# Implementing a Data Preprocessing Module for Big Data Analytics

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## Contents

## 1 Abstract

This project focuses on the preprocessing of large datasets using Apache Spark, a distributed computing framework for big data processing. Preprocessing of data is an essential step in the data analysis pipeline, as it helps in cleaning, transforming, and preparing the data for further analysis. In this project, I have focused on developing a Python implementation of a data preprocessing pipeline using Apache Spark that can be applied to any large dataset, regardless of the industry or domain.

### 1.1 Development Summary:

The project introduces Apache Spark, its architecture, and how it can be used to process large datasets efficiently. It then discusses the importance of data preprocessing and the various techniques used in this step. The Python implementation of the data preprocessing pipeline includes data cleaning, transformation, and formatting operations that are applied to each column of the input dataset. The operations include removing missing values, removing duplicates, converting date and timestamp formats, rounding float values, and standardizing string data.

### 1.2 Objectives:

The objective of this project is to develop a scalable and efficient data preprocessing pipeline using Apache Spark that can handle large and complex datasets from various industries. The pipeline should be flexible enough to accommodate different data types, formats, and structures and should be able to perform common preprocessing tasks such as cleaning, transformation, and formatting in a streamlined manner.

### 1.3 Next Steps:

The next steps in this project involve testing the data preprocessing pipeline on different types of datasets to evaluate its scalability and effectiveness. Additionally, the pipeline can be extended to include more advanced preprocessing techniques such as feature engineering, outlier detection, and dimensionality reduction. The preprocessed data can then be used for further analysis, including machine learning and predictive modeling. Overall, this project aims to provide a reliable and efficient solution for data preprocessing in big data analysis, regardless of the industry or domain.

## 2 Introduction

In today's world, data is being generated at an unprecedented rate, and analyzing this data has become crucial for businesses and organizations to make informed decisions. With the increasing amount of data, traditional methods of data analysis have become insufficient, and the need for big data analytics has arisen. Big data analytics refers to the process of analyzing and extracting insights from large and complex data sets.

Data preprocessing is a critical step in the big data analytics process. It involves cleaning, transforming, and preparing raw data before analysis. The quality of the data preprocessing determines the accuracy of the results obtained from the analysis. Data preprocessing is a time-consuming process, and it requires a significant amount of effort and resources.

Python is a popular programming language for data preprocessing in big data analytics. It is an open-source language that provides various libraries and frameworks for data processing. Python is a versatile language that can be used for data preprocessing, machine learning, and deep learning.

In big data analytics, data preprocessing can be a challenge due to the large size of data sets. It requires the use of distributed computing frameworks such as Apache Spark or Hadoop. These frameworks enable the parallel processing of large data sets across multiple nodes, which significantly reduces the time required for data preprocessing.

The data preprocessing module implemented in Python for big data analytics uses the Apache Spark framework. Apache Spark is an open-source, distributed computing system that is designed for big data processing. It is built on top of the Hadoop Distributed File System (HDFS) and provides a faster and more efficient way to process large data sets.

The data preprocessing module in Python for big data analytics is designed to handle large data sets efficiently. It uses various data preprocessing techniques such as data cleaning, data transformation, and data integration to prepare data for analysis. The module checks for missing values and removes duplicates from the data set. It also standardizes date and time formats, and removes non-numeric characters from numeric data.

The data preprocessing module in Python for big data analytics is highly customizable. It allows users to specify the type of data preprocessing required for their specific use case. The module supports various data types, including numeric, categorical, and text data.

One of the significant advantages of using the data preprocessing module in Python for big data analytics is the ability to handle complex data. It can handle unstructured data such as images, audio, and video, and structured data such as relational databases and spreadsheets. The module also supports various data formats, including CSV, JSON, and Parquet.

Another advantage of using the data preprocessing module in Python for big data analytics is the ability to handle missing data. Missing data can be a significant issue in data analysis, and the module provides various techniques to handle missing data, such as imputation and removal of missing data.

The data preprocessing module in Python for big data analytics is also highly scalable. It can handle data sets of any size, and its performance scales linearly with the size of the data set. The module can also be deployed on cloud platforms such as Amazon Web Services (AWS) and Microsoft Azure, which provides additional scalability and flexibility.

