ML | Overview of Data Cleaning

Data cleaning is one of the important parts of machine learning. It plays a significant part in building a model. It surely isn't the fanciest part of machine learning and at the same time, there aren't any hidden tricks or secrets to uncover. However, the success or failure of a project relies on proper data cleaning. Professional data scientists usually invest a very large portion of their time in this step because of the belief that **"Better data beats fancier algorithms"**.

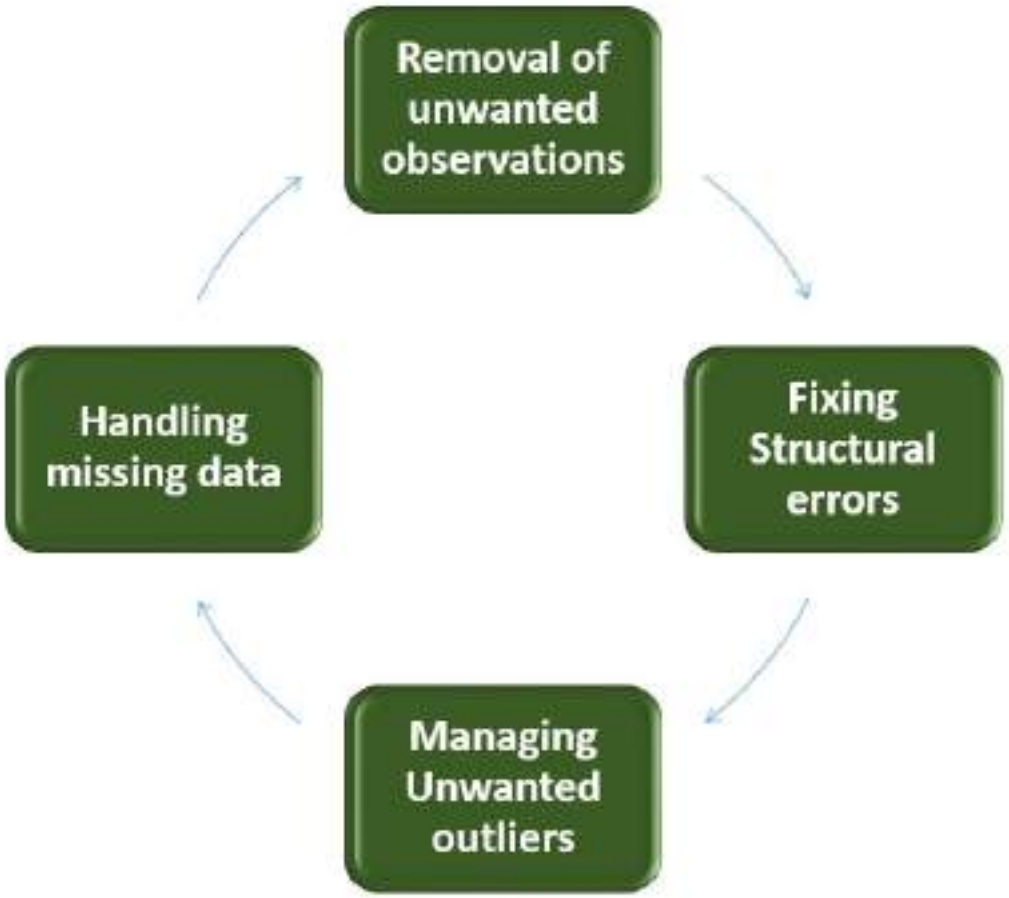
If we have a well-cleaned dataset, there are chances that we can get achieve good results with simple algorithms also, which can prove very beneficial at times especially in terms of computation when the dataset size is large. Obviously, different types of data will require different types of cleaning. However, this systematic approach can always serve as a good starting point.

Steps Involved in Data Cleaning

Data cleaning is a crucial step in the machine learning (ML) pipeline, as it involves identifying and removing any missing, duplicate, or irrelevant data. The goal of data cleaning is to ensure that the data is accurate, consistent, and free of errors, as incorrect or inconsistent data can negatively impact the performance of the ML model.

