47494,)
```

```
print(y_train.unique())
```

```
[0 2 1]
```

```
y_train = y_train.astype(str)  # Convert to strings
```

```
print("X_train_df type:", type(X_train_df))
print("X_train_df shape:", X_train_df.shape)
print("y_train type:", type(y_train))
print("y_train shape:", y_train.shape)
print("y_train unique values:", y_train.unique())
```

```
X_train_df type: <class 'pandas.core.frame.DataFrame'>
X_train_df shape: (47494, 3799)
y_train type: <class 'pandas.core.series.Series'>
y_train shape: (47494,)
y_train unique values: ['0' '2' '1']
```

```
# Convert y_train to integers
y_train = y_train.astype(int)
```

```
y_train.name
```

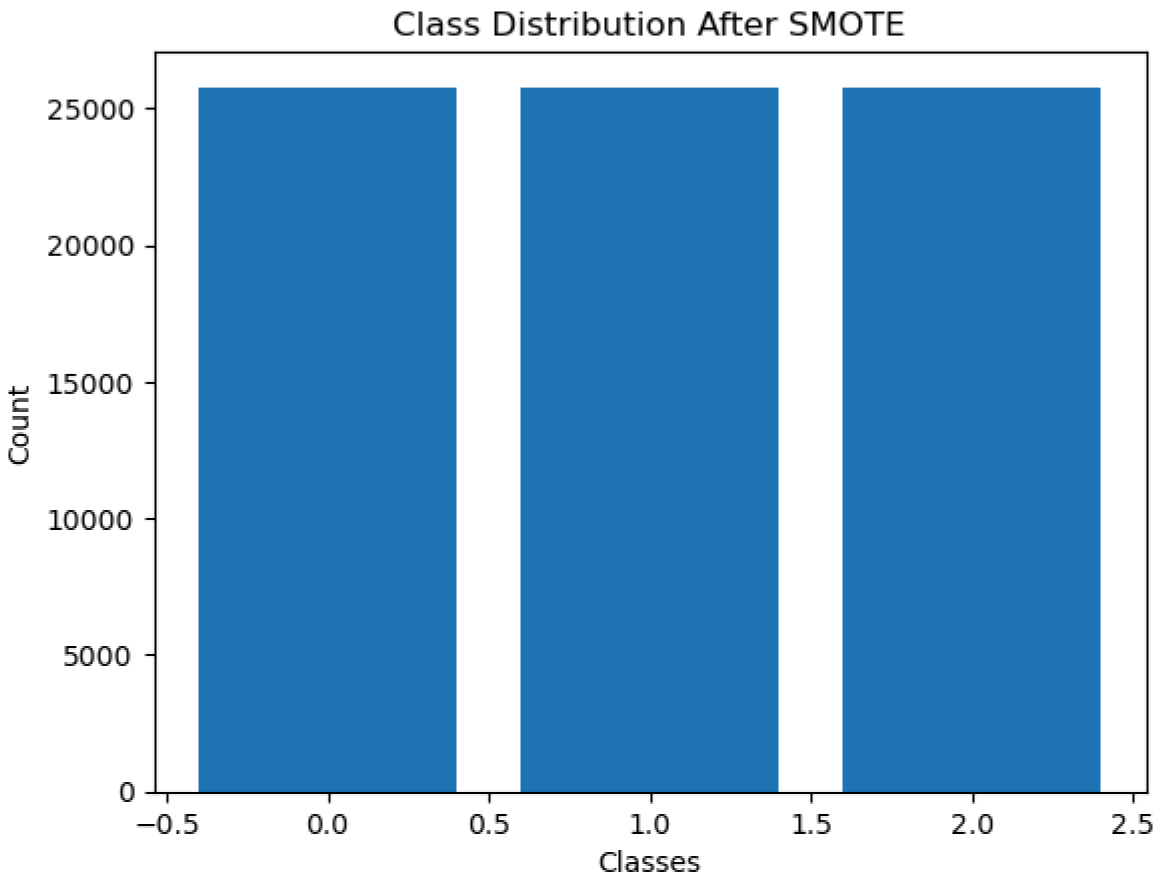
```
# Initialize SMOTE
smote = SMOTE(random_state=42)

