DATA CLEANING

11 October 2023 20:21

Data Cleaning or cleansing also known as Data Preprocessing is the process of detecting and correcting(or removing) corrupt or iaccurate records from record set,table or databse and referers to identifying incomplete incoorrect inaccurate or irrelevant parts of the data and then replacing , mdoifying or deleteing the dirty or coarse data

Data cleaning is essential because raw data is often noisy, incomplete, and inconsistent, which can negatively impact the accuracy and reliability of the insights derived from it.

1. Data inspection and exploration:

This step involves understanding the data by inspecting its structure and identifying missing values, outliers, and inconsistencies.

- Check the duplicate rows.
- Python3

```
df.duplicated()
```

Output:

```
0      False
1      False
       ...
889    False
890    False
Length: 891, dtype: bool
```

- Check the data information using df.info()

```
df.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
```

```
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

From the above data info, we can see that Age and Cabin have an unequal number of counts. And some of the columns are categorical and have data type objects and some are integer and float values.

Check the categorical and numerical columns

- Python3

```
# Categorical columns
cat_col = [col for col in df.columns if df[col].dtype == 'object']
print('Categorical columns :',cat_col)
# Numerical columns
num_col = [col for col in df.columns if df[col].dtype != 'object']
print('Numerical columns :',num_col)
```

Check the total number of unique values in the Categorical column

- `df[cat_col].nunique()`

Output:

```
Name        891
Sex           2
Ticket      681
Cabin       147
Embarked      3
dtype: int64
```

2. Removal of unwanted observations

This includes deleting duplicate/ redundant or irrelevant values from your dataset. Duplicate observations most frequently arise during data collection and Irrelevant observations are those that don't actually fit the specific problem that you're trying to solve.

- Redundant observations alter the efficiency to a great extent as the data repeats and may add towards the correct side or towards the incorrect side, thereby producing unfaithful results.
- Irrelevant observations are any type of data that is of no use to us and can be removed directly.

3. Handling missing data:

Missing data is a common issue in real-world datasets, and it can occur due to various reasons such as human errors, system failures, or data collection issues. Various techniques can be used to handle missing data, such as imputation, deletion, or substitution.

Let's check the % missing values columns-wise for each row using df.isnull() it checks whether the values are null or not and gives returns boolean values. and .sum() will sum the total number of null values rows and we divide it by the total number of rows present in the dataset then we multiply to get values in % i.e per 100 values how much values are null.

- Python3

```
round((df1.isnull().sum()/df1.shape[0])*100,2)
```

Output:

```
PassengerId     0.00
Survived        0.00
Pclass          0.00
Sex             0.00
Age            19.87
SibSp           0.00
Parch           0.00
Fare            0.00
Cabin          77.10
Embarked        0.22
dtype: float64
```

We cannot just ignore or remove the missing observation. They must be handled carefully as they can be an indication of something important.

The two most common ways to deal with missing data are:

- Dropping observations with missing values.
- The fact that the value was missing may be informative in itself.
- Plus, in the real world, you often need to make predictions on new data even if some of the features are missing!
  As we can see from the above result that Cabin has 77% null values and Age has 19.87% and Embarked has 0.22% of null values. So, it's not a good idea to fill 77% of null values. So, we will drop the Cabin column. Embarked column has only 0.22% of null values so, we drop the null values rows of Embarked column.

- Python3

```
df2 = df1.drop(columns='Cabin')
df2.dropna(subset=['Embarked'], axis=0, inplace=True)
df2.shape
```

Output:

```
(889, 9)
```

- Imputing the missing values from past observations.
- Again, "missingness" is almost always informative in itself, and you should tell your algorithm if a value was missing.
- Even if you build a model to impute your values, you're not adding any real information. You're just reinforcing the patterns already provided by other features.
  From the above describe table, we can see that there are very less differences between the mean and median i..e 29.6 and 28. So, here we can do any one from mean imputation or Median imputations.

Note:

- Mean imputation is suitable when the data is normally distributed and has no

extreme outliers.

- Median imputation is preferable when the data contains outliers or is skewed.
- Python3

```
# Mean imputation
df3 = df2.fillna(df2.Age.mean())
# Let's check the null values again
df3.isnull().sum()
```

Output:

```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       0
dtype: int64
```

4. Handling outliers:

Outliers are extreme values that deviate significantly from the majority of the data. They can negatively impact the analysis and model performance. Techniques such as clustering, interpolation, or transformation can be used to handle outliers.

To check the outliers, We generally use a box plot. A box plot, also referred to as a box-and-whisker plot, is a graphical representation of a dataset's distribution. It shows a variable's median, quartiles, and potential outliers. The line inside the box denotes the median, while the box itself denotes the interquartile range (IQR). The whiskers extend to the most extreme non-outlier values within 1.5 times the IQR. Individual points beyond the whiskers are considered potential outliers. A box plot offers an easy-to-understand overview of the range of the data and makes it possible to identify outliers or skewness in the distribution.

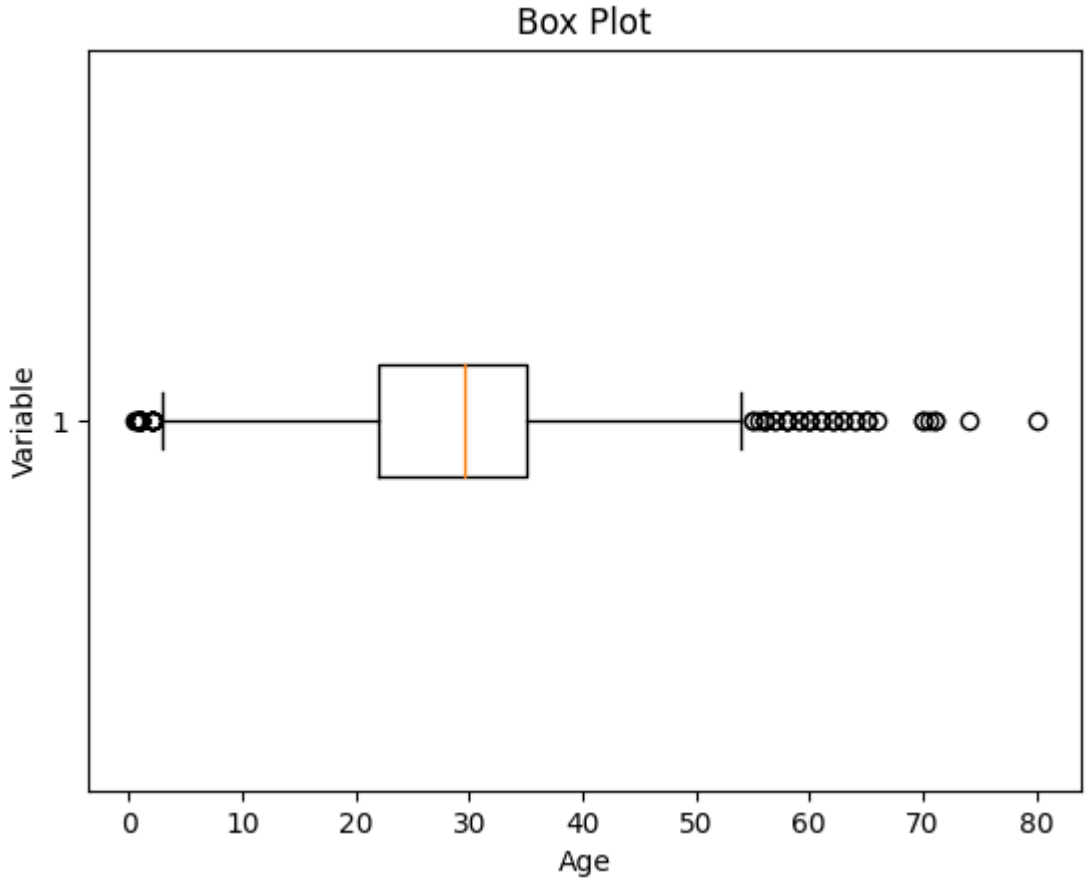
Let's plot the box plot for Age column data.

- Python3

```
import matplotlib.pyplot as plt

plt.boxplot(df3['Age'], vert=False)
plt.ylabel('Variable')
plt.xlabel('Age')
plt.title('Box Plot')
plt.show()
```

Output:



Box Plot

As we can see from the above Box and whisker plot, Our age dataset has outliers values. The values less than 5 and more 55 are outliers.

- Python3

```
# calculate summary statistics
mean = df3['Age'].mean()
std  = df3['Age'].std()

# Calculate the lower and upper bounds
lower_bound = mean - std*2
upper_bound = mean + std*2

print('Lower Bound :',lower_bound)
print('Upper Bound :',upper_bound)

# Drop the outliers
df4 = df3[(df3['Age'] >= lower_bound)
                & (df3['Age'] <= upper_bound)]
```

Output:

```
Lower Bound : 3.705400107925648
Upper Bound : 55.578785285332785
```

Similarly, we can remove the outliers of the remaining columns.

Zscore for removal and IQR for transformation.