House Prices - Advanced Regression Techniques Predict sales prices and practice feature engineering, RFs, and gradient boosting

```
%matplotlib inline
import pandas as pd                                           #For data analysis
import numpy as np                                          #for operations on numbers
import matplotlib.pyplot as plt                             #for figures
import seaborn as sns                                       #for detailed statistical analysis
from sklearn.impute import KNNImputer                       #for KNN imputation
from scipy.stats import zscore                              #for zscore
from sklearn.preprocessing import StandardScaler, MinMaxScaler  #For normalization and Standardization
```

```
data = pd.read_csv('/content/drive/MyDrive/train.csv')  #loading the data
```

```
data.head()       #first five rows of data
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0

5 rows × 81 columns

```
data.columns    #checking features
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

```
# Separate categorical and numerical features
categorical_features = data.select_dtypes(include=['object']).columns.tolist()
numerical_features = data.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Print the features
print("Categorical Features:", categorical_features)
print("Numerical Features:", numerical_features)
```

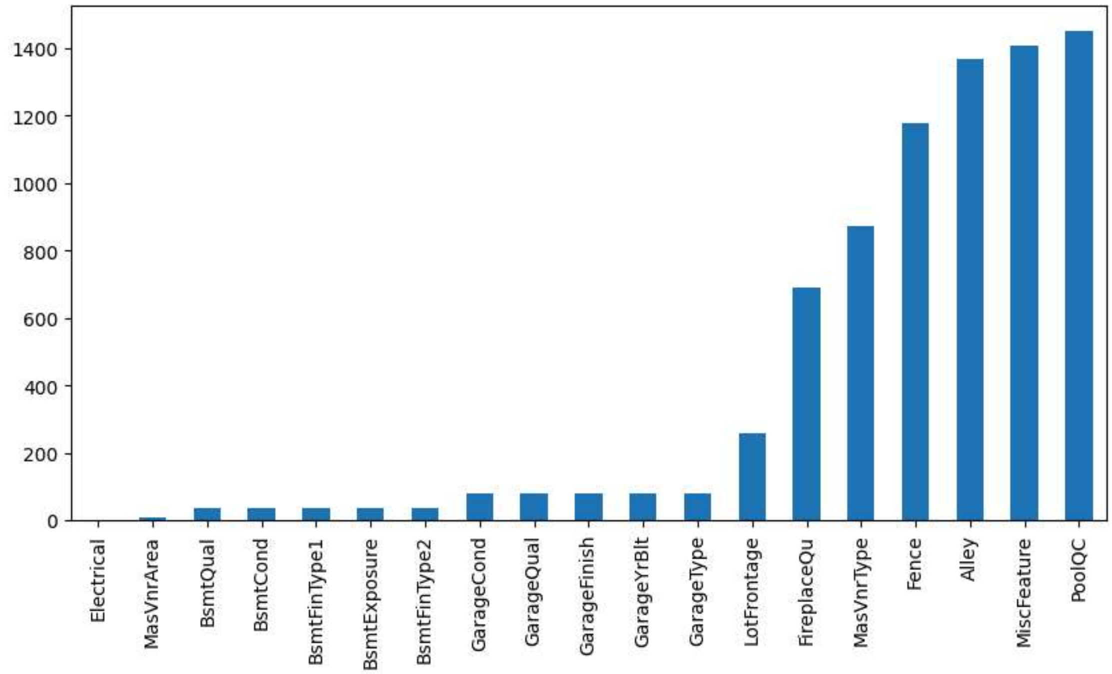
```
Categorical Features: ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1',
Numerical Features: ['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF
```

```
data.shape  #checking rows and columns
```

```
(1460, 81)
```

```
missing = data.isnull().sum()       #counting any null value
missing =  missing[missing > 0]     #make it greater than 0
missing.sort_values(inplace=True)   #sorting
plt.figure(figsize=(10,5))          #setting the size
missing.plot.bar()                  #visualize   (This data having so many null values as shown in the figure)
```

<Axes: >




```
data["SalePrice"].describe()      #Checking statistics of our target variable
```

	SalePrice
count	1460.000000
mean	180921.195890
std	79442.502883
min	34900.000000
25%	129975.000000
50%	163000.000000
75%	214000.000000
max	755000.000000

dtype: float64

```
#Now we have information of Outliers in the data. We have mean, median(50% value), mean is greater than median here.
#We'll now visualize this
sns.set(rc={'figure.figsize':(10,7)})
sns.distplot(data["SalePrice"], bins=20);
```