# Apply SMOTE
X_train_smote, y_train_smote = smote.fit_resample(X_train_df, y_train)
```

```
from collections import Counter
import matplotlib.pyplot as plt

class_distribution = Counter(y_train_smote)
plt.bar(class_distribution.keys(), class_distribution.values())
plt.title("Class Distribution After SMOTE")
plt.xlabel("Classes")
```

```
plt.ylabel("Count")
plt.show()
```




```
model = LogisticRegression(max_iter=500)
```

Start coding or generate with AI.

```
model_smote = model.fit(X_train_smote,y_train_smote)
```

```
C:\Users\Hp\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469: Converger
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
y_train_smote.value_counts()
```

```
0    25783
2    25783
```

```
1    25783
Name: count, dtype: int64
```

Start coding or generate with AI.

AUC

```
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import label_binarize

# Binarize the output (One-vs-Rest format)
classes = sorted(set(y_test))
y_test_bin = label_binarize(y_test, classes=classes)

# Get decision scores
y_score = model.decision_function(X_test_df)

# Calculate AUC for micro and macro averages
micro_auc = roc_auc_score(y_test_bin, y_score, average="micro")
macro_auc = roc_auc_score(y_test_bin, y_score, average="macro")

print(f"Micro-Averaged AUC: {micro_auc:.2f}")
print(f"Macro-Averaged AUC: {macro_auc:.2f}")
```

```
Micro-Averaged AUC: 0.64
Macro-Averaged AUC: 0.61
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
model_rfc = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=1)
model_rfc.fit(X_train_smote, y_train_smote)
predictions_rfc = model_rfc.predict(X_test_df)
```

```
report_rfc = classification_report(y_true=y_test,y_pred=predictions_rfc)
print(report_rfc)
```

```
              precision    recall  f1-score   support

           0       0.66      0.45      0.54      6456
           1       0.11      0.44      0.17       851
           2       0.57      0.49      0.52      4572

    accuracy                           0.46     11879
   macro avg       0.44      0.46      0.41     11879
```

```
    weighted avg       0.58      0.46      0.51     11879
```

```
# Get predicted probabilities for the test set
probabilities_rfc = model_rfc.predict_proba(X_test_df)

# Binarize the target variable for AUC calculation
classes = sorted(set(y_test))
y_test_rfc = label_binarize(y_test, classes=classes)

# Calculate micro- and macro-averaged AUC
micro_auc = roc_auc_score(y_test_rfc, probabilities_rfc, average="micro", multi_class="ovr")
macro_auc = roc_auc_score(y_test_rfc, probabilities_rfc, average="macro", multi_class="ovr")

print(f"Micro-Averaged AUC (rfc): {micro_auc:.2f}")
print(f"Macro-Averaged AUC(rfc): {macro_auc:.2f}")
```

```
Micro-Averaged AUC (rfc): 0.66
Macro-Averaged AUC(rfc): 0.63
```

Decision Trees

```
# Initialize the Decision Tree Classifier
model_dt = DecisionTreeClassifier(criterion="gini", max_depth=5, random_state=42)

# Fit the model
model_dt.fit(X_train_smote, y_train_smote)

# Make predictions
y_pred_train_dt = model_dt.predict(X_train_smote)
y_pred_test_dt = model_dt.predict(X_test_df)


# Evaluate the model
print("Train Accuracy:", accuracy_score(y_train_smote, y_pred_train_dt))
print("Test Accuracy:", accuracy_score(y_test, y_pred_test_dt))
```

```
Train Accuracy: 0.42668942067770754
Test Accuracy: 0.5693240171731627
```

```
report_dt = classification_report(y_true=y_test,y_pred=y_pred_test_dt)
```