# PROJECT REPORT

## HOUSE PRICE PREDICTION IN AMES, IOWA

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# PROJECT ROLES

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FEATURE ENGINEERING AND IMPORTANCE

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DATA CLEANING, FEATURE IMPORTANCE

# ABSTRACT

This project explores the application of machine learning and deep learning algorithms to predict real estate prices using a comprehensive dataset. The dataset includes 81 variables detailing various attributes of properties, such as building class, zoning classification, lot size, utility types, neighborhood characteristics, and overall quality and condition of the buildings. By employing machine learning and advanced neural network architectures, we aim to create a predictive model that accurately forecasts the sale price of properties. The model's performance will be evaluated using appropriate metrics, and the results will be analyzed to understand the influence of different features on property prices.

# OBJECTIVE

- Data Preprocessing: Clean and preprocess the dataset to handle missing values, encode categorical variables, and scale numerical features.
- Feature Engineering: Explore and engineer features to enhance the model's predictive power.
- Model Development: Design and implement various deep learning architectures to find the most effective model for price prediction.
- Model Evaluation: Assess the performance of the models using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared.
- Feature Analysis: Investigate the impact of different features on the prediction outcomes to gain insights into the key drivers of property prices.
- Optimization and Tuning: Optimize the model through hyperparameter tuning to achieve the best possible performance.
- Deployment: Create a deployment strategy for the model to be used in real-world applications, providing valuable predictions for stakeholders.

# DATASET OVERVIEW

The dataset has been collected from an ongoing Kaggle competition called “House Prices - Advanced Regression Techniques”. This dataset consists the house property attributes of IOWA Ames, USA. Total records of the dataset are **2919** and it has **81** columns. This dataset is a mix of numerical and categorical features with inconsistencies which we had to deal with. Following are the features of the dataset:

- SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.
- MSSubClass: The building class
- MSZoning: The general zoning classification
- LotFrontage: Linear feet of street connected to property
- LotArea: Lot size in square feet
- Street: Type of road access
- Alley: Type of alley access
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LotConfig: Lot configuration
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits
- Condition1: Proximity to main road or railroad
- Condition2: Proximity to main road or railroad (if a second is present)
- BldgType: Type of dwelling
- HouseStyle: Style of dwelling
- OverallQual: Overall material and finish quality
- OverallCond: Overall condition rating
- YearBuilt: Original construction date
- YearRemodAdd: Remodel date
- RoofStyle: Type of roof
- RoofMatl: Roof material
- Exterior1st: Exterior covering on house
- Exterior2nd: Exterior covering on house (if more than one material)
- MasVnrType: Masonry veneer type
- MasVnrArea: Masonry veneer area in square feet
- ExterQual: Exterior material quality
- ExterCond: Present condition of the material on the exterior
- Foundation: Type of foundation
- BsmtQual: Height of the basement
- BsmtCond: General condition of the basement
- BsmtExposure: Walkout or garden level basement walls
- BsmtFinType1: Quality of basement finished area
- BsmtFinSF1: Type 1 finished square feet
- BsmtFinType2: Quality of second finished area (if present)
- BsmtFinSF2: Type 2 finished square feet
- BsmtUnfSF: Unfinished square feet of basement area
- TotalBsmtSF: Total square feet of basement area
- Heating: Type of heating
- HeatingQC: Heating quality and condition

# DATASET OVERVIEW

- CentralAir: Central air conditioning
- Electrical: Electrical system
- 1stFlrSF: First Floor square feet
- 2ndFlrSF: Second floor square feet
- LowQualFinSF: Low quality finished square feet (all floors)
- GrLivArea: Above grade (ground) living area square feet
- BsmtFullBath: Basement full bathrooms
- BsmtHalfBath: Basement half bathrooms
- FullBath: Full bathrooms above grade
- HalfBath: Half baths above grade
- Bedroom: Number of bedrooms above basement level
- Kitchen: Number of kitchens
- KitchenQual: Kitchen quality
- TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
- Functional: Home functionality rating
- Fireplaces: Number of fireplaces
- FireplaceQu: Fireplace quality
- GarageType: Garage location
- GarageYrBlt: Year garage was built
- GarageFinish: Interior finish of the garage
- GarageCars: Size of garage in car capacity
- GarageArea: Size of garage in square feet
- GarageQual: Garage quality
- GarageCond: Garage condition
- PavedDrive: Paved driveway
- WoodDeckSF: Wood deck area in square feet
- OpenPorchSF: Open porch area in square feet
- EnclosedPorch: Enclosed porch area in square feet
- 3SsnPorch: Three season porch area in square feet
- ScreenPorch: Screen porch area in square feet
- PoolArea: Pool area in square feet
- PoolQC: Pool quality
- Fence: Fence quality
- MiscFeature: Miscellaneous feature not covered in other categories
- MiscVal: $Value of miscellaneous feature
- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale

