DATA CLEANING

(It's all about data Clean Up)

https://www.linkedin.com/in/nibedita-sarkar/

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Q) What is missing Value ?

The values or data that is not stored (or not present) for some variable/s in the given dataset.

Q) What are the methods to handle missing values?

1) Ignore missing values row/ Delete row
2) Fill missing value manually
3) Global Constant
4) Measure of central tendency (Mean, Median, Mode)
5) Measure of central tendency for each class
6) Most probable value (ML Algorithms)

1) Ignore missing values row/ Delete row :

In this approach, you simply ignore/ delete the rows or observations that contain missing values. This method is suitable when the missing values are minimal and do not significantly impact the analysis. However, if a large proportion of the data is missing, this method may result in the loss of valuable information.

If the dataset contains missing values equal to or less than 5%, we can consider deleting the corresponding rows.

If the columns contain more than 20% or 30% missing values, we can consider deleting those columns.

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2) Fill missing value manually :

For small datasets, you can manually examine the missing values and fill them based on your domain knowledge or by consulting subject matter experts. While this method ensures that the filled values are accurate, it can be time-consuming and subjective.

3) Global Constant :

In this approach, missing values are replaced with a global constant value. For example, you can replace missing numerical values with zero or missing categorical values with a specific category label. However, this method may introduce bias or distort the data if the missing values are not truly missing at random.

4) Measure of central tendency (Mean, Median, Mode) :

Missing values in numerical variables can be replaced by a measure of central tendency such as the mean, median, or mode. The mean is commonly used if the variable follows a normal distribution, while the median is preferred if the variable has outliers. The mode is suitable for categorical variables.

5) Measure of central tendency for each class :

If the data has categorical variables and missing values are present within specific classes or groups, you can replace the missing values with the measure of central tendency (mean, median, or mode) calculated separately for each class. This approach helps preserve the within-class characteristics and reduces bias.

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6) Most probable value (ML Algorithms) :

Machine learning algorithms can be used to predict the missing values based on the available data. You can train a model on the non-missing values and then use it to predict the missing values. This method utilizes the relationships and patterns in the data to estimate the missing values. However, it assumes that the missing values are predictable based on other variables.

Note :

Among the six methods mentioned, I have written a process to handle missing values for the first five methods. The sixth method involves handling missing values using a machine learning algorithm, which I will share at a later time.

Please consider following @Nibedita Sarkar on LinkedIn for more updates and information. You can find the link to her LinkedIn profile here:

[https://www.linkedin.com/in/nibedita-sarkar/]

tation-by-deleting-row-and-columns

June 11, 2023

1 Data Cleaning :

1.1 Missing value imputation by Deleting Rows and Columns :

Importing necessary libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

data (Original) :

[3]:
```
data = pd.read_csv("train.csv")  # Load dataset
```

[5]:
```
data.head(5) # Checking first 5 rows from the DataFrame.
```

[5]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	\
0	1	60	RL	65.0	8450	Pave	NaN	Reg	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	

	LandContour	Utilities	…	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	\
0	Lvl	AllPub	…	0	NaN	NaN	NaN	0	2	
1	Lvl	AllPub	…	0	NaN	NaN	NaN	0	5	
2	Lvl	AllPub	…	0	NaN	NaN	NaN	0	9	
3	Lvl	AllPub	…	0	NaN	NaN	NaN	0	2	
4	Lvl	AllPub	…	0	NaN	NaN	NaN	0	12	

	YrSold	SaleType	SaleCondition	SalePrice
0	2008	WD	Normal	208500
1	2007	WD	Normal	181500
2	2008	WD	Normal	223500
3	2006	WD	Abnorml	140000
4	2008	WD	Normal	250000

```
[5 rows x 81 columns]
```

[4]:
```
data.shape # Checking the shape of the dataset, dataset contains 1460 rows and␣
↪81 columns
```

[4]:
```
(1460, 81)
```

When we check the shape of the data using the command "data.shape", we can observe that the DataFrame consists of 1460 rows and 81 columns. However, when we examine the first five rows of the DataFrame using the command "data.head(5)", it doesn't display all 81 columns. As a result, we utilize the following code, specifically "pd.set_option()", to address this issue.

[6]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

pd.set_option('display.max_columns', None): This line sets the maximum number of columns to be displayed in the output to None, which means there is no limit. As a result, all columns in a DataFrame will be shown when you print or display it.

pd.set_option('display.max_rows', None): This line sets the maximum number of rows to be displayed in the output to None, removing any limit. As a result, all rows in a DataFrame will be shown when you print or display it.

[7]:
```
data.head(2) # The code `data.head(2)` displays the first two rows of the␣
↪dataset, showing all 81 columns.
```

[7]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg

  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd       None

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
1         0.0        TA        TA     CBlock       Gd       TA           Gd

  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
```

```
0          GLQ         706          Unf            0        150          856
1          ALQ         978          Unf            0        284         1262

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
1     Attchd       1976.0          RFn           2         460         TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
```

[8]:
```
data.tail(2) # The code `data.tail(2)` displays the last two rows of the␣
↪dataset.
```

[8]:
```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
1458  1459          20       RL         68.0     9717   Pave   NaN      Reg
1459  1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
1458         Lvl    AllPub    Inside       Gtl        NAmes       Norm
1459         Lvl    AllPub    Inside       Gtl      Edwards       Norm

     Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
1458       Norm     1Fam     1Story            5            6       1950
1459       Norm     1Fam     1Story            5            6       1965

      YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
```

```
1458          1996       Hip  CompShg     MetalSd     MetalSd       None
1459          1965     Gable  CompShg     HdBoard     HdBoard       None

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond  \
1458         0.0        TA        TA     CBlock       TA       TA
1459         0.0        Gd        TA     CBlock       TA       TA

     BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
1458           Mn          GLQ          49          Rec        1029
1459           No          BLQ         830          LwQ         290

      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
1458          0         1078    GasA        Gd          Y      FuseA
1459        136         1256    GasA        Gd          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
1458      1078         0             0       1078             1             0
1459      1256         0             0       1256             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
1458         1         0             2             1          Gd
1459         1         1             3             1          TA

      TotRmsAbvGrd Functional  Fireplaces FireplaceQu GarageType  GarageYrBlt  \
1458             5        Typ           0         NaN     Attchd       1950.0
1459             6        Typ           0         NaN     Attchd       1965.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
1458          Unf           1         240         TA         TA          Y
1459          Fin           1         276         TA         TA          Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
1458         366            0            112          0            0
1459         736           68              0          0            0

      PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold SaleType  \
1458         0    NaN   NaN         NaN        0       4    2010       WD
1459         0    NaN   NaN         NaN        0       6    2008       WD

     SaleCondition  SalePrice
1458        Normal     142125
1459        Normal     147500
```

[9]:
```
data.info()

'''
```

```
The `data.info()` function provides a concise summary of the dataset, including␣
 ↪information about the number of rows,
columns, data types, memory usage and missing values.

'''
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     1452 non-null   object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
```

```
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

[9]:
```
'\nThe `data.info()` function provides a concise summary of the dataset,
including information about the number of rows, \ncolumns, data types, memory
usage and missing values.\n\n'
```

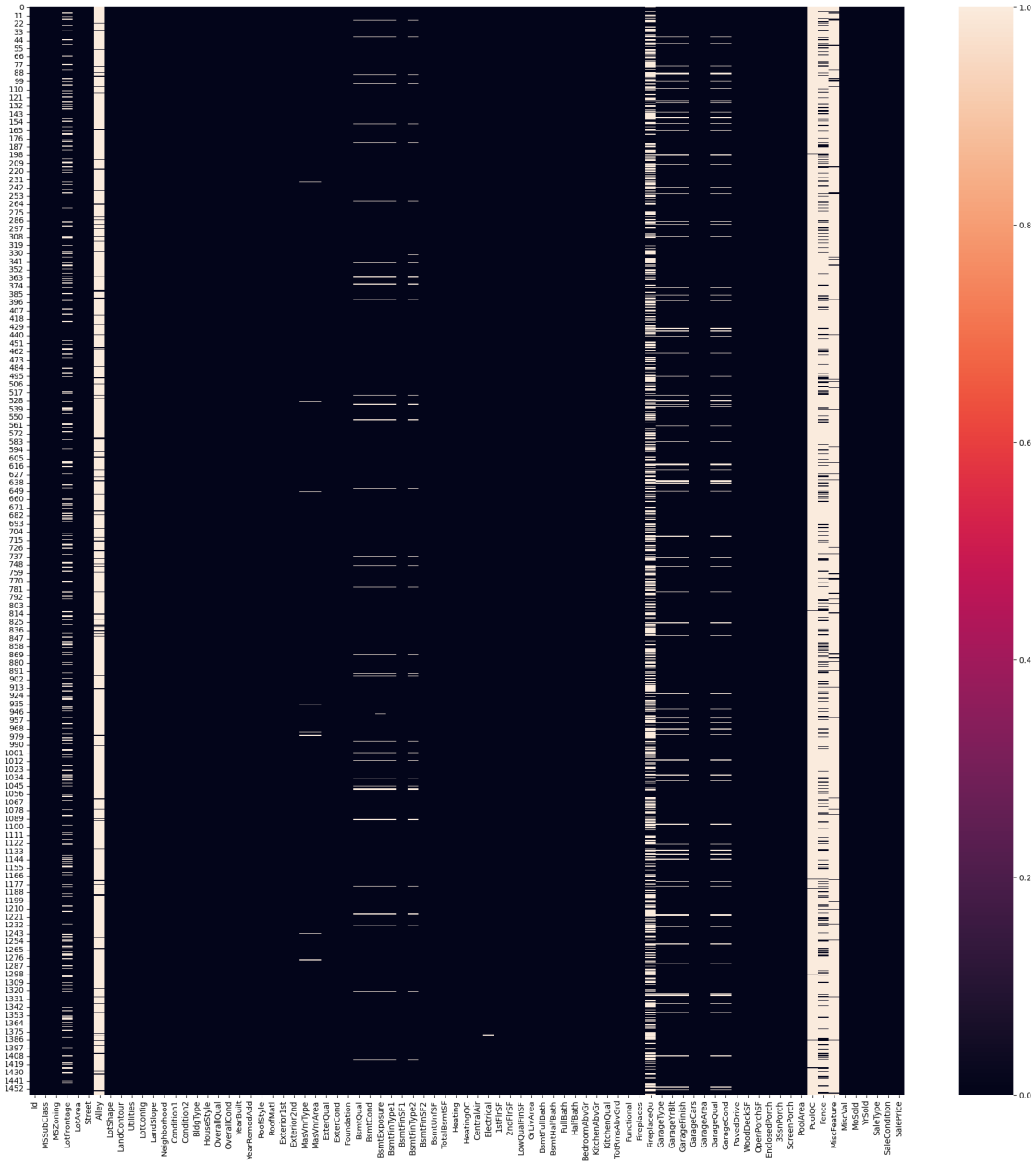
[10]:
```
data.isnull().sum()

# The code `data.isnull().sum()` calculates the sum of missing values in each␣
 ↪column of the dataset.
```

[10]:
```
Id                0
MSSubClass        0
MSZoning          0
LotFrontage     259
LotArea           0
Street            0
Alley          1369
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
LandSlope         0
Neighborhood      0
Condition1        0
Condition2        0
BldgType          0
HouseStyle        0
OverallQual       0
OverallCond       0
YearBuilt         0
YearRemodAdd      0
RoofStyle         0
RoofMatl          0
Exterior1st       0
Exterior2nd       0
MasVnrType        8
MasVnrArea        8
ExterQual         0
ExterCond         0
Foundation        0
BsmtQual         37
BsmtCond         37
BsmtExposure     38
BsmtFinType1     37
BsmtFinSF1        0
BsmtFinType2     38
BsmtFinSF2        0
BsmtUnfSF         0
```

```
TotalBsmtSF         0
Heating             0
HeatingQC           0
CentralAir          0
Electrical          1
1stFlrSF            0
2ndFlrSF            0
LowQualFinSF        0
GrLivArea           0
BsmtFullBath        0
BsmtHalfBath        0
FullBath            0
HalfBath            0
BedroomAbvGr        0
KitchenAbvGr        0
KitchenQual         0
TotRmsAbvGrd        0
Functional          0
Fireplaces          0
FireplaceQu       690
GarageType         81
GarageYrBlt        81
GarageFinish       81
GarageCars          0
GarageArea          0
GarageQual         81
GarageCond         81
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
PoolQC           1453
Fence            1179
MiscFeature      1406
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
dtype: int64
```

[11]:
```
plt.figure(figsize=(25,25))
sns.heatmap(data.isnull())
```

```
plt.show()

'''
The code `plt.figure(figsize=(25,25))` sets the figure size for the plot.

The next line `sns.heatmap(data.isnull())` creates a heatmap visualization of␣
 ↪the missing values in the dataset
using the seaborn library.

'''
```



[11]:
```
'\nThe code `plt.figure(figsize=(25,25))` sets the figure size for the plot.
\n\nThe next line `sns.heatmap(data.isnull())` creates a heatmap visualization
of the missing values in the dataset \nusing the seaborn library.\n\n'
```

[12]:
```
missing_value_percent = data.isnull().sum() / data.shape[0] * 100
print(missing_value_percent)

# The code calculates the percentage of missing values in each column of the␣
 ↪dataset and then prints the resulting percentages.
```

```
Id               0.000000
MSSubClass       0.000000
MSZoning         0.000000
LotFrontage     17.739726
LotArea          0.000000
Street           0.000000
Alley           93.767123
LotShape         0.000000
LandContour      0.000000
Utilities        0.000000
LotConfig        0.000000
LandSlope        0.000000
Neighborhood     0.000000
Condition1       0.000000
Condition2       0.000000
BldgType         0.000000
HouseStyle       0.000000
OverallQual      0.000000
OverallCond      0.000000
YearBuilt        0.000000
YearRemodAdd     0.000000
RoofStyle        0.000000
RoofMatl         0.000000
Exterior1st      0.000000
Exterior2nd      0.000000
MasVnrType       0.547945
MasVnrArea       0.547945
ExterQual        0.000000
ExterCond        0.000000
Foundation       0.000000
BsmtQual         2.534247
BsmtCond         2.534247
BsmtExposure     2.602740
BsmtFinType1     2.534247
BsmtFinSF1       0.000000
BsmtFinType2     2.602740
```

```
BsmtFinSF2        0.000000
BsmtUnfSF         0.000000
TotalBsmtSF       0.000000
Heating           0.000000
HeatingQC         0.000000
CentralAir        0.000000
Electrical        0.068493
1stFlrSF          0.000000
2ndFlrSF          0.000000
LowQualFinSF      0.000000
GrLivArea         0.000000
BsmtFullBath      0.000000
BsmtHalfBath      0.000000
FullBath          0.000000
HalfBath          0.000000
BedroomAbvGr      0.000000
KitchenAbvGr      0.000000
KitchenQual       0.000000
TotRmsAbvGrd      0.000000
Functional        0.000000
Fireplaces        0.000000
FireplaceQu      47.260274
GarageType        5.547945
GarageYrBlt       5.547945
GarageFinish      5.547945
GarageCars        0.000000
GarageArea        0.000000
GarageQual        5.547945
GarageCond        5.547945
PavedDrive        0.000000
WoodDeckSF        0.000000
OpenPorchSF       0.000000
EnclosedPorch     0.000000
3SsnPorch         0.000000
ScreenPorch       0.000000
PoolArea          0.000000
PoolQC           99.520548
Fence            80.753425
MiscFeature      96.301370
MiscVal           0.000000
MoSold            0.000000
YrSold            0.000000
SaleType          0.000000
SaleCondition     0.000000
SalePrice         0.000000
dtype: float64
```

[40]:
```
missing_value_column = missing_value_percent[missing_value_percent > 17].keys()
print(missing_value_column)

'''
The code is used to identify the columns in a dataset that have missing values␣
 ↪exceeding 17%.
It retrieves the keys (column names) from the `missing_value_percent`␣
 ↪dictionary where the corresponding values
are greater than 17%.

'''
```

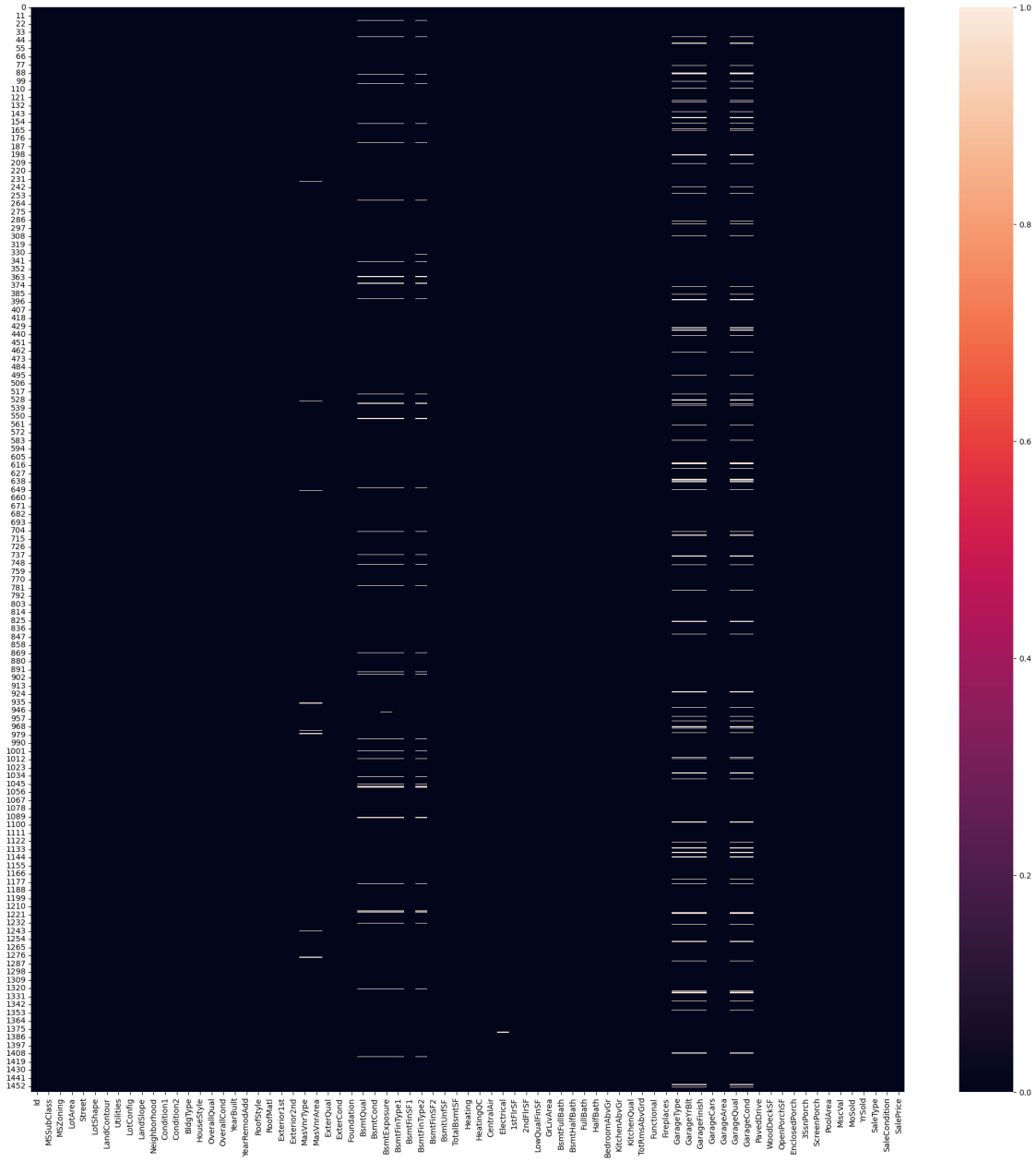
```
Index(['LotFrontage', 'Alley', 'FireplaceQu', 'PoolQC', 'Fence',
       'MiscFeature'],
      dtype='object')
```

