# house-1

July 15, 2025

## HOUSE PRICE PREDICTION

### STEP1: IMPORTING LIBRARIES AND DATASET

[236]:
```
#Importing libraries and the dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
dataset = pd.read_csv("/house1.csv")
dataset.head()
```

[236]:

| | Id | MSSubClass | MSZoning | LotArea | LotConfig | BldgType | OverallCond | \ |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 60 | RL | 8450 | Inside | 1Fam | 5 | |
| 1 | 1 | 20 | RL | 9600 | FR2 | 1Fam | 8 | |
| 2 | 2 | 60 | RL | 11250 | Inside | 1Fam | 5 | |
| 3 | 3 | 70 | RL | 9550 | Corner | 1Fam | 5 | |
| 4 | 4 | 60 | RL | 14260 | FR2 | 1Fam | 5 | |

| | YearBuilt | YearRemodAdd | Exterior1st | BsmtFinSF2 | TotalBsmtSF | SalePrice |
|---|---|---|---|---|---|---|
| 0 | 2003 | 2003 | VinylSd | 0.0 | 856.0 | 208500.0 |
| 1 | 1976 | 1976 | MetalSd | 0.0 | 1262.0 | 181500.0 |
| 2 | 2001 | 2002 | VinylSd | 0.0 | 920.0 | 223500.0 |
| 3 | 1915 | 1970 | Wd Sdng | 0.0 | 756.0 | 140000.0 |
| 4 | 2000 | 2000 | VinylSd | 0.0 | 1145.0 | 250000.0 |

[237]:
```
#we need to know the shape of the dataset
dataset.shape
```

[237]: (2919, 13)

### STEP 2: DATA PREPROCESSING.

[238]:
```
# Now we categorize the features depending on their datatype
obj = dataset.dtypes=="object"
obj_cols = list(obj[obj].index)
print("Categorical variables:",len(obj_cols))
int_ = dataset.dtypes=="int64"
num_cols = list(int_[int_].index)
```

```
print("Integer variables:",len(num_cols))
fl = dataset.dtypes=="float"
fl_cols = list(fl[fl].index)
print("Float variables:",len(fl_cols))
```

```
Categorical variables: 4
Integer variables: 6
Float variables: 3
```

### STEP 3: EXPLORATORY DATA ANALYSIS.

[239]:
```
# we have to identify patterns and spot anomalies in the dataset
numerical_dataset = dataset.select_dtypes(include= ["number"])
numerical_dataset.head()
```

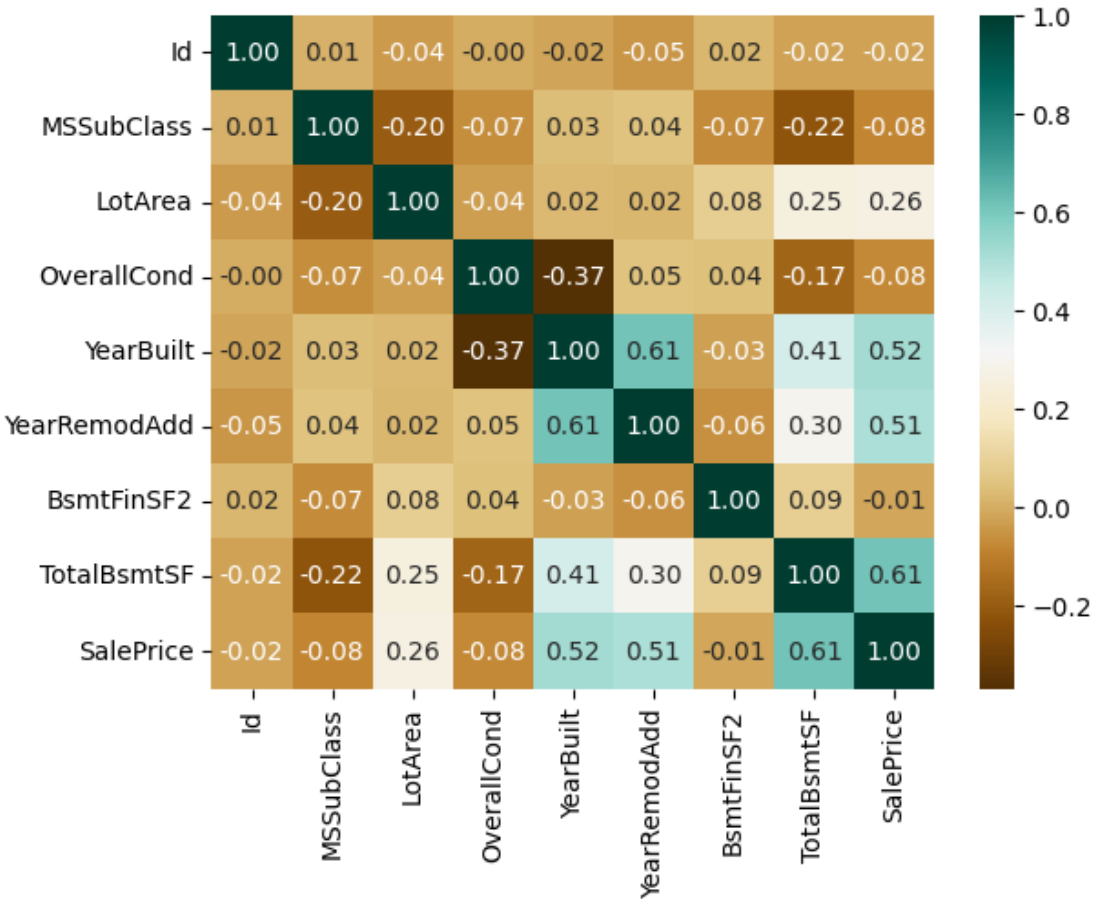
[239]:

| | Id | MSSubClass | LotArea | OverallCond | YearBuilt | YearRemodAdd | BsmtFinSF2 | \ |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 60 | 8450 | 5 | 2003 | 2003 | 0.0 | |
| 1 | 1 | 20 | 9600 | 8 | 1976 | 1976 | 0.0 | |
| 2 | 2 | 60 | 11250 | 5 | 2001 | 2002 | 0.0 | |
| 3 | 3 | 70 | 9550 | 5 | 1915 | 1970 | 0.0 | |
| 4 | 4 | 60 | 14260 | 5 | 2000 | 2000 | 0.0 | |

| | TotalBsmtSF | SalePrice |
|---|---|---|
| 0 | 856.0 | 208500.0 |
| 1 | 1262.0 | 181500.0 |
| 2 | 920.0 | 223500.0 |
| 3 | 756.0 | 140000.0 |
| 4 | 1145.0 | 250000.0 |

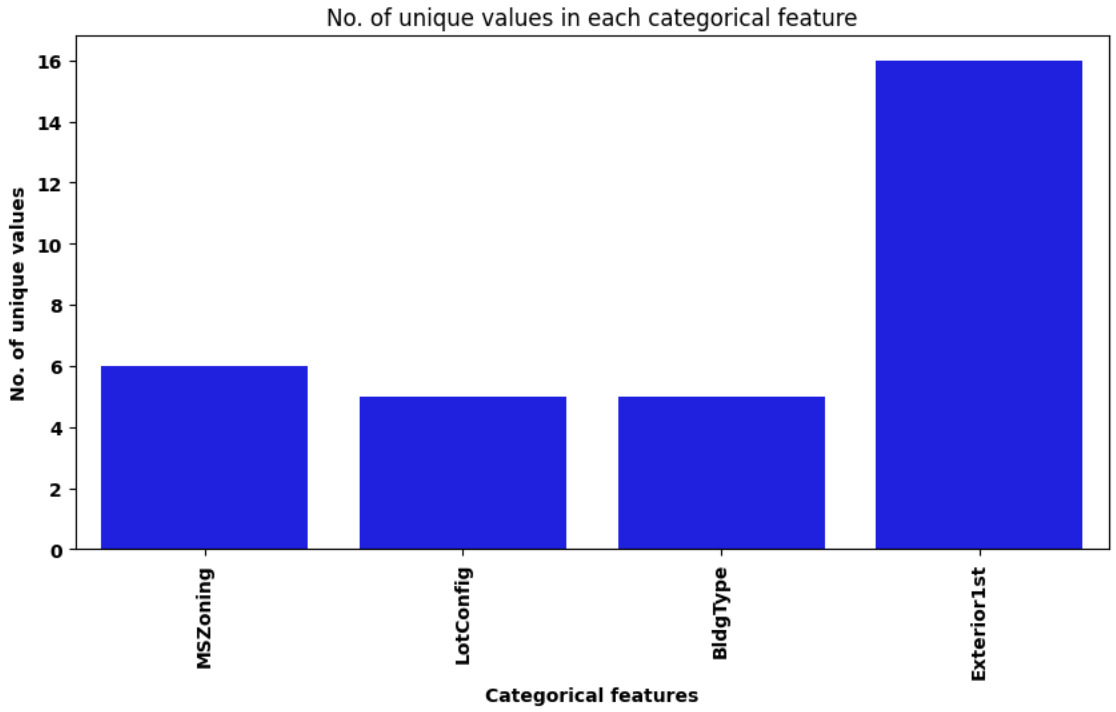
[240]:
```
# lets use seaborn to indicate the above patterns and anomalies.
sns.heatmap(numerical_dataset.corr(),cmap = "BrBG",fmt = ".2f",
            annot= True)
```

