

Project: Covid-19 Vaccine Analysis

Phase3: Development (part 1)

Question:

Begin conducting the Covid-19 vaccines analysis by collecting and preprocessing the dataset. Collect and preprocess the Covid-19 vaccine data for analysis.

Data set and its details:

The dataset "COVID-19 World Vaccination Progress" on Kaggle is a collection of data related to the COVID-19 vaccination efforts worldwide. It provides information about the progress of COVID-19 vaccinations in various countries and regions. This dataset is designed to help researchers, data scientists, and analysts understand and analyze the progress of COVID-19 vaccination campaigns across different countries. A second file, with manufacturers information, is included. Below is a detailed overview of the dataset:

Title: COVID-19 World Vaccination Progress

Dataset ID: gpreda/covid-world-vaccination-progress

Source: The dataset was created by a Kaggle user named Gabriel Preda, collected from various sources, including government health agencies, international organizations, and research institutions.

Description:

1. The dataset provides information about the COVID-19 vaccination progress from various countries around the world.
2. It includes data on vaccine distribution, vaccination coverage, and other related statistics.
3. The dataset may include information about the types of vaccines used, vaccination rates over time, and population demographics.

Columns/Attributes:

1. The dataset typically contains columns such as country, iso_code, date, total_vaccinations, people_vaccinated, people_fully_vaccinated, daily_vaccinations_raw, daily_vaccinations, and more.
2. These columns provide information about the total number of vaccinations, daily vaccination rates, and other vaccination-related metrics for each country.

Usage:

1. Analyzing vaccination progress over time for different countries.
2. Identifying countries with high vaccination rates or disparities.
3. Forecasting future vaccination trends.
4. Studying the impact of different vaccines on vaccination rates.
5. Correlating vaccination progress with COVID-19 infection and mortality rates.

Data Format:

The data is usually structured as a CSV (Comma-Separated Values) file, with rows representing different countries or regions and columns representing various attributes related to vaccination progress and population.

Updates:

The dataset may be updated regularly to reflect the latest vaccination data, making it useful for tracking changes and trends over time.

Columns:

- Country- this is the country for which the vaccination information is provided.
- Country ISO Code - ISO code for the country.
- Date - date for the data entry; for some of the dates we have only the daily vaccinations, for others, only the (cumulative) total.
- Total number of vaccinations - this is the absolute number of total immunizations in the country. Total number of people vaccinated - a person, depending on the immunization scheme, will receive one or more (typically 2) vaccines; at a certain moment, the number of vaccinations might be larger than the number of people.
- Total number of people fully vaccinated - this is the number of people that received the entire set of immunization according to the immunization scheme (typically 2); at a certain moment in time, there might be a certain number of people that received one vaccine and another number (smaller) of people that received all vaccines in the scheme.
- Daily vaccinations (raw) - for a certain data entry, the number of vaccinations for that date/country.
- Daily vaccinations - for a certain data entry, the number of vaccinations for that date/country.
- Total vaccinations per hundred - ratio (in percent) between vaccination number and total population up to the date in the country.
- Total number of people vaccinated per hour- ratio (in percent) between population immunized and total population up to the date in the country.
- Total number of people fully vaccinated per hundred - ratio (in percent) between population fully immunized and total population up to the date in the country.
- Number of vaccinations per day - number of daily vaccinations for that day and country.
- Daily vaccinations per million - ratio (in ppm) between vaccination number and total population for the current date in the country.
- Vaccines used in the country - total number of vaccines used in the country (up to date).
- Source name - source of the information (national authority, international organization, local organization etc.).

- Source website - website of the source of information.

