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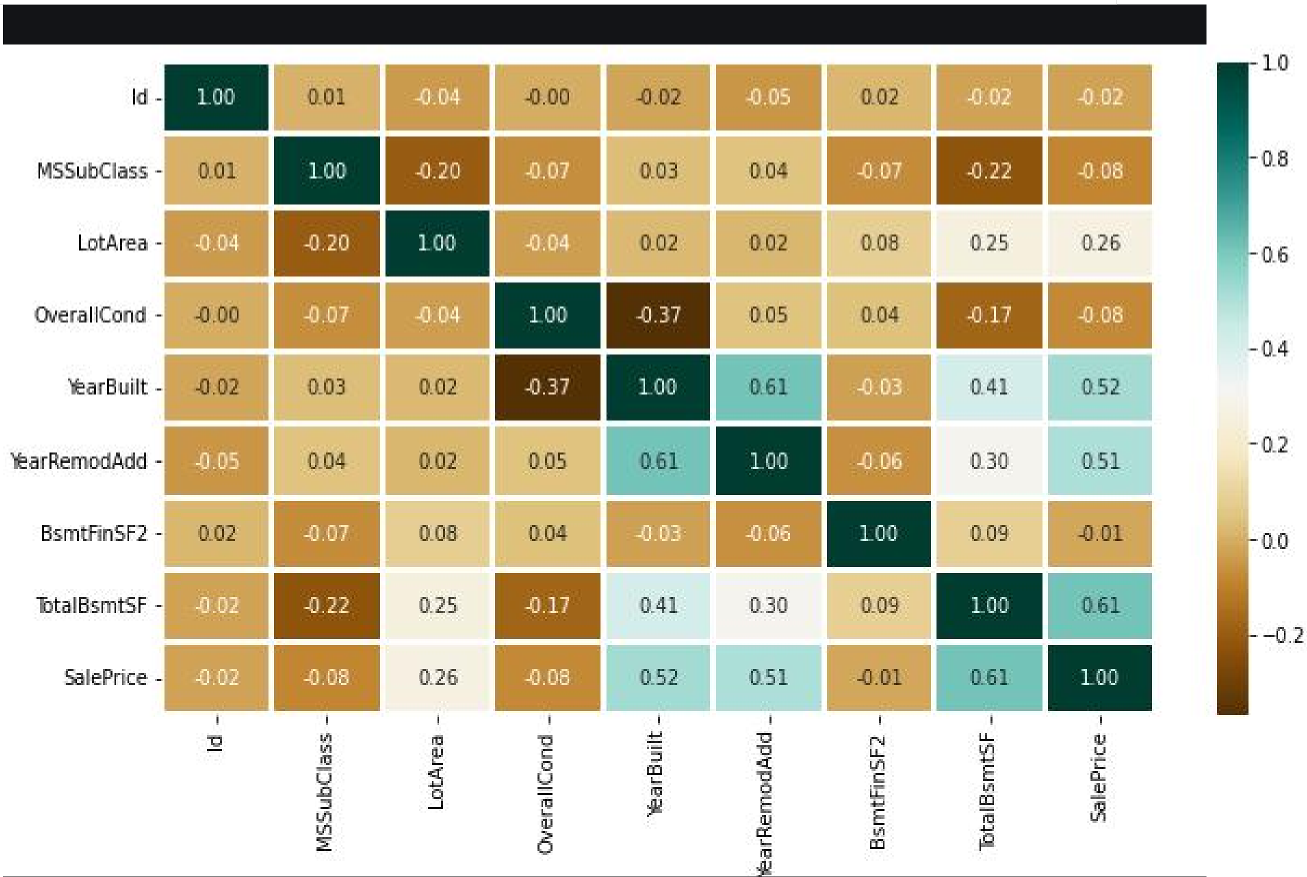
Exploratory Data Analysis

EDA refers to the deep analysis of data so as to discover different patterns and spot anomalies. Before making inferences from data it is essential to examine all your variables.
So here let's make a heatmap using seaborn library.

```
plt.figure(figsize=(12, 6))
```

