```
#!pip install pandas numpy seaborn matplotlib klib dtale scikit-learn joblib pandas-profiling
```

import pandas as pd import numpy as np %matplotlib inline import matplotlib.pyplot as plt import seaborn as sns

df\_train= pd.read\_csv(r'D:\Python37\Projects\iNeuron Intership Projects\ML\_BigMart Sales Prediction\Dataset\train.csv')  $\label{thm:csv} $$ df_test= pd.read_csv(r'D:\Python37\Projects\ineuron Intership Projects\ML_BigMart Sales Prediction\Dataset\test.csv') $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\ineuron Intership Projects\ML_BigMart Sales Prediction\Dataset\test.csv') $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\ineuron Intership Projects\ML_BigMart Sales Prediction\Dataset\test.csv') $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\ineuron Intership Projects\ML_BigMart Sales Prediction\Dataset\Test.csv') $$ $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\NL_BigMart Sales Prediction\Dataset\Test.csv') $$ $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\NL_BigMart Sales Prediction\Dataset\Test.csv') $$ $$ $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\NL_BigMart Sales Prediction\Dataset\Test.csv') $$ $$ $$ $$ $$ df_test= pd.read_csv(r'D:\Python37\Projects\NL_BigMart Sales Prediction\Dataset\NL_BigMart Sales Prediction\Dataset\NL_BigMart Sales Prediction\NL_BigMart Sales Prediction\Dataset\NL_BigMart Sales Prediction\Dataset\NL_BigMart Sales Prediction\NL_BigMart Sales Prediction\NL_BigMart Sales Prediction\Dataset\NL_BigMart Sales Prediction\NL_BigMart Sales Predictio$ 

df\_train.head()

	Item_Identifier	Item_Weight	<pre>Item_Fat_Content</pre>	Item_Visibility	<pre>Item_Type</pre>	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_S
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Med
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Med
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Med
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	١
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987	F

#df\_test

df\_train.shape

(8523, 12)

df\_train.isnull().sum()

 ${\tt Item\_Identifier}$ Item\_Weight 1463 Item\_Fat\_Content 0 Item\_Visibility Item\_Type 0  ${\tt Item\_MRP}$ 0 Outlet\_Identifier 0 Outlet\_Establishment\_Year 0 Outlet\_Size 2410 Outlet\_Location\_Type 0 Outlet\_Type
Item\_Outlet\_Sales 0 0 dtype: int64

#### df\_test.isnull().sum()

Item\_Identifier Item\_Weight 976  ${\tt Item\_Fat\_Content}$ 0 Item\_Visibility 0 0 Item\_Type  ${\tt Item\_MRP}$ 0 Outlet\_Identifier 0 Outlet\_Establishment\_Year 0 Outlet\_Size 1606 Outlet\_Location\_Type 0 Outlet\_Type 0 dtype: int64

#### df\_train.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 8523 entries, 0 to 8522 Data columns (total 12 columns):

# Column Non-Null Count Dtype --- -----

```
Item_Identifier
                             8523 non-null
                                            object
    Item_Weight
                             7060 non-null
                                            float64
                          8523 non-null object
8523 non-null float64
2
    Item_Fat_Content
    Item_Visibility
                                            float64
    Item_Type
                             8523 non-null
                                             object
    Item_MRP
5
                             8523 non-null float64
    Outlet_Identifier 8523 non-null object
6
    Outlet_Establishment_Year 8523 non-null
7
                                             int64
    Outlet_Size
                             6113 non-null
8
                                             object
9
    Outlet_Location_Type
                             8523 non-null
                                             object
11 Item_Outlet_Sales
                             8523 non-null
                                             object
                             8523 non-null float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

df\_train.describe()

std

min 25%

50%

75%

max

4.226124 4.555000

9.310000

12.857645

16.000000 21.350000

Name: Item\_Weight, dtype: float64

#### Item\_Weight Item\_Visibility Item\_MRP Outlet\_Establishment\_Year Item\_Outlet\_Sales count 7060.000000 8523.000000 8523.000000 8523.000000 8523.000000 12.857645 140.992782 1997.831867 2181.288914 0.066132 mean 4.643456 0.051598 62.275067 8.371760 1706.499616 std 4.555000 0.000000 31.290000 1985.000000 33.290000 min 25% 8.773750 0.026989 93.826500 1987.000000 834.247400 50% 12.600000 0.053931 143.012800 1999.000000 1794.331000 75% 16.850000 0.094585 185.643700 2004.000000 3101.296400 13086.964800 21.350000 0.328391 266.888400 2009.000000 max

▼ Item\_Weight is numerical column so we fill it with Mean Imputation