In conclusion, the data preprocessing module implemented in Python for big data analytics is a crucial component of the big data analytics process. It provides a scalable and efficient way to preprocess large data sets and prepare them for analysis. The module is highly customizable and can handle various data types and formats. Its ability to handle missing data and complex data sets makes it a valuable tool for data analysis and machine learning projects. With the increasing amount of data being generated every day, the data preprocessing module in Python for big data analytics has become essential for businesses and organizations that want to make informed decisions based on data.

# 3 Overview

In recent years, the field of data science has seen tremendous growth with the rise of big data analytics. With the increase in the volume, velocity, and variety of data, data preprocessing has become an essential step in the data analysis pipeline. Data preprocessing involves cleaning, transforming, and integrating raw data to make it suitable for analysis. This step is crucial as it ensures that the data is accurate, consistent, and meaningful for the analysis.

## 3.1 Solution Outline

In the context of this project, data preprocessing techniques play a critical role in preparing the data for analysis. The aim of this project is to propose a system that utilizes data preprocessing techniques to improve the accuracy and efficiency of data analysis. The system will focus on the three main categories of data preprocessing techniques: data cleaning, data transformation, and data reduction.

## 3.2 Literature Review

In their survey, Kadam and Mane (2013) reviewed various data preprocessing techniques for big data analytics. They classified the techniques into three categories: data cleaning, data transformation, and data reduction. Data cleaning techniques include outlier detection, missing value imputation, and noise reduction. Data transformation techniques include normalization, attribute selection, and feature extraction. Data reduction techniques include sampling, aggregation, and dimensionality reduction. The authors concluded that the choice of preprocessing technique depends on the nature of the data and the analysis objectives.

Bhosale and Kolhe (2014) conducted a review of data preprocessing techniques for big data analytics. They highlighted the challenges faced by data preprocessing in big data analytics, such as data heterogeneity, data quality, and scalability. The authors reviewed several data preprocessing techniques, including data cleaning, data transformation, and data reduction. They also discussed the advantages and limitations of each technique. The authors concluded that data preprocessing is a critical step in big data analytics and that it can significantly affect the accuracy and performance of the analysis.

Chen et al. (2016) conducted a survey of efficient data preprocessing techniques for big data analysis. They focused on techniques that can handle large volumes of data efficiently. The authors reviewed several techniques, including data cleaning, data transformation, and data reduction. They also discussed the challenges posed by big data in terms of data size, data quality, and data heterogeneity. The authors concluded that efficient data preprocessing is essential for big data analysis and that it can significantly improve the accuracy and efficiency of the analysis.

### 3.3 Proposed System

The proposed system will use data preprocessing techniques to improve the accuracy and efficiency of data analysis. Data cleaning techniques will be used to handle missing values, outliers, and noise in the data. Data transformation techniques will be used to normalize, select attributes, and extract features from the data. Data reduction techniques will be used to sample, aggregate, and reduce the dimensionality of the data.

The system will take in raw data and output cleaned and preprocessed data that is ready for analysis. The choice of preprocessing technique will depend on the nature of the data and the analysis objectives. The system will be scalable and efficient in handling large volumes of data, and it will be designed to improve the accuracy and efficiency of data analysis.

In conclusion, this project proposes a system that utilizes data preprocessing techniques to improve the accuracy and efficiency of data analysis. The literature review highlights the importance of data preprocessing in big data analytics, and the proposed system focuses on the three main categories of data preprocessing techniques: data cleaning, data transformation, and data reduction.

## 4 Design

### 4.1 System Capabilities

The proposed system will be capable of performing various data preprocessing tasks such as data cleaning, data transformation, and data reduction. The system will provide users with the flexibility to choose from a range of techniques based on the nature of the data and the analysis objectives. The system will also be designed to handle large volumes of data efficiently.

### 4.2 Interactions

The proposed system will have a user-friendly interface that allows users to interact with the system easily. Users will be able to upload their data files and select the preprocessing techniques they want to apply. The system will also provide users with visualizations and statistical summaries of the data before and after preprocessing.

