Sprint – 1 –Data Preprocessing

What is data preprocessing?

Data preprocessing, a component of data preparation, describes any type of processing performed on raw data to prepare it for another data processing procedure. It has traditionally been an important preliminary step for the data mining process. More recently, data preprocessing techniques have been adapted for training machine learning models and AI models and for running inferences against them.

Data preprocessing transforms the data into a format that is more easily and effectively processed in data mining, machine learning and other data science tasks. The techniques are generally used at the earliest stages of the machine learning and AI development pipeline to ensure accurate results.

There are several different tools and methods used for preprocessing data, including the following:

- Sampling, which selects a representative subset from a large population of data;
- Transformation, which manipulates raw data to produce a single input;

- Denoising, which removes noise from data;
- Imputation, which synthesizes statistically relevant data for missing values;
- Normalization, which organizes data for more efficient access; and
- Feature extraction, which pulls out a relevant feature subset that is significant in a particular context.

These tools and methods can be used on a variety of data sources, including data stored in files or databases and streaming data.

Why is data preprocessing important?

Virtually any type of data analysis, data science or AI development requires some type of data preprocessing to provide reliable, precise and robust results for enterprise applications.

Real-world data is messy and is often created, processed and stored by a variety of humans, business processes and applications. As a result, a data set may be missing individual fields, contain manual input errors, or have duplicate data or different names to describe the same thing. Humans can often identify and rectify these problems in the data they use in the line of business, but data used to train machine learning or deep learning algorithms needs to be automatically preprocessed.

What are the key steps in data preprocessing?

The steps used in data preprocessing include the following:

1. **Data profiling**. Data profiling is the process of examining, analyzing and reviewing data to collect statistics about its quality. It starts with a survey of existing data and its characteristics. Data scientists identify data sets that are pertinent to the problem at hand, inventory its significant attributes, and form a hypothesis of features that might be relevant for the proposed analytics or machine learning task. They also relate data sources to the relevant business concepts and consider which preprocessing libraries could be used.

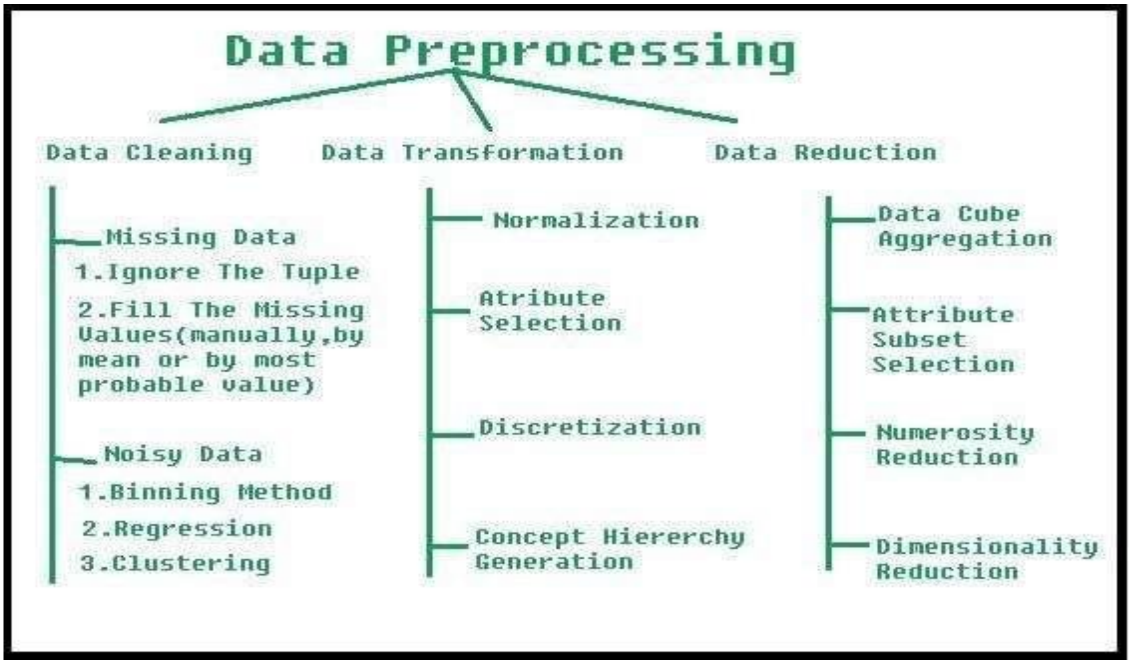
2. **Data cleansing**. The aim here is to find the easiest way to rectify quality issues, such as eliminating bad data, filling in missing data or otherwise ensuring the raw data is suitable for feature engineering.

3. **Data reduction.** Raw data sets often include redundant data that arise from characterizing phenomena in different ways or data that is not relevant to a particular ML, AI or analytics task. Data reduction uses techniques like principal component analysis to transform the raw data into a simpler form suitable for particular use cases.

4. **Data transformation**. Here, data scientists think about how different aspects of the data need to be organized to make the most sense for the goal. This could include things like structuring unstructured data, combining salient variables when it makes sense or identifying important ranges to focus on.

5. **Data enrichment**. In this step, data scientists apply the various feature engineering libraries to the data to effect the desired transformations. The result should be a data set organized to achieve the optimal balance between the training time for a new model and the required compute.

6. **Data validation**. At this stage, the data is split into two sets. The first set is used to train a machine learning or deep learning model. The second set is the testing data that is used to gauge the accuracy and robustness of the resulting model. This second step helps identify any problems in the hypothesis used in the cleaning and feature engineering of the data. If the data scientists are satisfied with the results, they can push the preprocessing task to a data engineer who figures out how to scale it for production. If not, the data scientists can go back and make changes to the way they implemented the data cleansing and feature engineering steps.



Data cleansing

Techniques for cleaning up messy data include the following:

Identify and sort out missing data. There are a variety of reasons a data set might be missing individual fields of data. Data scientists need to decide whether it is better to discard records with missing fields, ignore them or fill them in with a probable value. For example, in an IoT application that records temperature, adding in a missing average temperature between the previous and subsequent record might be a safe fix.

Reduce noisy data. Real-world data is often noisy, which can distort an analytic or AI model. For example, a temperature sensor that consistently reported a temperature of 75 degrees Fahrenheit might erroneously report a temperature as 250 degrees. A variety of statistical approaches can be used to reduce the noise, including binning, regression and clustering.

Noisy Data:

Noisy data is a meaningless data that can’t be interpreted by machines. It can be generated due to faulty data collection, data entry errors etc. It can be handled in following ways:

Binning Method:

This method works on sorted data in order to smooth it. The whole data is divided into segments of equal size and then various methods are performed to complete the task. Each segmented is handled separately. One can replace all data in a segment by its mean or boundary values can be used to complete the task.

Regression:

Here data can be made smooth by fitting it to a regression function.The regression used may be linear (having one independent variable) or multiple (having multiple independent variables).

Clustering:

This approach groups the similar data in a cluster. The outliers may be undetected or it will fall outside the clusters

Identify and remove duplicates. When two records seem to repeat, an algorithm needs to determine if the same measurement was recorded twice, or the records represent different events. In some cases, there may be slight differences in a record because one field was recorded incorrectly. In other cases, records that seem to be duplicates might indeed be different, as in a father and son with the same name who are living in the same house but should be represented as separate individuals. Techniques for identifying and removing or joining duplicates can help to automatically address these types of problems.