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 Duplicacy of records, incomplete or outdated data, and improper parsing can make data dirty.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

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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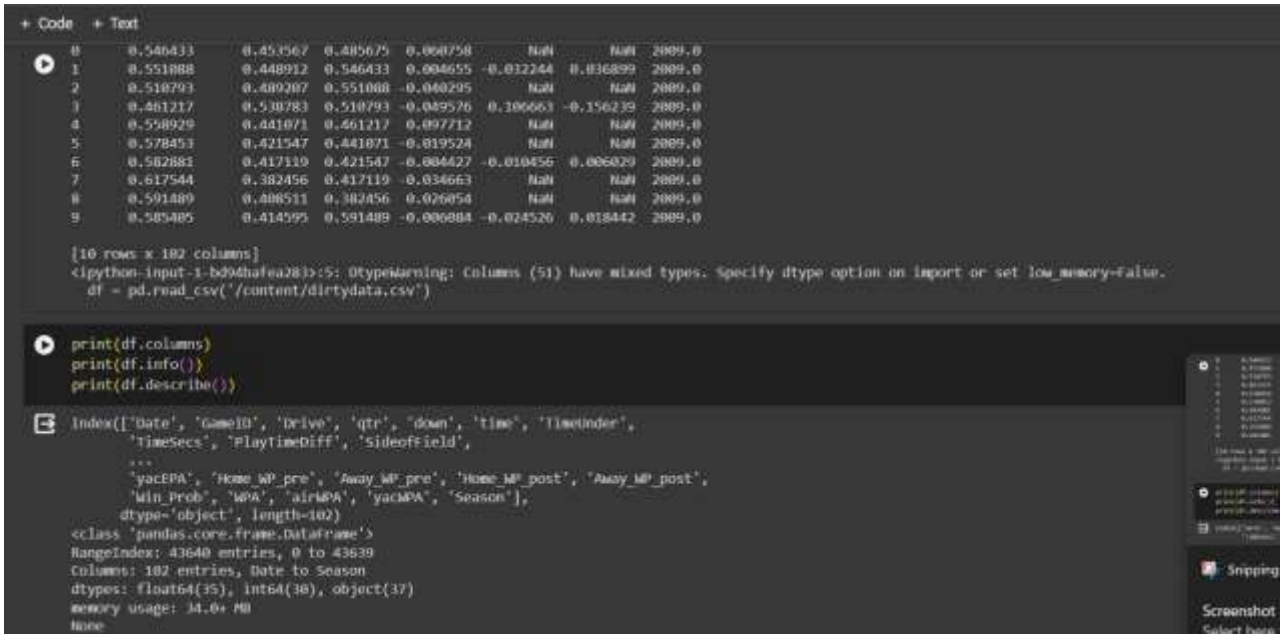
	Date	GameID	Drive	qtr	down	time	TimeUnder	TimeSecs	\
0	2009-09-10	2009091000	1	1	NaN	15:00	15	3600.0	
1	2009-09-10	2009091000	1	1	1.0	14:53	15	3593.0	
2	2009-09-10	2009091000	1	1	2.0	14:16	15	3556.0	
3	2009-09-10	2009091000	1	1	3.0	13:35	14	3515.0	
4	2009-09-10	2009091000	1	1	4.0	13:27	14	3507.0	
5	2009-09-10	2009091000	2	1	1.0	13:16	14	3496.0	
6	2009-09-10	2009091000	2	1	2.0	12:40	13	3460.0	
7	2009-09-10	2009091000	2	1	3.0	12:11	13	3431.0	
8	2009-09-10	2009091000	2	1	4.0	11:34	12	3394.0	
9	2009-09-10	2009091000	3	1	1.0	11:24	12	3384.0	

	PlayTimeDiff	SideofField	...	yacEPA	Home_WP_pre	Away_WP_pre	\
0	0.0	TEN	...	NaN	0.485675	0.514325	
1	7.0	PIT	...	1.146076	0.546433	0.453567	
2	37.0	PIT	...	NaN	0.551088	0.448912	
3	41.0	PIT	...	-5.031425	0.510793	0.489207	
4	8.0	PIT	...	NaN	0.461217	0.538783	
5	11.0	TEN	...	NaN	0.558929	0.441071	
6	36.0	TEN	...	0.163935	0.578453	0.421547	
7	29.0	TEN	...	NaN	0.582881	0.417119	
8	37.0	TEN	...	NaN	0.617544	0.382456	
9	10.0	TEN	...	0.541602	0.591489	0.408511	

	Home_WP_post	Away_WP_post	Win_Prob	WPA	airWPA	yacWPA	Season
0	0.546433	0.453567	0.485675	0.060758	NaN	NaN	2009.0
1	0.551088	0.448912	0.546433	0.004655	-0.032244	0.036899	2009.0
2	0.510793	0.489207	0.551088	-0.040295	NaN	NaN	2009.0
3	0.461217	0.538783	0.510793	-0.049576	0.106663	-0.156239	2009.0
4	0.558929	0.441071	0.461217	0.097712	NaN	NaN	2009.0
5	0.578453	0.421547	0.441071	-0.019524	NaN	NaN	2009.0
6	0.582881	0.417119	0.421547	-0.004427	-0.010456	0.006029	2009.0