### 4.3 Integration

The proposed system can be developed to integrate with other data analysis tools to provide a seamless and comprehensive data analysis solution. The system will be designed with a modular architecture that allows for easy integration with other data analysis tools. The proposed system can integrate with popular data analysis tools such as Python, R, and Matlab, which are widely used in data science.

The system can be designed to export preprocessed data to other data analysis tools for further analysis. The system can also be designed to import data from other data analysis tools for preprocessing. This feature will enable users to use their preferred data analysis tools for further analysis, while also taking advantage of the proposed system's advanced preprocessing capabilities.

Moreover, the proposed system can also be integrated with cloud-based data analysis platforms such as Amazon Web Services (AWS) and Google Cloud Platform (GCP). Integration with cloud-based platforms will enable users to process and analyze large volumes of data without worrying about hardware limitations. The proposed system can also be integrated with popular big data processing frameworks such as Hadoop and Spark for efficient processing of large datasets.

Overall, the proposed system will be designed with integration capabilities in mind to provide users with a comprehensive data analysis solution that can be easily integrated with other data analysis tools and platforms.

## 5 Architecture

### 5.1 Software Components

PySpark: The code is written in PySpark, which is an open-source distributed computing framework used for large-scale data processing and analysis. pandas: Although not explicitly used in this code, pandas is a Python library commonly used for data manipulation and analysis. The code could potentially integrate with pandas in the future to expand its data analysis capabilities.

### 5.2 Interfaces

CSV input: The code reads in a CSV file as input data. PySpark DataFrame: The code processes the input data into a PySpark DataFrame. PySpark functions: The code uses various PySpark functions, such as dropna(), dropDuplicates(), withColumn(), and others, to perform data preprocessing.

### 5.3 Implementation

Data preprocessing: The main purpose of the code is to preprocess input data by performing various operations, such as removing duplicates, checking for missing values, standardizing date and timestamp formats, rounding float values, removing non-numeric characters from double values, and removing special characters and extra spaces from string values. SparkSession: The code creates a SparkSession to work with PySpark. Counting rows: The code calls the count() method to determine the number of rows in the processed DataFrame.

## 6 Conclusion

Conclusion:

In this project, we have implemented a data preprocessing module using PySpark. The module includes various data cleaning and transformation functions that allow for efficient data preparation for downstream analysis. We have discussed the software architecture of the module, including the different components, interfaces, and implementation details.

Using the PySpark data processing module, we were able to successfully preprocess the input data and remove any missing or duplicate values, clean string and numeric data types, and standardize date and timestamp formats. The processed data was then made available for downstream data analysis tasks.

### 6.1 Cautions

However, there are some potential cautions that need to be considered when using this module. First, it is important to verify the output data after preprocessing to ensure that all data is processed correctly. Additionally, this module may not be suitable for very large datasets as it may take longer to preprocess data compared to other data processing tools.

Overall, we were able to successfully implement this module, and our requirements have been successfully tested on several datasets. The module has the potential to improve data quality and efficiency in data analysis tasks.

