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Introduction to Kaggle and Data preprocessing

AIM:

To perform Data preprocessing in a data set downloaded from Kaggle

EQUIPMENTS REQUIRED:

Hardware – PCs Anaconda – Python 3.7 Installation / Google Colab /Jupiter Notebook

RELATED THEORETICAL CONCEPT:

Kaggle : Kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges.
Data Preprocessing:
Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis. Data Preprocessing is the process of making data suitable for use while training a machine learning model. The dataset initially provided for training might not be in a ready-to-use state, for e.g. it might not be formatted properly, or may contain missing or null values.Solving all these problems using various methods is called Data Preprocessing, using a properly processed dataset while training will not only make life easier for you but also increase the efficiency and accuracy of your model.
Need of Data Preprocessing :
For achieving better results from the applied model in Machine Learning projects the format of the data has to be in a proper manner. Some specified Machine Learning model needs information in a specified format, for example, Random Forest algorithm does not support null values, therefore to execute random forest algorithm null values have to be managed from the original raw data set. Another aspect is that the data set should be formatted in such a way that more than one Machine Learning and Deep Learning algorithm are executed in one data set, and best out of them is chosen.

ALGORITHM:

STEP 1:Importing the libraries
STEP 2:Importing the dataset
STEP 3:Taking care of missing data
STEP 4:Encoding categorical data
STEP 5:Normalizing the data
STEP 6:Splitting the data into test and train

PROGRAM:

```
#import libraries
from google.colab import files
import pandas as pd
import io
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

#Opening the file
df = pd.read_csv("Churn_Modelling.csv")
df.head()
df.tail()
df.info()
df.columns

# Finding Missing Values
df.isnull().sum()

#Check for Duplicates
df["duplicated"] = df.duplicated()

df.loc[df["duplicated"] == True]

#Detect Outliers
import matplotlib.pyplot as plt
data = ["CreditScore", "NumOfProducts", "Balance", "Tenure", "Age"]
fig, axes =  plt.subplots(1, 5, figsize =(15,5))

for i, col in enumerate(data):
  axes[i].boxplot(df[col])
  axes[i].set_title(f"{col}")

plt.tight_layout()
plt.show()

#Normalize the dataset
standard = StandardScaler()

cols = ['Surname','Geography','Gender','duplicated']
df_copy = df.drop(columns = cols)
df_copy = pd.DataFrame(standard.fit_transform(df_copy_1), columns=df_copy_1.columns)
df_copy.head()

#split the dataset into input and output
input_df = df_copy.drop('Exited', axis = 1)
input_df.head()

output_df = df_copy['Exited']
output_df
```

```
#splitting the data for training & Testing
x_train, x_test, y_train, y_test = train_test_split(input_df, output_df, test_size = 0.3, r

#Print the training data and testing data
x_train
y_train
x_test
y_test
```

OUTPUT:

df.head()

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

df.tail()

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

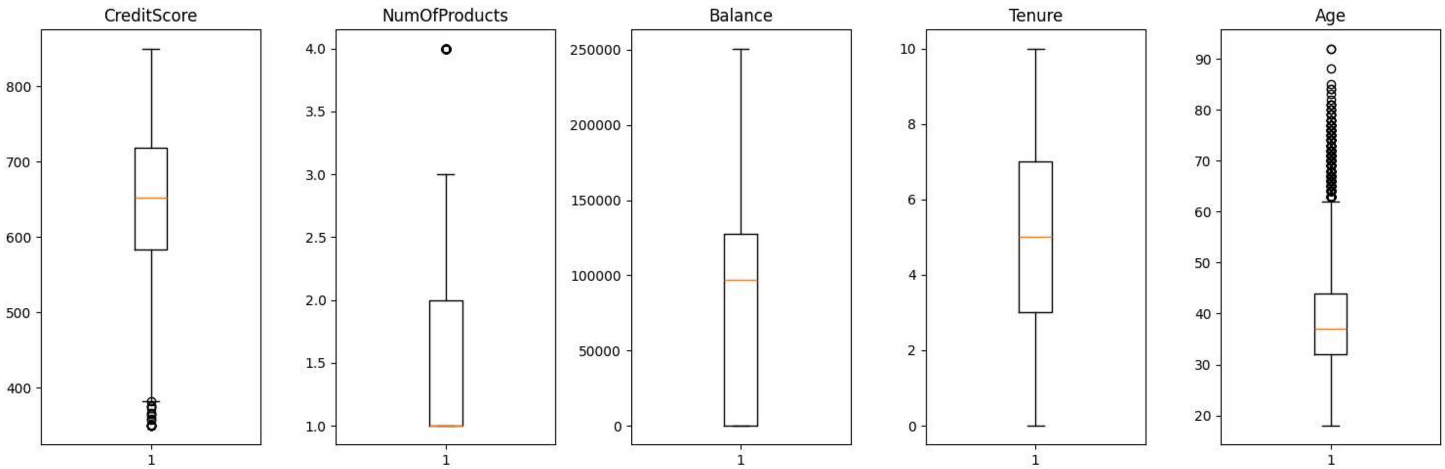
Missing values

	0
RowNumber	0
CustomerId	0
Surname	0
CreditScore	0
Geography	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0

duplicated values

RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	duplicated

Outliers



Normalizing

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-1.731878	-0.783213	-0.326221	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	1.977165
1	-1.731531	-0.606534	-0.440036	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	-0.505775
2	-1.731185	-0.995885	-1.536794	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	1.977165
3	-1.730838	0.144767	0.501521	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	-0.505775
4	-1.730492	0.652659	2.063884	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-0.505775