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```
[ ]  count  4.364000e+04  43640.000000  43640.000000  36950.000000  43640.000000
     mean   2.009144e+09     12.335060      2.560151      2.015264      7.334166
     std    1.778114e+05      7.106666      1.126115      1.009782      4.659195
     min    2.009091e+09      1.000000      1.000000      1.000000      0.000000
     25%    2.009101e+09      6.000000      2.000000      1.000000      3.000000
     50%    2.009111e+09     12.000000      2.000000      2.000000      7.000000
     75%    2.009121e+09     18.000000      4.000000      3.000000     11.000000
     max    2.010010e+09     32.000000      5.000000      4.000000     15.000000

              TimeSecs  PlayTimeDiff         yrdln    yrdline100       ydstogo  \
     count  43607.000000  43574.000000  43551.000000  43551.000000  43640.000000
     mean    1708.349554     20.799904     28.381323     47.692292      7.196471
     std     1057.388873     16.910683     13.129457     25.187992      4.796411
     min     -893.000000      0.000000      1.000000      1.000000      0.000000
     25%      803.000000      5.000000     20.000000     30.000000      3.000000
     50%     1800.000000     17.000000     30.000000     49.000000      9.000000
     75%     2597.000000     38.000000     39.000000     69.000000     10.000000
     max     3600.000000    234.000000     50.000000     99.000000     36.000000

           ...         yacEPA   Home_WP_pre   Away_WP_pre  Home_WP_post  \
     count ...  16595.000000  40762.000000  40762.000000  40584.000000
     mean  ...     -0.400900      0.534956      0.465486      0.535202
     std   ...      2.008798      0.289938      0.289991      0.292223
     min   ...    -14.000000      0.000000      0.000000      0.000000
     25%   ...     -0.957404      0.327666      0.221636      0.323830
     50%   ...      0.000000      0.530724      0.469555      0.533272
     75%   ...      0.479230      0.778942      0.672906      0.783487
     max   ...      9.059733      1.000000      1.000000      1.000000

           Away_WP_post      Win_Prob           WPA         airWPA         yacWPA  \
     count  40584.000000  40755.000000  4.296800e+04  16597.000000  16569.000000
     mean       0.465212      0.505817  1.841291e-03      0.014292     -0.010349
```

```
[ ]  #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
GameID          0.0
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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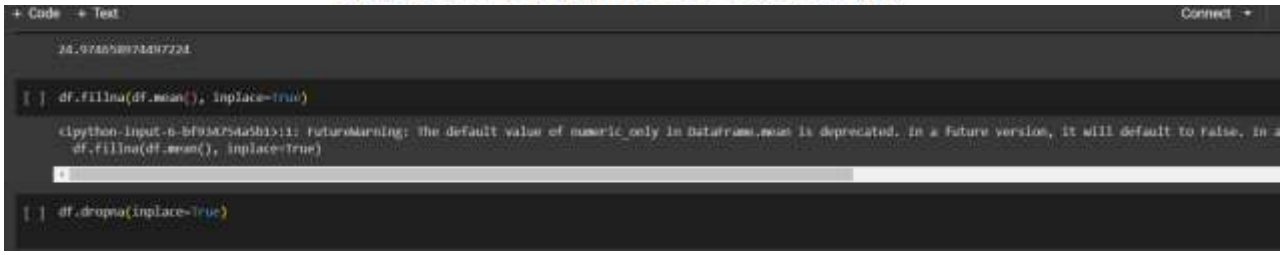

CONCLUSION:

So, we successfully implemented cleaning of data using python

Experiment 1

Shashwat Shah
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Aim: To perform data preprocessing in terms of handling missing data, removing outliers, eliminating outliers, eliminating duplicate rows & modifying the datatypes, etc.

Theory: Python an easy to learn programming language which makes it the most popular & preferred language 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 explications like machine learning & predictive modelling is clean. Data cleaning refers to the process of cleaning the dirty data by identifying the errors in data and rectifying them. Data cleanup is hence a very important step in ML.

Data cleaning consists of :-

* Missing values

We will start by calculating the percentage of values missing in each column and storing information in the dataset.

* Drop Observation - One way

We can drop observations that contain only null values in them for any of the columns. This works when

the percentage of missing values in each columns is less.

* Remove columns -
Drop columns / features which have significant percentage of missing values.

* Imp missing values -
we can also fill missing value in numerical columns, using mean, median, mode and other such structures.

* Outliers
It's an unusual observation that is random & wrong. They can affect the ML model significantly.

* Duplicate records
Data can sometimes contain duplicate values. Its important duplicate records from dataset before we process to ML model.

* Fixing a datatype
Often values in dataset went stored in the correct data type.

Procedure
Firstly we load the dataset in the dataframe, then we list columns & the no. of null values in that columns. Its observed that age has 177 null values, cabin has 687 null values. Next we fill the null values. We also obeen that the cleared data includes columns age and encoded values of columns embarked & p class as dependant values & survived column as largest.

Conclusion - Here we conclude that data cleaning is very important before applying data on ML models.