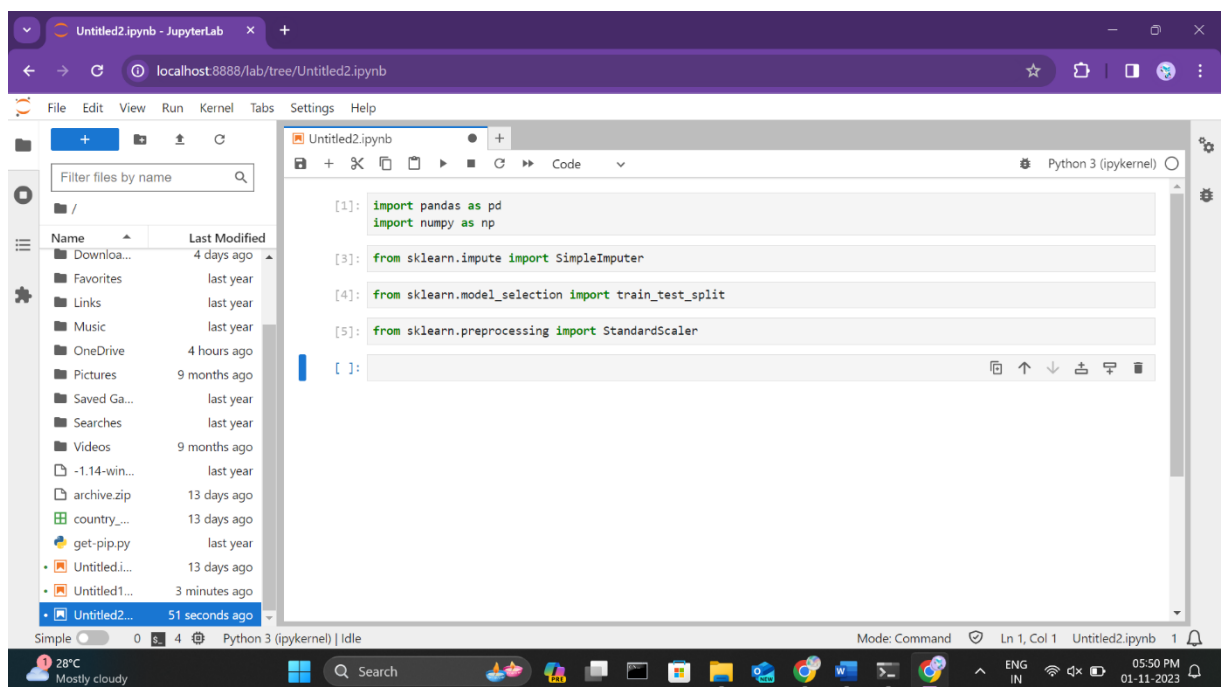
There is a second file added (country vaccinations by manufacturer), with the following columns:

- Location - country.
- Date - date.
- Vaccine - vaccine type.
- Total number of vaccinations - total number of vaccinations / current time and vaccine type.

Importing the required libraries:

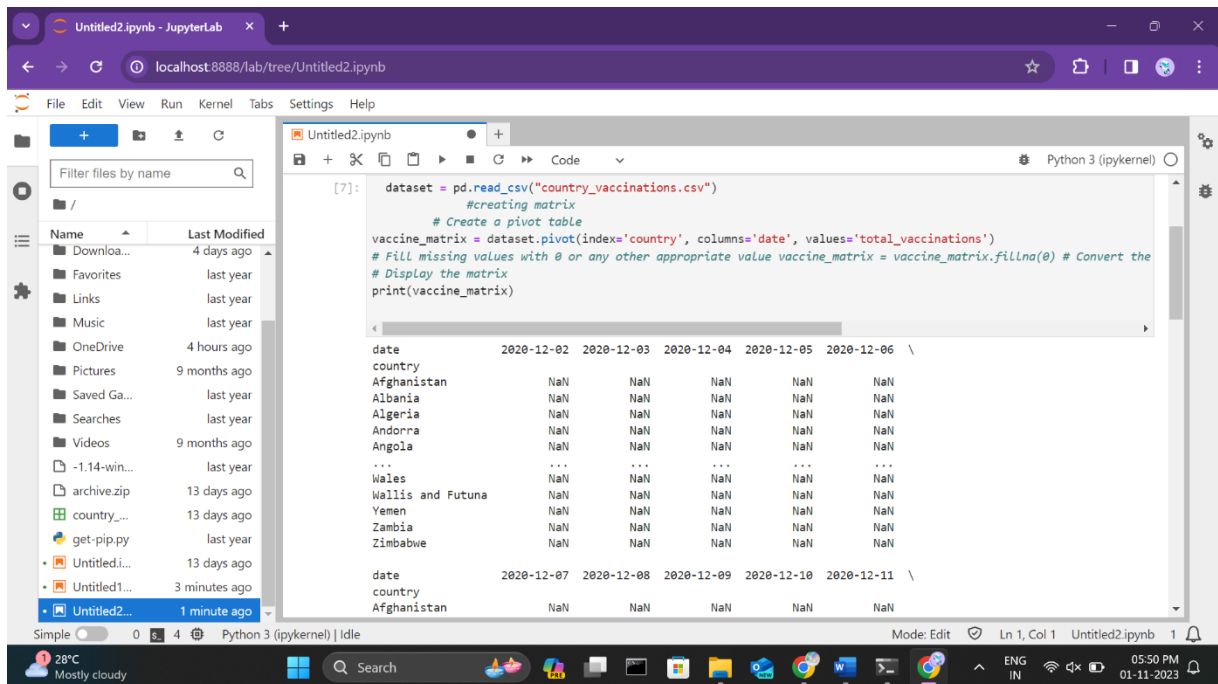
To perform the data preprocessing, splitting, scaling, and other tasks as described, several libraries in Python are needed to be imported. Here are the required libraries for the code:

1. For loading and preprocessing the dataset:
`import pandas as pd`
`import numpy as np`
2. For handling missing data:
`from sklearn.impute import SimpleImputer`
3. For splitting the dataset into training and test sets:
`from sklearn.model_selection import train_test_split`
4. For feature scaling: from sklearn.preprocessing
`import StandardScaler`



Importing the dataset:

Use Pandas to read the dataset file you downloaded into a DataFrame:

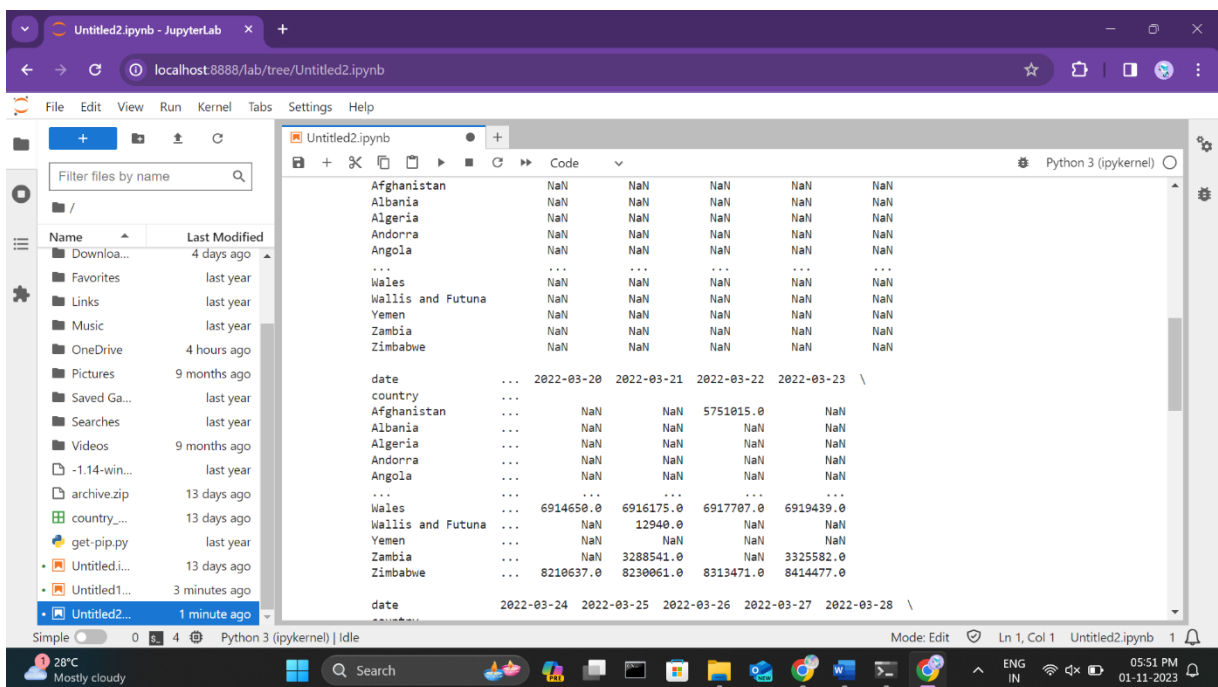


The JupyterLab interface shows the initial state of the dataset. The code cell contains the following script:

```
[7]: dataset = pd.read_csv("country_vaccinations.csv")
#creating matrix
# Create a pivot table
vaccine_matrix = dataset.pivot(index='country', columns='date', values='total_vaccinations')
# Fill missing values with 0 or any other appropriate value vaccine_matrix = vaccine_matrix.fillna(0) # Convert the
# Display the matrix
print(vaccine_matrix)
```

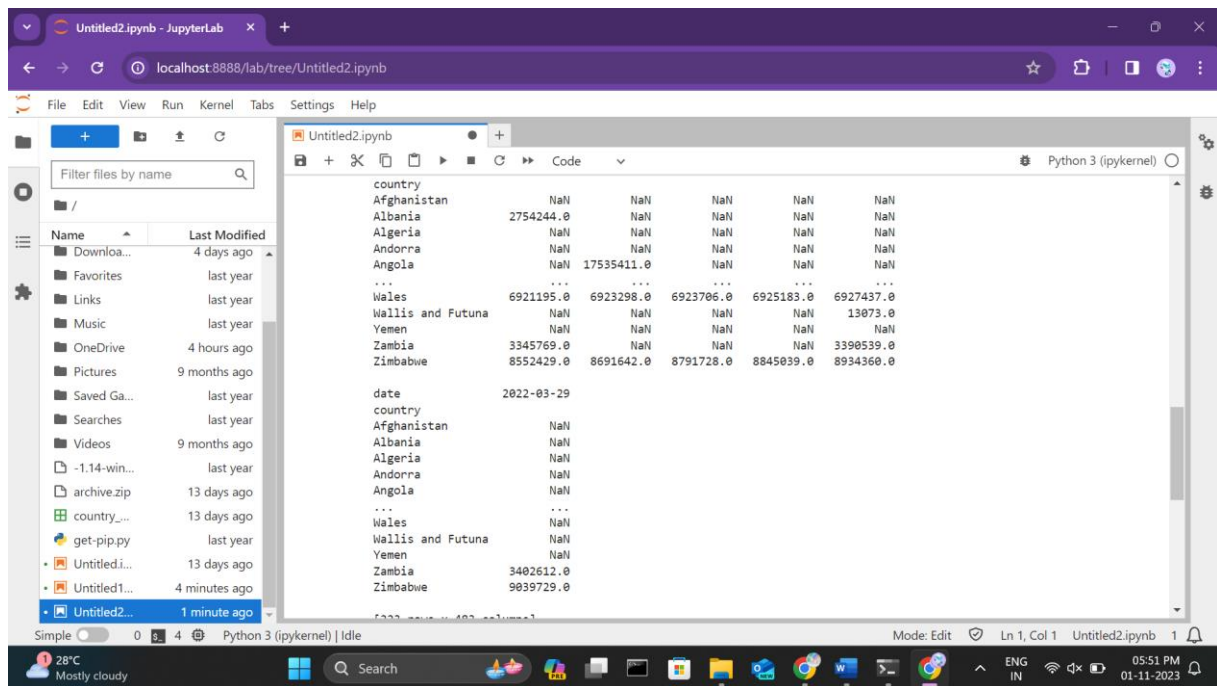
The output shows a preview of the data for December 2020:

	2020-12-02	2020-12-03	2020-12-04	2020-12-05	2020-12-06
date	2020-12-02	2020-12-03	2020-12-04	2020-12-05	2020-12-06
country					
Afghanistan	NaN	NaN	NaN	NaN	NaN
Albania	NaN	NaN	NaN	NaN	NaN
Algeria	NaN	NaN	NaN	NaN	NaN
Andorra	NaN	NaN	NaN	NaN	NaN
Angola	NaN	NaN	NaN	NaN	NaN
...
Wales	NaN	NaN	NaN	NaN	NaN
Wallis and Futuna	NaN	NaN	NaN	NaN	NaN
Yemen	NaN	NaN	NaN	NaN	NaN
Zambia	NaN	NaN	NaN	NaN	NaN
Zimbabwe	NaN	NaN	NaN	NaN	NaN



The JupyterLab interface shows the dataset after a date range extension. The code cell is the same as the first screenshot. The output shows a preview of the data for March 2022:

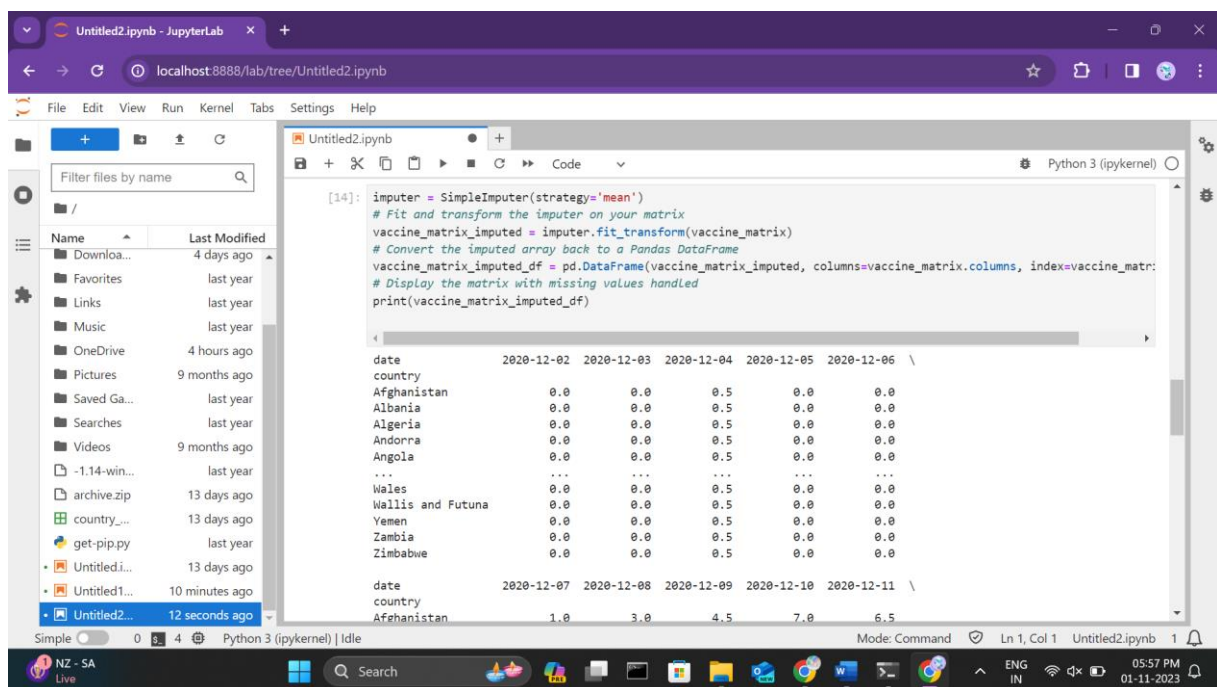
	2022-03-20	2022-03-21	2022-03-22	2022-03-23
date	2022-03-20	2022-03-21	2022-03-22	2022-03-23
country				
Afghanistan	NaN	NaN	5751815.0	NaN
Albania	NaN	NaN	NaN	NaN
Algeria	NaN	NaN	NaN	NaN
Andorra	NaN	NaN	NaN	NaN
Angola	NaN	NaN	NaN	NaN
...
Wales	6914650.0	6916175.0	6917707.0	6919439.0
Wallis and Futuna	NaN	12940.0	NaN	NaN
Yemen	NaN	NaN	NaN	NaN
Zambia	NaN	3288541.0	NaN	3325582.0
Zimbabwe	8210637.0	8230061.0	8313471.0	8414477.0



