Loading the data

In [2]:

```
# importing required libraries
import pandas as pd
```

In [3]:

```
#loading the data
data = pd.read_csv('titanic_train.csv')
data.head()
```

Out[3]:

| | Passengerld | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|-------------|----------|--------|---|--------|------|-------|-------|---------------------|---------|-------|----------|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | s |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | С |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S |

Missing Values

In [4]:

```
#missing values in the data data.isnull().sum()
```

Out[4]:

PassengerId 0 0 Survived Pclass 0 Name 0 Sex Age 177 SibSp Parch 0 Ticket 0 Fare 0 Cabin 687 Embarked 2 dtype: int64

- · Age and Cabin have a very high number of missing values
- Embarked has very low number of missing values

Imputing Missing Values Using central tendency

```
In [5]:
# finding mean value
mean_val = data['Age'].mean()
mean_val
Out[5]:
29.69911764705882
In [6]:
# making a copy
data_cleaned = data.copy()
#imputing missing values
data_cleaned['Age'] = data['Age'].fillna(value = mean_val)
data_cleaned['Age'].isnull().sum()
Out[6]:
In [7]:
data['Embarked'].value_counts()
Out[7]:
      644
C
     168
      77
Name: Embarked, dtype: int64
In [9]:
mode_val = data['Embarked'].mode()[0]
mode_val
Out[9]:
'S'
In [10]:
data_cleaned['Embarked'] = data['Embarked'].fillna(value = mode_val)
In [ ]:
```

Dealing with Categorical Variables

```
In [11]:
#Categorical variables in the data
data.dtypes
Out[11]:
PassengerId
                 int64
Survived
                 int64
Pclass
                 int64
Name
                object
Sex
                object
Age
               float64
SibSp
                 int64
                 int64
Parch
Ticket
                object
Fare
               float64
Cabin
                object
Embarked
                object
dtype: object
In [12]:
categorical_cols = ['Name', 'Sex', 'Ticket', 'Cabin', 'Embarked']
In [13]:
#number of unique values
data[categorical_cols].nunique()
Out[13]:
Name
            891
Sex
              2
Ticket
            681
            147
Cabin
Embarked
              3
dtype: int64
 · Can One-hot-Encode Sex and Embarked
 • Deal with them differently (extract features)
 · Name, Ticket and Cabin (when encoded) will have zeros
One-hot Encoding
In [14]:
pd.get_dummies(data['Embarked']).head()
Out[14]:
   C Q S
  0 0 1
   1
      0 0
2 0 0 1
3 0 0 1
4 0 0 1
In [15]:
```

data_cleaned = data_cleaned.drop(['Name','Ticket','Cabin'], axis=1)

In [16]:

```
data_cleaned = pd.get_dummies(data_cleaned)
data_cleaned.head()
```

Out[16]:

| | Passengerld | Survived | Pclass | Age | SibSp | Parch | Fare | Sex_female | Sex_male | Embarked_C | Embarked_Q | Embark |
|---|-------------|----------|--------|------|-------|-------|---------|------------|----------|------------|------------|--------|
| 0 | 1 | 0 | 3 | 22.0 | 1 | 0 | 7.2500 | 0 | 1 | 0 | 0 | |
| 1 | 2 | 1 | 1 | 38.0 | 1 | 0 | 71.2833 | 1 | 0 | 1 | 0 | |
| 2 | 3 | 1 | 3 | 26.0 | 0 | 0 | 7.9250 | 1 | 0 | 0 | 0 | |
| 3 | 4 | 1 | 1 | 35.0 | 1 | 0 | 53.1000 | 1 | 0 | 0 | 0 | |
| 4 | 5 | 0 | 3 | 35.0 | 0 | 0 | 8.0500 | 0 | 1 | 0 | 0 | |
| 4 | | | | | | | | | | | | • |

- SibSp and Parch hold discrete values
- We can convert them into separate columns as well

Label Encoding

In [17]:

data.head()

Out[17]:

| | Passengerld | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|-------------|----------|--------|---|--------|------|-------|-------|---------------------|---------|-------|----------|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | С |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S |

In [18]:

```
## map function
data['Embarked'].map({'Q': 0, 'S': 1, 'C':2})
```

Out[18]:

```
1.0
1
       2.0
       1.0
3
       1.0
4
       1.0
886
       1.0
887
       1.0
888
       1.0
889
       2.0
890
Name: Embarked, Length: 891, dtype: float64
```

```
In [19]:

data['Embarked'] = data['Embarked'].map({'Q': 0, 'S': 1, 'C':2})
data['Embarked'].head()

Out[19]:
0     1.0
1     2.0
2     1.0
3     1.0
4     1.0
Name: Embarked, dtype: float64

In []:
```