[40]:
```
'\nThe code is used to identify the columns in a dataset that have missing
values exceeding 17%. \nIt retrieves the keys (column names) from the
`missing_value_percent` dictionary where the corresponding values \nare greater
than 17%.\n\n'
```

data1 after dropping missing value column $> 17\%$:

[20]:
```
data1 = data.drop(columns = missing_value_column)
```

[21]:
```
plt.figure(figsize=(25,25))
sns.heatmap(data1.isnull())
plt.show()

'''
The code is used to get visualization of the missing values after removing␣
 ↪columns
where the missing values exceed 17% of the total data in those columns.

'''
```



[21]:
```
'\nThe code is used to get visualization of the missing values after removing
columns \nwhere the missing values exceed 20% of the total data in those
columns.\n\n'
```

Our objective is to eliminate all the white lines from the visualization in order to achieve a cleaner and more organized appearance.

[22]:
```
data1.shape # Checking the shape of the DataFrame , DataFrame contains Rows:␣
↪1460 and Columns: 76
```

[22]: (1460, 75)

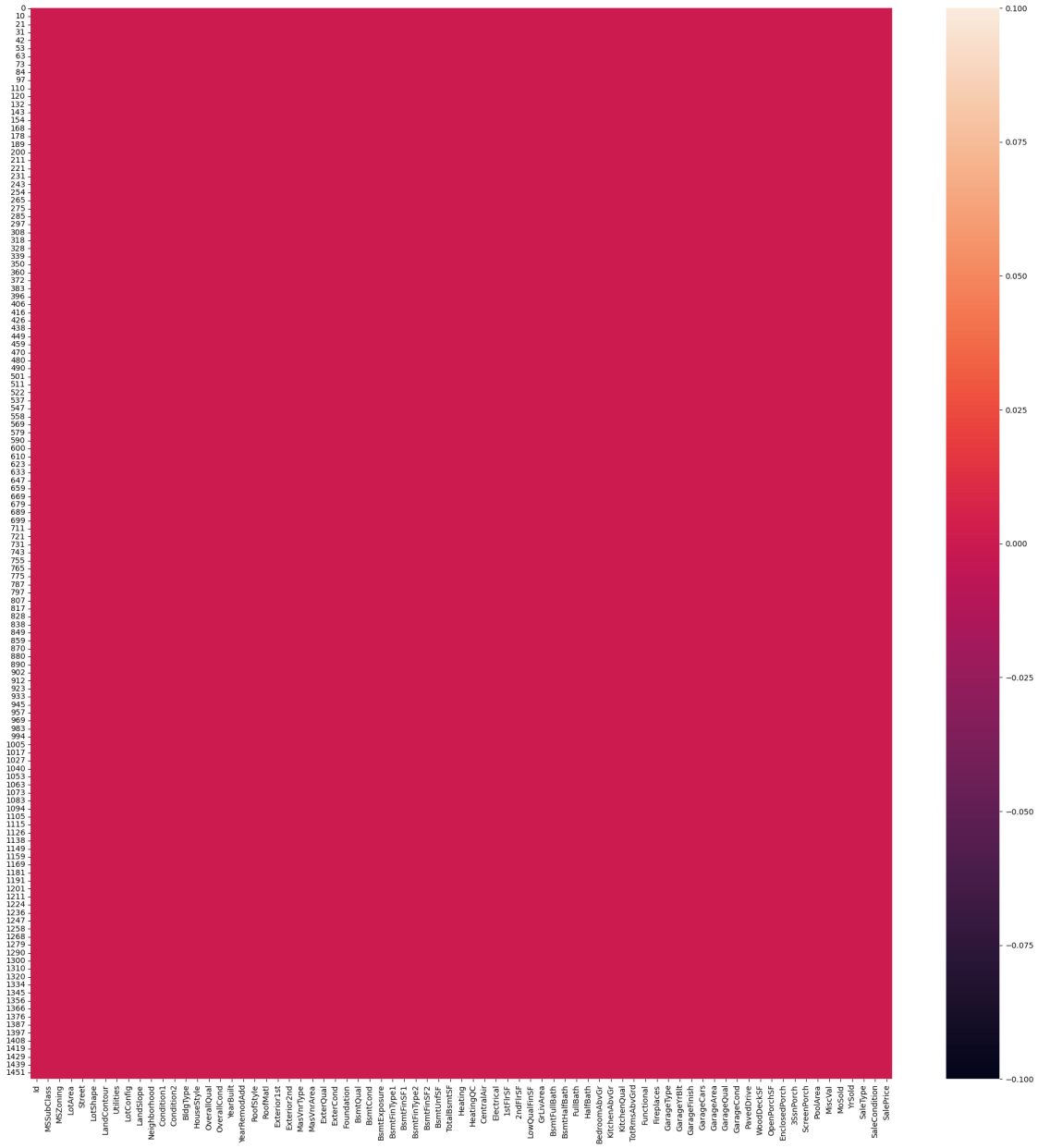
data2 after dropping missing value rows.

[23]:
```
data2 = data1.dropna() # deleting missing value rows.
```

[41]:
```
data2.shape
```

[41]: (1338, 75)

[18]:
```
plt.figure(figsize=(25,25))
sns.heatmap(df1.isnull())
plt.show()

#  This heatmap creates a visualization of missing values after dropping rows.
```



Here, we have achieved a cleaner and more organized appearance.

[26]:
```
data2.isnull().sum().sum() # Here, we can see that our DatFrame doesn't contain␣
↪ant null values.
```

[26]: 0

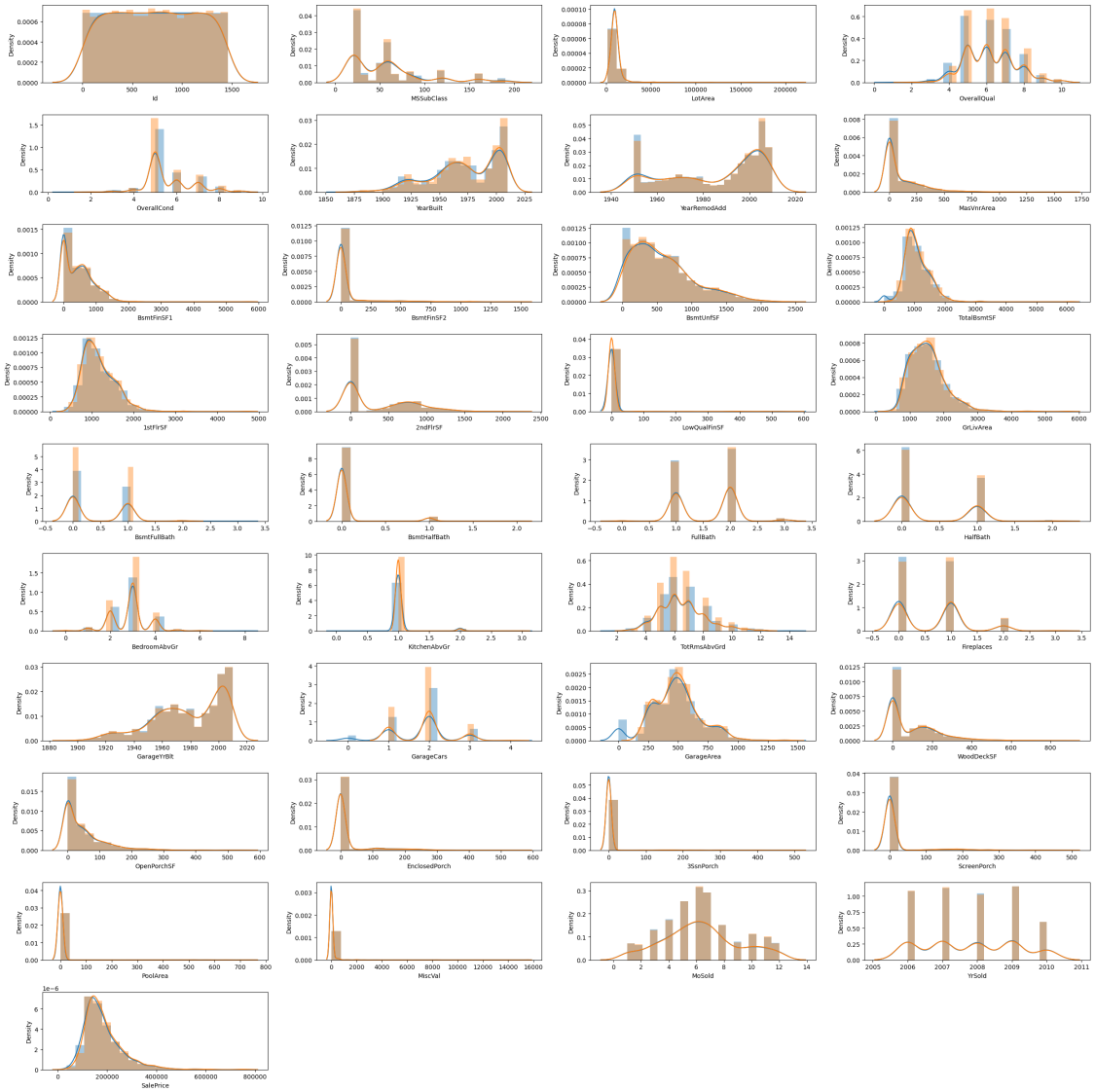
Checking the data distribution before and after dealing with missing values for numerical column.

[27]:
```
data2.select_dtypes(include=['int64','float64']).columns  # Cheking the column␣
↪names of numerical DataFrame.
```

[27]:
```
Index(['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

[28]:
```
num_var = ['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice']
```

[30]:
```
plt.figure(figsize=(25,25))

# Calculate the number of rows and columns for the subplots

num_rows = (len(num_var) + 3) // 4  # Adjust the number of columns as needed
num_cols = 4

for i, var in enumerate(num_var):
    plt.subplot(num_rows, num_cols, i+1)
    sns.distplot(data[var], bins=20)
    sns.distplot(data2[var], bins=20)

plt.tight_layout()  # Optional: Adjusts the spacing between subplots

plt.show()
```



We can see there is not much difference between original dataset and cleaned dataset.

Checking the data distribution before and after dealing with missing values for categorical column.

[32]:
```
data2.select_dtypes(include=['object']).columns

# It is used to retrieve the column names of a DataFrame df1 that have object␣
↪data type.
```

[32]:
```
Index(['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
```

```
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
```

[33]:
```
cat_var = ['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition']
```

[36]:
```
pd.concat([data['MSZoning'].value_counts() / data.shape[0] * 100,
           data2['MSZoning'].value_counts() / data2.shape[0] * 100], axis=1,
           keys=['MSZoning_orginal', 'MSZoning_clean'])
```

[36]:

	MSZoning_orginal	MSZoning_clean
RL	78.835616	79.671151
RM	14.931507	14.275037
FV	4.452055	4.633782
RH	1.095890	0.822123
C (all)	0.684932	0.597907

The code snippet you provided combines the value counts of the 'MSZoning' column from the original data (data) and the cleaned data (df1) using pd.concat(). It creates a DataFrame that shows the percentage distribution of the values in the 'MSZoning' column for both datasets.

[37]:
```
def cat_var_dist(var):
    return pd.concat([data[var].value_counts() / data.shape[0]*100,
           data2[var].value_counts() / data2.shape[0] * 100], axis=1,
           keys=[var + '_orginal', var + '_clean'])
```

[38]:
```
cat_var_dist('BsmtQual')
```

[38]:

	BsmtQual_orginal	BsmtQual_clean
TA	44.452055	44.394619
Gd	42.328767	44.245142
Ex	8.287671	8.968610
Fa	2.397260	2.391629

The cat_var_dist() function you provided calculates the percentage distribution of values in a categorical variable for both the original data (data) and the cleaned data (df1). It returns a DataFrame that combines these distributions side by side.

[39]:
```
for var in cat_var:
    result = cat_var_dist(var)
    print(result)
    print('\n')
```

```
         MSZoning_orginal  MSZoning_clean
RL               78.835616       79.671151
RM               14.931507       14.275037
FV                4.452055        4.633782
RH                1.095890        0.822123
C (all)           0.684932        0.597907


      Street_orginal  Street_clean
Pave       99.589041     99.626308
Grvl        0.410959      0.373692


     LotShape_orginal  LotShape_clean
Reg         63.356164       61.958146
IR1         33.150685       34.304933
IR2          2.808219        2.989537
IR3          0.684932        0.747384


     LandContour_orginal  LandContour_clean
Lvl            89.794521          90.134529
Bnk             4.315068           3.886398
HLS             3.424658           3.587444
Low             2.465753           2.391629


        Utilities_orginal  Utilities_clean
AllPub          99.931507        99.925262
NoSeWa           0.068493         0.074738


         LotConfig_orginal  LotConfig_clean
Inside           72.054795        71.524664
Corner           18.013699        18.236173
CulDSac           6.438356         6.726457
FR2               3.219178         3.213752
FR3               0.273973         0.298954