In this code, we first pivot the DataFrame to transform it into a matrix where rows represent countries, columns represent dates, and the values are the total vaccination counts. We fill any missing values with 0.

Handling the missing data:

Scikit-learn library provides the SimpleImputer class, which is a handy tool for handling missing data.



```

country
Afghanistan    1.0    3.0    4.5    7.0    6.5
Albania        1.0    3.0    4.5    7.0    6.5
Algeria        1.0    3.0    4.5    7.0    6.5
Andorra        1.0    3.0    4.5    7.0    6.5
Angola         1.0    3.0    4.5    7.0    6.5
...
Wales         1.0    3.0    4.5    7.0    6.5
Wallis and Futuna 1.0    3.0    4.5    7.0    6.5
Yemen         1.0    3.0    4.5    7.0    6.5
Zambia        1.0    3.0    4.5    7.0    6.5
Zimbabwe      1.0    3.0    4.5    7.0    6.5

date
country
Afghanistan    1.190563e+08  1.028194e+08  5.751015e+06
Albania        1.190563e+08  1.028194e+08  1.087853e+08
Algeria        1.190563e+08  1.028194e+08  1.087853e+08
Andorra        1.190563e+08  1.028194e+08  1.087853e+08
Angola         1.190563e+08  1.028194e+08  1.087853e+08
...
Wales         6.914650e+06  6.916175e+06  6.917707e+06
Wallis and Futuna 1.190563e+08  1.294000e+04  1.087853e+08
Yemen         1.190563e+08  1.028194e+08  1.087853e+08
Zambia        1.190563e+08  3.28541e+06  1.087853e+08
Zimbabwe      8.210637e+06  8.230061e+06  8.313471e+06

date
country
2022-03-23  2022-03-24  2022-03-25  2022-03-26

```

```

country
Afghanistan    9.796660e+07  1.160827e+08  8.982927e+07  1.220260e+08
Albania        9.796660e+07  2.754244e+06  8.982927e+07  1.220260e+08
Algeria        9.796660e+07  1.160827e+08  8.982927e+07  1.220260e+08
Andorra        9.796660e+07  1.160827e+08  8.982927e+07  1.220260e+08
Angola         9.796660e+07  1.160827e+08  1.753541e+07  1.220260e+08
...
Wales         6.919439e+06  6.921195e+06  6.923298e+06  6.923706e+06
Wallis and Futuna 9.796660e+07  1.160827e+08  8.982927e+07  1.220260e+08
Yemen         9.796660e+07  1.160827e+08  8.982927e+07  1.220260e+08
Zambia        3.325582e+06  3.345769e+06  8.982927e+07  1.220260e+08
Zimbabwe      8.414477e+06  8.552429e+06  8.691642e+06  8.791728e+06

date
country
2022-03-27  2022-03-28  2022-03-29
Afghanistan    1.324064e+08  1.301745e+08  1.604524e+08
Albania        1.324064e+08  1.301745e+08  1.604524e+08
Algeria        1.324064e+08  1.301745e+08  1.604524e+08
Andorra        1.324064e+08  1.301745e+08  1.604524e+08
Angola         1.324064e+08  1.301745e+08  1.604524e+08
...
Wales         6.925183e+06  6.927437e+06  1.604524e+08
Wallis and Futuna 1.324064e+08  1.307300e+04  1.604524e+08
Yemen         1.324064e+08  1.301745e+08  1.604524e+08
Zambia        1.324064e+08  3.390539e+06  3.402612e+06
Zimbabwe      8.845039e+06  8.934360e+06  9.039729e+06

```

The SimpleImputer is used to replace missing values in the vaccine_matrix with the mean of the non-missing values.