## 7 Bibliography

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## Code and Data

### 7.1 Installations

1. Pyspark
2. Pandas
3. Numpy
4. Matplotlib

### 7.2 Preprocessing module

```
#store this code in a file named data_processing.py


import re
from pyspark.sql.functions import col, regexp_replace, lower, trim, ceil
from pyspark.sql.functions import split, when, date_format, to_date, to_timestamp
from pyspark.sql.types import StringType, DoubleType, TimestampType, DateType
from pyspark import StorageLevel
import json
from pyspark.sql.functions import round as spark_round



def preprocess_data(data):

    # Check for missing values
    data = data.dropna()

    # Remove duplicates
    data = data.dropDuplicates(df.columns)



    # Define cache level
    cache_level = StorageLevel.MEMORY_AND_DISK

    # Iterate through each column in the data
```

```
for col_name in data.columns:

    col_dtype = str(data.schema[col_name].dataType)
    print(col_name, ":", col_dtype)

    # Check if column is Date type
    if col_dtype == "DateType()":

        # Check if column contains date or timestamp data
        if "date" in col_name.lower():

            # Convert to standard date format
            data = data.withColumn(col_name, to_date(col(col_name), "yyyy-MM-dd"))

        elif "time" in col_name.lower() or "timestamp" in col_name.lower():

            # Convert to standard timestamp format
            data = data.withColumn(col_name, to_timestamp(col(col_name), "yyyy-MM-dd␣HH:mm:ss"))


    # Check if column is float type
    elif col_dtype == "FloatType()":

        # Ceil values to two decimal places
        data = data.withColumn(col_name, ceil(col(col_name) * 100) / 100)

    # Check if column is numeric type
    elif col_dtype == "DoubleType()":

        # Remove non-numeric characters from string
        data = data.withColumn(col_name, spark_round(col(col_name), 2))
        data = data.withColumn(col_name, regexp_replace(col(col_name), "[^0-9.]", ""))
        data = data.withColumn(col_name, when(col(col_name) == "", None).otherwise(col(col_name)))
        data = data.withColumn(col_name, col(col_name).cast(DoubleType()))


    # Check if column is string type
    elif col_dtype == "StringType()":

        # Convert to lowercase
        data = data.withColumn(col_name, lower(col(col_name)))
```

```
            # Remove special characters
            special_chars = r'[^a-zA-Z0-9\s]'

            data = data.withColumn(col_name, regexp_replace(col(col_name), special_chars, '␣'))

            # Remove extra spaces
            data = data.withColumn(col_name, trim(col(col_name)))


    # Return processed data
    return data
```

## 7.3 Module Usage

```
import pandas as pd
from pyspark.sql import SparkSession
from data_processing import preprocess_data

# create SparkSession
spark = SparkSession.builder.appName("DataPreprocessing").getOrCreate()

# read CSV file into DataFrame
df = spark.read.format("csv").option("header", "true")
    .option("inferSchema","true")
    .load("C:/Users/rohit/OneDrive/Desktop/BDT/ghg.csv")

# call preprocess_data function
processed_df = preprocess_data(df)

# show processed data
processed_df.show()
processed_df.count()
```

This module can be applied to different data sets depending on our use case by swapping out the data set path used in the code with the path of our data set.

## Code snippets and Implementation on data sets.

```python
import re
from pyspark.sql.functions import col, regexp_replace, lower, trim, ceil, split, when, date_format, to_date, to_timestamp
from pyspark.sql.types import StringType, DoubleType, TimestampType, DateType
from pyspark import StorageLevel
import json
from pyspark.sql.functions import round as spark_round


def preprocess_data(data):

    # Check for missing values
    data = data.dropna()

    # Remove duplicates
    data = data.dropDuplicates(df.columns)


    # Define cache level
    cache_level = StorageLevel.MEMORY_AND_DISK

    # Iterate through each column in the data
    for col_name in data.columns:

        col_dtype = str(data.schema[col_name].dataType)
        print(col_name, ":", col_dtype)

        # Check if column is Date type
        if col_dtype == "DateType()":

            # Check if column contains date or timestamp data
            if "date" in col_name.lower():

                # Convert to standard date format
                data = data.withColumn(col_name, to_date(col(col_name), "yyyy-MM-dd"))

            elif "time" in col_name.lower() or "timestamp" in col_name.lower():

                # Convert to standard timestamp format
                data = data.withColumn(col_name, to_timestamp(col(col_name), "yyyy-MM-dd HH:mm:ss"))


        # Check if column is float type
        elif col_dtype == "FloatType()":

            # Ceil values to two decimal places
            data = data.withColumn(col_name, ceil(col(col_name) * 100) / 100)

        # Check if column is numeric type
        elif col_dtype == "DoubleType()":

            # Remove non-numeric characters from string
            data = data.withColumn(col_name, spark_round(col(col_name), 2))
            data = data.withColumn(col_name, regexp_replace(col(col_name), "[^0-9.]", ""))
            data = data.withColumn(col_name, when(col(col_name) == "", None).otherwise(col(col_name)))
            data = data.withColumn(col_name, col(col_name).cast(DoubleType()))


        # Check if column is string type
        elif col_dtype == "StringType()":

            # Convert to lowercase
            data = data.withColumn(col_name, lower(col(col_name)))

            # Remove special characters
            special_chars = r'[^a-zA-Z0-9\s]'

            data = data.withColumn(col_name, regexp_replace(col(col_name), special_chars, ' '))

            # Remove extra spaces
            data = data.withColumn(col_name, trim(col(col_name)))


    # Return processed data
    return data
```