     LandSlope_orginal  LandSlope_clean
Gtl          94.657534        94.544096
```

Mod	4.452055	4.559043
Sev	0.890411	0.896861

	Neighborhood_orginal	Neighborhood_clean
NAmes	15.410959	15.620329
CollgCr	10.273973	10.911809
OldTown	7.739726	7.473842
Edwards	6.849315	5.231689
Somerst	5.890411	6.203288
Gilbert	5.410959	5.754858
NridgHt	5.273973	5.605381
Sawyer	5.068493	5.156951
NWAmes	5.000000	5.455904
SawyerW	4.041096	3.961136
BrkSide	3.972603	3.512706
Crawfor	3.493151	3.736921
Mitchel	3.356164	3.139013
NoRidge	2.808219	3.064275
Timber	2.602740	2.765321
IDOTRR	2.534247	2.167414
ClearCr	1.917808	1.943199
StoneBr	1.712329	1.868460
SWISU	1.712329	1.494768
MeadowV	1.164384	0.896861
Blmngtn	1.164384	1.270553
BrDale	1.095890	1.121076
Veenker	0.753425	0.822123
NPkVill	0.616438	0.672646
Blueste	0.136986	0.149477

	Condition1_orginal	Condition1_clean
Norm	86.301370	86.846039
Feedr	5.547945	4.708520
Artery	3.287671	3.213752
RRAn	1.780822	1.943199
PosN	1.301370	1.420030
RRAe	0.753425	0.747384
PosA	0.547945	0.597907
RRNn	0.342466	0.373692
RRNe	0.136986	0.149477

	Condition2_orginal	Condition2_clean
Norm	98.972603	98.953662
Feedr	0.410959	0.373692
Artery	0.136986	0.149477

RRNn	0.136986
PosN	0.136986
PosA	0.068493
RRAn	0.068493
RRAe	0.068493

	BldgType_orginal	BldgType_clean
1Fam	83.561644	85.052317
TwnhsE	7.808219	8.370703
Duplex	3.561644	2.092676
Twnhs	2.945205	2.840060
2fmCon	2.123288	1.644245

	HouseStyle_orginal	HouseStyle_clean
1Story	49.726027	49.103139
2Story	30.479452	31.838565
1.5Fin	10.547945	10.014948
SLvl	4.452055	4.783259
SFoyer	2.534247	2.242152
1.5Unf	0.958904	0.822123
2.5Unf	0.753425	0.747384
2.5Fin	0.547945	0.448430

	RoofStyle_orginal	RoofStyle_clean
Gable	78.150685	77.503737
Hip	19.589041	20.328849
Flat	0.890411	0.822123
Gambrel	0.753425	0.747384
Mansard	0.479452	0.448430
Shed	0.136986	0.149477

	RoofMatl_orginal	RoofMatl_clean
CompShg	98.219178	98.206278
Tar&Grv	0.753425	0.672646
WdShngl	0.410959	0.448430
WdShake	0.342466	0.373692
Metal	0.068493	0.074738
Membran	0.068493	0.074738
Roll	0.068493	0.074738
ClyTile	0.068493	0.074738

	Exterior1st_orginal	Exterior1st_clean
VinylSd	35.273973	36.322870

HdBoard	15.205479	15.769806
MetalSd	15.068493	15.022422
Wd Sdng	14.109589	13.677130
Plywood	7.397260	7.473842
CemntBd	4.178082	3.886398
BrkFace	3.424658	3.288490
WdShing	1.780822	1.494768
Stucco	1.712329	1.569507
AsbShng	1.369863	1.121076
BrkComm	0.136986	0.074738
Stone	0.136986	0.149477
AsphShn	0.068493	NaN
ImStucc	0.068493	0.074738
CBlock	0.068493	0.074738

	Exterior2nd_orginal	Exterior2nd_clean
VinylSd	34.520548	35.500747
MetalSd	14.657534	14.723468
HdBoard	14.178082	14.723468
Wd Sdng	13.493151	13.153961
Plywood	9.726027	9.491779
CmentBd	4.109589	3.811659
Wd Shng	2.602740	2.391629
Stucco	1.780822	1.718984
BrkFace	1.712329	1.644245
AsbShng	1.369863	1.195815
ImStucc	0.684932	0.747384
Brk Cmn	0.479452	0.448430
Stone	0.342466	0.149477
AsphShn	0.205479	0.149477
Other	0.068493	0.074738
CBlock	0.068493	0.074738

	MasVnrType_orginal	MasVnrType_clean
None	59.178082	57.025411
BrkFace	30.479452	32.286996
Stone	8.767123	9.566517
BrkCmn	1.027397	1.121076

	ExterQual_orginal	ExterQual_clean
TA	62.054795	60.014948
Gd	33.424658	35.650224
Ex	3.561644	3.811659
Fa	0.958904	0.523169

	ExterCond_orginal	ExterCond_clean
TA	87.808219	88.415546
Gd	10.000000	10.239163
Fa	1.917808	1.195815
Ex	0.205479	0.149477
Po	0.068493	NaN

	Foundation_orginal	Foundation_clean
PConc	44.315068	46.337818
CBlock	43.424658	43.348281
BrkTil	10.000000	9.641256
Slab	1.643836	NaN
Stone	0.410959	0.448430
Wood	0.205479	0.224215

	BsmtQual_orginal	BsmtQual_clean
TA	44.452055	44.394619
Gd	42.328767	44.245142
Ex	8.287671	8.968610
Fa	2.397260	2.391629

	BsmtCond_orginal	BsmtCond_clean
TA	89.794521	92.451420
Gd	4.452055	4.633782
Fa	3.082192	2.840060
Po	0.136986	0.074738

	BsmtExposure_orginal	BsmtExposure_clean
No	65.273973	66.292975
Av	15.136986	15.919283
Gd	9.178082	9.491779
Mn	7.808219	8.295964

	BsmtFinType1_orginal	BsmtFinType1_clean
Unf	29.452055	29.297459
GLQ	28.630137	30.044843
ALQ	15.068493	15.620329
BLQ	10.136986	10.538117
Rec	9.109589	9.342302
LwQ	5.068493	5.156951

	BsmtFinType2_orginal	BsmtFinType2_clean
Unf	86.027397	87.892377
Rec	3.698630	3.961136
LwQ	3.150685	3.437967
BLQ	2.260274	2.391629
ALQ	1.301370	1.420030
GLQ	0.958904	0.896861

	Heating_orginal	Heating_clean
GasA	97.808219	98.505232
GasW	1.232877	1.195815
Grav	0.479452	0.224215
Wall	0.273973	NaN
OthW	0.136986	0.074738
Floor	0.068493	NaN

	HeatingQC_orginal	HeatingQC_clean
Ex	50.753425	52.615845
TA	29.315068	28.400598
Gd	16.506849	16.218236
Fa	3.356164	2.690583
Po	0.068493	0.074738

	CentralAir_orginal	CentralAir_clean
Y	93.493151	95.440957
N	6.506849	4.559043

	Electrical_orginal	Electrical_clean
SBrkr	91.369863	92.825112
FuseA	6.438356	5.680120
FuseF	1.849315	1.270553
FuseP	0.205479	0.149477
Mix	0.068493	0.074738

	KitchenQual_orginal	KitchenQual_clean
TA	50.342466	48.579970
Gd	40.136986	42.451420
Ex	6.849315	7.249626
Fa	2.671233	1.718984

	Functional_orginal	Functional_clean
Typ	93.150685	93.721973

Min2	2.328767	2.242152
Min1	2.123288	2.092676
Mod	1.027397	0.822123
Maj1	0.958904	0.747384
Maj2	0.342466	0.298954
Sev	0.068493	0.074738

	GarageType_orginal	GarageType_clean
Attchd	59.589041	63.677130
Detchd	26.506849	27.578475
BuiltIn	6.027397	6.352765
Basment	1.301370	1.420030
CarPort	0.616438	0.523169
2Types	0.410959	0.448430

	GarageFinish_orginal	GarageFinish_clean
Unf	41.438356	43.348281
RFn	28.904110	30.866966
Fin	24.109589	25.784753

	GarageQual_orginal	GarageQual_clean
TA	89.794521	94.917788
Fa	3.287671	3.587444
Gd	0.958904	1.046338
Ex	0.205479	0.224215
Po	0.205479	0.224215

	GarageCond_orginal	GarageCond_clean
TA	90.821918	96.188341
Fa	2.397260	2.466368
Gd	0.616438	0.672646
Po	0.479452	0.523169
Ex	0.136986	0.149477

	PavedDrive_orginal	PavedDrive_clean
Y	91.780822	93.946188
N	6.164384	4.035874
P	2.054795	2.017937

	SaleType_orginal	SaleType_clean
WD	86.780822	86.547085
New	8.356164	8.744395

```
COD            2.945205        3.139013
ConLD          0.616438        0.448430
ConLI          0.342466        0.298954
ConLw          0.342466        0.298954
CWD            0.273973        0.298954
Oth            0.205479        0.074738
Con            0.136986        0.149477
```

```
         SaleCondition_orginal  SaleCondition_clean
Normal               82.054795            82.511211
Partial               8.561644             8.968610
Abnorml               6.917808             6.427504
Family                1.369863             1.494768
Alloca                0.821918             0.523169
AdjLand               0.273973             0.074738
```

Above code iterate over each variable in the cat_var list, call the cat_var_dist() function for each variable, and print the resulting DataFrame.

e-imputation-by-mean-and-median-2

June 11, 2023

1 Data Cleaning :

1.1 Missing value imputation by Mean and Median :

Importing necessary libraries :

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from IPython.display import Image
```

data (Original) :

[3]:
```
data = pd.read_csv('train.csv') # Loading dataset
```

[4]:
```
data.shape  # Checking the shape of the DataFrame, DataFrame contains Rows:␣
↪1460 and Columns: 81.
```

[4]:
```
(1460, 81)
```

[5]:
```
data.head(2) # Checking first 2 rows from the DataFrame.
```

[5]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500

[2 rows x 81 columns]
```

When we check the shape of the data using the command “data.shape”, we can observe that the DataFrame consists of 1460 rows and 81 columns. However, when we examine the first two rows of the DataFrame using the command “data.head(2)”, it doesn’t display all 81 columns. As a result, we utilize the following code, specifically “pd.set_option()”, to address this issue.

[6]:
```
pd.set_option('display.max_column', None)
pd.set_option('display.max_rows', None)
```

pd.set_option(‘display.max_columns’, None): This line sets the maximum number of columns to be displayed in the output to None, which means there is no limit. As a result, all columns in a DataFrame will be shown when you print or display it.

pd.set_option(‘display.max_rows’, None): This line sets the maximum number of rows to be displayed in the output to None, removing any limit. As a result, all rows in a DataFrame will be shown when you print or display it.

[7]:
```
data.head(2) # The code `data.head(2)` displays the first two rows of the␣
 ↪dataset, showing all 81 columns.
```

[7]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg

  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd       None

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
1         0.0        TA        TA     CBlock       Gd       TA           Gd

  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          GLQ         706          Unf           0        150          856
1          ALQ         978          Unf           0        284         1262

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
```

```
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
1     Attchd       1976.0          RFn           2         460         TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
```

[8]:
```
data.tail(2)  # The code `data.tail(2)` displays the last two rows of the␣
↪dataset.
```

[8]:
```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
1458  1459          20       RL         68.0     9717   Pave   NaN      Reg
1459  1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
1458         Lvl    AllPub    Inside       Gtl        NAmes       Norm
1459         Lvl    AllPub    Inside       Gtl      Edwards       Norm

     Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
1458       Norm     1Fam     1Story            5            6       1950
1459       Norm     1Fam     1Story            5            6       1965

      YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
1458          1996       Hip  CompShg     MetalSd     MetalSd       None
1459          1965     Gable  CompShg     HdBoard     HdBoard       None

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond  \
1458         0.0        TA        TA     CBlock       TA       TA
1459         0.0        Gd        TA     CBlock       TA       TA

     BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
```

```
1458           Mn          GLQ          49          Rec        1029
1459           No          BLQ         830          LwQ         290

      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
1458          0         1078    GasA        Gd          Y      FuseA
1459        136         1256    GasA        Gd          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
1458      1078         0             0       1078             1             0
1459      1256         0             0       1256             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
1458         1         0             2             1          Gd
1459         1         1             3             1          TA

      TotRmsAbvGrd Functional  Fireplaces FireplaceQu GarageType  GarageYrBlt  \
1458             5        Typ           0         NaN     Attchd       1950.0
1459             6        Typ           0         NaN     Attchd       1965.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
1458          Unf           1         240         TA         TA          Y
1459          Fin           1         276         TA         TA          Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
1458         366            0            112          0            0
1459         736           68              0          0            0

      PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold SaleType  \
1458         0    NaN   NaN         NaN        0       4    2010       WD
1459         0    NaN   NaN         NaN        0       6    2008       WD

     SaleCondition  SalePrice
1458        Normal     142125
1459        Normal     147500
```

[9]:
```
data.info()

'''
The `data.info()` function provides a concise summary of the dataset, including␣
 ↪information about the number of rows,
columns, data types, memory usage and missing values.

'''
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
```

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     1452 non-null   object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
```

```
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

[9]:
```
'\nThe `data.info()` function provides a concise summary of the dataset,
including information about the number of rows, \ncolumns, data types, memory
usage and missing values.\n\n'
```

[10]:
```
data.isnull().sum()

# The code `data.isnull().sum()` calculates the sum of missing values in each␣
↪column of the dataset.
```

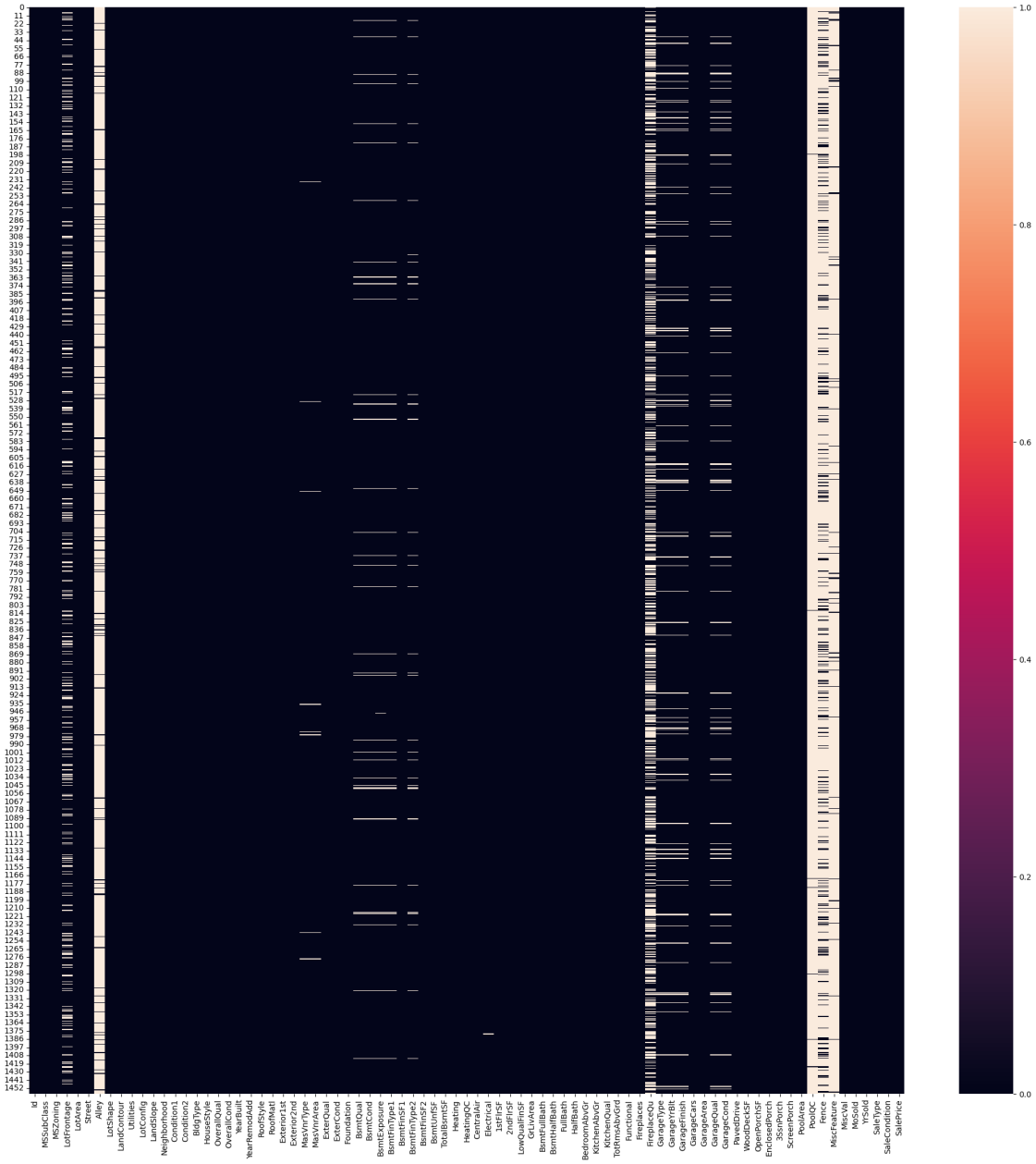
[10]:

Id	0
MSSubClass	0
MSZoning	0
LotFrontage	259
LotArea	0
Street	0
Alley	1369
LotShape	0
LandContour	0
Utilities	0
LotConfig	0
LandSlope	0
Neighborhood	0
Condition1	0
Condition2	0
BldgType	0
HouseStyle	0
OverallQual	0
OverallCond	0
YearBuilt	0
YearRemodAdd	0
RoofStyle	0
RoofMatl	0
Exterior1st	0
Exterior2nd	0
MasVnrType	8
MasVnrArea	8
ExterQual	0
ExterCond	0
Foundation	0
BsmtQual	37
BsmtCond	37
BsmtExposure	38
BsmtFinType1	37
BsmtFinSF1	0
BsmtFinType2	38
BsmtFinSF2	0
BsmtUnfSF	0
TotalBsmtSF	0
Heating	0
HeatingQC	0
CentralAir	0
Electrical	1
1stFlrSF	0
2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0

```
BsmtFullBath        0
BsmtHalfBath        0
FullBath            0
HalfBath            0
BedroomAbvGr        0
KitchenAbvGr        0
KitchenQual         0
TotRmsAbvGrd        0
Functional          0
Fireplaces          0
FireplaceQu       690
GarageType         81
GarageYrBlt        81
GarageFinish       81
GarageCars          0
GarageArea          0
GarageQual         81
GarageCond         81
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
PoolQC           1453
Fence            1179
MiscFeature      1406
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
dtype: int64
```

[11]:
```
plt.figure(figsize=(25,25))
sns.heatmap(data.isnull())
plt.show()

'''
The code `plt.figure(figsize=(25,25))` sets the figure size for the plot.

The next line `sns.heatmap(data.isnull())` creates a heatmap visualization of␣
 ↪the missing values in the dataset
using the seaborn library.
```

```
'''
```



[11]:
```
'\nThe code `plt.figure(figsize=(25,25))` sets the figure size for the plot.
\n\nThe next line `sns.heatmap(data.isnull())` creates a heatmap visualization
of the missing values in the dataset \nusing the seaborn library.\n\n'
```

[12]:
```
missing_value_percent = data.isnull().sum() / data.shape[0] * 100
print(missing_value_percent)
```

```
# The code calculates the percentage of missing values in each column of the␣
↪dataset and then prints the resulting percentages.
```

```
Id               0.000000
MSSubClass       0.000000
MSZoning         0.000000
LotFrontage     17.739726
LotArea          0.000000
Street           0.000000
Alley           93.767123
LotShape         0.000000
LandContour      0.000000
Utilities        0.000000
LotConfig        0.000000
LandSlope        0.000000
Neighborhood     0.000000
Condition1       0.000000
Condition2       0.000000
BldgType         0.000000
HouseStyle       0.000000
OverallQual      0.000000
OverallCond      0.000000
YearBuilt        0.000000
YearRemodAdd     0.000000
RoofStyle        0.000000
RoofMatl         0.000000
Exterior1st      0.000000
Exterior2nd      0.000000
MasVnrType       0.547945
MasVnrArea       0.547945
ExterQual        0.000000
ExterCond        0.000000
Foundation       0.000000
BsmtQual         2.534247
BsmtCond         2.534247
BsmtExposure     2.602740
BsmtFinType1     2.534247
BsmtFinSF1       0.000000
BsmtFinType2     2.602740
BsmtFinSF2       0.000000
BsmtUnfSF        0.000000
TotalBsmtSF      0.000000
Heating          0.000000
HeatingQC        0.000000
CentralAir       0.000000
Electrical       0.068493
1stFlrSF         0.000000
```

```
2ndFlrSF          0.000000
LowQualFinSF      0.000000
GrLivArea         0.000000
BsmtFullBath      0.000000
BsmtHalfBath      0.000000
FullBath          0.000000
HalfBath          0.000000
BedroomAbvGr      0.000000
KitchenAbvGr      0.000000
KitchenQual       0.000000
TotRmsAbvGrd      0.000000
Functional        0.000000
Fireplaces        0.000000
FireplaceQu      47.260274
GarageType        5.547945
GarageYrBlt       5.547945
GarageFinish      5.547945
GarageCars        0.000000
GarageArea        0.000000
GarageQual        5.547945
GarageCond        5.547945
PavedDrive        0.000000
WoodDeckSF        0.000000
OpenPorchSF       0.000000
EnclosedPorch     0.000000
3SsnPorch         0.000000
ScreenPorch       0.000000
PoolArea          0.000000
PoolQC           99.520548
Fence            80.753425
MiscFeature      96.301370
MiscVal           0.000000
MoSold            0.000000
YrSold            0.000000
SaleType          0.000000
SaleCondition     0.000000
SalePrice         0.000000
dtype: float64
```