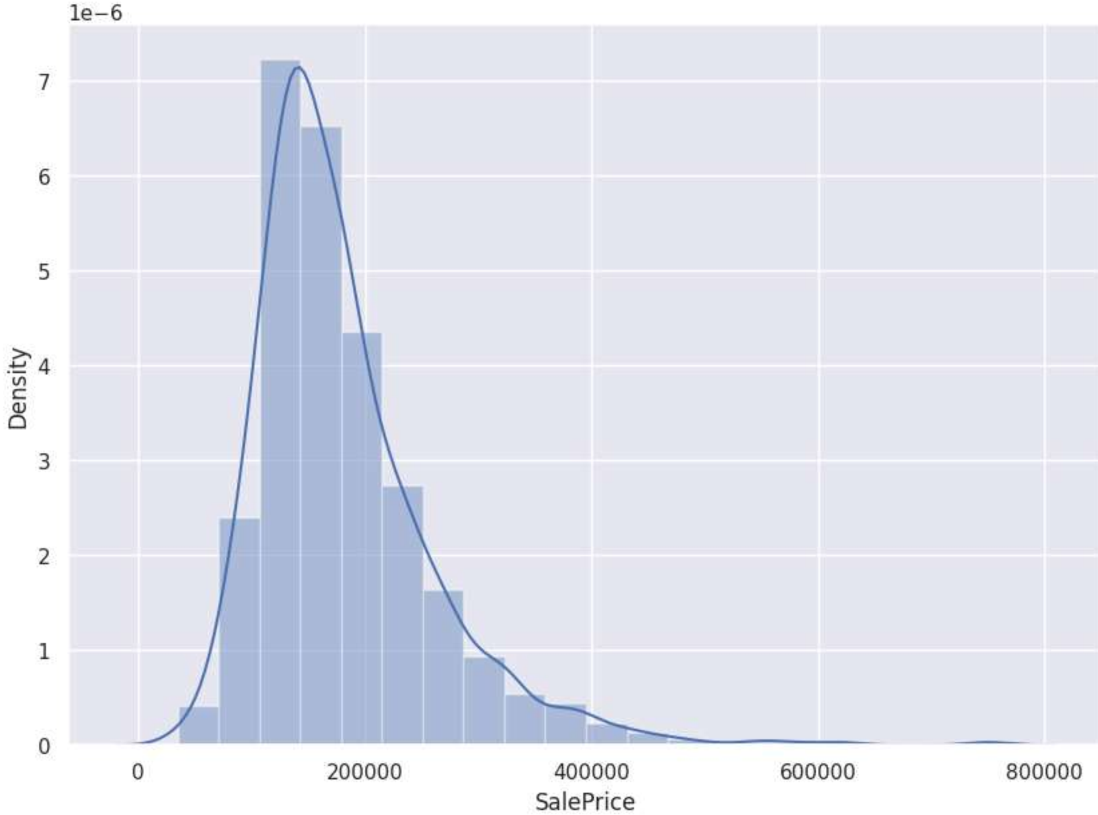
<ipython-input-11-b015270fd6a9>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