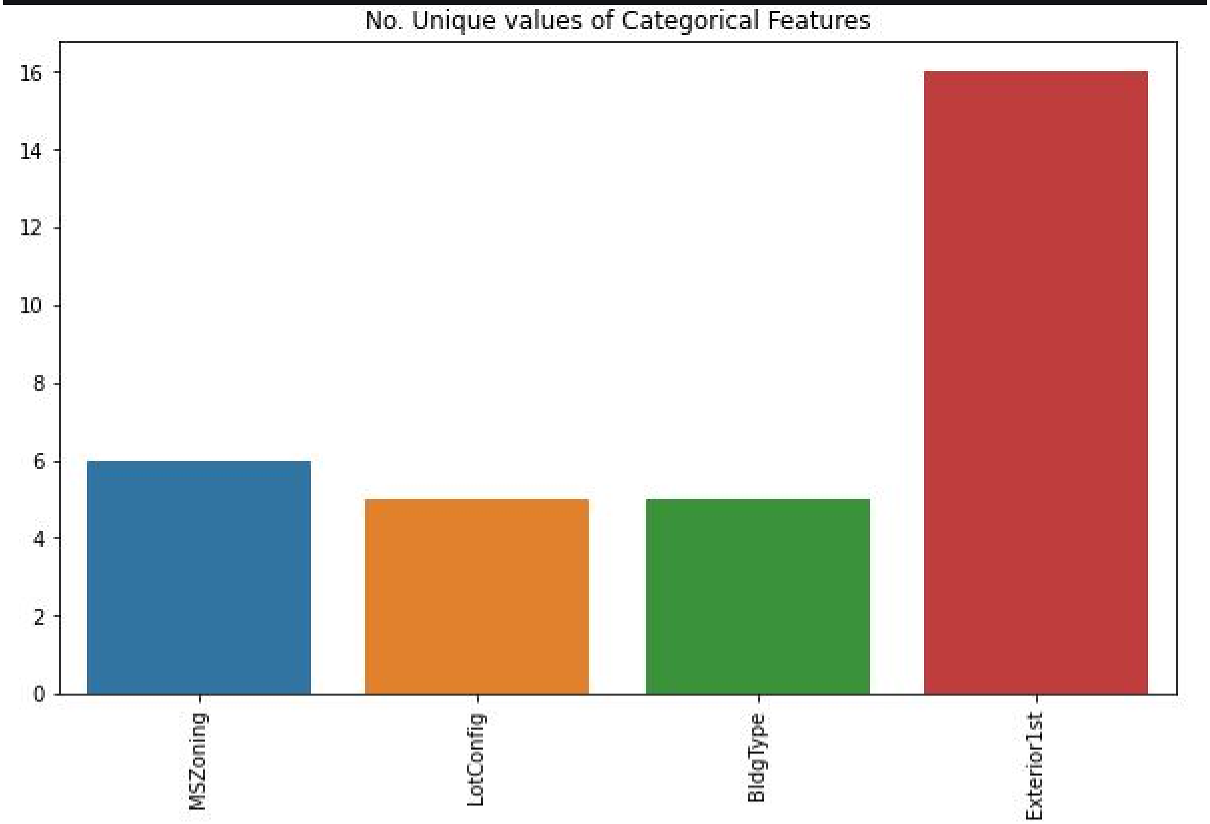
```
sns.heatmap(dataset.corr(),

            cmap = 'BrBG',

            fmt = '.2f',

            linewidths = 2,           annot = True)
```



To analyze the different categorical features. Let's draw the [barplot](#).

```
unique_values = []

for col in object_cols:

  unique_values.append(dataset[col].unique().size)

plt.figure(figsize=(10,6))
```

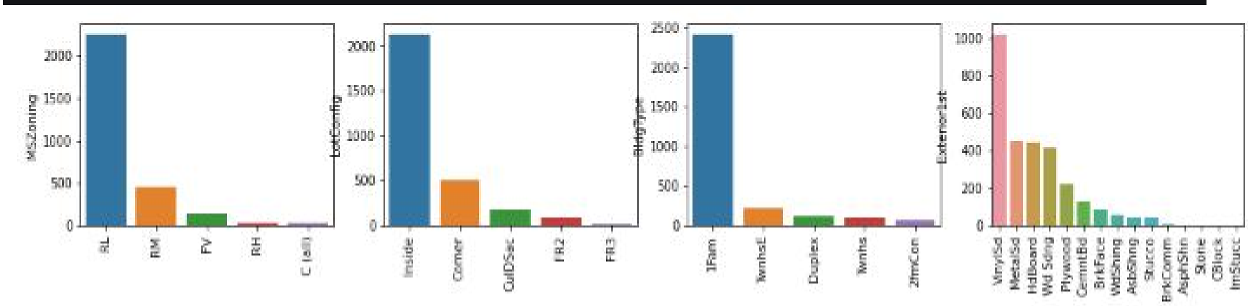
```
plt.title('No. Unique values of Categorical Features')

plt.xticks(rotation=90)

sns.barplot(x=object_cols,y=unique_values)
```



The plot shows that Exterior1st has around 16 unique categories and other features have around 6 unique categories. To findout the actual count of each category we can plot the bargraph of each four features separately.

```
plt.figure(figsize=(18, 36))

plt.title('Categorical Features: Distribution')

plt.xticks(rotation=90)

index = 1
```

```
for col in object_cols:

    y = dataset[col].value_counts()

    plt.subplot(11, 4, index)

    plt.xticks(rotation=90)

    sns.barplot(x=list(y.index), y=y)

    index += 1
```



Data Cleaning

[Data Cleaning](#) is the way to improvise the data or remove incorrect, corrupted or irrelevant data.