[13]:
```
missing_value_column = missing_value_percent[missing_value_percent > 20].keys()
print(missing_value_column)

'''
The code is used to identify the columns in a dataset that have missing values␣
 ↪exceeding 20%.
It retrieves the keys (column names) from the `missing_value_percent`␣
 ↪dictionary where the corresponding values
```

```
are greater than 20%.

'''
```

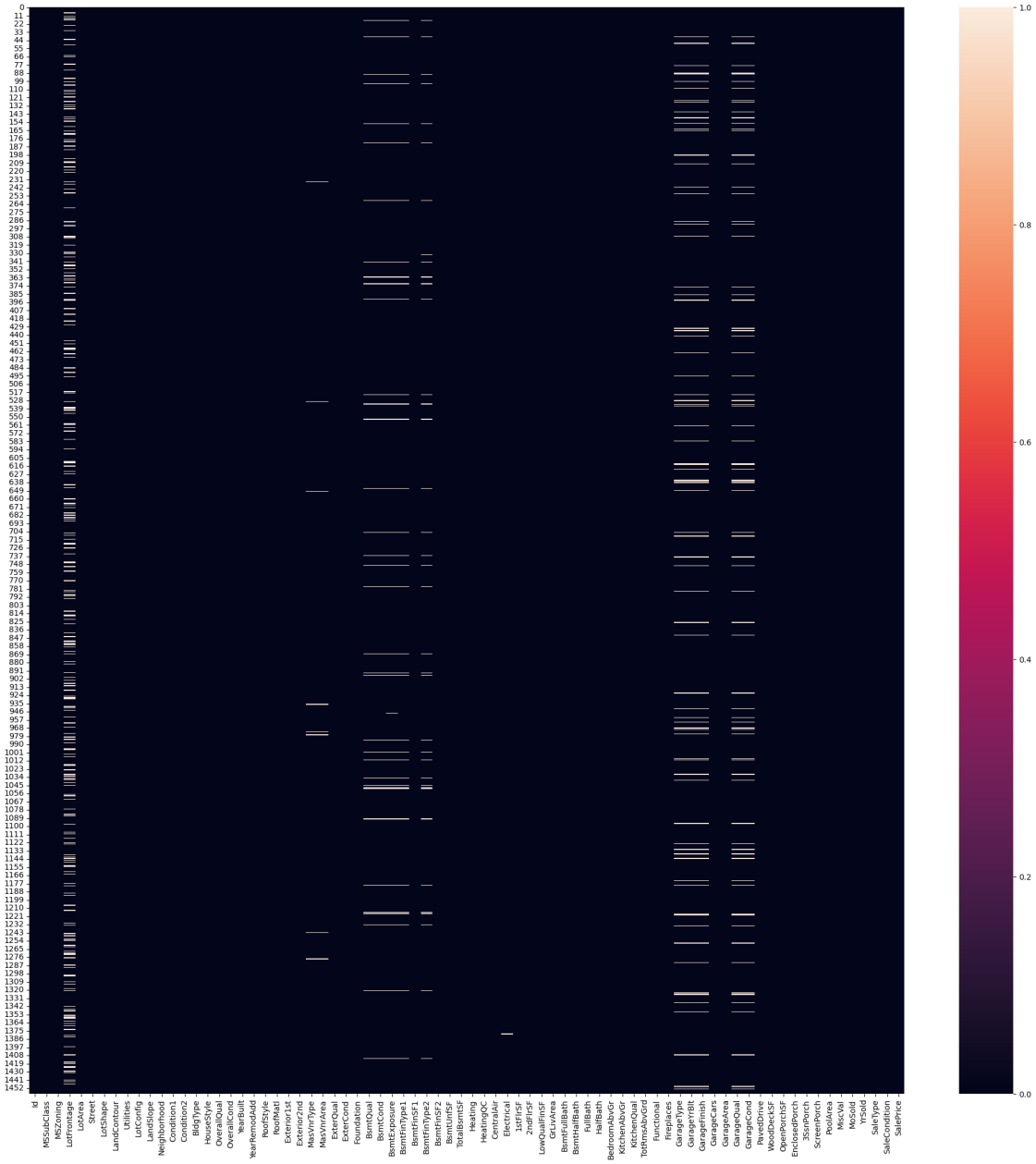
```
Index(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'],
dtype='object')
```

[13]:
```
'\nThe code is used to identify the columns in a dataset that have missing
values exceeding 20%. \nIt retrieves the keys (column names) from the
`missing_value_percent` dictionary where the corresponding values \nare greater
than 20%.\n\n'
```

data1 after dropping missing value column > 20% :

[14]:
```
data1 = data.drop(columns = missing_value_column)
```

[15]:
```
plt.figure(figsize=(25,25))
sns.heatmap(data1.isnull())
plt.show()

'''
The code is used to get visualization of the missing values after removing␣
 ↪columns
where the missing values exceed 20% of the total data in those columns.

'''
```



[15]:
```
'\nThe code is used to get visualization of the missing values after removing
columns \nwhere the missing values exceed 20% of the total data in those
columns.\n\n'
```

[16]:
```
data1.shape # Checking the shape of the DataFrame , DataFrame contains Rows:␣
↪1460 and Columns: 76
```

[16]:
```
(1460, 76)
```

numerical_DataFrame (selecting DataFrame that contains only numerical data types) :

[17]:
```
numerical_DataFrame = data1.select_dtypes(include=['int64', 'float64'])
numerical_DataFrame.head(2)
```

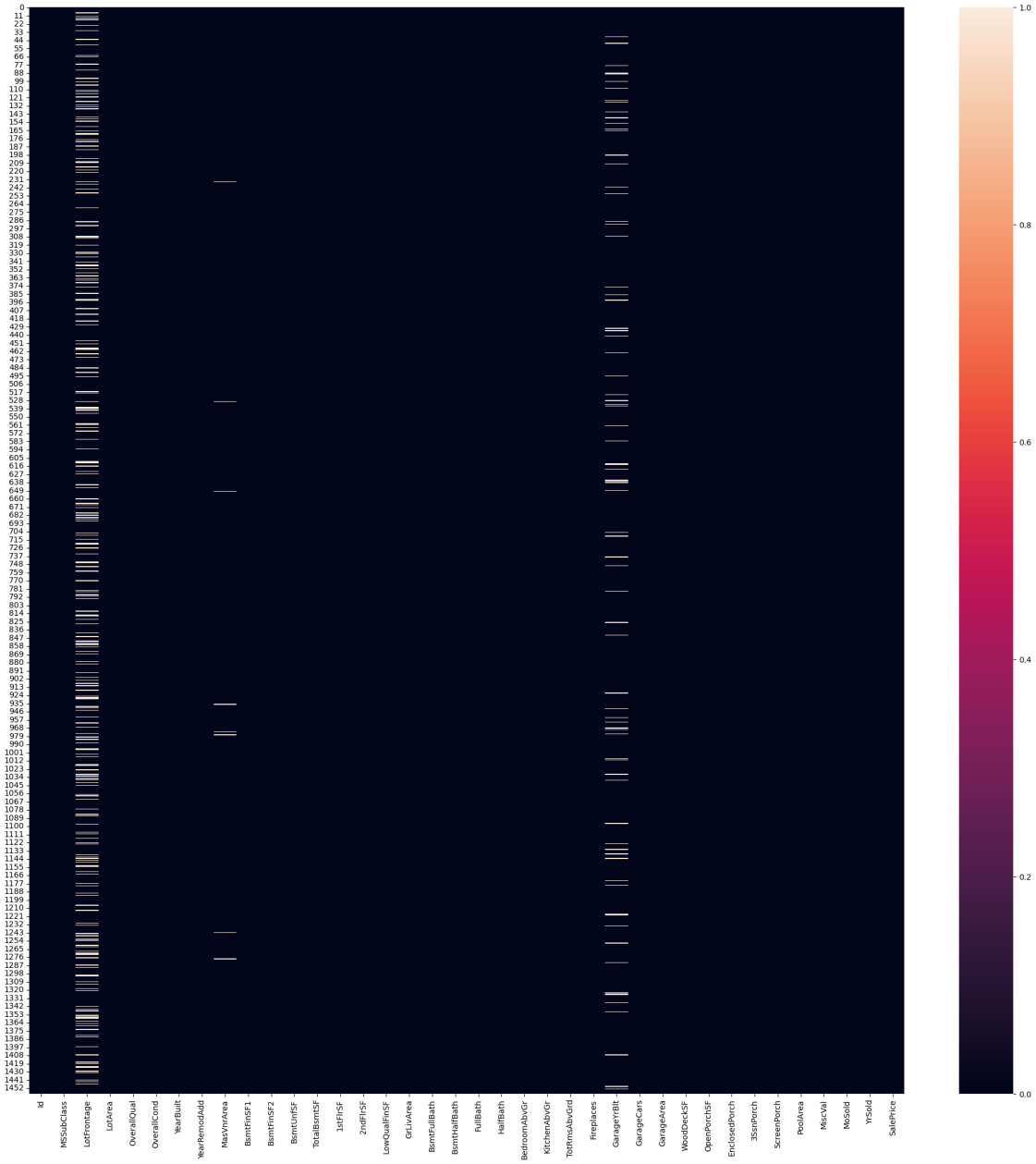
[17]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold	YrSold	SalePrice
0	1	60	65.0	8450	7	5	2003	2003	196.0	706	0	150	856	856	854	0	1710	1	0	2	1	3	1	8	0	2003.0	2	548	0	61	0	0	0	0	0	2	2008	208500
1	2	20	80.0	9600	6	8	1976	1976	0.0	978	0	284	1262	1262	0	0	1262	0	1	2	0	3	1	6	1	1976.0	2	460	298	0	0	0	0	0	0	5	2007	181500

[18]:
```
numerical_DataFrame.shape
# Here, the numerical_DataFrame contains 1460 rows and 38 columns.
```

[18]:
```
(1460, 38)
```

[19]:
```
plt.figure(figsize=(25,25))
sns.heatmap(numerical_DataFrame.isnull())
plt.show()

# The code is used to get visualization of the missing values of numerical␣
 ↪DataFrame.
```



[63]:
```
numerical_DataFrame_null_Rows = numerical_DataFrame[numerical_DataFrame.
 ↪isnull().any(axis=1)]
numerical_DataFrame_null_Rows.head(5)

'''
The code `numerical_DataFrame[numerical_DataFrame.isnull().any(axis=1)]` is␣
 ↪used to filter rows in a DataFrame
called `numerical_DataFrame` that contain at least one null value.
```

```
'''
```

[63]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	\
7	8	60	NaN	10382	7	6	1973	
12	13	20	NaN	12968	5	6	1962	
14	15	20	NaN	10920	6	5	1960	
16	17	20	NaN	11241	6	7	1970	
24	25	20	NaN	8246	5	8	1968	

	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	\
7	1973	240.0	859	32	216	1107	
12	1962	0.0	737	0	175	912	
14	1960	212.0	733	0	520	1253	
16	1970	180.0	578	0	426	1004	
24	2001	0.0	188	668	204	1060	

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	\
7	1107	983	0	2090	1	0	
12	912	0	0	912	1	0	
14	1253	0	0	1253	1	0	
16	1004	0	0	1004	1	0	
24	1060	0	0	1060	1	0	

	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces	\
7	2	1	3	1	7	2	
12	1	0	2	1	4	0	
14	1	1	2	1	5	1	
16	1	0	2	1	5	1	
24	1	0	3	1	6	1	

	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF	\
7	1973.0	2	484	235	204	
12	1962.0	1	352	140	0	
14	1960.0	1	352	0	213	
16	1970.0	2	480	0	0	
24	1968.0	1	270	406	90	

	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold	YrSold	\
7	228	0	0	0	350	11	2009	
12	0	0	176	0	0	9	2008	
14	176	0	0	0	0	5	2008	
16	0	0	0	0	700	3	2010	
24	0	0	0	0	0	5	2010	

	SalePrice
7	200000
12	144000

```
14      157000
16      149000
24      154000
```

[22]:
```
num_DF_MissingValue = numerical_DataFrame.isnull().sum()
print(num_DF_MissingValue)
```

```
Id                0
MSSubClass        0
LotFrontage     259
LotArea           0
OverallQual       0
OverallCond       0
YearBuilt         0
YearRemodAdd      0
MasVnrArea        8
BsmtFinSF1        0
BsmtFinSF2        0
BsmtUnfSF         0
TotalBsmtSF       0
1stFlrSF          0
2ndFlrSF          0
LowQualFinSF      0
GrLivArea         0
BsmtFullBath      0
BsmtHalfBath      0
FullBath          0
HalfBath          0
BedroomAbvGr      0
KitchenAbvGr      0
TotRmsAbvGrd      0
Fireplaces        0
GarageYrBlt      81
GarageCars        0
GarageArea        0
WoodDeckSF        0
OpenPorchSF       0
EnclosedPorch     0
3SsnPorch         0
ScreenPorch       0
PoolArea          0
MiscVal           0
MoSold            0
YrSold            0
SalePrice         0
dtype: int64
```

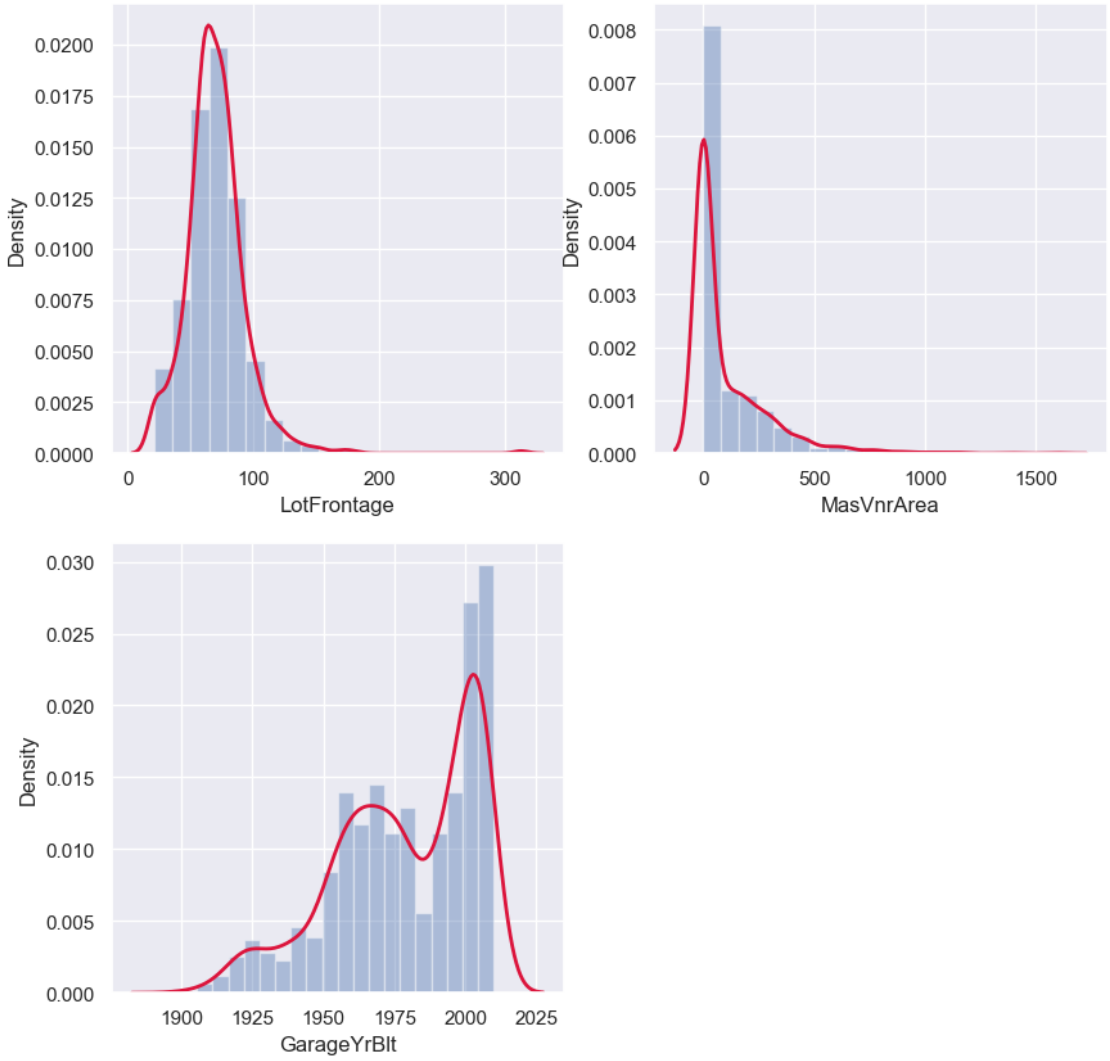
[23]:
```
num_DF_MissingValue_columns = num_DF_MissingValue[num_DF_MissingValue > 0].
 ↪keys()
print(num_DF_MissingValue_columns)

'''
This code is used to retrieve the column names from a DataFrame called␣
 ↪num_DF_MissingValue where
the corresponding values are greater than zero (indicating missing values).

'''
```

```
Index(['LotFrontage', 'MasVnrArea', 'GarageYrBlt'], dtype='object')
```

[23]:
```
'\nThis code is used to retrieve the column names from a DataFrame called
num_DF_MissingValue where \nthe corresponding values are greater than zero
(indicating missing values).\n\n'
```

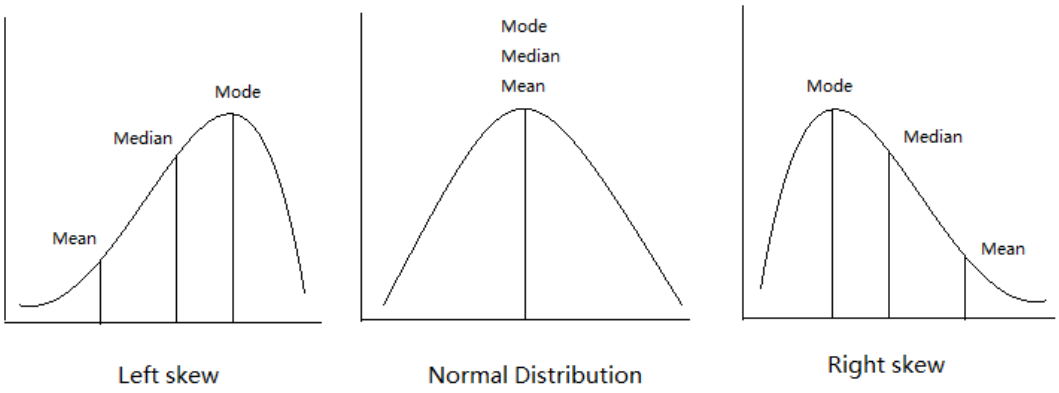
The code creates a figure with a specific size, sets the seaborn style, and then iterates over the num_DF_MissingValue_columns. For each column, it creates a subplot and plots the distribution of the corresponding column from the numerical_DataFrame using the seaborn distplot function. The bins parameter specifies the number of bins in the histogram, and the kde_kws parameter sets the properties of the kernel density estimation line (linewidth and color).