Input and Output

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	-1.731878	-0.783213	-0.326221	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886
1	-1.731531	-0.606534	-0.440036	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534
2	-1.731185	-0.995885	-1.536794	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687
3	-1.730838	0.144767	0.501521	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918
4	-1.730492	0.652659	2.063884	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276

	Exited
0	1.977165
1	-0.505775
2	1.977165
3	-0.505775
4	-0.505775
...	...
9995	-0.505775
9996	-0.505775
9997	1.977165
9998	1.977165
9999	-0.505775

10000 rows × 1 columns

Training Values (x_train and y_train)

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
2626	-0.822205	-1.621192	-0.853907	-0.946079	-1.041760	0.844486	0.807737	-1.547768	0.970243	0.078733
8368	1.166883	-0.740284	-0.295181	-0.469311	0.687130	0.355639	-0.911583	0.646092	-1.030670	0.674982
7330	0.807309	1.545411	-2.405923	-0.469311	1.032908	1.273963	-0.911583	0.646092	-1.030670	0.941070
9464	1.546548	1.321994	0.925738	0.007457	1.378686	-1.225848	0.807737	0.646092	-1.030670	-1.409257
1013	-1.380964	-1.214284	-0.160673	-1.422847	-0.350204	-1.225848	0.807737	0.646092	0.970243	-0.511610
...	...	...	...	...	...	...	...	...	...	...
6341	0.464709	-0.452876	1.618972	0.102810	-1.387538	0.931244	-0.911583	0.646092	0.970243	-0.936165
5697	0.241621	-0.266382	-0.864254	0.007457	-0.004426	-1.225848	0.807737	-1.547768	-1.030670	1.189955
9541	1.573222	-0.300984	-0.491770	-0.087897	1.032908	-0.274466	-0.911583	0.646092	0.970243	1.588778
5554	0.192084	1.296734	-0.315875	-0.087897	-1.733315	-1.225848	0.807737	0.646092	0.970243	-1.079420
1809	-1.105222	1.105124	-0.119286	1.056346	0.341352	0.622644	0.807737	0.646092	0.970243	-0.816585

7000 rows × 10 columns

	Exited
2626	-0.505775
8368	1.977165
7330	-0.505775
9464	-0.505775
1013	-0.505775
...	...
6341	-0.505775
5697	-0.505775
9541	-0.505775
5554	-0.505775
1809	-0.505775

Testing Values (x_test and y_test)

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
9934	1.709361	1.162831	0.429093	0.388871	1.724464	0.674788	-0.911583	0.646092	0.970243	1.063362
9186	1.450246	-1.688923	0.015222	1.819175	-0.695982	0.638958	0.807737	-1.547768	0.970243	1.624353
7267	0.785485	0.471420	-1.485060	-0.755372	1.378686	0.562612	-0.911583	0.646092	-1.030670	0.868528
3070	-0.668398	1.441912	0.242851	-0.660018	-1.041760	-1.225848	0.807737	0.646092	-1.030670	0.704062
1514	-1.207413	1.358709	-1.153963	-0.087897	1.032908	-0.080540	0.807737	0.646092	0.970243	-1.565292
...	...	...	...	...	...	...	...	...	...	...
6986	0.688144	0.158988	-0.243447	0.865639	-1.387538	0.901908	-0.911583	0.646092	-1.030670	-0.368491
1864	-1.086169	1.589981	-0.450383	0.579578	0.687130	0.759264	-0.911583	-1.547768	0.970243	0.225385
4002	-0.345544	1.675811	-0.171020	-0.946079	1.032908	0.858257	0.807737	-1.547768	0.970243	-0.525855
4157	-0.291851	0.401104	2.063884	2.200589	-0.004426	-1.225848	0.807737	0.646092	0.970243	1.393786
2124	-0.996102	-1.210711	0.553255	-0.660018	0.687130	0.822179	4.246377	-1.547768	-1.030670	1.467188

	Exited
9934	1.977165
9186	-0.505775
7267	-0.505775
3070	-0.505775
1514	-0.505775
...	...
6986	-0.505775
1864	-0.505775
4002	-0.505775
4157	-0.505775
2124	1.977165

3000 rows × 1 columns

RESULT:

Thus, Implementation of Data Preprocessing is done in python using a data set downloaded from Kaggle.