```
df_train['Item_Weight'].describe()
              7060.000000
     count
     mean
                12.857645
                 4.643456
     std
                 4,555000
     min
     25%
                 8.773750
     50%
                12.600000
     75%
                16.850000
     max
                21.350000
     Name: Item_Weight, dtype: float64
df_train['Item_Weight'].fillna(df_train['Item_Weight'].mean(),inplace=True)
df_test['Item_Weight'].fillna(df_test['Item_Weight'].mean(),inplace=True)
df_train.isnull().sum()
                                     0
     Item_Identifier
     Item_Weight
                                     0
     Item_Fat_Content
     Item Visibility
                                     0
     Item_Type
                                     0
     Item_MRP
     Outlet_Identifier
                                     0
                                     a
     Outlet_Establishment_Year
     Outlet_Size
                                   2410
     Outlet_Location_Type
                                     0
     Outlet_Type
                                      0
     Item_Outlet_Sales
                                     0
     dtype: int64
df_train['Item_Weight'].describe()
              8523.000000
     count
     mean
                12.857645
```

Outlet\_Size is catagorical column so we fill it with Mode Imputation

```
df_train['Outlet_Size'].value_counts()
     Medium
               2793
     Small
               2388
     High
               932
     Name: Outlet_Size, dtype: int64
df_train['Outlet_Size'].mode()
     0 Medium
     dtype: object
df_train['Outlet_Size'].fillna(df_train['Outlet_Size'].mode()[0],inplace=True)
df_test['Outlet_Size'].fillna(df_test['Outlet_Size'].mode()[0],inplace=True)
df_train.isnull().sum()
     {\tt Item\_Identifier}
     Item_Weight
     Item_Fat_Content
     Item_Visibility
                                   0
     {\tt Item\_Type}
     {\tt Item\_MRP}
                                   0
     Outlet_Identifier
     Outlet_Establishment_Year
                                   0
     Outlet_Size
                                   0
     Outlet_Location_Type
                                   0
     Outlet_Type
     Item_Outlet_Sales
     dtype: int64
df_test.isnull().sum()
     Item_Identifier
                                   0
     Item_Weight
                                   0
     {\tt Item\_Fat\_Content}
     Item_Visibility
     Item_Type
                                   0
                                   0
     Item_MRP
     Outlet_Identifier
     Outlet Establishment Year
                                   0
     Outlet_Size
                                   0
     Outlet_Location_Type
     Outlet_Type
     dtype: int64
```

### Selecting features based on general requirements

```
df_train.drop(['Item_Identifier','Outlet_Identifier'],axis=1,inplace=True)
df_test.drop(['Item_Identifier','Outlet_Identifier'],axis=1,inplace=True)

df_train
```

	Item_Weight	Item_Fat_Content	Item_Visibility	<pre>Item_Type</pre>	Item_MRP	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	0
0	9.300	Low Fat	0.016047	Dairy	249.8092	1999	Medium	Tier 1	Superm
1	5.920	Regular	0.019278	Soft Drinks	48.2692	2009	Medium	Tier 3	Superm
2	17.500	Low Fat	0.016760	Meat	141.6180	1999	Medium	Tier 1	Superm
3	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	1998	Medium	Tier 3	G
4	8.930	Low Fat	0.000000	Household	53.8614	1987	High	Tier 3	Superm
		***							
8518	6.865	Low Fat	0.056783	Snack Foods	214.5218	1987	High	Tier 3	Superm
8519	8.380	Regular	0.046982	Baking Goods	108.1570	2002	Medium	Tier 2	Superm
8520	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	2004	Small	Tier 2	Superm
8521	7.210	Regular	0.145221	Snack Foods	103.1332	2009	Medium	Tier 3	Superm
8522	14 800	I ow Fat	0 044878	Soft Drinks	75 4670	1997	Small	Tier 1	Sunern

## ▼ EDA with Dtale Library

import dtale

 $\verb|C:\Users \land Anaconda \& lib \leqslant e-packages \land dash\_application \land e-packages \land dash\_application \land e-packages \land dash\_application \land e-packages \land dash\_application \land e-packages \land e$ 

The dash\_core\_components package is deprecated. Please replace

import dash\_core\_components as dcc

 $\label{linear_cond} C: \begin{tabular}{ll} C: \begin{tabular}{ll}$ 

import dash\_html\_components as html

dtale.show(df\_train)

2021-10-18 12:57:23,097 - INFO - NumExpr defaulting to 8 threads.

# ▼ EDA using Pandas Profiling

from pandas\_profiling import ProfileReport

profile = ProfileReport(df\_train, title="Pandas Profiling Report")



<sup>`</sup>import dash\_core\_components as dcc` with `from dash import dcc`

The dash\_html\_components package is deprecated. Please replace `import dash\_html\_components as html` with `from dash import html`

profile

## Overview

Dataset statistics		
Number of variables		10
Number of observations	8523	
Missing cells	0	
Missing cells (%)	0.0%	
Duplicate rows		0
Duplicate rows (%)		0.0%
Total size in memory		3.0 MiB
Average record size in memory		371.1 B
/ariable types		
NUM	5	

## **Variables**

Item Weiaht