[24]:
```
# Visualization of Missing Numeric Data Distribution

plt.figure(figsize=(10,10))

sns.set()

for i, var in enumerate(num_DF_MissingValue_columns):
    plt.subplot(2,2,i+1)
    sns.distplot(numerical_DataFrame[var], bins=20, kde_kws={'linewidth':2,␣
 ↪'color':'#DC143C'})
```



[25]:
```
Image('C:/Users/Server/Desktop/NIBZZ/Intellipaat/SQL Project/img.png')
```

[25]:



When we compare the visualization with the image, we can observe that LotFrontage follows an almost normal distribution, MasVnrArea is skewed to the right, and GarageYrBlt is skewed to the left. Therefore, we use the mean as a measure of central tendency for LotFrontage, and the mode as a measure of central tendency for the other two variables.

Filling Missing Values in "LotFrontage" Column with Mean as Measure of Central Tendency :

[65]:
```
numerical_DataFrame_copy1 = numerical_DataFrame.copy() # Creating a copy of␣
↪numerical_DataFrame
numerical_DataFrame_copy1.shape
```

[65]:
```
(1460, 38)
```

[66]:
```
lotfrontage_mean = numerical_DataFrame_copy1['LotFrontage'].mean() #␣
↪Calculating mean of column LotFrontage and printing it.
print('LotFrontage Mean: ',lotfrontage_mean)
```

```
LotFrontage Mean:  70.04995836802665
```

[69]:
```
numerical_DataFrame_copy1['LotFrontage'].fillna(LotFrontage_mean,inplace=True)
numerical_DataFrame_copy1[num_DF_MissingValue_columns].isnull().sum()
# Filling the missing value LotFrontage column with it's mean and checking if␣
↪the missing values of that column is handled.
```

[69]:
```
LotFrontage     0
MasVnrArea      8
GarageYrBlt    81
dtype: int64
```

Filling Missing Values in "MasVnrArea" and "GarageYrBlt" Column with Median as Measure of Central Tendency :

[70]:
```
MasVnrArea_Median = numerical_DataFrame_copy1['MasVnrArea'].median()
print("MasVnrArea_Median: ", MasVnrArea_Median)

# Finding the median of column MasVnrArea and printing it.
```

```
MasVnrArea_Median:  0.0
```

[71]:
```
GarageYrBlt_Median = numerical_DataFrame_copy1['GarageYrBlt'].median()
print("GarageYrBlt_Median: ",GarageYrBlt_Median)

# Finding the median of column GarageYrBlt and printing it.
```

```
GarageYrBlt_Median:  1980.0
```

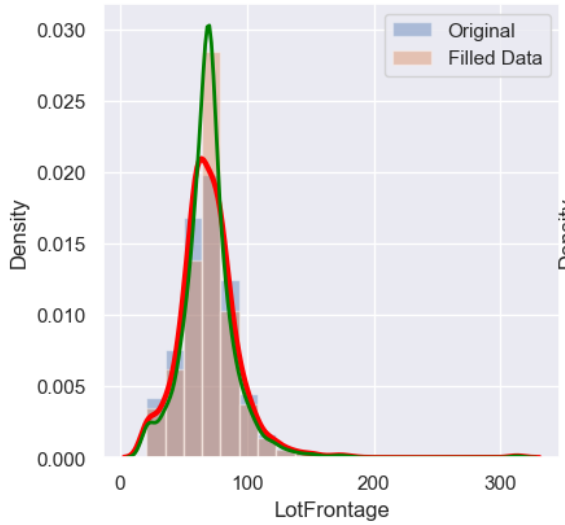
[72]:
```
numerical_DataFrame_copy1['MasVnrArea'].fillna(MasVnrArea_Median, inplace=True)
numerical_DataFrame_copy1['GarageYrBlt'].fillna(GarageYrBlt_Median,␣
 ↪inplace=True)

# Filling the missing value MasVnrArea, GarageYrBlt columns with it's median.
```

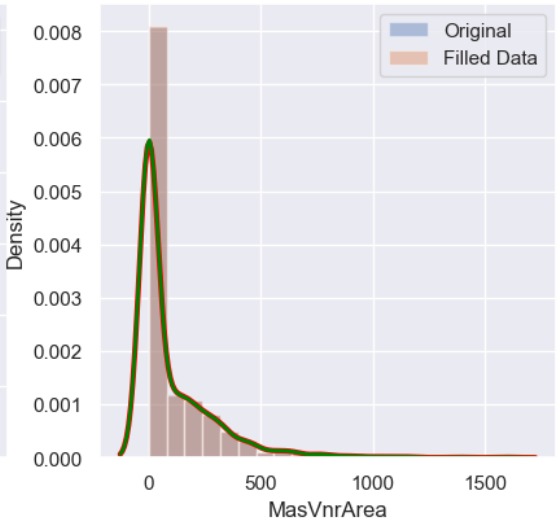
[73]:
```
numerical_DataFrame_copy1[num_DF_MissingValue_columns].isnull().sum()

# Checking if the missing values of that column is handled.
```

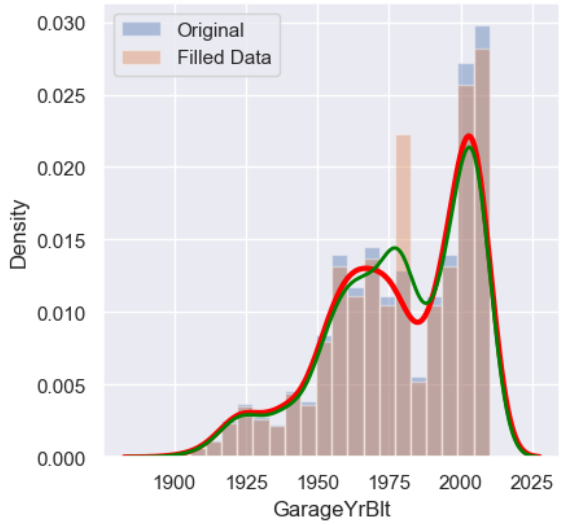
[73]:
```
LotFrontage    0
MasVnrArea     0
GarageYrBlt    0
dtype: int64
```

Visualizing Original and Filled Data Distributions for Numerical DataFrame :

[74]:
```
plt.figure(figsize=(10,10))

sns.set()

for i, var in enumerate(num_DF_MissingValue_columns):
    plt.subplot(2,2,i+1)
    sns.distplot(numerical_DataFrame[var], bins=20, kde_kws={'linewidth':3,␣
 ↪'color':'red'}, label="Original",)
    sns.distplot(numerical_DataFrame_copy1[var], bins=20, kde_kws={'linewidth':
 ↪2, 'color':'green'},label="Filled Data",)

    plt.legend()
```







Concatenating Numerical DataFrames to Fill Missing Values :

[75]:
```
df_concat = pd.
↪concat([numerical_DataFrame[num_DF_MissingValue_columns],numerical_DataFrame_copy1[num_DF_M
```

[76]:
```
df_concat_DF = df_concat[df_concat.isnull().any(axis=1)]
df_concat_DF.head(5)
```

[76]:

	LotFrontage	MasVnrArea	GarageYrBlt	LotFrontage	MasVnrArea	GarageYrBlt
7	NaN	240.0	1973.0	70.049958	240.0	1973.0
12	NaN	0.0	1962.0	70.049958	0.0	1962.0
14	NaN	212.0	1960.0	70.049958	212.0	1960.0
16	NaN	180.0	1970.0	70.049958	180.0	1970.0
24	NaN	0.0	1968.0	70.049958	0.0	1968.0

Based on the information provided above, it is evident that the missing value in the LotFrontage column has been replaced with the mean value of the LotFrontage column. Similarly, the missing values in the MasVnrArea and GarageYrBlt columns have been replaced with the median values of the MasVnrArea and GarageYrBlt columns respectively.

central-tendency-for-each-class-1

June 11, 2023

1 Data Cleaning :

1.1 Missing value imputation of numerical column by Measure of central tendency for each class:

Importing necessary libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

data (Original) :

[2]:
```
data = pd.read_csv("train.csv") # Loading dataset
```

[3]:
```
data.shape data.shape # Checking the shape of the dataset, dataset contains␣
↪1460 rows and 81 columns
```

[3]:
```
(1460, 81)
```

[4]:
```
data.head() # Checking first 5 rows from the DataFrame.
```

[4]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12
```

```
  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

When we check the shape of the data using the command "data.shape", we can observe that the DataFrame consists of 1460 rows and 81 columns. However, when we examine the first five rows of the DataFrame using the command "data.head(5)", it doesn't display all 81 columns. As a result, we utilize the following code, specifically "pd.set_option()", to address this issue.

[6]:
```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
```

pd.set_option('display.max_columns', None): This line sets the maximum number of columns to be displayed in the output to None, which means there is no limit. As a result, all columns in a DataFrame will be shown when you print or display it.

pd.set_option('display.max_rows', None): This line sets the maximum number of rows to be displayed in the output to None, removing any limit. As a result, all rows in a DataFrame will be shown when you print or display it.

[7]:
```
data.head(2) # The code `data.head(2)` displays the first two rows of the␣
 ↪dataset, showing all 81 columns.
```

[7]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg

  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd       None

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
1         0.0        TA        TA     CBlock       Gd       TA           Gd
```

```
  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          GLQ         706          Unf           0        150          856
1          ALQ         978          Unf           0        284         1262

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
1     Attchd       1976.0          RFn           2         460         TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
```

[8]:
```
data.tail(2) # The code `data.tail(2)` displays the last two rows of the␣
↪dataset.
```

[8]:
```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
1458  1459          20       RL         68.0     9717   Pave   NaN      Reg
1459  1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
1458         Lvl    AllPub    Inside       Gtl        NAmes       Norm
1459         Lvl    AllPub    Inside       Gtl      Edwards       Norm

     Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
1458       Norm     1Fam     1Story            5            6       1950
1459       Norm     1Fam     1Story            5            6       1965
```

```
      YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
1458          1996       Hip  CompShg     MetalSd     MetalSd       None
1459          1965     Gable  CompShg     HdBoard     HdBoard       None

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond  \
1458         0.0        TA        TA     CBlock       TA       TA
1459         0.0        Gd        TA     CBlock       TA       TA

     BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
1458           Mn          GLQ          49          Rec        1029
1459           No          BLQ         830          LwQ         290

      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
1458          0         1078    GasA        Gd          Y      FuseA
1459        136         1256    GasA        Gd          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
1458      1078         0             0       1078             1             0
1459      1256         0             0       1256             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
1458         1         0             2             1          Gd
1459         1         1             3             1          TA

      TotRmsAbvGrd Functional  Fireplaces FireplaceQu GarageType  GarageYrBlt  \
1458             5        Typ           0         NaN     Attchd       1950.0
1459             6        Typ           0         NaN     Attchd       1965.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
1458          Unf           1         240         TA         TA          Y
1459          Fin           1         276         TA         TA          Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
1458         366            0            112          0            0
1459         736           68              0          0            0

      PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold SaleType  \
1458         0    NaN   NaN         NaN        0       4    2010       WD
1459         0    NaN   NaN         NaN        0       6    2008       WD

     SaleCondition  SalePrice
1458        Normal     142125
1459        Normal     147500
```

[9]:
```
data.info()

'''
```

```
The `data.info()` function provides a concise summary of the dataset, including␣
 ↪information about the number of rows,
columns, data types, memory usage and missing values.

'''
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     1452 non-null   object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
```

```
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

[9]:
```
'\nThe `data.info()` function provides a concise summary of the dataset,
including information about the number of rows, \ncolumns, data types, memory
usage and missing values.\n\n'
```

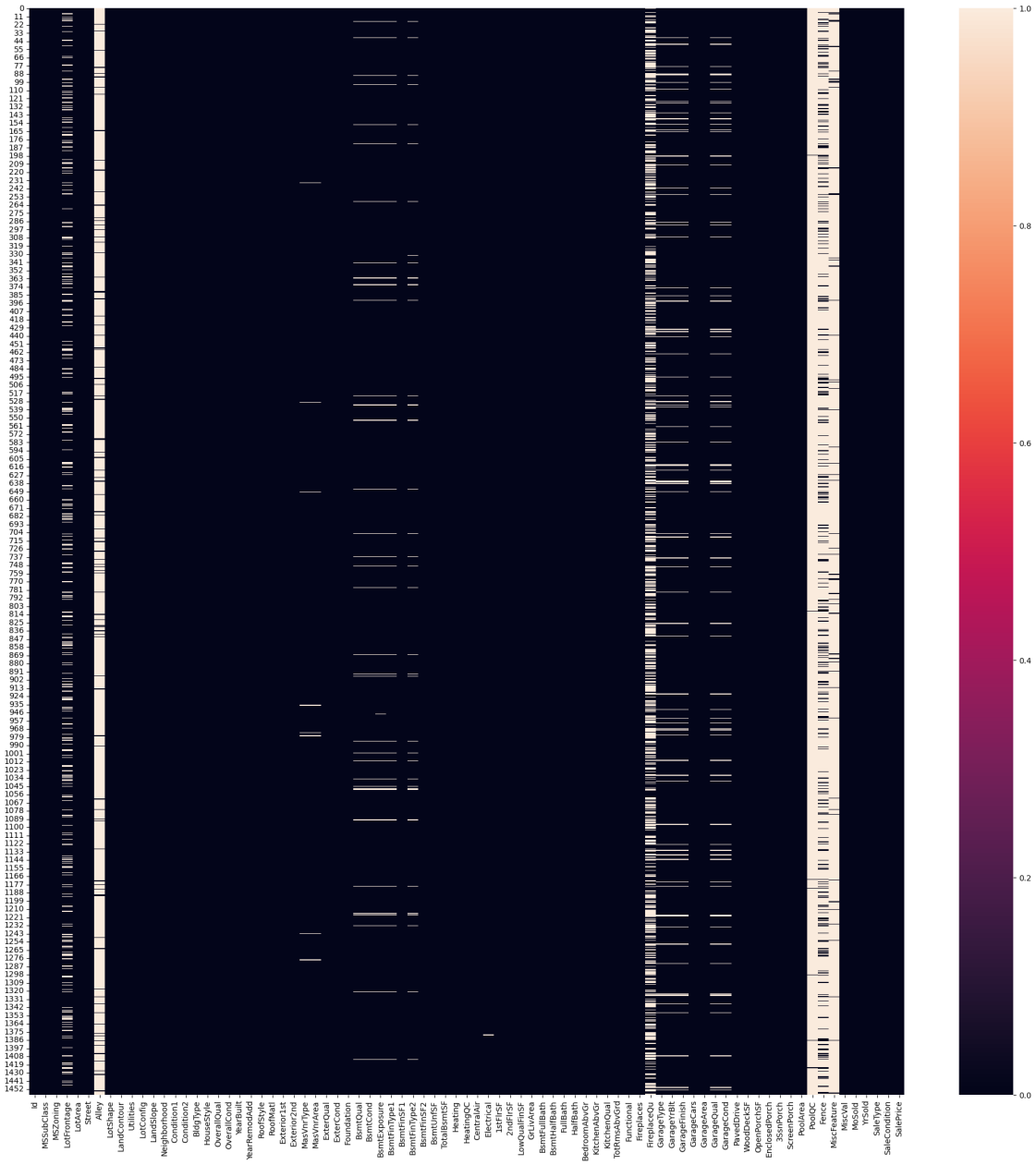
[10]:
```
data.isnull().sum()
```

[10]:
```
Id                0
MSSubClass        0
MSZoning          0
LotFrontage     259
LotArea           0
Street            0
Alley          1369
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
LandSlope         0
Neighborhood      0
Condition1        0
Condition2        0
BldgType          0
HouseStyle        0
OverallQual       0
OverallCond       0
YearBuilt         0
YearRemodAdd      0
RoofStyle         0
RoofMatl          0
Exterior1st       0
Exterior2nd       0
MasVnrType        8
MasVnrArea        8
ExterQual         0
ExterCond         0
Foundation        0
BsmtQual         37
BsmtCond         37
BsmtExposure     38
BsmtFinType1     37
BsmtFinSF1        0
BsmtFinType2     38
BsmtFinSF2        0
BsmtUnfSF         0
TotalBsmtSF       0
Heating           0
HeatingQC         0
```

```
CentralAir          0
Electrical          1
1stFlrSF            0
2ndFlrSF            0
LowQualFinSF        0
GrLivArea           0
BsmtFullBath        0
BsmtHalfBath        0
FullBath            0
HalfBath            0
BedroomAbvGr        0
KitchenAbvGr        0
KitchenQual         0
TotRmsAbvGrd        0
Functional          0
Fireplaces          0
FireplaceQu       690
GarageType         81
GarageYrBlt        81
GarageFinish       81
GarageCars          0
GarageArea          0
GarageQual         81
GarageCond         81
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
PoolQC           1453
Fence            1179
MiscFeature      1406
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
dtype: int64
```