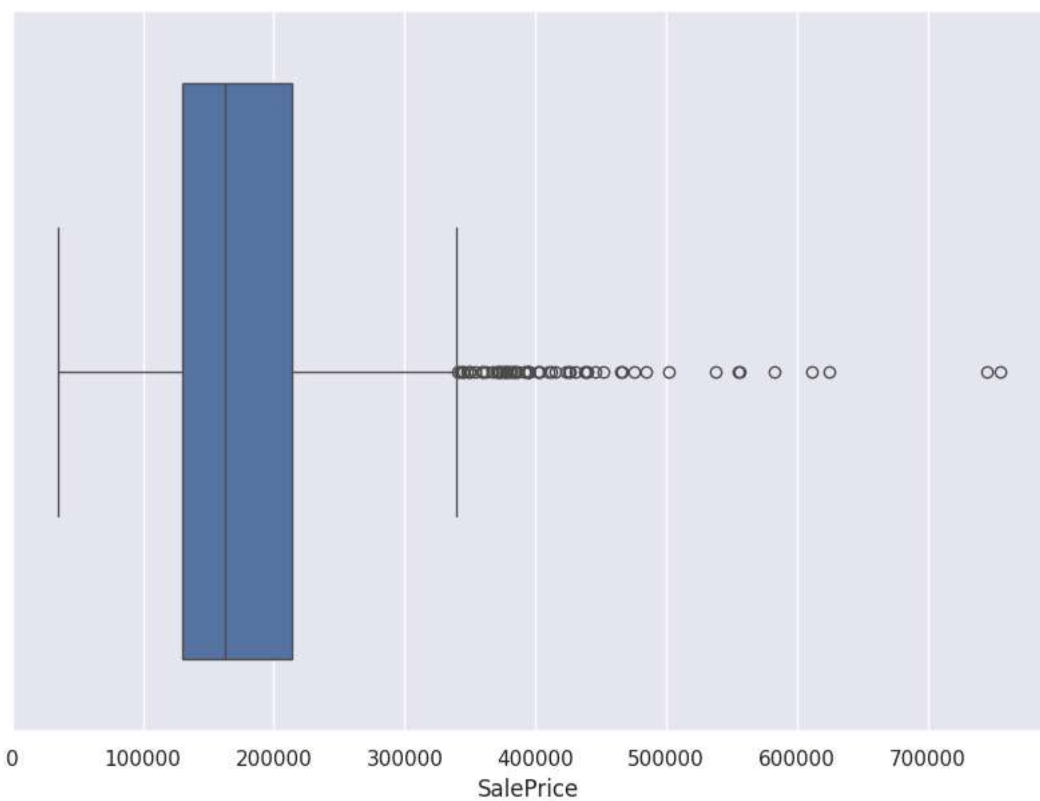
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

```
  sns.distplot(data["SalePrice"], bins=20);
```

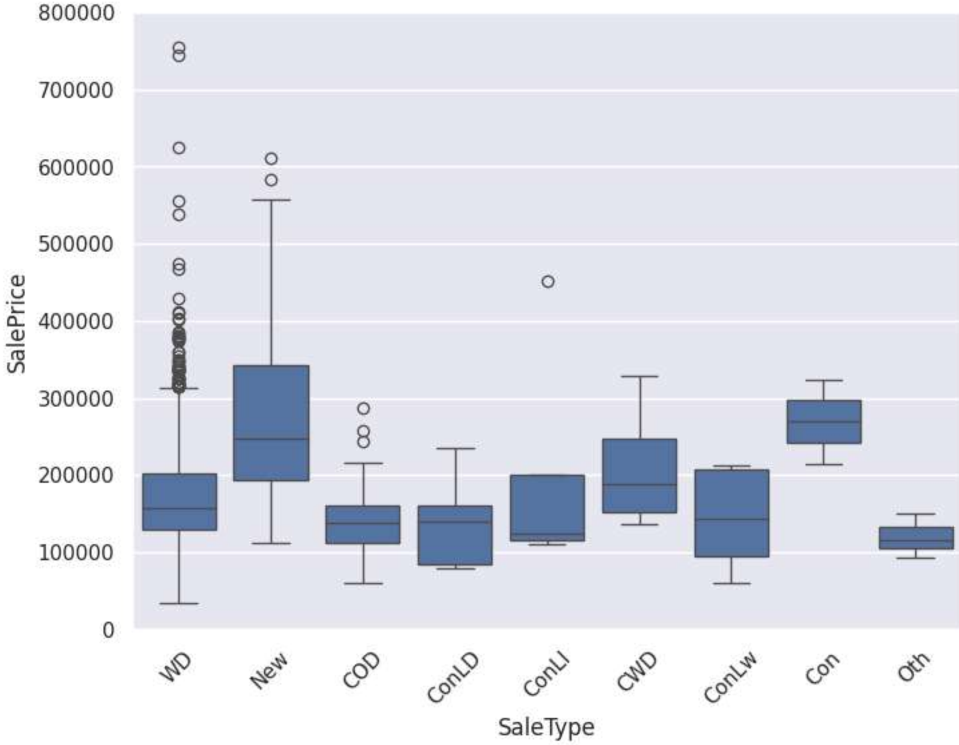



```
sns.boxplot(x=data["SalePrice"])          #Visualizing outliers with respected to saleprice.
```