Encoding Categorical Data:

To encode categorical data using one-hot encoding in Python, you can use the `pd.get_dummies` function in the Pandas library. One-hot encoding converts categorical variables into binary (0/1) format, making them suitable for machine learning algorithms.

```
[16]: # Use get_dummies to perform one-hot encoding
dataset_encoded = pd.get_dummies(dataset, columns=['country'])
# Display the DataFrame with one-hot encoding
print(dataset_encoded.head())
```

	iso_code	date	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations
0	AFG	2021-02-22	0.0	0.0	NaN	NaN	NaN
1	AFG	2021-02-23	NaN	NaN	NaN	1367.0	1367.0
2	AFG	2021-02-24	NaN	NaN	NaN	1367.0	1367.0
3	AFG	2021-02-25	NaN	NaN	NaN	1367.0	1367.0
4	AFG	2021-02-26	NaN	NaN	NaN	1367.0	1367.0

```
people_fully_vaccinated_per_hundred ... country_Uruguay \
0 NaN ... 0
1 NaN ... 0
2 NaN ... 0
3 NaN ... 0
4 NaN ... 0

country_Uzbekistan country_Vanuatu country_Venezuela country_Vietnam \
0 0 0 0 0
1 0 0 0 0
2 0 0 0 0
3 0 0 0 0
4 0 0 0 0

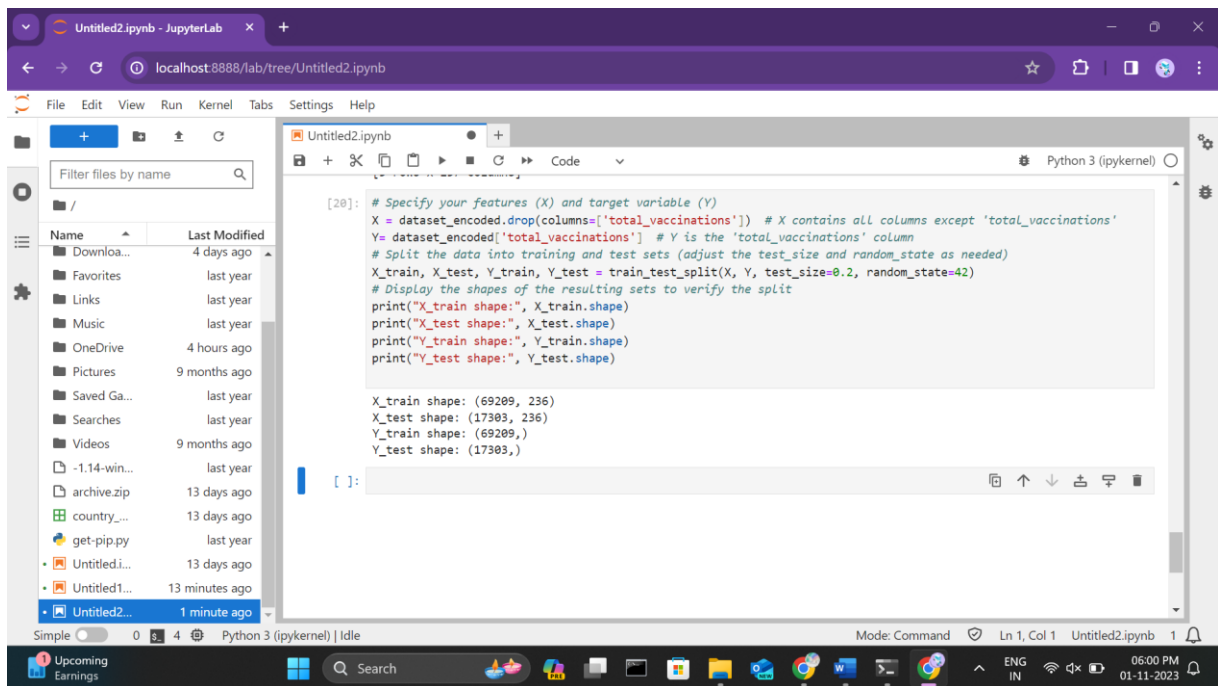
country_Wales country_Wallis and Futuna country_Yemen country_Zambia \
0 0 0 0 0
1 0 0 0 0
2 0 0 0 0
3 0 0 0 0
4 0 0 0 0

country_Zimbabwe
0 0
1 0
2 0
3 0
4 0
```

