Academic Year 2023-24 SAP ID: 60004220126



SHRI VILEPARLE KELAVANI MANDAL'S DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING



(Autonomous College Affiliated to the University of Mumbai)
NAAC ACCREDITED with "A" GRADE (CGPA: 3.18)

COURSE NAME: Machine Learning CLASS: Third Year BTech

NAME: Shashwat Shah

BATCH: C22

EXPERIMENT NO. 1

AIM / OBJECTIVE:

To perform data preprocessing in terms of handling, missing data, removing outliers, eliminating duplicate rows and modifying the datatype, etc.

DESCRIPTION OF EXPERIMENT:

Python is an easy-to-learn programming language, which makes it the most preferred choice for beginners in Data Science, Data Analytics, and Machine Learning. It also has a great community of online learners and excellent data-centric libraries. With so much data being generated, it becomes important that the data we use for Data Science applications like Machine Learning and Predictive Modeling is clean. But what do we mean by clean data? And what makes data dirty in the first place? Dirty data simply means data that is erroneous. Duplicacy of records, incomplete or outdated data, and improper parsing can make data dirty. This data needs to be cleaned. Data cleaning (or data cleansing) refers to the process of "cleaning" this dirty data, by identifying errors in the data and then rectifying them. Data cleaning is an important step in and Machine Learning project, and we will cover some basic data cleaning techniques (in Python).

Cleaning Data in Python

We will now separate the numeric columns from the categorical columns.

Missing values

We will start by calculating the percentage of values missing in each column, and then storing this information in a DataFrame.

Drop observations

One way could be to drop those observations that contain any null value in them for any of the columns. This will work when the percentage of missing values in each column is very less.

Remove columns (features)

Another way to tackle missing values in a dataset would be to drop those columns or features that have a significant percentage of values missing.

Impute missing values

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There is still missing data left in our dataset. We will now impute the missing values in each numerical column with the median value of that column.

Outliers

An outlier is an unusual observation that lies away from the majority of the data. Outliers can affect the performance of a Machine Learning model significantly.

Duplicate records

Data can sometimes contain duplicate values. It is important to remove duplicate records from your dataset before you proceed with any Machine Learning project. In our data, since the ID column is a unique identifier, we will drop duplicate records by considering all but the ID column.

Fixing data type

Often in the dataset, values are not stored in the correct data type. This can create a problem in later stages, and we may not get the desired output or may get errors while execution.

PROCEDURE:

Describe the procedure that is used to carry out the experiment step-by-step. Describe every line of code with the proper interpretation of the output.

Perform data preprocessing with respect to your case study and discuss results of all the steps.

Code and output:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

df = pd.read_csv('/content/dirtydata.csv')
print(df.head(10))
```

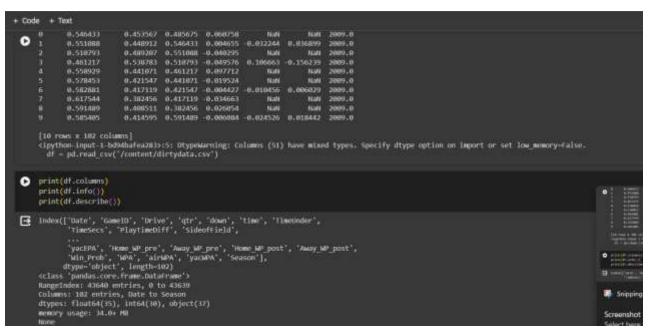


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```

```
#Dropping duplicates
    df.drop_duplicates(inplace = True)
[ ] # get the number of missing data points per column
    missing values count = df.isnull().sum()
    # look at the # of missing points in the first ten columns
    missing values count[0:10]
    Date
                     0.0
                     0.0
    GameID
    Drive
                    0.0
    qtr
                    0.0
    down
                    0.0
    time
                    0.0
    TimeUnder
                    0.0
    TimeSecs
                     0.0
    PlayTimeDiff
                     0.0
    SideofField
                     0.0
    dtype: float64
    total_cells = np.product(df.shape)
    total missing = missing values count.sum()
    # percent of data that is missing
    (total_missing/total_cells) * 100
    24.974658974497224
```

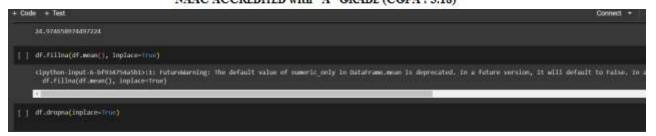
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CONCLUSION:

So, we successfully implemented cleaning of data using python