```
plt.figure(figsize=(10,5))
sns.heatmap(df_train.corr(),annot=True)
plt.show()
```

C:\Users\thero\Anaconda3\lib\site-packages\ipykernel\_launcher.py:3: UserWarning:

Matplotlib is currently using agg, which is a non-GUI backend, so cannot show the figure.

## ▼ EDA using Klib Library

```
import klib

# klib.describe - functions for visualizing datasets
klib.cat_plot(df_train) # returns a visualization of the number and frequency of categorical features

GridSpec(6, 5)

klib.corr_mat(df_train) # returns a color-encoded correlation matrix
```

#### 

<matplotlib.axes.\_subplots.AxesSubplot at 0x1daa3b33ec8>

klib.dist\_plot(df\_train) # returns a distribution plot for every numeric feature

<matplotlib.axes.\_subplots.AxesSubplot at 0x1daa9e7d688>

 $\verb|klib.missingval_plot(df_train)| \# \ returns \ a \ figure \ containing \ information \ about \ missing \ values$ 

No missing values found in the dataset.

### Data Cleaning using Klib Library

```
# klib.clean - functions for cleaning datasets klib.data_cleaning(df_train) # performs datacleaning(drop duplicates & empty rows/cols, adjust dtypes,...)
```

Shape of cleaned data: (8523, 10) Remaining NAs: 0

Changes:

Dropped rows: 0

of which 0 duplicates. (Rows: [])

Dropped columns: 0

of which 0 single valued. Columns: [] Dropped missing values: 0 Reduced memory by at least: 0.08 MB (-12.31%)

	item_weight	<pre>item_fat_content</pre>	<pre>item_visibility</pre>	item_type	item_mrp	<pre>outlet_establishment_</pre>
0	9.300000	Low Fat	0.016047	Dairy	249.809204	
1	5.920000	Regular	0.019278	Soft Drinks	48.269199	
2	17.500000	Low Fat	0.016760	Meat	141.617996	
3	19.200001	Regular	0.000000	Fruits and Vegetables	182.095001	
4	8.930000	Low Fat	0.000000	Household	53.861401	
8518	6.865000	Low Fat	0.056783	Snack Foods	214.521805	
8519	8.380000	Regular	0.046982	Baking Goods	108.156998	
8520	10.600000	Low Fat	0.035186	Health and Hygiene	85.122398	
8521	7.210000	Regular	0.145221	Snack Foods	103.133202	
8522	14.800000	Low Fat	0.044878	Soft Drinks	75.467003	
0E02 **	v 40 aal	-				<b>&gt;</b>

	item_weight	item_fat_content	item_visibility	item_type	item_mrp	outlet_establishment_ye
0	9.300	Low Fat	0.016047	Dairy	249.8092	19
1	5.920	Regular	0.019278	Soft Drinks	48.2692	20
2	17.500	Low Fat	0.016760	Meat	141.6180	19
3	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	19
4	8.930	Low Fat	0.000000	Household	53.8614	19
8518	6.865	Low Fat	0.056783	Snack Foods	214.5218	19
8519	8.380	Regular	0.046982	Baking Goods	108.1570	20
8520	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	20
8521	7.210	Regular	0.145221	Snack Foods	103.1332	20
8522	14.800	Low Fat	0.044878	Soft Drinks	75.4670	19

df\_train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522 RangeIndex. 0323 chicles,

Data columns (total 10 columns):

Non-Null Count Dt

#	Column	Non-Null Count	Dtype
0	item_weight	8523 non-null	float64
1	item_fat_content	8523 non-null	object
2	item_visibility	8523 non-null	float64