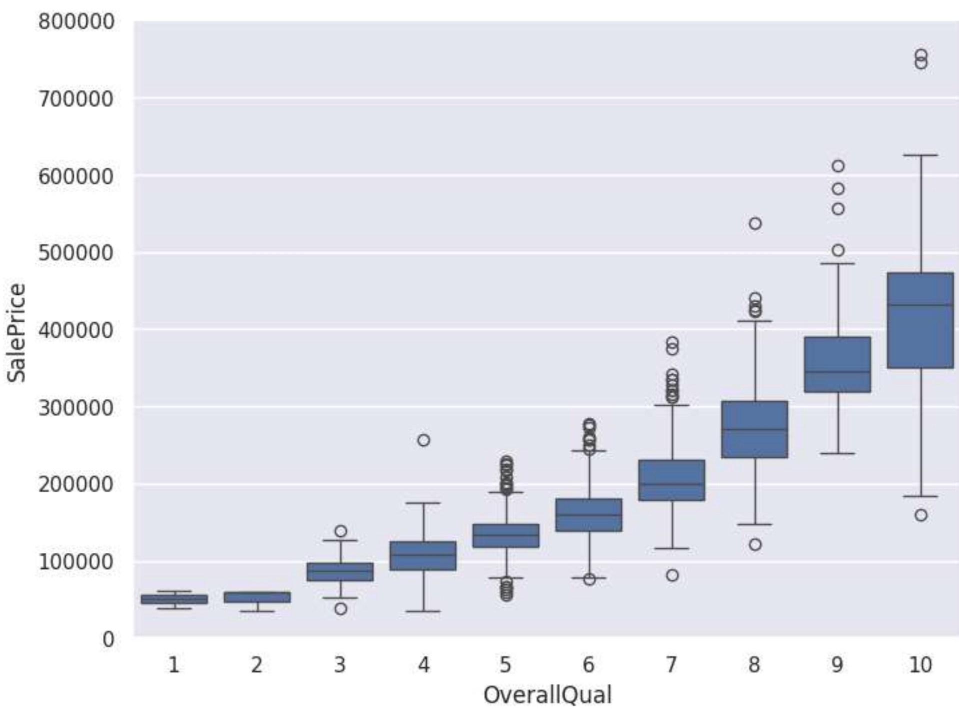
<Axes: xlabel='SalePrice'>



```
f, ax = plt.subplots(figsize=(8, 6))                          #Analyzing outliers for different saletypes
fig = sns.boxplot(x="SaleType", y="SalePrice", data=data)
fig.axis(ymin=0, ymax=800000);
xt=plt.xticks(rotation=45)
```




```
f, ax = plt.subplots(figsize=(8, 6))                       #For overall quality, sale price is plotting.
fig = sns.boxplot(x="OverallQual", y="SalePrice", data=data)
fig.axis(ymin=0, ymax=800000);
```




```
first_quartile = data["SalePrice"].quantile(0.25)
third_quartile = data["SalePrice"].quantile(0.75)
IQR = third_quartile - first_quartile
```

```
new_boundry = third_quartile + 3* IQR
```

```
data.drop(data[data["SalePrice"]>new_boundry].index,axis=0,inplace=True)
```

```
# Drop columns with more than 40% missing values
threshold = 0.4 * len(data)
```

```
columns_to_drop = missing[missing > threshold].index
data_cleaned = data.drop(columns=columns_to_drop)
```

```
# Impute missing numerical data using median
numerical_features = data_cleaned.select_dtypes(include=['int64', 'float64']).columns
for col in numerical_features:
    data_cleaned[col] = data_cleaned[col].fillna(data_cleaned[col].median())
data_cleaned[numerical_features]
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	WoodDeckSF	OpenPorchSF	E
0	1	60	65.0	8450	7	5	2003	2003	196.0	706	...	0	61	
1	2	20	80.0	9600	6	8	1976	1976	0.0	978	...	298	0	
2	3	60	68.0	11250	7	5	2001	2002	162.0	486	...	0	42	
3	4	70	60.0	9550	7	5	1915	1970	0.0	216	...	0	35	
4	5	60	84.0	14260	8	5	2000	2000	350.0	655	...	192	84	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1455	1456	60	62.0	7917	6	5	1999	2000	0.0	0	...	0	40	
1456	1457	20	85.0	13175	6	6	1978	1988	119.0	790	...	349	0	
1457	1458	70	66.0	9042	7	9	1941	2006	0.0	275	...	0	60	
1458	1459	20	68.0	9717	5	6	1950	1996	0.0	49	...	366	0	
1459	1460	20	75.0	9937	5	6	1965	1965	0.0	830	...	736	68	

1448 rows × 38 columns