[12]:
```
plt.figure(figsize=(25,25))

sns.heatmap(data.isnull())
plt.show()
```

```
'''
The code `plt.figure(figsize=(25,25))` sets the figure size for the plot.

The next line `sns.heatmap(data.isnull())` creates a heatmap visualization of␣
 ↪the missing values in the dataset
using the seaborn library.

'''
```



[12]:
```
'\nThe code `plt.figure(figsize=(25,25))` sets the figure size for the plot.
\n\nThe next line `sns.heatmap(data.isnull())` creates a heatmap visualization
of the missing values in the dataset \nusing the seaborn library.\n\n'
```

[15]:
```
missing_value_percent = data.isnull().mean() * 100
print(missing_value_percent)

# The code calculates the percentage of missing values in each column of the␣
 ↪dataset and then prints the resulting percentages.
```

```
Id               0.000000
MSSubClass       0.000000
MSZoning         0.000000
LotFrontage     17.739726
LotArea          0.000000
Street           0.000000
Alley           93.767123
LotShape         0.000000
LandContour      0.000000
Utilities        0.000000
LotConfig        0.000000
LandSlope        0.000000
Neighborhood     0.000000
Condition1       0.000000
Condition2       0.000000
BldgType         0.000000
HouseStyle       0.000000
OverallQual      0.000000
OverallCond      0.000000
YearBuilt        0.000000
YearRemodAdd     0.000000
RoofStyle        0.000000
RoofMatl         0.000000
Exterior1st      0.000000
Exterior2nd      0.000000
MasVnrType       0.547945
MasVnrArea       0.547945
ExterQual        0.000000
ExterCond        0.000000
Foundation       0.000000
BsmtQual         2.534247
BsmtCond         2.534247
BsmtExposure     2.602740
BsmtFinType1     2.534247
BsmtFinSF1       0.000000
BsmtFinType2     2.602740
BsmtFinSF2       0.000000
```

```
BsmtUnfSF         0.000000
TotalBsmtSF       0.000000
Heating           0.000000
HeatingQC         0.000000
CentralAir        0.000000
Electrical        0.068493
1stFlrSF          0.000000
2ndFlrSF          0.000000
LowQualFinSF      0.000000
GrLivArea         0.000000
BsmtFullBath      0.000000
BsmtHalfBath      0.000000
FullBath          0.000000
HalfBath          0.000000
BedroomAbvGr      0.000000
KitchenAbvGr      0.000000
KitchenQual       0.000000
TotRmsAbvGrd      0.000000
Functional        0.000000
Fireplaces        0.000000
FireplaceQu      47.260274
GarageType        5.547945
GarageYrBlt       5.547945
GarageFinish      5.547945
GarageCars        0.000000
GarageArea        0.000000
GarageQual        5.547945
GarageCond        5.547945
PavedDrive        0.000000
WoodDeckSF        0.000000
OpenPorchSF       0.000000
EnclosedPorch     0.000000
3SsnPorch         0.000000
ScreenPorch       0.000000
PoolArea          0.000000
PoolQC           99.520548
Fence            80.753425
MiscFeature      96.301370
MiscVal           0.000000
MoSold            0.000000
YrSold            0.000000
SaleType          0.000000
SaleCondition     0.000000
SalePrice         0.000000
dtype: float64
```

[16]:
```
missing_value_column = missing_value_percent[missing_value_percent > 20].keys()
print(missing_value_column)

'''
The code is used to identify the columns in a dataset that have missing values␣
 ↪exceeding 20%.
It retrieves the keys (column names) from the `missing_value_percent`␣
 ↪dictionary where the corresponding values
are greater than 20%.

'''
```

```
Index(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'],
dtype='object')
```

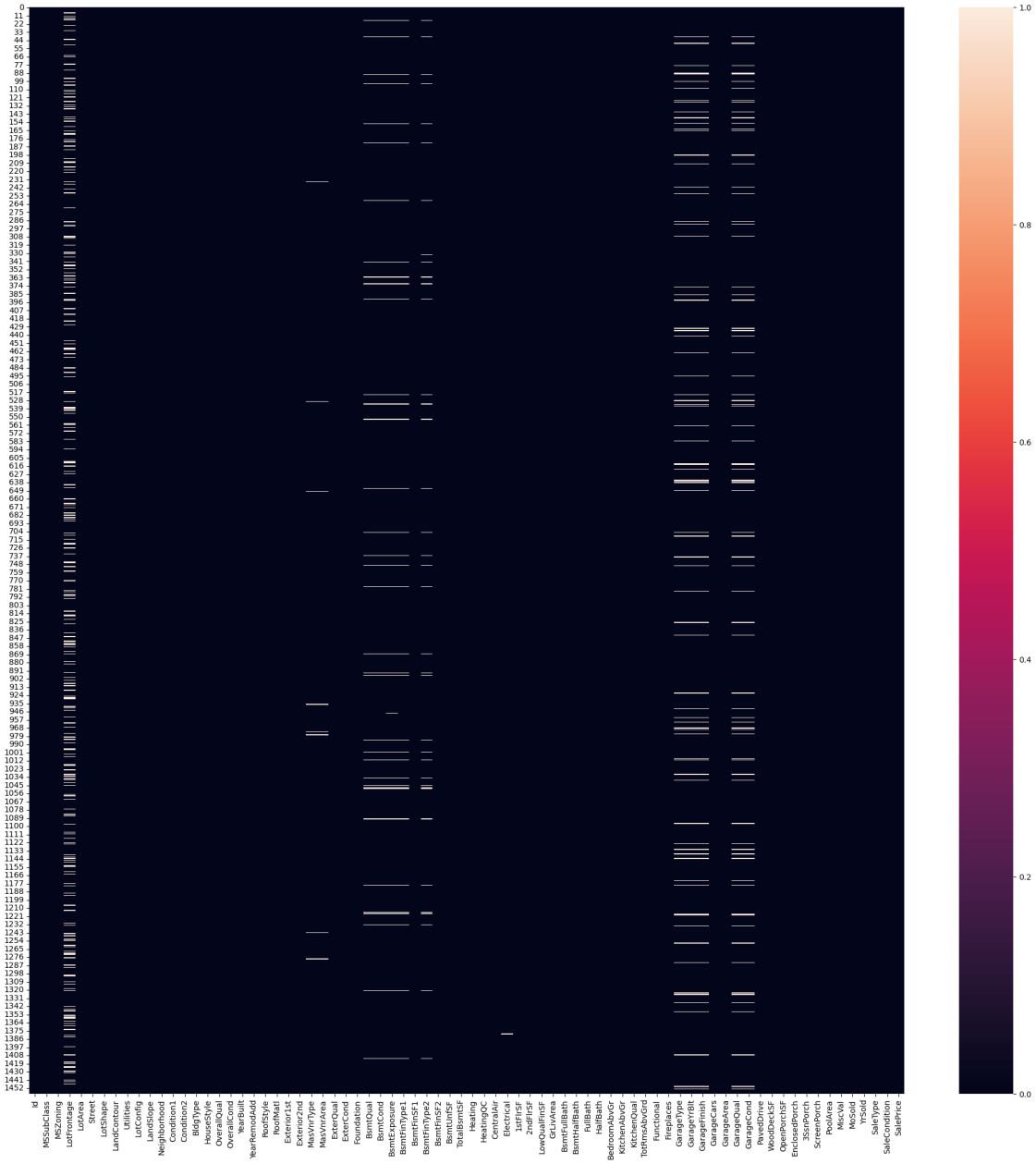
data1 after dropping missing value column > 20% :

[17]:
```
data1 = data.drop(columns=missing_value_column)
```

[18]:
```
data1.shape # Checking the shape of the DataFrame , DataFrame contains Rows:␣
 ↪1460 and Columns: 76
```

[18]:
```
(1460, 76)
```

[20]:
```
plt.figure(figsize=(25,25))

sns.heatmap(data1.isnull())
plt.show()

'''
The code is used to get visualization of the missing values after removing␣
 ↪columns
where the missing values exceed 17% of the total data in those columns.

'''
```



Our objective is to eliminate all the white lines from the visualization in order to achieve a cleaner and more organized appearance.

numerical_DataFrame (selecting DataFrame that contains only numerical data types) :

[22]:
```
numerical_dataFrame = data.select_dtypes(include=['int64','float64'])
numerical_dataFrame.head(2)
```

[22]:
```
   Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0   1          60         65.0     8450            7            5       2003
1   2          20         80.0     9600            6            8       1976

   YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          2003       196.0         706           0        150          856
1          1976         0.0         978           0        284         1262

   1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
0       856       854             0       1710             1             0
1      1262         0             0       1262             0             1

   FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  TotRmsAbvGrd  Fireplaces  \
0         2         1             3             1             8           0
1         2         0             3             1             6           1

   GarageYrBlt  GarageCars  GarageArea  WoodDeckSF  OpenPorchSF  \
0       2003.0           2         548           0           61
1       1976.0           2         460         298            0

   EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold  \
0              0          0            0         0        0       2    2008
1              0          0            0         0        0       5    2007

   SalePrice
0     208500
1     181500
```

[23]:
```
numerical_dataFrame.shape # Here, the numerical_DataFrame contains 1460 rows␣
↪and 38 columns.
```

[23]:
```
(1460, 38)
```

[27]:
```
Numerical_DF_missing_value = numerical_dataFrame.isnull().sum() # Checking the␣
↪null values of numerical DataFrame.
Numerical_DF_missing_value
```

[27]:
```
Id               0
MSSubClass       0
LotFrontage    259
LotArea          0
OverallQual      0
OverallCond      0
YearBuilt        0
YearRemodAdd     0
MasVnrArea       8
BsmtFinSF1       0
```

```
BsmtFinSF2         0
BsmtUnfSF          0
TotalBsmtSF        0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       0
BsmtHalfBath       0
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
TotRmsAbvGrd       0
Fireplaces         0
GarageYrBlt       81
GarageCars         0
GarageArea         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
MoSold             0
YrSold             0
SalePrice          0
dtype: int64
```

[30]:
```
Num_DF_missing_value_columns =␣
 ↪Numerical_DF_missing_value[Numerical_DF_missing_value > 0].keys()
Num_DF_missing_value_columns

# Checking columns names of numerical_dataFrame having missing value > 0
```

[30]:
```
Index(['LotFrontage', 'MasVnrArea', 'GarageYrBlt'], dtype='object')
```

[33]:
```
Missing_col_DF =␣
 ↪numerical_dataFrame[Num_DF_missing_value_columns][numerical_dataFrame[Num_DF_missing_value_
 ↪isnull().any(axis=1)]
Missing_col_DF.head()

# Having look at columns having missing value
```

[33]:
```
    LotFrontage  MasVnrArea  GarageYrBlt
7           NaN       240.0       1973.0
```

```
12          NaN         0.0       1962.0
14          NaN       212.0       1960.0
16          NaN       180.0       1970.0
24          NaN         0.0       1968.0
```

In this process, we impute missing values in a numerical column by using a measure of central tendency for each class. To find the missing value, we need to consider a categorical column that is related to it. This requires having domain knowledge. Then, we proceed to impute the missing value by taking the mean or median, depending on the different categories within the categorical column.

Handling missing value by class :

[81]:
```
data1.head()
```

[81]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour  \
0   1          60       RL         65.0     8450   Pave      Reg         Lvl
1   2          20       RL         80.0     9600   Pave      Reg         Lvl
2   3          60       RL         68.0    11250   Pave      IR1         Lvl
3   4          70       RL         60.0     9550   Pave      IR1         Lvl
4   5          60       RL         84.0    14260   Pave      IR1         Lvl

  Utilities LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType  \
0    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
1    AllPub       FR2       Gtl      Veenker      Feedr       Norm     1Fam
2    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
3    AllPub    Corner       Gtl      Crawfor       Norm       Norm     1Fam
4    AllPub       FR2       Gtl      NoRidge       Norm       Norm     1Fam

  HouseStyle  OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle  \
0     2Story            7            5       2003          2003     Gable
1     1Story            6            8       1976          1976     Gable
2     2Story            7            5       2001          2002     Gable
3     2Story            7            5       1915          1970     Gable
4     2Story            8            5       2000          2000     Gable

  RoofMatl Exterior1st Exterior2nd MasVnrType  MasVnrArea ExterQual ExterCond  \
0  CompShg     VinylSd     VinylSd    BrkFace       196.0        Gd        TA
1  CompShg     MetalSd     MetalSd       None         0.0        TA        TA
2  CompShg     VinylSd     VinylSd    BrkFace       162.0        Gd        TA
3  CompShg     Wd Sdng     Wd Shng       None         0.0        TA        TA
4  CompShg     VinylSd     VinylSd    BrkFace       350.0        Gd        TA

  Foundation BsmtQual BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1  \
0      PConc       Gd       TA           No          GLQ         706
1     CBlock       Gd       TA           Gd          ALQ         978
2      PConc       Gd       TA           Mn          GLQ         486
3     BrkTil       TA       Gd           No          ALQ         216
```

```
4      PConc       Gd       TA           Av          GLQ         655

  BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF Heating HeatingQC  \
0          Unf           0        150          856    GasA        Ex
1          Unf           0        284         1262    GasA        Ex
2          Unf           0        434          920    GasA        Ex
3          Unf           0        540          756    GasA        Gd
4          Unf           0        490         1145    GasA        Ex

  CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  \
0          Y      SBrkr       856       854             0       1710
1          Y      SBrkr      1262         0             0       1262
2          Y      SBrkr       920       866             0       1786
3          Y      SBrkr       961       756             0       1717
4          Y      SBrkr      1145      1053             0       2198

   BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  \
0             1             0         2         1             3             1
1             0             1         2         0             3             1
2             1             0         2         1             3             1
3             1             0         1         0             3             1
4             1             0         2         1             4             1

  KitchenQual  TotRmsAbvGrd Functional  Fireplaces GarageType  GarageYrBlt  \
0          Gd             8        Typ           0     Attchd       2003.0
1          TA             6        Typ           1     Attchd       1976.0
2          Gd             6        Typ           1     Attchd       2001.0
3          Gd             7        Typ           1     Detchd       1998.0
4          Gd             9        Typ           1     Attchd       2000.0

  GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
0          RFn           2         548         TA         TA          Y
1          RFn           2         460         TA         TA          Y
2          RFn           2         608         TA         TA          Y
3          Unf           3         642         TA         TA          Y
4          RFn           3         836         TA         TA          Y

   WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  \
0           0           61              0          0            0         0
1         298            0              0          0            0         0
2           0           42              0          0            0         0
3           0           35            272          0            0         0
4         192           84              0          0            0         0

   MiscVal  MoSold  YrSold SaleType SaleCondition  SalePrice
0        0       2    2008       WD        Normal     208500
1        0       5    2007       WD        Normal     181500
```

```
2          0        9    2008        WD         Normal     223500
3          0        2    2006        WD        Abnorml     140000
4          0       12    2008        WD         Normal     250000
```

To analyze missing value of LotFrontage let's analyze LotConfig column.

[82]:
```
data1['LotConfig'].unique() # Here, we check different categories under␣
↪LotConfig column.
```

[82]:
```
array(['Inside', 'FR2', 'Corner', 'CulDSac', 'FR3'], dtype=object)
```

[83]:
```
mean_lotfrontage = data1[data1.loc[:,'LotConfig'] == "Inside"]["LotFrontage"].
↪replace(np.nan, data1[data1.loc[:,'LotConfig'] == "Inside"]["LotFrontage"].
↪mean())
mean_lotfrontage.head(10)
```

[83]:
```
0     65.000000
2     68.000000
5     85.000000
6     75.000000
8     51.000000
10    70.000000
11    85.000000
12    67.715686
13    91.000000
17    72.000000
Name: LotFrontage, dtype: float64
```

[87]:
```
data1_copy_1 = data1.copy()
data1_copy_1.isnull().sum()
```

[87]:
```
Id                0
MSSubClass        0
MSZoning          0
LotFrontage     259
LotArea           0
Street            0
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
LandSlope         0
Neighborhood      0
Condition1        0
Condition2        0
BldgType          0
HouseStyle        0
```

```
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
RoofStyle          0
RoofMatl           0
Exterior1st        0
Exterior2nd        0
MasVnrType         8
MasVnrArea         8
ExterQual          0
ExterCond          0
Foundation         0
BsmtQual          37
BsmtCond          37
BsmtExposure      38
BsmtFinType1      37
BsmtFinSF1         0
BsmtFinType2      38
BsmtFinSF2         0
BsmtUnfSF          0
TotalBsmtSF        0
Heating            0
HeatingQC          0
CentralAir         0
Electrical         1
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       0
BsmtHalfBath       0
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
KitchenQual        0
TotRmsAbvGrd       0
Functional         0
Fireplaces         0
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageCars         0
GarageArea         0
GarageQual        81
GarageCond        81
```

```
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
dtype: int64
```

[88]:
```
for var_class in data1['LotConfig'].unique():
    data1_copy_1.update(data1[data1.loc[:,'LotConfig'] ==␣
 ↪var_class]["LotFrontage"].replace(np.nan, data1[data1.loc[:,'LotConfig'] ==␣
 ↪var_class]["LotFrontage"].mean()))

# This code performs missing value imputation in the "LotFrontage" column based␣
 ↪on different categories in the "LotConfig" column.
```

[91]:
```
data1_copy_1[Num_DF_missing_value_columns].isnull().sum()