[240]: <Axes: >

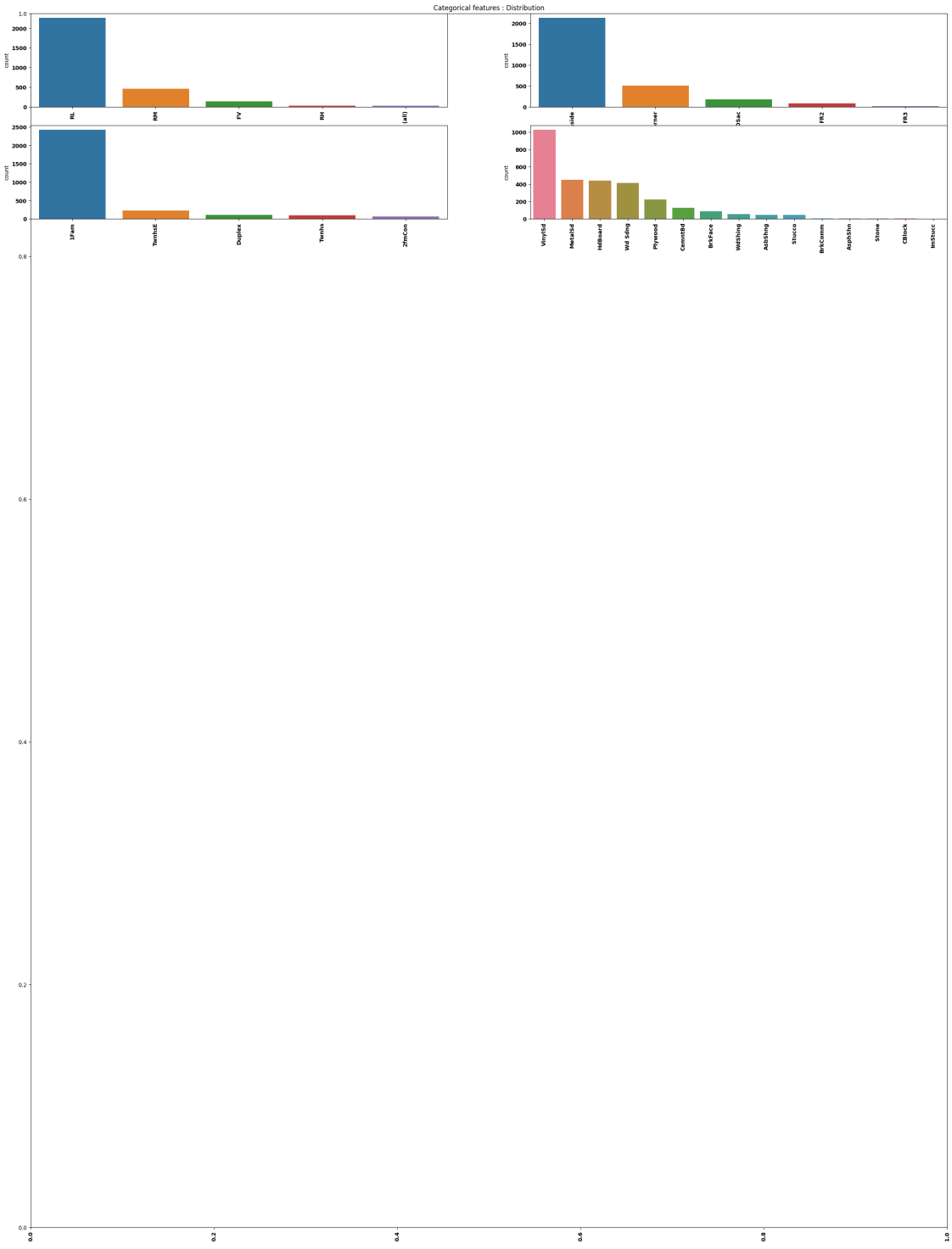



[241]:
```
# using the bar graph to analysize the different categorical features.
unique_values = []
for col in obj_cols:
  unique_values.append(dataset[col].unique().size)
#print(unique_values)
plt.figure(figsize=(10,5))
plt.title("No. of unique values in each categorical feature")
plt.xticks(rotation=90,fontweight = "bold")
plt.yticks(fontweight = "bold")
sns.barplot(x = obj_cols,y=unique_values,color = "blue",)
plt.xlabel("Categorical features",fontweight = "bold")
plt.ylabel("No. of unique values",fontweight = "bold")
```

