Template for Data Cleaning using Python

BEGINNER DATA CLEANING PANDAS PYTHON

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Introduction

Data cleaning is one area in **the Data Science life cycle** that not even data analysts have to do. Still, data scientists and their daily task are to clean the data so that machine learning algorithms will have the data good enough to be fed. Hence we need to have some sort of **template for cleaning the dataset**.

In this article, we will learn how to **clean a dataset,** i.e., some mandatory steps required that one has to know before getting started with the data preparation phase of a data science project. In this way, the newbies who have started their journey will understand the critical steps in cleaning/preparing the dataset for different processes like **feature engineering** and **machine learning model development**.

In a nutshell, we will try to build a **template** for data cleaning using Python and its famous libraries (**Numpy and Pandas**).

Source: Inzata Analytics

The very first thing that we should do before actually getting started with data cleaning is – **Ask Questions to ourselves** i.e. **What insights you wanna draw from your analysis? what needs to be corrected based on the business requirements?** Similarly, we have curated down some of the key tasks for us (particularly for this instance):

- How does the dataset handle invalid values?
- What do we want to do with null values?
- Do we want to summarise, group, or filter the data?

Importing Libraries Required for Data Cleaning

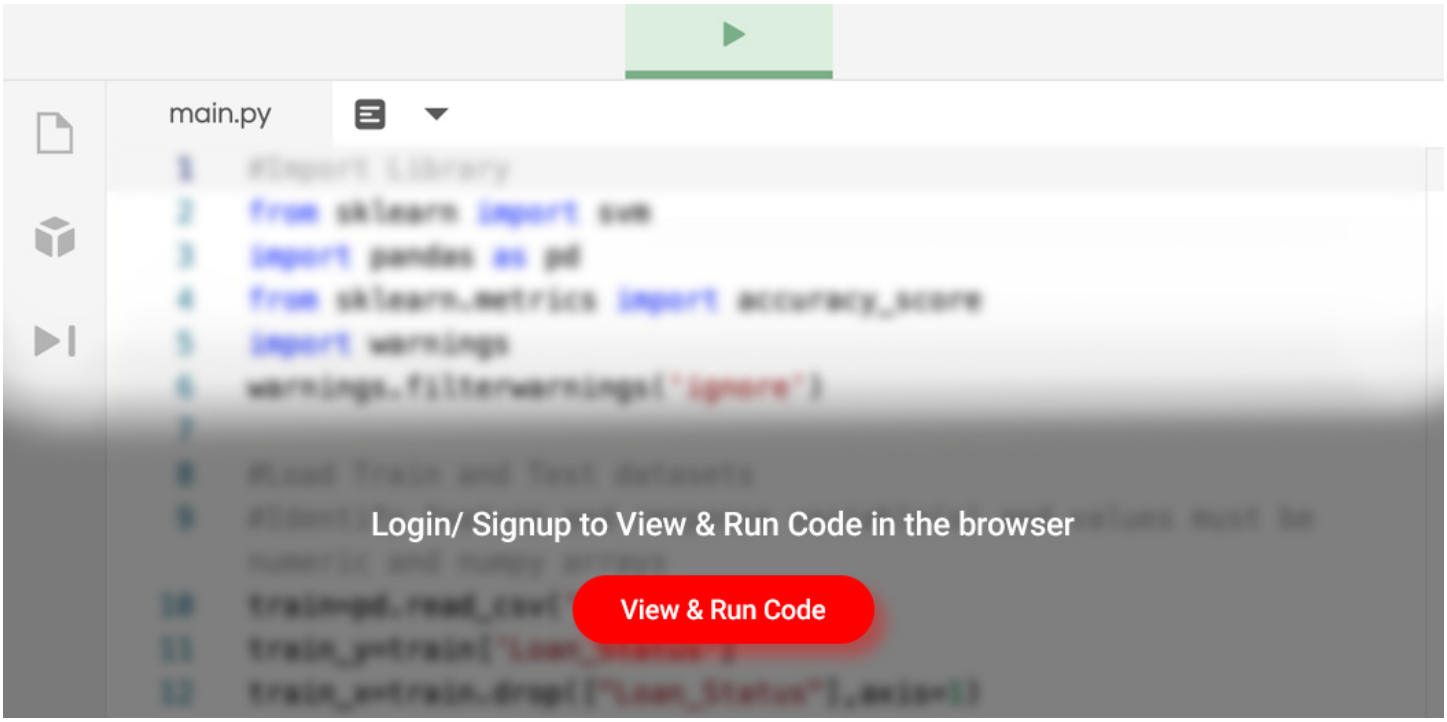
Firstly, we will import all the libraries required to build up the template.

```
import pandas as pd2 import numpy as np
```

Pandas and **Numpy** are the most recommended and powerful libraries when it comes to dealing with structured data or the **tabular data**

1. **Pandas:** Pandas are tagged as the data manipulation library by every data analyst (both experienced and freshers) as it is enriched with vital functionalities and more than **everything to deal with tabular data**.

2. **Numpy:** Numpy is mainly used to work with arrays and **complex mathematical calculations** by providing some useful functions in linear algebra, Fourier transform, and matrices.