# We can see that missing value of LotFrontage column is handled
```

[91]:
```
LotFrontage     0
MasVnrArea      8
GarageYrBlt    81
dtype: int64
```

Similarly, we will handle missing value of other numerical columns columns.

[92]:
```
data1_copy2_mean = data1.copy()
data1_copy2_mean.head(10)
```

[92]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	\
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	
5	6	50	RL	85.0	14115	Pave	IR1	Lvl	
6	7	20	RL	75.0	10084	Pave	Reg	Lvl	
7	8	60	RL	NaN	10382	Pave	IR1	Lvl	
8	9	50	RM	51.0	6120	Pave	Reg	Lvl	

```
9  10         190       RL         50.0     7420   Pave      Reg         Lvl

  Utilities LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType  \
0    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
1    AllPub       FR2       Gtl      Veenker      Feedr       Norm     1Fam
2    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
3    AllPub    Corner       Gtl      Crawfor       Norm       Norm     1Fam
4    AllPub       FR2       Gtl      NoRidge       Norm       Norm     1Fam
5    AllPub    Inside       Gtl      Mitchel       Norm       Norm     1Fam
6    AllPub    Inside       Gtl      Somerst       Norm       Norm     1Fam
7    AllPub    Corner       Gtl       NWAmes       PosN       Norm     1Fam
8    AllPub    Inside       Gtl      OldTown     Artery       Norm     1Fam
9    AllPub    Corner       Gtl      BrkSide     Artery     Artery   2fmCon

  HouseStyle  OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle  \
0     2Story            7            5       2003          2003     Gable
1     1Story            6            8       1976          1976     Gable
2     2Story            7            5       2001          2002     Gable
3     2Story            7            5       1915          1970     Gable
4     2Story            8            5       2000          2000     Gable
5     1.5Fin            5            5       1993          1995     Gable
6     1Story            8            5       2004          2005     Gable
7     2Story            7            6       1973          1973     Gable
8     1.5Fin            7            5       1931          1950     Gable
9     1.5Unf            5            6       1939          1950     Gable

  RoofMatl Exterior1st Exterior2nd MasVnrType  MasVnrArea ExterQual ExterCond  \
0  CompShg     VinylSd     VinylSd    BrkFace       196.0        Gd        TA
1  CompShg     MetalSd     MetalSd       None         0.0        TA        TA
2  CompShg     VinylSd     VinylSd    BrkFace       162.0        Gd        TA
3  CompShg     Wd Sdng     Wd Shng       None         0.0        TA        TA
4  CompShg     VinylSd     VinylSd    BrkFace       350.0        Gd        TA
5  CompShg     VinylSd     VinylSd       None         0.0        TA        TA
6  CompShg     VinylSd     VinylSd      Stone       186.0        Gd        TA
7  CompShg     HdBoard     HdBoard      Stone       240.0        TA        TA
8  CompShg     BrkFace     Wd Shng       None         0.0        TA        TA
9  CompShg     MetalSd     MetalSd       None         0.0        TA        TA

  Foundation BsmtQual BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1  \
0      PConc       Gd       TA           No          GLQ         706
1     CBlock       Gd       TA           Gd          ALQ         978
2      PConc       Gd       TA           Mn          GLQ         486
3     BrkTil       TA       Gd           No          ALQ         216
4      PConc       Gd       TA           Av          GLQ         655
5       Wood       Gd       TA           No          GLQ         732
6      PConc       Ex       TA           Av          GLQ        1369
7     CBlock       Gd       TA           Mn          ALQ         859
```

```
8     BrkTil       TA       TA           No          Unf           0
9     BrkTil       TA       TA           No          GLQ         851

  BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF Heating HeatingQC  \
0          Unf           0        150          856    GasA        Ex
1          Unf           0        284         1262    GasA        Ex
2          Unf           0        434          920    GasA        Ex
3          Unf           0        540          756    GasA        Gd
4          Unf           0        490         1145    GasA        Ex
5          Unf           0         64          796    GasA        Ex
6          Unf           0        317         1686    GasA        Ex
7          BLQ          32        216         1107    GasA        Ex
8          Unf           0        952          952    GasA        Gd
9          Unf           0        140          991    GasA        Ex

  CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  \
0          Y      SBrkr       856       854             0       1710
1          Y      SBrkr      1262         0             0       1262
2          Y      SBrkr       920       866             0       1786
3          Y      SBrkr       961       756             0       1717
4          Y      SBrkr      1145      1053             0       2198
5          Y      SBrkr       796       566             0       1362
6          Y      SBrkr      1694         0             0       1694
7          Y      SBrkr      1107       983             0       2090
8          Y      FuseF      1022       752             0       1774
9          Y      SBrkr      1077         0             0       1077

   BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  \
0             1             0         2         1             3             1
1             0             1         2         0             3             1
2             1             0         2         1             3             1
3             1             0         1         0             3             1
4             1             0         2         1             4             1
5             1             0         1         1             1             1
6             1             0         2         0             3             1
7             1             0         2         1             3             1
8             0             0         2         0             2             2
9             1             0         1         0             2             2

  KitchenQual  TotRmsAbvGrd Functional  Fireplaces GarageType  GarageYrBlt  \
0          Gd             8        Typ           0     Attchd       2003.0
1          TA             6        Typ           1     Attchd       1976.0
2          Gd             6        Typ           1     Attchd       2001.0
3          Gd             7        Typ           1     Detchd       1998.0
4          Gd             9        Typ           1     Attchd       2000.0
5          TA             5        Typ           0     Attchd       1993.0
6          Gd             7        Typ           1     Attchd       2004.0
```

```
7          TA             7        Typ           2     Attchd       1973.0
8          TA             8       Min1           2     Detchd       1931.0
9          TA             5        Typ           2     Attchd       1939.0

  GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
0          RFn           2         548         TA         TA          Y
1          RFn           2         460         TA         TA          Y
2          RFn           2         608         TA         TA          Y
3          Unf           3         642         TA         TA          Y
4          RFn           3         836         TA         TA          Y
5          Unf           2         480         TA         TA          Y
6          RFn           2         636         TA         TA          Y
7          RFn           2         484         TA         TA          Y
8          Unf           2         468         Fa         TA          Y
9          RFn           1         205         Gd         TA          Y

   WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  \
0           0           61              0          0            0         0
1         298            0              0          0            0         0
2           0           42              0          0            0         0
3           0           35            272          0            0         0
4         192           84              0          0            0         0
5          40           30              0        320            0         0
6         255           57              0          0            0         0
7         235          204            228          0            0         0
8          90            0            205          0            0         0
9           0            4              0          0            0         0

   MiscVal  MoSold  YrSold SaleType SaleCondition  SalePrice
0        0       2    2008       WD        Normal     208500
1        0       5    2007       WD        Normal     181500
2        0       9    2008       WD        Normal     223500
3        0       2    2006       WD       Abnorml     140000
4        0      12    2008       WD        Normal     250000
5      700      10    2009       WD        Normal     143000
6        0       8    2007       WD        Normal     307000
7      350      11    2009       WD        Normal     200000
8        0       4    2008       WD       Abnorml     129900
9        0       1    2008       WD        Normal     118000
```

1.2 Mean :

[95]:
```
num_vars_miss = ['LotFrontage', 'MasVnrArea', 'GarageYrBlt']
cat_vars = ['LotConfig','Exterior2nd','KitchenQual']

for cat_var, num_var_miss in zip(cat_vars,num_vars_miss):
    for var_class in data[cat_var].unique():
```

```
        data1_copy2_mean.update(data[data.loc[:,cat_var] ==␣
↪var_class][num_var_miss].replace(np.nan,data[data.loc[:,cat_var] ==␣
↪var_class][num_var_miss].mean()))
```

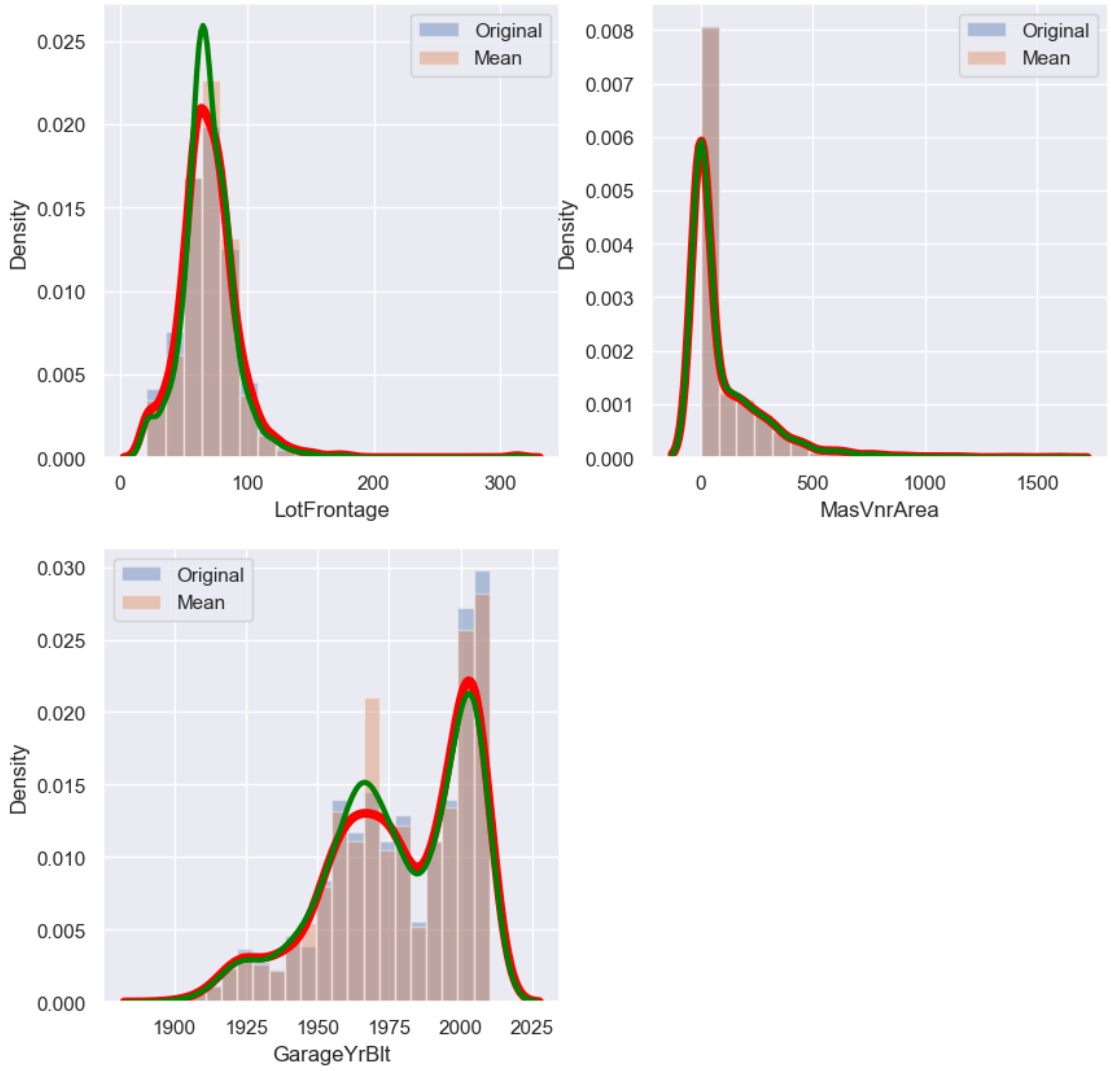
[97]:
```
data1_copy2_mean[num_vars_miss].isnull().sum()
```

[97]:
```
LotFrontage    0
MasVnrArea     0
GarageYrBlt    0
dtype: int64
```

Here, we have addressed the issue of missing values in the numerical column by calculating the mean for each category in the categorical column.

1.2.1 Data Distribution :

[99]:
```
plt.figure(figsize=(10,10))
sns.set()
for i, var in enumerate(num_vars_miss):
    plt.subplot(2,2,i+1)
    sns.distplot(data[var], bins=20, kde_kws={'linewidth':5, 'color':'red'},␣
↪label="Original",)
    sns.distplot(data1_copy2_mean[var], bins=20, kde_kws={'linewidth':3,␣
↪'color':'green'},label="Mean",)
    plt.legend()
```



1.3 Median :

[100]:
```
data1_copy2_median = data1.copy()
data1_copy2_median.head()
```

[100]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	\
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	

	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	BldgType	\
0	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	

```
1    AllPub       FR2       Gtl      Veenker      Feedr       Norm     1Fam
2    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
3    AllPub    Corner       Gtl      Crawfor       Norm       Norm     1Fam
4    AllPub       FR2       Gtl      NoRidge       Norm       Norm     1Fam

  HouseStyle  OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle  \
0     2Story            7            5       2003          2003     Gable
1     1Story            6            8       1976          1976     Gable
2     2Story            7            5       2001          2002     Gable
3     2Story            7            5       1915          1970     Gable
4     2Story            8            5       2000          2000     Gable

  RoofMatl Exterior1st Exterior2nd MasVnrType  MasVnrArea ExterQual ExterCond  \
0  CompShg     VinylSd     VinylSd    BrkFace       196.0        Gd        TA
1  CompShg     MetalSd     MetalSd       None         0.0        TA        TA
2  CompShg     VinylSd     VinylSd    BrkFace       162.0        Gd        TA
3  CompShg     Wd Sdng     Wd Shng       None         0.0        TA        TA
4  CompShg     VinylSd     VinylSd    BrkFace       350.0        Gd        TA

  Foundation BsmtQual BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1  \
0      PConc       Gd       TA           No          GLQ         706
1     CBlock       Gd       TA           Gd          ALQ         978
2      PConc       Gd       TA           Mn          GLQ         486
3     BrkTil       TA       Gd           No          ALQ         216
4      PConc       Gd       TA           Av          GLQ         655

  BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF Heating HeatingQC  \
0          Unf           0        150          856    GasA        Ex
1          Unf           0        284         1262    GasA        Ex
2          Unf           0        434          920    GasA        Ex
3          Unf           0        540          756    GasA        Gd
4          Unf           0        490         1145    GasA        Ex

  CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  \
0          Y      SBrkr       856       854             0       1710
1          Y      SBrkr      1262         0             0       1262
2          Y      SBrkr       920       866             0       1786
3          Y      SBrkr       961       756             0       1717
4          Y      SBrkr      1145      1053             0       2198

   BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  \
0             1             0         2         1             3             1
1             0             1         2         0             3             1
2             1             0         2         1             3             1
3             1             0         1         0             3             1
4             1             0         2         1             4             1
```

```
  KitchenQual  TotRmsAbvGrd Functional  Fireplaces GarageType  GarageYrBlt  \
0          Gd             8        Typ           0     Attchd       2003.0
1          TA             6        Typ           1     Attchd       1976.0
2          Gd             6        Typ           1     Attchd       2001.0
3          Gd             7        Typ           1     Detchd       1998.0
4          Gd             9        Typ           1     Attchd       2000.0

  GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
0          RFn           2         548         TA         TA          Y
1          RFn           2         460         TA         TA          Y
2          RFn           2         608         TA         TA          Y
3          Unf           3         642         TA         TA          Y
4          RFn           3         836         TA         TA          Y

   WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  \
0           0           61              0          0            0         0
1         298            0              0          0            0         0
2           0           42              0          0            0         0
3           0           35            272          0            0         0
4         192           84              0          0            0         0

   MiscVal  MoSold  YrSold SaleType SaleCondition  SalePrice
0        0       2    2008       WD        Normal     208500
1        0       5    2007       WD        Normal     181500
2        0       9    2008       WD        Normal     223500
3        0       2    2006       WD       Abnorml     140000
4        0      12    2008       WD        Normal     250000
```

[101]:
```
data1_copy2_median[num_vars_miss].isnull().sum()
```

[101]:
```
LotFrontage    259
MasVnrArea       8
GarageYrBlt     81
dtype: int64
```

[102]:
```
num_vars_miss = ['LotFrontage', 'MasVnrArea', 'GarageYrBlt']
cat_vars = ['LotConfig','Exterior2nd','KitchenQual']

for cat_var, num_var_miss in zip(cat_vars,num_vars_miss):
    for var_class in data[cat_var].unique():
        data1_copy2_median.update(data[data.loc[:,cat_var] ==␣
 ↪var_class][num_var_miss].replace(np.nan,data[data.loc[:,cat_var] ==␣
 ↪var_class][num_var_miss].median()))
```

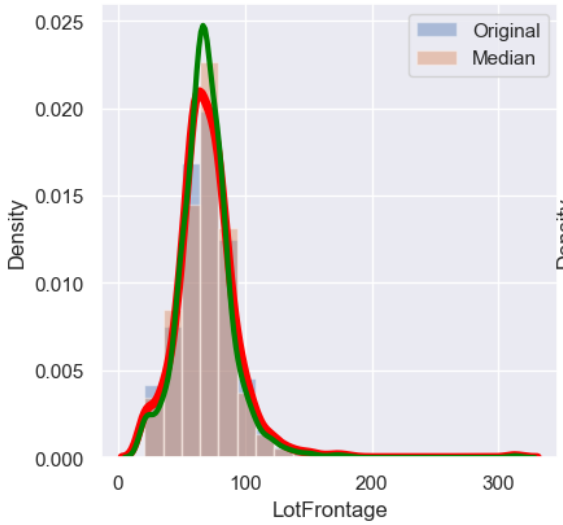
[103]:
```
data1_copy2_median[num_vars_miss].isnull().sum()
```

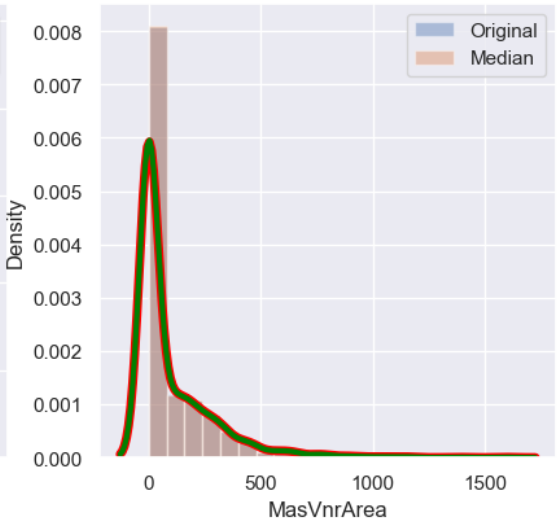
[103]:
```
LotFrontage    0
MasVnrArea     0
GarageYrBlt    0
dtype: int64
```

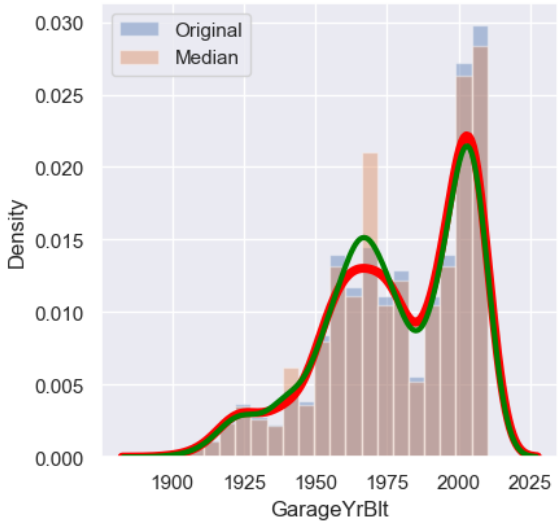
Here, we have addressed the issue of missing values in the numerical column by calculating the mean for each category in the categorical column.

1.3.1 Data Distribution :

[104]:
```
plt.figure(figsize=(10,10))
sns.set()
for i, var in enumerate(num_vars_miss):
    plt.subplot(2,2,i+1)
    sns.distplot(data[var], bins=20, kde_kws={'linewidth':5, 'color':'red'},␣
 ↪label="Original",)
    sns.distplot(data1_copy2_median[var], bins=20, kde_kws={'linewidth':3,␣
 ↪'color':'green'},label="Median",)
    plt.legend()
```


Original
Median
Density
LotFrontage
0.025
0.020
0.015
0.010
0.005
0.000
0
100
200
300


Original
Median
Density
MasVnrArea
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
0
500
1000
1500


Original
Median
Density
GarageYrBlt
0.030
0.025
0.020
0.015
0.010
0.005
0.000
1900
1925
1950
1975
2000
2025

tegorical-missing-value-imputation

June 11, 2023

1 Data Cleaning :

1.1 Categorical Missing value imputation :

Importing necessary libraries :

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from IPython.display import Image
```

data (Original) :