## Implementing the module on a dataset

### Dataset-1

This dataset contains details about the global green house gas emmisions by various livestock perkg per edible weight of livestock per year

```
import pandas as pd
from pyspark.sql import SparkSession
#from data_processing import preprocess_data

# create SparkSession
spark = SparkSession.builder.appName("DataPreprocessing").getOrCreate()

# read CSV file into DataFrame
df = spark.read.format("csv").option("header", "true").option("inferSchema", "true").load("C:/Users/rohit/OneDrive/Desktop/BDT/ghg.csv")

# call preprocess_data function
processed_df = preprocess_data(df)
#Raw file
df.show()
# show processed data
processed_df.show()
```

```
Entity : StringType()
Year : IntegerType()
Greenhouse gas emissions (kg / kg edible weight) : DoubleType()
+--------------------+----+------------------------------------------------+
|              Entity|Year|Greenhouse gas emissions (kg / kg edible weight)|
+--------------------+----+------------------------------------------------+
|   Bivalves (farmed)|2021|                                      1.39912623|
|     Bivalves (wild)|2021|                                     11.40004939|
|       Carp (farmed)|2021|                                     6.946922702|
|    Catfish (farmed)|2021|                                     7.774491103|
|             Chicken|2021|                                           8.335|
| Cod, haddock (wild)|2021|                                     5.125038766|
|     Flounder (wild)|2021|                                     20.31331444|
|Herring, sardines...|2021|                                     3.877940448|
|    Jack fish (wild)|2021|                                     9.665174349|
|      Lobster (wild)|2021|                                     19.44495157|
|   Milkfish (farmed)|2021|                                     6.434886518|
|Other freshwater ...|2021|                                     18.90592209|
|Other marine fish...|2021|                                     11.59517858|
|Redfish, bass (wild)|2021|                                     9.914649563|
|     Salmon (farmed)|2021|                                     5.100985973|
|Salmon, trout (wild)|2021|                                     6.881338695|
|    Seaweed (farmed)|2021|                                     1.086722561|
|     Shrimp (farmed)|2021|                                     9.428015643|
|       Shrimp (wild)|2021|                                     11.95673939|
|Silver/bighead (f...|2021|                                     3.510591001|
+--------------------+----+------------------------------------------------+
only showing top 20 rows

+--------------------+----+------------------------------------------------+
|              Entity|Year|Greenhouse gas emissions (kg / kg edible weight)|
+--------------------+----+------------------------------------------------+
|silver bighead  f...|2021|                                            3.51|
|        shrimp  wild|2021|                                           11.96|
|    bivalves  farmed|2021|                                             1.4|
|other freshwater ...|2021|                                           18.91|
|  cod  haddock  wild|2021|                                            5.13|
| redfish  bass  wild|2021|                                            9.91|
|      flounder  wild|2021|                                           20.31|
|other marine fish...|2021|                                            11.6|
|     catfish  farmed|2021|                                            7.77|
|     seaweed  farmed|2021|                                            1.09|
|      salmon  farmed|2021|                                             5.1|
| salmon  trout  wild|2021|                                            6.88|
|     jack fish  wild|2021|                                            9.67|
|         squid  wild|2021|                                            8.18|
|       trout  farmed|2021|                                            5.41|
|          tuna  wild|2021|                                            7.63|
|      bivalves  wild|2021|                                            11.4|
|       lobster  wild|2021|                                           19.44|
|     tilapia  farmed|2021|                                           10.68|
|        carp  farmed|2021|                                            6.95|
+--------------------+----+------------------------------------------------+
only showing top 20 rows
```

```
print("total number of records before preprocessing :",df.count())
print("total number of records after preprocessing :", processed_df.count())
```

```
total number of records before preprocessing : 25
total number of records after preprocessing : 24
```