3	item_type	8523 non-null	object
4	item_mrp	8523 non-null	float64
5	outlet_establishment_year	8523 non-null	int64
6	outlet_size	8523 non-null	object
7	outlet_location_type	8523 non-null	object
8	outlet_type	8523 non-null	object
9	item_outlet_sales	8523 non-null	float64
Attended	C1+C4/4\ !-+C4/4\ -	L. J L. / E. \	

dtypes:  $\overline{\text{float64}(4)}$ , int64(1), object(5)

memory usage: 666.0+ KB

df\_train=klib.convert\_datatypes(df\_train) # converts existing to more efficient dtypes, also called inside data\_cleaning() df\_train.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 8523 entries, 0 to 8522 Data columns (total 10 columns):

Data	cordinis (cocar to cordinis)	•	
#	Column	Non-Null Count	Dtype
0	item_weight	8523 non-null	float32
1	item_fat_content	8523 non-null	category
2	item_visibility	8523 non-null	float32
3	item_type	8523 non-null	category
4	item_mrp	8523 non-null	float32
5	outlet_establishment_year	8523 non-null	int16
6	outlet_size	8523 non-null	category
7	outlet_location_type	8523 non-null	category
8	outlet_type	8523 non-null	category
9	item_outlet_sales	8523 non-null	float32
dtype	es: category(5), float32(4)	, int16(1)	
memoi	ry usage: 192.9 KB		

klib.mv\_col\_handling(df\_train)

	item_weight	item_fat_content	item_visibility	item_type	item_mrp	outlet_establishment_
0	9.300000	Low Fat	0.016047	Dairy	249.809204	
1	5.920000	Regular	0.019278	Soft Drinks	48.269199	
2	17.500000	Low Fat	0.016760	Meat	141.617996	
3	19.200001	Regular	0.000000	Fruits and Vegetables	182.095001	
4	8.930000	Low Fat	0.000000	Household	53.861401	
8518	6.865000	Low Fat	0.056783	Snack Foods	214.521805	
8519	8.380000	Regular	0.046982	Baking Goods	108.156998	

#### Preprocessing Task before Model Building

Foods

#### ▼ 1) Label Encoding

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()

df_train['item_fat_content']= le.fit_transform(df_train['item_fat_content'])
df_train['item_type']= le.fit_transform(df_train['item_type'])
df_train['outlet_size']= le.fit_transform(df_train['outlet_size'])
df_train['outlet_location_type']= le.fit_transform(df_train['outlet_location_type'])
df_train['outlet_type']= le.fit_transform(df_train['outlet_type'])

df_train
```

	item_weight	item_fat_content	item_visibility	item_type	item_mrp	<pre>outlet_establishment_</pre>
0	9.300000	1	0.016047	4	249.809204	
1	5.920000	2	0.019278	14	48.269199	
2	17.500000	1	0.016760	10	141.617996	
3	19.200001	2	0.000000	6	182.095001	
4	8.930000	1	0.000000	9	53.861401	
8518	6.865000	1	0.056783	13	214.521805	
8519	8.380000	2	0.046982	0	108.156998	
8520	10.600000	1	0.035186	8	85.122398	
8521	7.210000	2	0.145221	13	103.133202	
8522	14.800000	1	0.044878	14	75.467003	
0E22 r	uua v 10 aaliimn	^				<b>&gt;</b>

## - 2) Splitting our data into train and test

```
X=df_train.drop('item_outlet_sales',axis=1)

Y=df_train['item_outlet_sales']

from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X,Y, random_state=101, test_size=0.2)
```