The `get_dummies` function will create binary (0/1) columns for each unique category in the 'country' column. This process effectively converts the categorical data into a numerical form at suitable for analysis or machine learning.

Splitting the dataset into test set and training set:

To split dataset into training and test sets using the `train_test_split` function from `scikitlearn`, input features (X) and target variable (Y) needed to be specified first.

The image shows a JupyterLab interface in a web browser. The browser address bar shows 'localhost:8888/lab/tree/Untitled2.ipynb'. The JupyterLab interface has a left sidebar with a file explorer showing a directory structure with files like 'Downloads', 'Favorites', 'Links', 'Music', 'OneDrive', 'Pictures', 'Saved Ga...', 'Searches', 'Videos', and several zip files. The main area displays a Python notebook with a code cell. The code cell contains the following Python code:

```
[20]: # Specify your features (X) and target variable (Y)
X = dataset_encoded.drop(columns=['total_vaccinations']) # X contains all columns except 'total_vaccinations'
Y = dataset_encoded['total_vaccinations'] # Y is the 'total_vaccinations' column
# Split the data into training and test sets (adjust the test_size and random_state as needed)
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
# Display the shapes of the resulting sets to verify the split
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)

X_train shape: (69209, 236)
X_test shape: (17303, 236)
Y_train shape: (69209,)
Y_test shape: (17303,)
```

The output of the code cell shows the shapes of the resulting sets. The bottom status bar indicates 'Simple', '0', '4', 'Python 3 (ipykernel) | Idle', 'Mode: Command', 'Ln 1, Col 1', 'Untitled2.ipynb', and '1'.

In this code, we first separate the features (X) and the target variable (Y) from the dataset. Then, we use `train_test_split` to split the data into training and test sets. The `test_size` parameter determines the proportion of the data that will be allocated to the test set, and `random_state` is set to a specific value (e.g., 42) to ensure reproducibility.

Feature Scaling:

Feature scaling is an important preprocessing step in many machine learning algorithms. You can use the `StandardScaler` from `scikit-learn` to scale your features so that they have a mean of 0 and a standard deviation of 1.

The screenshot displays the JupyterLab web interface in a browser. The address bar shows 'localhost:8888/lab/tree/Untitled2.ipynb'. The left sidebar contains a file explorer with a search bar and a list of files and folders, including 'Downloads', 'Favorites', 'Links', 'Music', 'OneDrive', 'Pictures', 'Saved Ga...', 'Searches', 'Videos', and various zip files. The main area shows a code editor for 'Untitled2.ipynb' with the following Python code:

```
[ ]: from sklearn.preprocessing import StandardScaler
# Assuming you have your training and test data (X_train and X_test) defined
# Create a StandardScaler instance
scaler = StandardScaler()
# Fit the scaler on the training data and transform both training and test data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Display the scaled features
print("Scaled X_train:")
print(X_train_scaled)
print("Scaled X_test:")
print(X_test_scaled)
```

The bottom status bar indicates 'Simple', '0', '4', 'Python 3 (ipykernel) | Idle', 'Saving completed', 'Mode: Edit', 'Ln 13, Col 1', 'Untitled2.ipynb', and 'Show desktop'. The Windows taskbar at the very bottom shows the date and time as '06:03 PM 01-11-2023'.

In this code, we first create a `StandardScaler` instance. We then fit the scaler on the training data using the `fit_transform` method, and apply the same transformation to both the training and test data using the `transform` method. This ensures that the scaling is consistent between the two sets.

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