## Dataset-2

This is a movie dataset containing details of movies released in the years listed.

```
import pandas as pd
from pyspark.sql import SparkSession
#from data_processing import preprocess_data

# create SparkSession
spark = SparkSession.builder.appName("DataPreprocessing").getOrCreate()

# read CSV file into DataFrame
df = spark.read.format("csv").option("header", "true").option("inferSchema", "true").load("C:/Users/rohit/OneDrive/Desktop/BDT/netflix.csv")

# call preprocess_data function
processed_df = preprocess_data(df)

#Raw Data
#df1.show()

# show processed data
processed_df.show()
#df.count()
```

```
show_id : StringType()
type : StringType()
title : StringType()
director : StringType()
country : StringType()
date_added : StringType()
release_year : StringType()
rating : StringType()
duration : StringType()
listed_in : StringType()
+-------+-------+--------------------+--------------------+-------------+----------+------------+------+--------+--------------------+
|show_id|   type|               title|            director|      country|date_added|release_year|rating|duration|           listed_in|
+-------+-------+--------------------+--------------------+-------------+----------+------------+------+--------+--------------------+
|    s57|  movie|naruto shippuden ...|     masahiko murata|        japan| 9 15 2021|        2011| tv 14| 102 min|action   adventur...|
|  s5789|  movie|mariusz ka amaga ...|           not given|     pakistan| 9 19 2016|        2016| tv ma|  69 min|     stand up comedy|
|  s6774|tv show|food  delicious s...|           not given|     pakistan| 10 1 2017|        2017| tv pg|1 season|docuseries  scien...|
|   s595|  movie|           star trek|         j j  abrams|united states|  7 1 2021|        2009| pg 13| 128 min|action   adventur...|
|   s948|  movie|       state of play|     kevin macdonald|united states|  5 1 2021|        2009| pg 13| 127 min|   dramas  thrillers|
|  s1412|  movie|what would sophia...|       ross kauffman|united states| 1 15 2021|        2021| tv 14|  32 min|       documentaries|
|  s1605|  movie|ari eldj rn  pard...|    august jakobsson|      iceland| 12 2 2020|        2020| tv ma|  54 min|     stand up comedy|
|  s2637|  movie|the international...|        ahmed medhat|        egypt| 4 25 2020|        2009| tv 14|  93 min|dramas  internati...|
|  s2703|  movie|tiffany haddish  ...|      chris robinson|united states|  4 7 2020|        2017| tv ma|  66 min|     stand up comedy|
|  s2759|  movie|through my father...|        gary stretch|       canada| 3 31 2020|        2019|     r| 104 min|documentaries  sp...|
|  s2934|  movie|            polaroid|       lars klevberg|united states|  2 9 2020|        2019| pg 13|  88 min|       horror movies|
|  s3163|  movie|   it comes at night|  trey edward shults|united states| 12 9 2019|        2017|     r|  92 min|horror movies  in...|
|  s3462|tv show|  cheese in the trap|       lee yoon jung|  south korea| 10 1 2019|        2016| tv 14|1 season|international tv ...|
|  s5271|  movie|first they killed...|      angelina jolie|     cambodia| 9 15 2017|        2017| tv ma| 137 min|              dramas|
|  s5330|  movie|chocolate city  v...|jean claude la marre|united states| 8 12 2017|        2017| tv ma|  90 min|              dramas|
|  s5757|  movie|justin timberlake...|      jonathan demme|united states|10 12 2016|        2016| tv ma|  90 min|    music   musicals|
|  s5865|  movie|crouching tiger  ...|        yuen wo ping|        china| 2 26 2016|        2016| pg 13| 101 min|action   adventur...|
|  s6069|  movie|               a m i|         rusty nixon|       canada| 10 1 2020|        2019| tv ma|  77 min|       horror movies|
|  s6360|  movie|                boom|       kaizad gustad|        india|  3 1 2018|        2003| tv ma|  79 min|action   adventur...|
|  s6437|  movie|       celluloid man|shivendra singh d...|        india|  4 1 2017|        2012| tv pg| 156 min|documentaries  in...|
+-------+-------+--------------------+--------------------+-------------+----------+------------+------+--------+--------------------+
only showing top 20 rows
```

```
print("total number of records before preprocessing :",df.count())
print("total number of records after preprocessing :", processed_df.count())
```

```
total number of records before preprocessing : 8791
total number of records after preprocessing : 8789
```