Inference: Firstly we started with reading the dataset (this is the famous **Diabetes dataset from the UCI machine learning repository**) using **the read.csv()** function. Then for further intervention using the **info()** method, which is giving us the following insights:

- Does our dataset have any null values? The answer is no! as we can see **768 non-null values**.
- Real data types are detected for each column for **BMI** and **Pedigree function** it is **a float. For** the rest, it is **an integer.**

```
df.head()
```

Output:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Inference: So it looks like they are using **0** values where they don't have data. I don't think they're using **NaN** at all, but if they were we could either drop those rows (**drop a**) or fill them to some value (**file**). Because they're using **0** already, it might be prudent to do this just in case.

```
df = df.fillna(0)
```

Inference: So now we know there are **NaN** values. We could also have just, you know, checked for **NaN**, but now I'm trying to show functions you can use.

So, what to do with these zero values? Sometimes, we could fill them with something sensible, but that normally just biases the data. So mostly, we'd ignore them. So we want to ask **how** we want to use the data. Will we be using **SkinThickness**? Do we care if there are non-physical outliers?

If we primarily cared about Glucose, BMI, and Age, we could get rid of a ton of these issues but only look at those columns.

```
df2 = df[["Glucose", "BMI", "Age", "Outcome"]] df2.head()
```

Output:

Inference: Here, we have grabbed the columns in which we are more interested to do our analysis, and this can be a widespread and essential step in any data cleaning process as we don't need all the columns in hand to deal with. Hence selecting the right set of data is very important.

One can notice that We chose the **Glucose**, **BMI**, **Age**, and **Outcome** column, where the last one is the target, and the rest are features. They are extracted using **multi-indexing.**

```
df2.describe()
```

Output:

Inference: But now, let's get rid of any stray zeros. What we want to do is find a row with **any** number of zeros and remove that row. Or in terms of applying a mask, find the rows which have any **zero (True)**, and invert that **(to False)** so when we apply the mask using **loc**, the False entries get dropped.

```
df3 = df2.loc[~(df2[df2.columns[:-1]] == 0).any(axis=1)] df3.describe() df3.info()
```

Output:

Inference: Great, so we've selected the data we cared about and ensured it has no **null-like** values. We'll go on to check things look sane with some plots in the next section. One final thing we could do is to **group the data by the outcome**. It might make it easier to look for patterns in diagnoses.

We can do this either by splitting out the DataFrame into two (one for yes and one for no), or if we wanted summary statistics, we could use the **groupBy** function:

```
df3.groupby("Outcome").mean()
```

Output:

Inference: What this can tell us is that, in general, the **higher your glucose level, the more overweight you are**, and the **older you are, the greater your chance of being diagnosed with diabetes**. Which, perhaps, is not that surprising.

We can do other things using the **group by** the statement, like so:

```
df3.groupby("Outcome").agg({"Glucose": "mean", "BMI": "median", "Age": "sum"})
```

Output:

Inference: There are multiple ways of using the **GroupBy** function. This is the second way where we can use the AGG function to help us with utilizing multiple **central tendency** methods like **mean**, **median**, **sum**, and so on.

The same thing is visible in the output, where Glucose, BMI, and age are grouped by all three mean, median, and sum.

```
df3.groupby("Outcome").agg(["mean", "median"])
```

Output:

Inference: We can also see more than one statistical method using **.agg([“method1”, “method2", …”methods”)**.

We can also split the dataset into positive and negative outcomes.

```
positive = df3.loc[df3["Outcome"] == 1] negative = df3.loc[df3["Outcome"] == 0] print(positive.shape, negative.shape)
```

Output:

```
(264, 4) (488, 4)
```

Inference: To know whether our **dataset is balanced or not,** we need to see how many **positive outcomes** are there and how many **negative**. From the above output, we can conclude that the dataset is **imbalanced** as **negative** cases > **positive** cases.

We won't use this splitting just yet, so let's save out the cleaned and prepared dataset, **df3,** to file, so our analysis code can load it in the future without having to copy-paste the data prep code into the future notebooks.

```
df3.to_csv("clean_diabetes.csv", index=False)
```

Conclusion

Here we are in the last section of this article, where we will try to **summarize everything** we did so far so that one would get a rough idea and a sort of revision and end goal we reached by closing this blog. Let's have a look in a nutshell at what kind of template we build:

1. First, we started by getting some statistical insights from a dataset using methods like **info()** and **describe().** Then we had a look **overhead the dataset** to have a look and feel of the same.

2. Then we move forward to **deal with the missing values** (in our case, it was **0**) so first, we analyze that and remove those rows with unusual zeros.

3. Finally, we also learned about different ways of grouping the dataset on top of **the target** column using all the proper **groupBy functions like mean, median, or sum. Later,** we saved the cleaned data in the **format of CSV** so that we could use that for further analysis.

Here's the repo link to this article. I hope you liked my article on **Template for cleaning data using Python**. If you have any opinions or questions, comment below.

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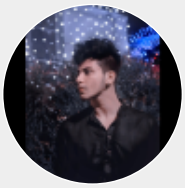

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