```
# Impute missing categorical data using the most frequent value (mode)
categorical_features = data_cleaned.select_dtypes(include=['object']).columns
for col in categorical_features:
    data_cleaned[col].fillna(data_cleaned[col].mode()[0])
data_cleaned[categorical_features]
```

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	...	Electrical	KitchenQual	Func
0	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	...	SBrkr	Gd	
1	RL	Pave	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	Norm	...	SBrkr	TA	
2	RL	Pave	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	...	SBrkr	Gd	
3	RL	Pave	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	Norm	...	SBrkr	Gd	
4	RL	Pave	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	Norm	Norm	...	SBrkr	Gd	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1455	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	Gilbert	Norm	Norm	...	SBrkr	TA	
1456	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	NWAmes	Norm	Norm	...	SBrkr	TA	
1457	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	Crawfor	Norm	Norm	...	SBrkr	Gd	
1458	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	NAmes	Norm	Norm	...	FuseA	Gd	
1459	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	Edwards	Norm	Norm	...	SBrkr	TA	

1448 rows × 37 columns

```
# Apply KNN imputation for remaining missing values in numerical data
knn_imputer = KNNImputer(n_neighbors=5)
data_cleaned[numerical_features] = knn_imputer.fit_transform(data_cleaned[numerical_features])
data_cleaned[numerical_features]
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	WoodDeckSF	OpenPorchSF
0	1.0	60.0	65.0	8450.0	7.0	5.0	2003.0	2003.0	196.0	706.0	...	0.0	61.0
1	2.0	20.0	80.0	9600.0	6.0	8.0	1976.0	1976.0	0.0	978.0	...	298.0	0.0
2	3.0	60.0	68.0	11250.0	7.0	5.0	2001.0	2002.0	162.0	486.0	...	0.0	42.0
3	4.0	70.0	60.0	9550.0	7.0	5.0	1915.0	1970.0	0.0	216.0	...	0.0	35.0
4	5.0	60.0	84.0	14260.0	8.0	5.0	2000.0	2000.0	350.0	655.0	...	192.0	84.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456.0	60.0	62.0	7917.0	6.0	5.0	1999.0	2000.0	0.0	0.0	...	0.0	40.0
1456	1457.0	20.0	85.0	13175.0	6.0	6.0	1978.0	1988.0	119.0	790.0	...	349.0	0.0
1457	1458.0	70.0	66.0	9042.0	7.0	9.0	1941.0	2006.0	0.0	275.0	...	0.0	60.0
1458	1459.0	20.0	68.0	9717.0	5.0	6.0	1950.0	1996.0	0.0	49.0	...	366.0	0.0
1459	1460.0	20.0	75.0	9937.0	5.0	6.0	1965.0	1965.0	0.0	830.0	...	736.0	68.0