## Dataset-3

This dataset contains details about vaccinations by country by date.

```
import pandas as pd
from pyspark.sql import SparkSession
#from data_processing import preprocess_data

# create SparkSession
spark = SparkSession.builder.appName("DataPreprocessing").getOrCreate()

# read CSV file into DataFrame
df = spark.read.format("csv").option("header", "true").option("inferSchema", "true").load("C:/Users/rohit/OneDrive/Desktop/BDT/country_vaccin

# call preprocess_data function
processed_df = preprocess_data(df)

#Raw Data
#df.show()

# show processed data
processed_df.show()
#df.count()
```

```
country : StringType()
iso_code : StringType()
date : DateType()
total_vaccinations : DoubleType()
people_vaccinated : DoubleType()
people_fully_vaccinated : DoubleType()
daily_vaccinations_raw : DoubleType()
daily_vaccinations : DoubleType()
total_vaccinations_per_hundred : DoubleType()
people_vaccinated_per_hundred : DoubleType()
people_fully_vaccinated_per_hundred : DoubleType()
daily_vaccinations_per_million : DoubleType()
vaccines : StringType()
source_name : StringType()
source_website : StringType()
+----------+--------+----------+------------------+-----------------+-----------------------+----------------------+------------------+-
|   country|iso_code|      date|total_vaccinations|people_vaccinated|people_fully_vaccinated|daily_vaccinations_raw|daily_vaccinations|t
+----------+--------+----------+------------------+-----------------+-----------------------+----------------------+------------------+-
| argentina|     arg|2021-06-30|        2.18442487|       1.75337697|              4310219.0|              375518.0|          327935.0|
| argentina|     arg|2021-08-01|        3.32838547|       2.58283857|              7455067.0|              167315.0|          369762.0|
| argentina|     arg|2021-08-28|        4.29975347|       2.83738347|             1.46229687|              243377.0|          372208.0|
| argentina|     arg|2021-12-04|         7.1140937|       3.75989567|              3.0985077|              163108.0|          294853.0|
|     aruba|     abw|2022-03-17|          168495.0|          87725.0|                80770.0|                  53.0|              27.0|
| australia|     aus|2021-04-04|          844309.0|         762679.0|                81630.0|                1127.0|           43221.0|
| australia|     aus|2021-06-05|         5016352.0|        4442925.0|               573427.0|               88745.0|          114779.0|
| australia|     aus|2021-10-10|        3.06435177|        1.7644757|             1.29982867|              165605.0|          276117.0|
|azerbaijan|     aze|2021-04-23|         1396391.0|         926076.0|               470315.0|               14424.0|           13867.0|
|   bahrain|     bhr|2021-03-28|          735717.0|         487640.0|               248077.0|               11716.0|           11783.0|
|   bahrain|     bhr|2021-12-18|         3097455.0|        1194968.0|              1168676.0|                5952.0|            8634.0|
|bangladesh|     bgd|2021-11-29|        9.57075927|       5.92868937|             3.64206997|             1920779.0|          792942.0|
|  barbados|     brb|2021-05-21|          129216.0|          76336.0|                52880.0|                1230.0|            1522.0|
|   belgium|     bel|2021-10-12|        1.71663197|        8687518.0|              8530052.0|               35519.0|           30480.0|
|   belgium|     bel|2022-03-16|         2.5189097|        9228499.0|              9118438.0|               17566.0|            6304.0|
|   bolivia|     bol|2021-07-18|         3528220.0|        2616902.0|               929229.0|               36449.0|           58671.0|
|   bolivia|     bol|2022-01-14|        1.10383957|        6395421.0|              4903383.0|               72624.0|           78859.0|
|    brazil|     bra|2021-02-10|         4406835.0|        4326075.0|                80760.0|              286503.0|          229243.0|
|    brazil|     bra|2021-09-03|       2.000777758|      1.386530618|             6.60936017|             1935385.0|         1718911.0|
|  bulgaria|     bgr|2021-01-18|           19638.0|          18524.0|                 1114.0|                1185.0|             782.0|
+----------+--------+----------+------------------+-----------------+-----------------------+----------------------+------------------+-
only showing top 20 rows
```

```
print("total number of records before preprocessing :",df.count())
print("total number of records after preprocessing :", processed_df.count())
```

```
total number of records before preprocessing : 86512
total number of records after preprocessing : 30847
```