[2]:
```
data = pd.read_csv('train.csv')
```

[3]:
```
data.shape  # Checking the shape of the DataFrame, DataFrame contains Rows:␣
↪1460 and Columns: 81.
```

[3]:
```
(1460, 81)
```

[4]:
```
data.head(2)  # Checking first 2 rows from the DataFrame.
```

[4]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500

[2 rows x 81 columns]
```

When we check the shape of the data using the command “data.shape”, we can observe that the DataFrame consists of 1460 rows and 81 columns. However, when we examine the first two rows of the DataFrame using the command “data.head(2)”, it doesn’t display all 81 columns. As a result, we utilize the following code, specifically “pd.set_option()”, to address this issue.

[5]:
```
pd.set_option('display.max_column', None)
pd.set_option('display.max_rows', None)
```

pd.set_option(‘display.max_columns’, None): This line sets the maximum number of columns to be displayed in the output to None, which means there is no limit. As a result, all columns in a DataFrame will be shown when you print or display it.

pd.set_option(‘display.max_rows’, None): This line sets the maximum number of rows to be displayed in the output to None, removing any limit. As a result, all rows in a DataFrame will be shown when you print or display it.

[7]:
```
categorical_DataFrame = data.select_dtypes(include='object') # selecting only␣
↪categorical columns
```

[8]:
```
categorical_DataFrame.head() # Checking first 5 rows of categorical DataFrame.
```

[8]:

	MSZoning	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	\
0	RL	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	
1	RL	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	
2	RL	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	
3	RL	Pave	NaN	IR1	Lvl	AllPub	Corner	Gtl	
4	RL	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	

	Neighborhood	Condition1	Condition2	BldgType	HouseStyle	RoofStyle	RoofMatl	\
0	CollgCr	Norm	Norm	1Fam	2Story	Gable	CompShg	
1	Veenker	Feedr	Norm	1Fam	1Story	Gable	CompShg	
2	CollgCr	Norm	Norm	1Fam	2Story	Gable	CompShg	
3	Crawfor	Norm	Norm	1Fam	2Story	Gable	CompShg	
4	NoRidge	Norm	Norm	1Fam	2Story	Gable	CompShg	

	Exterior1st	Exterior2nd	MasVnrType	ExterQual	ExterCond	Foundation	BsmtQual	\
0	VinylSd	VinylSd	BrkFace	Gd	TA	PConc	Gd	
1	MetalSd	MetalSd	None	TA	TA	CBlock	Gd	
2	VinylSd	VinylSd	BrkFace	Gd	TA	PConc	Gd	
3	Wd Sdng	Wd Shng	None	TA	TA	BrkTil	TA	
4	VinylSd	VinylSd	BrkFace	Gd	TA	PConc	Gd	

	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinType2	Heating	HeatingQC	\
0	TA	No	GLQ	Unf	GasA	Ex	
1	TA	Gd	ALQ	Unf	GasA	Ex	
2	TA	Mn	GLQ	Unf	GasA	Ex	
3	Gd	No	ALQ	Unf	GasA	Gd	
4	TA	Av	GLQ	Unf	GasA	Ex	

```
  CentralAir Electrical KitchenQual Functional FireplaceQu GarageType  \
0          Y      SBrkr          Gd        Typ         NaN     Attchd
1          Y      SBrkr          TA        Typ          TA     Attchd
2          Y      SBrkr          Gd        Typ          TA     Attchd
3          Y      SBrkr          Gd        Typ          Gd     Detchd
4          Y      SBrkr          Gd        Typ          TA     Attchd

  GarageFinish GarageQual GarageCond PavedDrive PoolQC Fence MiscFeature  \
0          RFn         TA         TA          Y    NaN   NaN         NaN
1          RFn         TA         TA          Y    NaN   NaN         NaN
2          RFn         TA         TA          Y    NaN   NaN         NaN
3          Unf         TA         TA          Y    NaN   NaN         NaN
4          RFn         TA         TA          Y    NaN   NaN         NaN

  SaleType SaleCondition
0       WD        Normal
1       WD        Normal
2       WD        Normal
3       WD       Abnorml
4       WD        Normal
```

[9]:
```
categorical_DataFrame.isnull().sum()

# It used to calculate the number of missing values in each column of a␣
 ↪DataFrame called categorical_DataFrame.
```

[9]:
```
MSZoning           0
Street             0
Alley           1369
LotShape           0
LandContour        0
Utilities          0
LotConfig          0
LandSlope          0
Neighborhood       0
Condition1         0
Condition2         0
BldgType           0
HouseStyle         0
RoofStyle          0
RoofMatl           0
Exterior1st        0
Exterior2nd        0
MasVnrType         8
ExterQual          0
ExterCond          0
```

```
Foundation          0
BsmtQual           37
BsmtCond           37
BsmtExposure       38
BsmtFinType1       37
BsmtFinType2       38
Heating             0
HeatingQC           0
CentralAir          0
Electrical          1
KitchenQual         0
Functional          0
FireplaceQu       690
GarageType         81
GarageFinish       81
GarageQual         81
GarageCond         81
PavedDrive          0
PoolQC           1453
Fence            1179
MiscFeature      1406
SaleType            0
SaleCondition       0
dtype: int64
```

[11]:
```
missing_value_percent = categorical_DataFrame.isnull().mean()*100
missing_value_percent

#calculates the percentage of missing values in each column of the␣
 ↪categorical_DataFrame.
```

[11]:
```
MSZoning          0.000000
Street            0.000000
Alley            93.767123
LotShape          0.000000
LandContour       0.000000
Utilities         0.000000
LotConfig         0.000000
LandSlope         0.000000
Neighborhood      0.000000
Condition1        0.000000
Condition2        0.000000
BldgType          0.000000
HouseStyle        0.000000
RoofStyle         0.000000
RoofMatl          0.000000
Exterior1st       0.000000
```

```
Exterior2nd       0.000000
MasVnrType        0.547945
ExterQual         0.000000
ExterCond         0.000000
Foundation        0.000000
BsmtQual          2.534247
BsmtCond          2.534247
BsmtExposure      2.602740
BsmtFinType1      2.534247
BsmtFinType2      2.602740
Heating           0.000000
HeatingQC         0.000000
CentralAir        0.000000
Electrical        0.068493
KitchenQual       0.000000
Functional        0.000000
FireplaceQu      47.260274
GarageType        5.547945
GarageFinish      5.547945
GarageQual        5.547945
GarageCond        5.547945
PavedDrive        0.000000
PoolQC           99.520548
Fence            80.753425
MiscFeature      96.301370
SaleType          0.000000
SaleCondition     0.000000
dtype: float64
```

[15]:
```
drop_column = missing_value_percent[missing_value_percent > 20].keys()
print(drop_column)

'''

The code `drop_column = missing_value_percent[missing_value_percent > 20].
 ↪keys()` selects the columns from
`missing_value_percent` that have missing value percentages greater than 20%␣
 ↪and assigns them to the `drop_column` variable.

'''
```

```
Index(['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'],
dtype='object')
```

[21]:
```
new_data = categorical_DataFrame.drop(columns = drop_column)
new_data.head()
```

```
'''

The code new_data = categorical_DataFrame.drop(columns=drop_column) creates a␣
 ↪new DataFrame called new_data by dropping the
columns specified in the drop_column variable from the categorical_DataFrame

'''
```

[21]:

```
  MSZoning Street LotShape LandContour Utilities LotConfig LandSlope  \
0       RL   Pave      Reg         Lvl    AllPub    Inside       Gtl
1       RL   Pave      Reg         Lvl    AllPub       FR2       Gtl
2       RL   Pave      IR1         Lvl    AllPub    Inside       Gtl
3       RL   Pave      IR1         Lvl    AllPub    Corner       Gtl
4       RL   Pave      IR1         Lvl    AllPub       FR2       Gtl

  Neighborhood Condition1 Condition2 BldgType HouseStyle RoofStyle RoofMatl  \
0      CollgCr       Norm       Norm     1Fam     2Story     Gable  CompShg
1      Veenker      Feedr       Norm     1Fam     1Story     Gable  CompShg
2      CollgCr       Norm       Norm     1Fam     2Story     Gable  CompShg
3      Crawfor       Norm       Norm     1Fam     2Story     Gable  CompShg
4      NoRidge       Norm       Norm     1Fam     2Story     Gable  CompShg

  Exterior1st Exterior2nd MasVnrType ExterQual ExterCond Foundation BsmtQual  \
0     VinylSd     VinylSd    BrkFace        Gd        TA      PConc       Gd
1     MetalSd     MetalSd       None        TA        TA      CBlock      Gd
2     VinylSd     VinylSd    BrkFace        Gd        TA      PConc       Gd
3     Wd Sdng     Wd Shng       None        TA        TA      BrkTil      TA
4     VinylSd     VinylSd    BrkFace        Gd        TA      PConc       Gd

  BsmtCond BsmtExposure BsmtFinType1 BsmtFinType2 Heating HeatingQC  \
0       TA           No          GLQ          Unf    GasA        Ex
1       TA           Gd          ALQ          Unf    GasA        Ex
2       TA           Mn          GLQ          Unf    GasA        Ex
3       Gd           No          ALQ          Unf    GasA        Gd
4       TA           Av          GLQ          Unf    GasA        Ex

  CentralAir Electrical KitchenQual Functional GarageType GarageFinish  \
0          Y      SBrkr          Gd        Typ     Attchd          RFn
1          Y      SBrkr          TA        Typ     Attchd          RFn
2          Y      SBrkr          Gd        Typ     Attchd          RFn
3          Y      SBrkr          Gd        Typ     Detchd          Unf
4          Y      SBrkr          Gd        Typ     Attchd          RFn

  GarageQual GarageCond PavedDrive SaleType SaleCondition
0         TA         TA          Y       WD        Normal
1         TA         TA          Y       WD        Normal
2         TA         TA          Y       WD        Normal
```

```
3          TA          TA           Y        WD        Abnorml
4          TA          TA           Y        WD         Normal
```

[24]:
```
Missing_val_columns = new_data.isnull().sum()
print(Missing_val_columns)

'''
The code Missing_val_columns = new_data.isnull().sum() calculates the number of␣
 ↪missing values in each column of the
new_data DataFrame and assigns the result to the Missing_val_columns variable.
'''
```

```
MSZoning          0
Street            0
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
LandSlope         0
Neighborhood      0
Condition1        0
Condition2        0
BldgType          0
HouseStyle        0
RoofStyle         0
RoofMatl          0
Exterior1st       0
Exterior2nd       0
MasVnrType        8
ExterQual         0
ExterCond         0
Foundation        0
BsmtQual         37
BsmtCond         37
BsmtExposure     38
BsmtFinType1     37
BsmtFinType2     38
Heating           0
HeatingQC         0
CentralAir        0
Electrical        1
KitchenQual       0
Functional        0
GarageType       81
GarageFinish     81
GarageQual       81
GarageCond       81
```

```
PavedDrive        0
SaleType          0
SaleCondition     0
dtype: int64
```

[26]:
```
Null_column = Missing_val_columns[Missing_val_columns > 0].keys()
print(Null_column)

'''
The code `Null_column = Missing_val_columns[Missing_val_columns > 0].keys()`␣
 ↪selects the columns from the
`Missing_val_columns` variable that have a count of missing values greater than␣
 ↪0 and assigns their column names to the
`Null_column` variable.

'''
```

```
Index(['MasVnrType', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
       'BsmtFinType2', 'Electrical', 'GarageType', 'GarageFinish',
       'GarageQual', 'GarageCond'],
      dtype='object')
```

[27]:
```
new_data_copy = new_data.copy()
new_data_copy.shape
```

[27]:
```
(1460, 38)
```

[28]:
```
for var in Null_column:
    new_data_copy[var].fillna(new_data_copy[var].mode()[0], inplace = True)
    print(var,'=',new_data[var].mode()[0])
```

```
MasVnrType = None
BsmtQual = TA
BsmtCond = TA
BsmtExposure = No
BsmtFinType1 = Unf
BsmtFinType2 = Unf
Electrical = SBrkr
GarageType = Attchd
GarageFinish = Unf
GarageQual = TA
GarageCond = TA
```

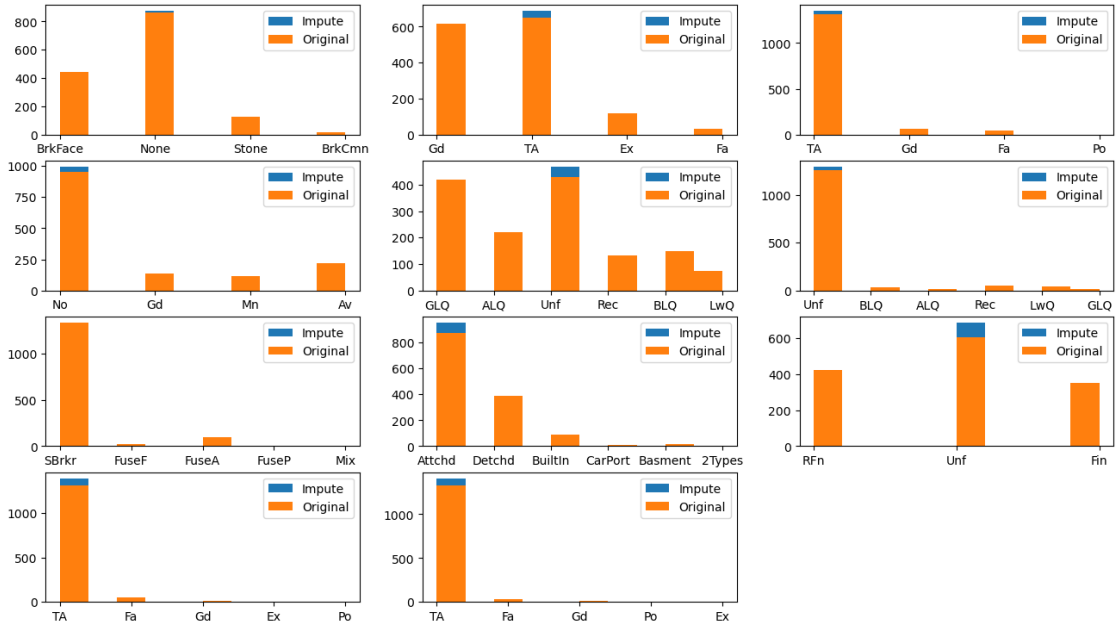
This loop iterates over each column name stored in Null_column, fills the missing values in that column with the mode (most frequent value), and then prints the column name along with the mode value. The fillna function is used to replace the missing values with the specified mode value in place.

[30]:
```
new_data_copy.isnull().sum() # We can see null value is handled
```

[30]:
```
MSZoning         0
Street           0
LotShape         0
LandContour      0
Utilities        0
LotConfig        0
LandSlope        0
Neighborhood     0
Condition1       0
Condition2       0
BldgType         0
HouseStyle       0
RoofStyle        0
RoofMatl         0
Exterior1st      0
Exterior2nd      0
MasVnrType       0
ExterQual        0
ExterCond        0
Foundation       0
BsmtQual         0
BsmtCond         0
BsmtExposure     0
BsmtFinType1     0
BsmtFinType2     0
Heating          0
HeatingQC        0
CentralAir       0
Electrical       0
KitchenQual      0
Functional       0
GarageType       0
GarageFinish     0
GarageQual       0
GarageCond       0
PavedDrive       0
SaleType         0
SaleCondition    0
dtype: int64
```

[31]:
```
plt.figure(figsize=(16,9))
for i,var in enumerate(Null_column):
    plt.subplot(4,3,i+1)
    plt.hist(new_data_copy[var],label="Impute")
    plt.hist(new_data[var].dropna(),label="Original")
```

```
    plt.legend()
```



The code you provided is creating a figure and subplots using plt.subplot() to visualize the distribution of the imputed values (new_data_copy[var]) compared to the original values (new_data[var]) for each column in Null_column.