1448 rows × 38 columns

```
# Display missing values after handling
remaining_missing = data_cleaned.isnull().sum().sum()
print("Remaining Missing Values:", remaining_missing)
```

```
Remaining Missing Values: 512
```

```
missing = data_cleaned.isnull().sum()
missing = missing[missing > 0]  # Filter columns with missing values
print(missing)
```

```
BsmtQual        37
BsmtCond        37
BsmtExposure    38
BsmtFinType1    37
BsmtFinType2    38
Electrical       1
GarageType      81
GarageFinish    81
GarageQual      81
GarageCond      81
dtype: int64
```

```
# Fill missing Electrical value with mode
data_cleaned["Electrical"].fillna(data_cleaned["Electrical"].mode()[0], inplace=True)

# Fill missing categorical basement/garage features with "None"
for col in ['BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
            'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond']:
    data_cleaned[col].fillna("None", inplace=True)
```

```
<ipython-input-24-4df306bdf496>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an ir
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always beha

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) ins


  data_cleaned["Electrical"].fillna(data_cleaned["Electrical"].mode()[0], inplace=True)
<ipython-input-24-4df306bdf496>:7: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an ir
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always beha

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) ins


  data_cleaned[col].fillna("None", inplace=True)
```

```
print("Remaining Missing Values:", data_cleaned.isnull().sum().sum())
```

```
Remaining Missing Values: 0
```

```
# Check for duplicate records in the dataset
duplicate_count = data_cleaned.duplicated().sum()
print(f"Number of duplicate records: {duplicate_count}")
```

```
Number of duplicate records: 0
```

```
# Identify categorical columns
categorical_features = data.select_dtypes(include=['object']).columns.tolist()
print("Categorical Features:", categorical_features)
```

```
Categorical Features: ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1',
```

```
from sklearn.preprocessing import LabelEncoder

# Apply Label Encoding to categorical features  (for ordinal categories)
label_encoders = {}
for col in categorical_features:
    le = LabelEncoder()
    data[col] = le.fit_transform(data[col])
    label_encoders[col] = le  # Store the encoder for future reference

# Check encoded data
data.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal
0	1	60	3	65.0	8450	1	2	3	3	0	...	0	3	4	4	0
1	2	20	3	80.0	9600	1	2	3	3	0	...	0	3	4	4	0
2	3	60	3	68.0	11250	1	2	0	3	0	...	0	3	4	4	0
3	4	70	3	60.0	9550	1	2	0	3	0	...	0	3	4	4	0
4	5	60	3	84.0	14260	1	2	0	3	0	...	0	3	4	4	0

5 rows × 81 columns

```
# Apply One-Hot Encoding , (for non-ordinal categories)
data = pd.get_dummies(data, columns=categorical_features, drop_first=True)

# Check new dataset structure
data.head()
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	SaleType_4	SaleType_5	SaleTyp
0	1	60	65.0	8450	7	5	2003	2003	196.0	706	...	False	False	F
1	2	20	80.0	9600	6	8	1976	1976	0.0	978	...	False	False	F
2	3	60	68.0	11250	7	5	2001	2002	162.0	486	...	False	False	F
3	4	70	60.0	9550	7	5	1915	1970	0.0	216	...	False	False	F
4	5	60	84.0	14260	8	5	2000	2000	350.0	655	...	False	False	F

5 rows × 262 columns

```
print("Data Types After Encoding:\n", data.dtypes)
```

```
Data Types After Encoding:
 Id                   int64
MSSubClass           int64
LotFrontage        float64
LotArea              int64
OverallQual          int64
                    ...
SaleCondition_1       bool
SaleCondition_2       bool
SaleCondition_3       bool
SaleCondition_4       bool
SaleCondition_5       bool
Length: 262, dtype: object
```

```
print(data.dtypes.value_counts())  # See counts of data types
```

```
bool       224
int64       35
float64      3
Name: count, dtype: int64
```

```
categorical_remaining = data.select_dtypes(include=['object']).columns
print("Remaining Categorical Columns:", categorical_remaining)
```

```
Remaining Categorical Columns: Index([], dtype='object')
```

```
# Identify numerical columns again after preprocessing (for normalization and standardization)
numerical_features = data_cleaned.select_dtypes(include=['int64', 'float64']).columns.tolist()
print("Numerical Features:", numerical_features)
```

```
Numerical Features: ['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF
```

```
# Apply Min-Max Scaling (Normalization: 0 to 1)
min_max_scaler = MinMaxScaler()
data_normalized = data_cleaned.copy()
data_normalized[numerical_features] = min_max_scaler.fit_transform(data_cleaned[numerical_features])
```

```
# Apply Standardization (Z-score: mean = 0, std = 1)
standard_scaler = StandardScaler()
data_standardized = data_cleaned.copy()
data_standardized[numerical_features] = standard_scaler.fit_transform(data_cleaned[numerical_features])
```

```
print("Now the Data is Normalized (Min-Max Scaling")
```

```
Now the Data is Normalized (Min-Max Scaling
```

