Problem Statement:

For a given noisy or inconsistent dataset, implement data cleaning and preprocessing using different data mining techniques.

Dataset Used: Titanic Survivor Datasets

Kaggle Link: https://www.kaggle.com/vermaamitesh/titanic-survivor-datasets

Import Libraries

```
import numpy as np
import pandas as pd
import·matplotlib.pyplot·as·plt
import·seaborn·as·sns
```

Load Dataset

```
url = 'https://raw.githubusercontent.com/prajaktajoshi2390/data-cleaning-and-preprocessing/ma
df1 = pd.read_csv(url)
```

```
df1.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.283

```
df1.info()
```

```
<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
```

```
df1.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

--> Handle NA Values

```
df1.isnull().sum()
```

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

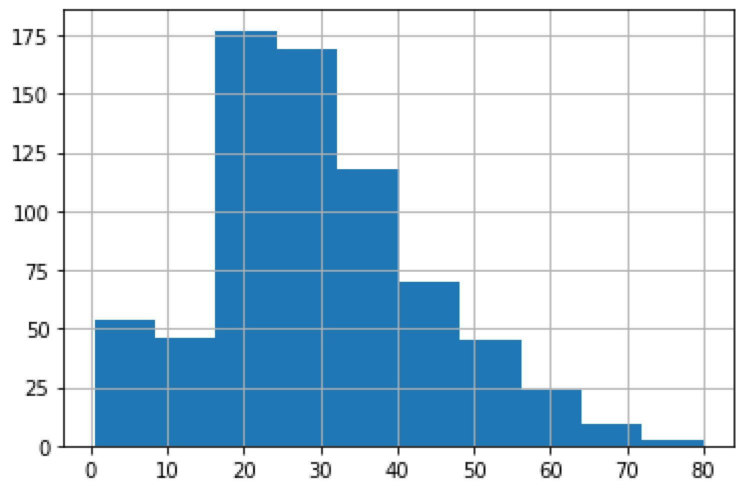
```
df1.drop(columns='Cabin', inplace=True)
#df1.Cabin = df1.Cabin.fillna("unknown")
```

```
df1.isnull().sum()
```

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

--> Apply Univariate Imputation

```
df1['Age'].hist();
```




```
age_mean = df1['Age'].mean()
df1['Age'].replace(np.nan, age_mean, inplace=True)
fare_mean = df1['Fare'].mean()
df1['Fare'].replace(np.nan, fare_mean, inplace=True)
```

```
df1['Embarked'].value_counts()
```

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

--> Categorical Variable Substitution

```
df1['Embarked'].replace(np.nan, 'S', inplace=True)
```

```
df1.isnull().sum()
```

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

--> Drop unimportant columns

```
columns_dropped = ['PassengerId','Ticket','Name']
df1.drop(columns=columns_dropped, inplace=True)
```

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  891 non-null    int64
 1   Pclass    891 non-null    int64
 2   Sex       891 non-null    object
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Fare      891 non-null    float64
 7   Embarked  891 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 55.8+ KB
```

```
!pip install category_encoders
```

```
Requirement already satisfied: category_encoders in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from patsy
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (f
```

--> Use category encoder with One Hot Encoding for sex and embarked attributes.

```
import category_encoders as cat_encoder

columns_encoded = ['Sex', 'Embarked']
one_hot_enc = cat_encoder.OneHotEncoder(cols=columns_encoded)
df1 = one_hot_enc.fit_transform(df1)
```

```
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_
  elif pd.api.types.is_categorical(cols):
```

```
df1.head()
```

	Survived	Pclass	Sex_1	Sex_2	Age	SibSp	Parch	Fare	Embarked_1	Embarked_2	E
0	0	3	1	0	22.0	1	0	7.2500	1	0	
1	1	1	0	1	38.0	1	0	71.2833	0	1	
2	1	3	0	1	26.0	0	0	7.9250	1	0	
3	1	1	0	1	35.0	1	0	53.1000	1	0	
4	0	3	1	0	35.0	0	0	8.0500	1	0	