Data cleaning, also known as **data cleansing** or **data preprocessing**, is a crucial step in the data science pipeline that involves identifying and correcting or removing errors, inconsistencies, and inaccuracies in the data to improve its quality and usability. Data cleaning is essential because raw data is often no
incomplete, and inconsistent, which can negatively impact the accuracy and

The following are the most common steps involved in data cleaning:



Data Cleaning

- Import the necessary libraries
- Load the dataset

Python3

```
import pandas as pd
import numpy as np

# Load the dataset
df = pd.read_csv('train.csv')
df.head()
```

Output:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parc
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parc
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	

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
```

```
889    False
890    False
Length: 891, dtype: bool
```

- Check the data information using df.info()

Python3

```
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

Python3

```
df1.describe()
```

Output:

	PassengerId	Survived	Pclass	Age	SibSp	I
ount	891.000000	891.000000	891.000000	714.000000	891.000000	891
ıean	446.000000	0.383838	2.308642	29.699118	0.523008	0
std	257.353842	0.486592	0.836071	14.526497	1.102743	0
min	1.000000	0.000000	1.000000	0.420000	0.000000	0
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0
max	891.000000	1.000000	3.000000	80.000000	8.000000	6

Check the categorical and numerical columns

Python3

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

Output:


```
Categorical columns : ['Name', 'Sex', 'Ticket', 'Cabin', 'Embarked']
Numerical columns : ['PassengerId', 'Survived', 'Pclass', 'Age',
'SibSp', 'Parch', 'Fare']
```

Check the total number of unique values in the Categorical columns

Python3

```
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.

Now we have to make a decision according to the subject of analysis, which factor is important for our discussion. As we know our machines don't understand the text data. So, we have to either drop or convert the categorical column values into numerical types. Here we are dropping the Name columns because the Name will be always unique and it hasn't a great influence on target variables. For the ticket, Let's first print the 50 unique tickets.

Python3

```
df['Ticket'].unique()[:50]
```

Output:

```
array(['A/5 21171', 'PC 17599', 'STON/O2. 3101282', '113803', '373450',
       '330877', '17463', '349909', '347742', '237736', 'PP 9549',
       '113783', 'A/5. 2151', '347082', '350406', '248706', '382652',
       '244373', '345763', '2649', '239865', '248698', '330923',
'113788',
       '347077', '2631', '19950', '330959', '349216', 'PC 17601',
       'PC 17569', '335677', 'C.A. 24579', 'PC 17604', '113789', '2677',
       'A/5 2152', '345764', '2651', '7546', '11668', '349253',
```

```
'SC/Paris 2123', '330958', 'S.C./A.4. 23567', '370371', '14311',
'2662', '349237', '3101295'], dtype=object)
```

From the above tickets, we can observe that it is made of two like first values ‘A/5 21171’ is joint from of ‘A/5’ and ‘21171’ this may influence our target variables. It will the case of **Feature Engineering**. where we derived new features from a column or a group of columns. In the current case, we are dropping the “Name” and “Ticket” columns.

Drop Name and Ticket columns.

Python3

```
df1 = df.drop(columns=['Name','Ticket'])
df1.shape
```

Output:

```
(891, 10)
```

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

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
```

```
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.

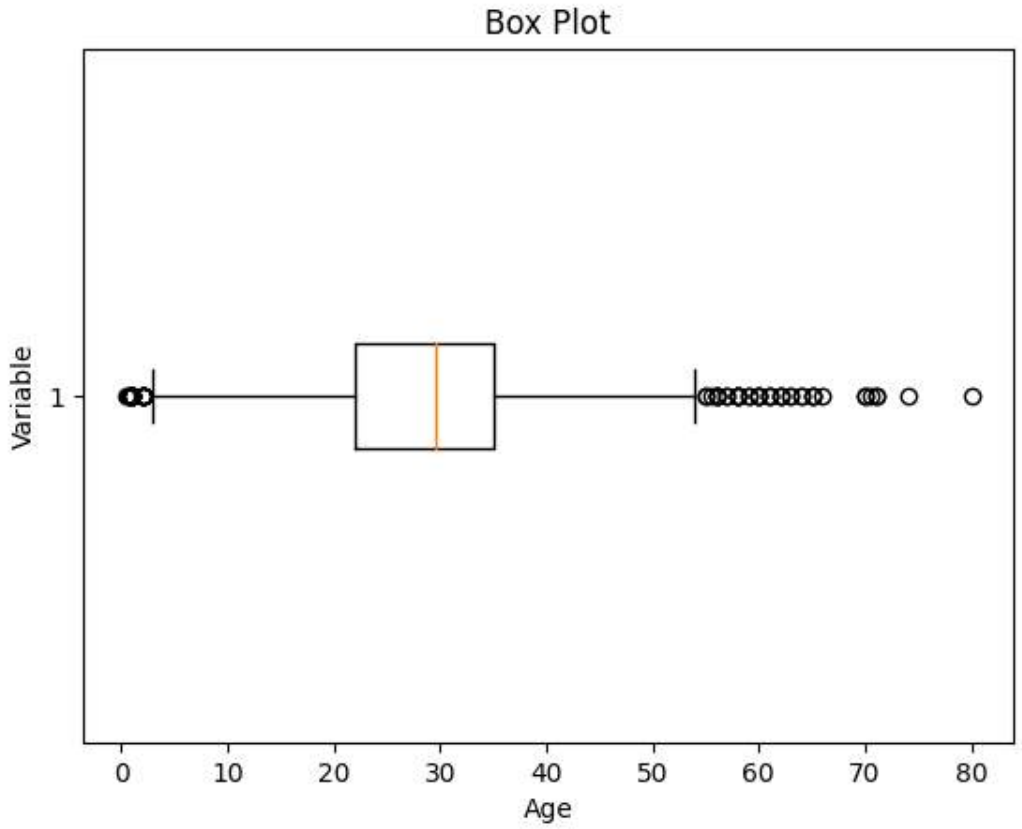
To check the outliers, We generally use a box plot. A box plot, also referred to as a box-and-whisker plot, is a graphical representation of a dataset's distribution. It shows a variable's median, quartiles, and potential outliers. The line inside the box denotes the median, while the box itself denotes 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()
```



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)]
```

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

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

5. Data transformation

Data transformation involves converting the data from one form to another to make it more suitable for analysis. Techniques such as normalization, scaling, or encoding can be used to transform the data.

- **Data validation and verification:** Data validation and verification involve ensuring that the data is accurate and consistent by comparing it with external sources or expert knowledge.

For the machine learning prediction, First, we separate independent and target features. Here we will consider only **'Sex' 'Age' 'SibSp', 'Parch' 'Fare' 'Embarked'** only as the independent features and **Survived** as target variables. Because PassengerId will not affect the survival rate.

Python3

```
X = df3[['Pclass','Sex','Age', 'SibSp','Parch','Fare','Embarked']]
Y = df3['Survived']
```

- **Data formatting:** Data formatting involves converting the data into a standard format or structure that can be easily processed by the algorithms or models used for analysis. Here we will discuss commonly used data formatting techniques i.e. Scaling and Normalization.

Scaling:

- Scaling involves transforming the values of features to a specific range. It maintains the shape of the original distribution while changing the scale.
- Scaling is particularly useful when features have different scales, and

- Common scaling methods include Min-Max scaling and Standardization (Z-score scaling).

Min-Max Scaling:

- Min-Max scaling rescales the values to a specified range, typically between 0 and 1.
- It preserves the original distribution and ensures that the minimum value maps to 0 and the maximum value maps to 1.

Python3