As in our dataset, there are some columns that are not important and irrelevant for the model training. So, we can drop that column before training. There are 2 approaches to dealing with empty/null values

- We can easily delete the column/row (if the feature or record is not much important).
- Filling the empty slots with mean/mode/0/NA/etc. (depending on the dataset requirement).

As Id Column will not be participating in any prediction. So we can Drop it.

```
dataset.drop(['Id'],

             axis=1,
```

```
              inplace=True)
```

Replacing SalePrice empty values with their mean values to make the data distribution symmetric.

```
dataset['SalePrice'] = dataset['SalePrice'].fillna(

  dataset['SalePrice'].mean())
```

Drop records with null values (as the empty records are very less).

```
new_dataset = dataset.dropna()
```

Checking features which have null values in the new dataframe (if there are still any).

```
new_dataset.isnull().sum()
```

```
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
```

OneHotEncoder – For Label categorical features

One hot Encoding is the best way to convert categorical data into binary vectors. This maps the values to integer values. By using OneHotEncoder, we can easily convert object data into int. So for that, firstly we have to collect all the features which have the object datatype. To do so, we will make a loop.

```
from sklearn.preprocessing import OneHotEncoder



s = (new_dataset.dtypes == 'object')

object_cols = list(s[s].index)

print("Categorical variables:")

print(object_cols)

print('No. of. categorical features: ',

      len(object_cols))
```

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

Then once we have a list of all the features. We can apply OneHotEncoding to the whole list.

```
OH_encoder = OneHotEncoder(sparse=False)

OH_cols = pd.DataFrame(OH_encoder.fit_transform(new_dataset[object_cols]))

OH_cols.index = new_dataset.index

OH_cols.columns = OH_encoder.get_feature_names()

df_final = new_dataset.drop(object_cols, axis=1)
```

```
df_final = pd.concat([df_final, OH_cols], axis=1)
```

Splitting Dataset into Training and Testing

X and Y splitting (i.e. Y is the SalePrice column and the rest of the other columns are X)

```
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']



# Split the training set into

# training and validation set

X_train, X_valid, Y_train, Y_valid = train_test_split(

    X, Y, train_size=0.8, test_size=0.2, random_state=0)
```

Model and Accuracy

As we have to train the model to determine the continuous values, so we will be using these regression models.

- SVM-Support Vector Machine
- Random Forest Regressor
- Linear Regressor

And To calculate loss we will be using the mean_absolute_percentage_error module. It can easily be imported by using sklearn library. The formula for Mean Absolute Error :

$$\mathrm{MAE} = \underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{\text{Test Set}} \left| \underbrace{y_i}_{\text{predicted value}} - \underbrace{\hat{y}_i}_{\text{Actual Value}} \right|$$

SVM – Support vector Machine
SVM can be used for both regression and classification model. It finds the hyperplane in the n-dimensional plane. To read more about svm [refer this.]

```
from sklearn import svm

from sklearn.svm import SVC

from sklearn.metrics import mean_absolute_percentage_error



model_SVR = svm.SVR()

model_SVR.fit(X_train,Y_train)
```

```
Y_pred = model_SVR.predict(X_valid)



print(mean_absolute_percentage_error(Y_valid, Y_pred))
```

Random Forest Regression

Random Forest is an ensemble technique that uses multiple of decision trees and can be used for both regression and classification tasks. To read more about random forests refer this.

```
from sklearn.ensemble import RandomForestRegressor



model_RFR = RandomForestRegressor(n_estimators=10)

model_RFR.fit(X_train, Y_train)

Y_pred = model_RFR.predict(X_valid)



mean_absolute_percentage_error(Y_valid, Y_pred)
```

Linear Regression

Linear Regression predicts the final output-dependent value based on the given independent features. Like, here we have to predict SalePrice depending on features like MSSubClass, YearBuilt, BldgType, Exterior1st etc To read more about Linear Regression refer this.

```
from sklearn.linear_model import LinearRegression



model_LR = LinearRegression()

model_LR.fit(X_train, Y_train)

Y_pred = model_LR.predict(X_valid)



print(mean_absolute_percentage_error(Y_valid, Y_pred))
```

CatBoost Classifier

CatBoost is a machine learning algorithm implemented by Yandex and is open-source. It is simple to interface with deep learning frameworks such as Apple's Core ML and Google's TensorFlow. Performance, ease-of-use, and robustness are the main advantages of the CatBoost library. To read more about CatBoost refer this.

```
# This code is contributed by @amartajisce

from catboost import CatBoostRegressor

cb_model = CatBoostRegressor()

cb_model.fit(X_train, y_train)

preds = cb_model.predict(X_valid)
```

```
cb_r2_score=r2_score(Y_valid, preds)

cb_r2_score
```

Conclusion

Clearly, SVM model is giving better accuracy as the mean absolute error is the least among all the other regressor models i.e. 0.18 approx. To get much better results ensemble learning techniques like Bagging and Boosting can also be used.