[241]: Text(0, 0.5, 'No. of unique values')




[242]:
```
plt.figure(figsize=(30,40))
plt.title("Categorical features : Distribution")
plt.xticks(rotation =90,fontweight = "bold")
index = 1
for col in obj_cols:
  y = dataset[col].value_counts()
  plt.subplot(11,2,index)
  plt.xticks(rotation=90,fontweight = "bold")
  plt.yticks(fontweight = "bold")
  sns.barplot(x = list(y.index),y=y,hue = list(y.index))
  index+=1
```




## STEP 4:DATA CLEANING.

[243]:
```
# We dropping the id column as it unnecessarly required in our dataset.
dataset.drop(["Id"],axis=1,inplace= True)
```

[244]:
```
dataset["SalePrice"] = dataset["SalePrice"].fillna(dataset["SalePrice"].mean())
dataset.head()
```

[244]:

| | MSSubClass | MSZoning | LotArea | LotConfig | BldgType | OverallCond | YearBuilt | YearRemodAdd | Exterior1st | BsmtFinSF2 | TotalBsmtSF | SalePrice |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 60 | RL | 8450 | Inside | 1Fam | 5 | 2003 | 2003 | VinylSd | 0.0 | 856.0 | 208500.0 |
| 1 | 20 | RL | 9600 | FR2 | 1Fam | 8 | 1976 | 1976 | MetalSd | 0.0 | 1262.0 | 181500.0 |
| 2 | 60 | RL | 11250 | Inside | 1Fam | 5 | 2001 | 2002 | VinylSd | 0.0 | 920.0 | 223500.0 |
| 3 | 70 | RL | 9550 | Corner | 1Fam | 5 | 1915 | 1970 | Wd Sdng | 0.0 | 756.0 | 140000.0 |
| 4 | 60 | RL | 14260 | FR2 | 1Fam | 5 | 2000 | 2000 | VinylSd | 0.0 | 1145.0 | 250000.0 |

[245]:
```
# dropping null values
new_dataset = dataset.dropna()
new_dataset.head()
```

[245]:

| | MSSubClass | MSZoning | LotArea | LotConfig | BldgType | OverallCond | YearBuilt | YearRemodAdd | Exterior1st | BsmtFinSF2 | TotalBsmtSF | SalePrice |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 60 | RL | 8450 | Inside | 1Fam | 5 | 2003 | 2003 | VinylSd | 0.0 | 856.0 | 208500.0 |
| 1 | 20 | RL | 9600 | FR2 | 1Fam | 8 | 1976 | 1976 | MetalSd | 0.0 | 1262.0 | 181500.0 |
| 2 | 60 | RL | 11250 | Inside | 1Fam | 5 | 2001 | 2002 | VinylSd | 0.0 | 920.0 | 223500.0 |
| 3 | 70 | RL | 9550 | Corner | 1Fam | 5 | 1915 | 1970 | Wd Sdng | 0.0 | 756.0 | 140000.0 |
| 4 | 60 | RL | 14260 | FR2 | 1Fam | 5 | 2000 | 2000 | VinylSd | 0.0 | 1145.0 | 250000.0 |

[246]:
```
# checking of any remaining null values in the features
new_dataset.isnull().sum()
```

[246]:
```
MSSubClass      0
MSZoning        0
LotArea         0
LotConfig       0
BldgType        0
OverallCond     0
YearBuilt       0
YearRemodAdd    0
Exterior1st     0
```

```
BsmtFinSF2      0
TotalBsmtSF     0
SalePrice       0
dtype: int64
```

### STEP 5: ONE HOT ENCODER.

[247]:
```
# we are converting categoricl data into bibary vectors.
from sklearn.preprocessing import OneHotEncoder
s = new_dataset.dtypes =="object"
obj_cols = list(s[s].index)
print("Categorical variables:",obj_cols)
print("No.of categorical features:",len(obj_cols))
```

```
Categorical variables: ['MSZoning', 'LotConfig', 'BldgType', 'Exterior1st']
No.of categorical features: 4
```