```
from sklearn.preprocessing import MinMaxScaler

# initialising the MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))

# Numerical columns
num_col_ = [col for col in X.columns if X[col].dtype != 'object']
x1 = X
# learning the statistical parameters for each of the data and transforming
x1[num_col_] = scaler.fit_transform(x1[num_col_])
x1.head()
```

Output:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1.0	male	0.271174	0.125	0.0	0.014151	S
1	0.0	female	0.472229	0.125	0.0	0.139136	C
2	1.0	female	0.321438	0.000	0.0	0.015469	S

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
4	1.0	male	0.434531	0.000	0.0	0.015713	S

Standardization (Z-score scaling):

- Standardization transforms the values to have a mean of 0 and a standard deviation of 1.
- It centers the data around the mean and scales it based on the standard deviation.
- Standardization makes the data more suitable for algorithms that assume a Gaussian distribution or require features to have zero mean and unit variance.

```
z = (x - μ) / σ
```

Where,

- X = Data
- μ = Mean value of X
- σ = Standard deviation of X

Some data cleansing tools:

- OpenRefine
- Trifacta Wrangler
- TIBCO Clarity
- Cloudingo
- IBM Infosphere Quality Stage

Advantages of Data Cleaning in Machine Learning:

1. Improved model performance: Data cleaning helps improve the performance of the ML model by removing errors, inconsistencies, and irrelevant data, which can help the model to better learn from the data.
2. Increased accuracy: Data cleaning helps ensure that the data is accurate

model.

3. Better representation of the data: Data cleaning allows the data to be transformed into a format that better represents the underlying relationships and patterns in the data, making it easier for the ML model to learn from the data.
4. Improved data quality: Data cleaning helps to improve the quality of the data, making it more reliable and accurate. This ensures that the machine learning models are trained on high-quality data, which can lead to better predictions and outcomes.
5. Improved data security: Data cleaning can help to identify and remove sensitive or confidential information that could compromise data security. By eliminating this information, data cleaning can help to ensure that only the necessary and relevant data is used for machine learning.

Disadvantages of Data Cleaning in Machine Learning:

1. Time-consuming: Data cleaning can be a time-consuming task, especially for large and complex datasets.
2. Error-prone: Data cleaning can be error-prone, as it involves transforming and cleaning the data, which can result in the loss of important information or the introduction of new errors.
3. Limited understanding of the data: Data cleaning can lead to a limited understanding of the data, as the transformed data may not be representative of the underlying relationships and patterns in the data.
4. Data loss: Data cleaning can result in the loss of important information that may be valuable for machine learning analysis. In some cases, data cleaning may result in the removal of data that appears to be irrelevant or inconsistent, but which may contain valuable insights or patterns.
5. Cost and resource-intensive: Data cleaning can be a resource-intensive process that requires significant time, effort, and expertise. It can also require the use of specialized software tools, which can add to the cost and complexity of data cleaning.
6. Overfitting: Overfitting occurs when a machine learning model is trained too closely on a particular dataset, resulting in poor performance when applied

overfitting by removing too much data, leading to a loss of information that could be important for model training and performance.

Conclusion: So, we have discussed four different steps in data cleaning to make the data more reliable and to produce good results. After properly completing the Data Cleaning steps, we'll have a robust dataset that avoids many of the most common pitfalls. This step should not be rushed as it proves very beneficial in the further process.

In summary, data cleaning is a crucial step in the data science pipeline that involves identifying and correcting errors, inconsistencies, and inaccuracies in the data to improve its quality and usability. It involves various techniques such as handling missing data, handling outliers, data transformation, data integration, data validation and verification, and data formatting. The goal of data cleaning is to prepare the data for analysis and ensure that the insights derived from it are accurate and reliable.

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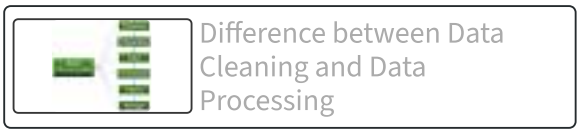

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