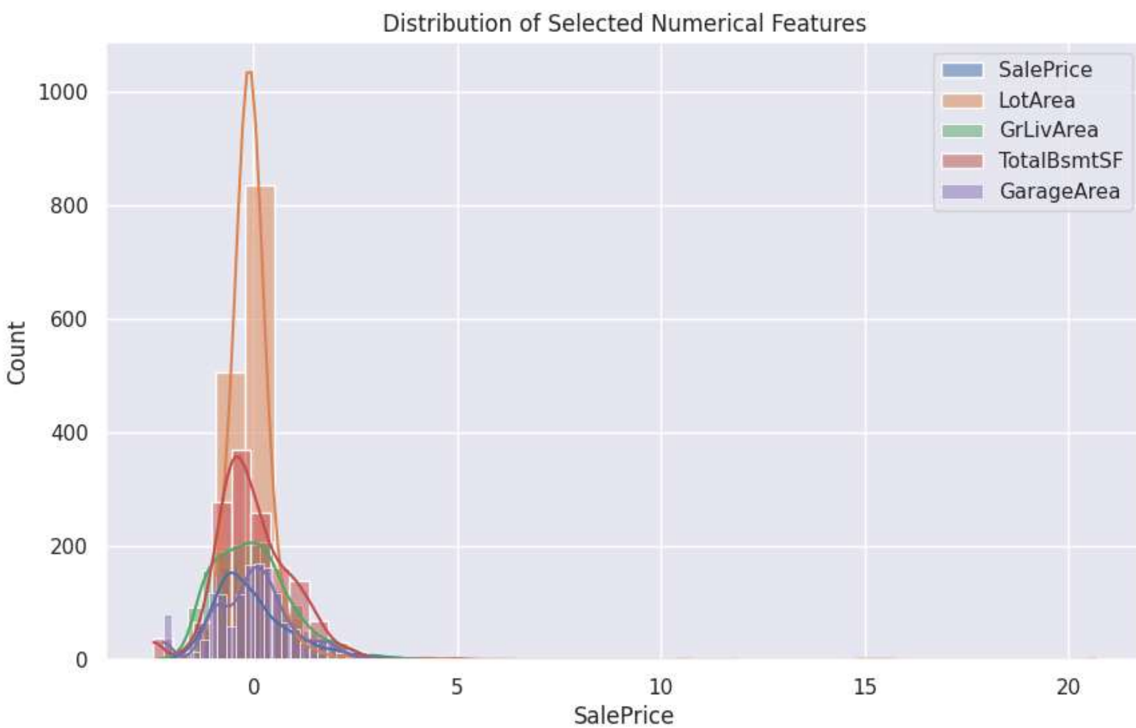
```
print("Standardized Data (Z-score)")
```

```
Standardized Data (Z-score)
```

```
# Select a few key numerical features for visualization
selected_features = ['SalePrice', 'LotArea', 'GrLivArea', 'TotalBsmtSF', 'GarageArea']

plt.figure(figsize=(10, 6))
for feature in selected_features:
    sns.histplot(data_standardized[feature], bins=30, kde=True, label=feature)

plt.title("Distribution of Selected Numerical Features")
plt.legend()
plt.show()
```