#### → 3) Standarization

Y\_test

```
X.describe()
              item_weight item_fat_content item_visibility
                                                                   item_type
                                                                                  item_mrp outlet_establishment_year outlet_size outlet_location_type outlet_type
      count 8523.000000
                                  8523.000000
                                                    8523.000000 8523.000000 8523.000000
                                                                                                            8523.000000
                                                                                                                          8523.000000
                                                                                                                                                  8523.000000
                                                                                                                                                                8523.0000
                12.858088
                                     1.369354
                                                       0.066132
                                                                     7.226681
                                                                                140.992767
                                                                                                            1997.831867
                                                                                                                             1.170832
                                                                                                                                                     1.112871
                                                                                                                                                                   1.2012
      mean
                 4.226130
                                                       0.051598
                                                                     4.209990
                                                                                 62.275051
                                                                                                               8.371760
                                                                                                                                                     0.812757
       std
                                     0.644810
                                                                                                                             0.600327
                                                                                                                                                                   0.7964
                 4.555000
                                     0.000000
                                                       0.000000
                                                                     0.000000
                                                                                 31.290001
                                                                                                            1985.000000
                                                                                                                             0.000000
                                                                                                                                                     0.000000
                                                                                                                                                                   0.0000
       min
       25%
                 9.310000
                                     1.000000
                                                       0.026989
                                                                     4.000000
                                                                                 93.826500
                                                                                                            1987.000000
                                                                                                                                                     0.000000
                                                                                                                                                                   1.0000
                                                                                                                              1.000000
       50%
                12.857645
                                     1.000000
                                                       0.053931
                                                                     6.000000
                                                                                143.012802
                                                                                                            1999.000000
                                                                                                                              1.000000
                                                                                                                                                     1.000000
                                                                                                                                                                    1.0000
       75%
                 16.000000
                                     2.000000
                                                       0.094585
                                                                    10.000000
                                                                                185.643700
                                                                                                            2004.000000
                                                                                                                             2.000000
                                                                                                                                                     2.000000
                                                                                                                                                                    1.0000
       max
                21.350000
                                     4.000000
                                                       0.328391
                                                                    15.000000
                                                                                266.888397
                                                                                                            2009.000000
                                                                                                                             2.000000
                                                                                                                                                     2.000000
                                                                                                                                                                   3.0000
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
X_train_std= sc.fit_transform(X_train)
X_test_std= sc.transform(X_test)
X_train_std
     array([[ 1.52290023, -0.57382672, 0.68469731, ..., -1.95699503,
               1.08786619, -0.25964107],
             [-1.239856 , -0.57382672, -0.09514746, ..., -0.28872895,
              -0.13870429, -0.25964107],
            [ 1.54667619, 0.97378032, -0.0083859 , ..., -0.28872895, -0.13870429, -0.25964107],
             [-0.08197109, -0.57382672, -0.91916229, ..., 1.37953713,
              -1.36527477, -0.25964107],
             [-0.74888436, \quad 0.97378032, \quad 1.21363045, \quad \dots, \quad -0.28872895,
               -0.13870429, -0.25964107],
             [\ 0.67885675,\ -0.57382672,\ \ 1.83915361,\ \ldots,\ -0.28872895,
               1.08786619, 0.98524841]])
X_test_std
     array([[-0.43860916, -0.57382672, -0.21609253, ..., -0.28872895,
             1.08786619, 0.98524841],
[ 1.22570184, -0.57382672, -0.52943464, ..., -1.95699503,
               1.08786619, -0.25964107],
             [-1.2184578, 0.97378032, 0.16277341, ..., 1.37953713, -1.36527477, -0.25964107],
             [\ 0.65508101,\ -0.57382672,\ 0.8782423,\ \ldots,\ -0.28872895,
               1.08786619, -1.50453056],
             [\ \ 1.01171909,\ -0.57382672,\ -1.28409256,\ \ldots,\ -0.28872895,
               1.08786619, 0.98524841],
             [-1.56558541, 0.97378032, -1.09265374, ..., -0.28872895,
              -0.13870429, -0.25964107]])
Y_train
     3684
               163.786804
     1935
              1607.241211
              1510.034424
     5142
              1784.343994
     4978
     2299
              3558.035156
     599
              5502.836914
     5695
              1436.796387
     8006
              2167.844727
     1361
              2700.484863
     1547
               829.586792
     Name: item_outlet_sales, Length: 6818, dtype: float32
```

```
8179 904.822205

8355 2795.694092

3411 1947.464966

7089 872.863770

6954 2450.144043

...

1317 1721.093018

4996 914.809204

531 370.184814

3891 1358.232056

6629 2418.185547

Name: item_outlet_sales, Length: 1705, dtype: float32
```

import joblib