```
df1.drop(columns=['Sex_2','Embarked_3'], inplace=True)
```

```
df1.head()
```

	Survived	Pclass	Sex_1	Age	SibSp	Parch	Fare	Embarked_1	Embarked_2
0	0	3	1	22.0	1	0	7.2500	1	0
1	1	1	0	38.0	1	0	71.2833	0	1
2	1	3	0	26.0	0	0	7.9250	1	0
3	1	1	0	35.0	1	0	53.1000	1	0
4	0	3	1	35.0	0	0	8.0500	1	0

--> Feature Enginnering: Creation of new variable to replace multiple existing related variables

```
df1['members_per_family'] = df1['SibSp'] + df1['Parch'] + 1
df1.drop(columns=['SibSp','Parch'], inplace=True)
```

```
df1.head()
```

	Survived	Pclass	Sex_1	Age	Fare	Embarked_1	Embarked_2	members_per_family
0	0	3	1	22.0	7.2500	1	0	2
1	1	1	0	38.0	71.2833	0	1	2
2	1	3	0	26.0	7.9250	1	0	1
3	1	1	0	35.0	53.1000	1	0	2
4	0	3	1	35.0	8.0500	1	0	1

```
target = df1['Survived']
metricList = ['Pclass', 'Sex_1', 'Age', 'Fare', 'Embarked_1', 'Embarked_2', 'members_per_fami
inputs = df1[metricList]
```

--> Implement Scaling and Normalization

```
from sklearn.preprocessing import MinMaxScaler

# Create a scaler object
scaler = MinMaxScaler()

# Fit the inputs (calculate the mean and standard deviation feature-wise)
scaler.fit(inputs)

# Scale the features and store them in a new variable (the actual scaling procedure)
inputs_scaled = scaler.transform(inputs)
```

Build the model

```
# Import module for splitting data
from sklearn.model_selection import train_test_split

# split dataset into 75% training and 25% test          #x          #y                    #sa
x_train, x_test, y_train, y_test = train_test_split(inputs_scaled, target, test_size=0.25, ra
```

Test the model with different regression techniques

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

```
regressors = []
regressors.append(('Linear Regression', LinearRegression()))
regressors.append(('KNN Regression', KNeighborsRegressor(n_neighbors=2, weights='uniform')))
regressors.append(('Random Forest Regression', RandomForestRegressor(n_estimators=500, random
regressors.append(('AdaBoost Regression', AdaBoostRegressor(n_estimators=50, random_state=Non
regressors.append(('XGBoost Regression', XGBRegressor(verbosity=0, n_estimators=500)))

x_train, x_test, y_train, y_test = train_test_split(inputs_scaled, target,  test_size=0.25, r


from sklearn.metrics import r2_score, mean_squared_error
from sklearn import metrics

results = []
predictions = []

for name, regressor in regressors:
  regressor.fit(x_train, y_train)
  y_pred = regressor.predict(x_train)
  r2 = metrics.r2_score(y_train, y_pred)
  mse = mean_squared_error(y_train, y_pred)
  mae = mean_absolute_error(y_train, y_pred)
  acc = (regressor.score(x_train, y_train)) * 100
  results.append([name, r2, mse, mae, acc])
  predictions.append([name, y_pred])

df_regressions = pd.DataFrame(results, columns=['Name', 'R2 Score', 'MSE', 'MAE', 'Accuracy']
df_predictions = pd.DataFrame(predictions, columns = ['Name', 'Predictions'])
```

Find out the model prediction accuracy

```
df_regressions
```

	Name	R2 Score	MSE	MAE	Accuracy
0	Linear Regression	0.391824	0.144172	0.295163	39.182390
1	KNN Regression	0.747400	0.059880	0.116766	74.740026
2	Random Forest Regression	0.881746	0.028033	0.101039	88.174622
3	AdaBoost Regression	0.423835	0.136583	0.318412	42.383454
4	XGBoost Regression	0.802083	0.046917	0.143090	80.208256

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