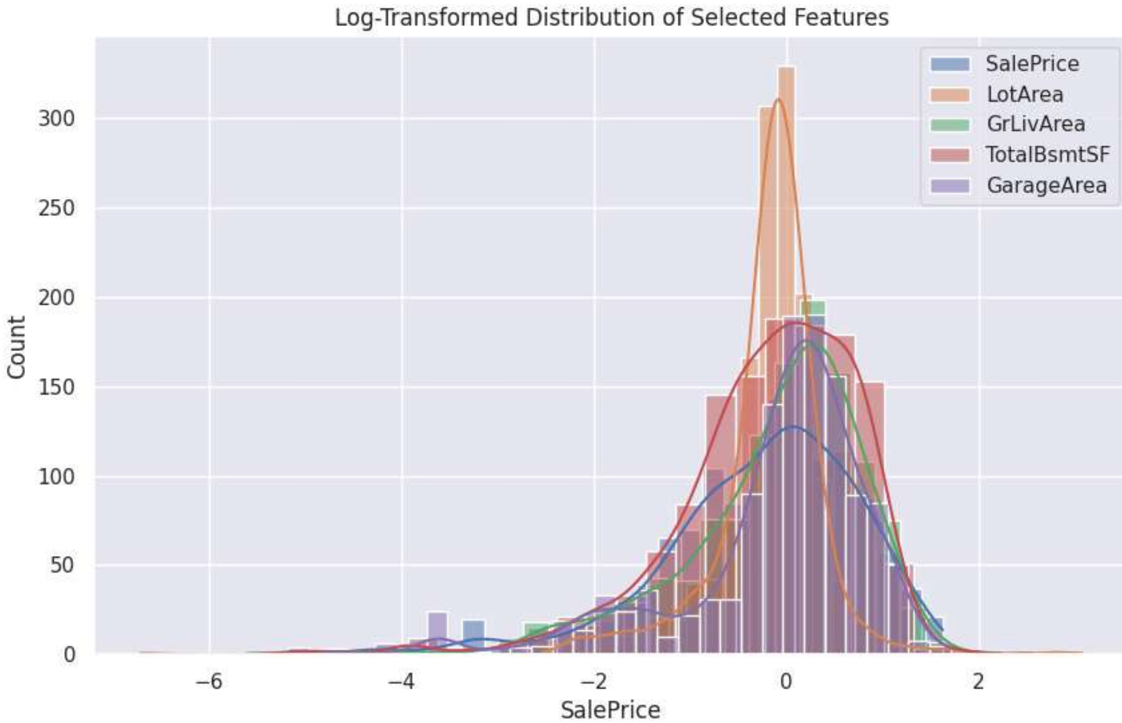

```
import numpy as np
for col in selected_features:
    data_standardized[col] = np.log1p(data_standardized[col])  # log(1 + x) to handle zeros

# Replot after transformation
plt.figure(figsize=(10, 6))
for feature in selected_features:
    sns.histplot(data_standardized[feature], bins=30, kde=True, label=feature)

plt.title("Log-Transformed Distribution of Selected Features")
```

```
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py:399: RuntimeWarning: invalid value encountered in log1p
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
# Step 3: Check Data Types
print("Data Types Summary:")
print(data_standardized.dtypes.value_counts())
```

```
Data Types Summary:
float64    38
object     37
Name: count, dtype: int64
```

```
cleaned_file_path = "/content/drive/MyDrive/cleaned_dataset.csv"
data_standardized.to_csv(cleaned_file_path, index=False)
print(f"Cleaned dataset saved successfully at: {cleaned_file_path}")
```

```
Cleaned dataset saved successfully at: /content/drive/MyDrive/cleaned_dataset.csv
```

""" **## Data Cleaning Report**

1. Dataset Overview

The dataset was chosen because it included a wide range of data cleaning challenges, such as handling missing values, encoding categorical variables, detecting outliers, and applying feature scaling. Working with this dataset provided valuable hands-on experience in data preprocessing, which will be beneficial for future projects and real-world applications. The dataset contains real estate features, including lot size, basement area, garage details, and sale price. It was chosen for its relevance in housing price prediction and data preprocessing.

2. Challenges Faced

- **Missing Values**: Some features had significant gaps.
- **Categorical Data**: Needed encoding for machine learning.
- **Outliers**: Extreme values distorted analysis.
- **Feature Scaling**: Varying feature scales required normalization.

3. Cleaning Steps and Impact

- **Missing Values**: Dropped columns (>40% missing), imputed numerical (median) and categorical (mode) data.
- **Encoding**: Applied One-Hot Encoding to categorical variables.
- **Outliers**: Used IQR method to remove extreme values.
- **Scaling**: Min-Max Scaling for normalization, Z-score for standardization, log transformation for skewed features.

4. Insights and Readiness

- Log transformation improved feature distribution.
- Feature scaling ensured consistent data ranges.
- Encoded categorical variables are model-ready.
- No missing values remain, making the dataset reliable.

5. Conclusion

The dataset is now prepared for exploratory data analysis and model training, ensuring meaningful insights and improved predictive accuracy."""

Start coding or generate with AI.

```
from google.colab import drive
drive.mount('/content/drive')

!jupyter nbconvert --to PDF "/content/drive/MyDrive/24i_8020_DSTT_A1.ipynb"
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
[NbConvertApp] WARNING | pattern '/content/drive/MyDrive/24i_8020_DSTT_A1.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and include the error message in the cell output (the default behaviour is t
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False --NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False --NbConvertApp.export_format=notebook --FilesWriter.build_directory= --ClearOutputPreproce
--coalesce-streams
    Coalesce consecutive stdout and stderr outputs into one stream (within each cell).
    Equivalent to: [--NbConvertApp.use_output_suffix=False --NbConvertApp.export_format=notebook --FilesWriter.build_directory= --CoalesceStreamsPrep
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True --TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
```

```
!jupyter nbconvert --to PDF "24i_8020_DSTT_A1.ipynb"
```

```
[NbConvertApp] WARNING | pattern '24i_8020_DSTT_A1.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.
```