[248]:
```
#Lets apply the one hot encoder to the whole list
OH_encoder = OneHotEncoder(sparse_output=False,handle_unknown="ignore")
OH_cols = pd.DataFrame(OH_encoder.fit_transform(new_dataset[obj_cols]))
OH_cols.index = new_dataset.index
OH_cols.columns = OH_encoder.get_feature_names_out(obj_cols)
df_final = new_dataset.drop(obj_cols,axis=1)
df_final = pd.concat([df_final,OH_cols],axis=1)
df_final.head()
```

[248]:

| | MSSubClass | LotArea | OverallCond | YearBuilt | YearRemodAdd | BsmtFinSF2 | \ |
|---|---|---|---|---|---|---|---|
| 0 | 60 | 8450 | 5 | 2003 | 2003 | 0.0 | |
| 1 | 20 | 9600 | 8 | 1976 | 1976 | 0.0 | |
| 2 | 60 | 11250 | 5 | 2001 | 2002 | 0.0 | |
| 3 | 70 | 9550 | 5 | 1915 | 1970 | 0.0 | |
| 4 | 60 | 14260 | 5 | 2000 | 2000 | 0.0 | |

| | TotalBsmtSF | SalePrice | MSZoning_C (all) | MSZoning_FV | … | \ |
|---|---|---|---|---|---|---|
| 0 | 856.0 | 208500.0 | 0.0 | 0.0 | … | |
| 1 | 1262.0 | 181500.0 | 0.0 | 0.0 | … | |
| 2 | 920.0 | 223500.0 | 0.0 | 0.0 | … | |
| 3 | 756.0 | 140000.0 | 0.0 | 0.0 | … | |
| 4 | 1145.0 | 250000.0 | 0.0 | 0.0 | … | |

| | Exterior1st_CemntBd | Exterior1st_HdBoard | Exterior1st_ImStucc | \ |
|---|---|---|---|---|
| 0 | 0.0 | 0.0 | 0.0 | |
| 1 | 0.0 | 0.0 | 0.0 | |
| 2 | 0.0 | 0.0 | 0.0 | |
| 3 | 0.0 | 0.0 | 0.0 | |
| 4 | 0.0 | 0.0 | 0.0 | |

| | Exterior1st_MetalSd | Exterior1st_Plywood | Exterior1st_Stone | \ |
|---|---|---|---|---|

```
0                   0.0                   0.0                   0.0
1                   1.0                   0.0                   0.0
2                   0.0                   0.0                   0.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Exterior1st_Stucco  Exterior1st_VinylSd  Exterior1st_Wd Sdng  \
0                 0.0                  1.0                  0.0
1                 0.0                  0.0                  0.0
2                 0.0                  1.0                  0.0
3                 0.0                  0.0                  1.0
4                 0.0                  1.0                  0.0

   Exterior1st_WdShing
0                  0.0
1                  0.0
2                  0.0
3                  0.0
4                  0.0

[5 rows x 38 columns]
```

### STEP 6: SPLITTING DATASET INTO TRAINING AND TESTING.

[249]:
```
#X and y splitting where the X represents other features and y is the saleprice
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
X= df_final.drop("SalePrice",axis=1)
y = df_final["SalePrice"]
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2)
```

**STEP 7 : MODEL TRAINING AND ACCURACY** * Using Support vector machines * Using Random forest * Using Linear regression

[250]:
```
# We will be using the support vector machines to train our model
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_percentage_error
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model_svm = SVR()
model_svm.fit(X_train_scaled,y_train)
y_pred = model_svm.predict(X_test_scaled)
print("Mean absolute percentage error:",
      f"{mean_absolute_percentage_error(y_test, y_pred) * 100:.2f}%")
```

```
Mean absolute percentage error: 16.75%
```

[251]:
```
# Now will be using Randomforest
from sklearn.ensemble import RandomForestRegressor
model_RFR = RandomForestRegressor(n_estimators=10)
model_RFR.fit(X_train,y_train)
y_pred =model_RFR.predict(X_test)
print("Mean absolute percentage error:",
      f"{mean_absolute_percentage_error(y_test, y_pred) * 100:.2f}%")
```

```
Mean absolute percentage error: 18.70%
```

[252]:
```
#Using linear regression
from sklearn.linear_model import LinearRegression
model_LR = LinearRegression()
model_LR.fit(X_train,y_train)
y_pred = model_LR.predict(X_test)
print("Mean absolute percentage error:",
      f"{mean_absolute_percentage_error(y_test, y_pred) * 100:.2f}%")
```

```
Mean absolute percentage error: 18.83%
```