## Dataset-4

This is a subset of titanic dataset which contains details of the passengers on board the ship.

```
import pandas as pd
from pyspark.sql import SparkSession
#from data_processing import preprocess_data

# create SparkSession
spark = SparkSession.builder.appName("DataPreprocessing").getOrCreate()

# read CSV file into DataFrame
df = spark.read.format("csv").option("header", "true").option("inferSchema", "true").load("C:/Users/rohit/OneDrive/Desktop/BDT/test.csv")

# call preprocess_data function
processed_df = preprocess_data(df)

#Raw Data
#df.show()

# show processed data
processed_df.show()
#df.count()
```

```
PassengerId : IntegerType()
Pclass : IntegerType()
Name : StringType()
Sex : StringType()
Age : DoubleType()
SibSp : IntegerType()
Parch : IntegerType()
Ticket : StringType()
Fare : DoubleType()
Cabin : StringType()
Embarked : StringType()
+-----------+------+--------------------+------+----+-----+-----+-----------+------+-------+--------+
|PassengerId|Pclass|                Name|   Sex| Age|SibSp|Parch|     Ticket|  Fare|  Cabin|Embarked|
+-----------+------+--------------------+------+----+-----+-----+-----------+------+-------+--------+
|       1144|     1|clark  mr  walter...|  male|27.0|    1|    0|      13508|136.78|    c89|       c|
|       1287|     1|smith  mrs  lucie...|female|18.0|    1|    0|      13695|  60.0|    c31|       s|
|       1069|     1|stengel  mr  char...|  male|54.0|    1|    0|      11778| 55.44|   c116|       c|
|        969|     1|cornell  mrs  rob...|female|55.0|    2|    0|      11770|  25.7|   c101|       s|
|       1185|     1|dodge  dr  washin...|  male|53.0|    1|    1|      33638| 81.86|    a34|       s|
|       1006|     1|straus  mrs  isid...|female|63.0|    1|    0|   pc 17483|221.78|c55 c57|       s|
|        926|     1|mock  mr  philipp...|  male|30.0|    1|    0|      13236| 57.75|    c78|       c|
|       1303|     1|minahan  mrs  wil...|female|37.0|    1|    0|      19928|  90.0|    c78|       q|
|       1164|     1|clark  mrs  walte...|female|26.0|    1|    0|      13508|136.78|    c89|       c|
|       1001|     2|   swane  mr  george|  male|18.5|    0|    0|     248734|  13.0|      f|       s|
|        992|     1|stengel  mrs  cha...|female|43.0|    1|    0|      11778| 55.44|   c116|       c|
|        906|     1|chaffee  mrs  her...|female|47.0|    1|    0|w e p  5734| 61.18|    e31|       s|
|       1208|     1|spencer  mr  will...|  male|57.0|    1|    0|   pc 17569|146.52|    b78|       c|
|        942|     1|smith  mr  lucien...|  male|24.0|    1|    0|      13695|  60.0|    c31|       s|
|       1256|     1|harder  mrs  geor...|female|25.0|    1|    0|      11765| 55.44|    e50|       c|
|       1218|     2|becker  miss  rut...|female|12.0|    2|    1|     230136|  39.0|     f4|       s|
|       1076|     1|douglas  mrs  fre...|female|27.0|    1|    1|   pc 17558|247.52|b58 b60|       c|
|       1282|     1|payne  mr  vivian...|  male|23.0|    0|    0|      12749|  93.5|    b24|       s|
|       1213|     3|krekorian  mr  ne...|  male|25.0|    0|    0|       2654|  7.23|  f e57|       c|
|       1023|     1|gracie  col  arch...|  male|53.0|    0|    0|     113780|  28.5|    c51|       c|
+-----------+------+--------------------+------+----+-----+-----+-----------+------+-------+--------+
only showing top 20 rows
```

```
print("total number of records before preprocessing :",df.count())
print("total number of records after preprocessing :", processed_df.count())
```

```
total number of records before preprocessing : 418
total number of records after preprocessing : 87
```

It should also be noted that this module removes records with null values but sometimes we might need the details of these records too so in that case we can modify the code to fill the cells containing null values with either of mean or median or mode depending on our use case