# MISSING VALUE PERCENTAGE

## There are some values missing in some features

| | |
|---|---|
| Id | 0.000000 |
| MSSubClass | 0.000000 |
| MSZoning | 0.137033 |
| LotFrontage | 16.649538 |
| LotArea | 0.000000 |
| Street | 0.000000 |
| Alley | 93.216855 |
| LotShape | 0.000000 |
| LandContour | 0.000000 |
| Utilities | 0.068517 |
| 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 | 0.034258 |
| Exterior2nd | 0.034258 |
| MasVnrType | 60.500171 |
| MasVnrArea | 0.787941 |
| ExterQual | 0.000000 |
| ExterCond | 0.000000 |
| Foundation | 0.000000 |
| BsmtQual | 2.774923 |
| BsmtCond | 2.809181 |
| BsmtExposure | 2.809181 |
| BsmtFinType1 | 2.706406 |
| BsmtFinSF1 | 0.034258 |
| BsmtFinType2 | 2.740665 |
| BsmtFinSF2 | 0.034258 |
| BsmtUnfSF | 0.034258 |
| TotalBsmtSF | 0.034258 |
| Heating | 0.000000 |
| HeatingQC | 0.000000 |
| CentralAir | 0.000000 |
| Electrical | 0.034258 |
| 1stFlrSF | 0.000000 |
| 2ndFlrSF | 0.000000 |
| LowQualFinSF | 0.000000 |
| GrLivArea | 0.000000 |
| BsmtFullBath | 0.068517 |
| BsmtHalfBath | 0.068517 |
| FullBath | 0.000000 |
| HalfBath | 0.000000 |
| BedroomAbvGr | 0.000000 |
| KitchenAbvGr | 0.000000 |
| KitchenQual | 0.034258 |
| TotRmsAbvGrd | 0.000000 |
| Functional | 0.068517 |
| Fireplaces | 0.000000 |
| FireplaceQu | 48.646797 |
| GarageType | 5.378554 |
| GarageYrBlt | 5.447071 |
| GarageFinish | 5.447071 |
| GarageCars | 0.034258 |
| GarageArea | 0.034258 |
| GarageQual | 5.447071 |
| GarageCond | 5.447071 |
| PavedDrive | 0.000000 |
| WoodDeckSF | 0.000000 |
| OpenPorchSF | 0.000000 |
| EnclosedPorch | 0.000000 |
| 3SsnPorch | 0.000000 |
| ScreenPorch | 0.000000 |
| PoolArea | 0.000000 |
| PoolQC | 99.657417 |
| Fence | 80.438506 |
| MiscFeature | 96.402878 |
| MiscVal | 0.000000 |
| MoSold | 0.000000 |
| YrSold | 0.000000 |
| SaleType | 0.034258 |
| SaleCondition | 0.000000 |
| SalePrice | 49.982871 |

# DATA CLEANING

There are variety of features in the dataset. We will take a look at the features but before that we need to deeal with the missing values. As we have mentioned already, few features will not be able to help our model which have more than 80% missing values. We will remove them now.

```
# remove features with a high number of missing values

rem_cols = ['Alley', 'PoolQC', 'Fence', 'MiscFeature']
df.drop(columns=rem_cols, inplace=True)
```

FireplaceQu and MasVnrType columns have 40 - 60% data missing. We need to deal with these columns but before that lets take a look at what they mean. MasVnrType means Masonry veneer type and FireplaceQu means Fireplace Quality. For MasVnrType, we will use 'mode' and for FireplaceQu we will use 'mean' to fill the null values. But before that, we need to encode the categorical columns to number.

# DATA CLEANING

We checked the numeric and non numeric features so that we can encode them.

| | |
|---|---|
| Id | int64 |
| MSSubClass | int64 |
| LotFrontage | float64 |
| LotArea | int64 |
| OverallQual | int64 |
| OverallCond | int64 |
| YearBuilt | int64 |
| YearRemodAdd | int64 |
| MasVnrArea | float64 |
| BsmtFinSF1 | float64 |
| BsmtFinSF2 | float64 |
| BsmtUnfSF | float64 |
| TotalBsmtSF | float64 |
| 1stFlrSF | int64 |
| 2ndFlrSF | int64 |
| LowQualFinSF | int64 |
| GrLivArea | int64 |
| BsmtFullBath | float64 |
| BsmtHalfBath | float64 |
| FullBath | int64 |
| HalfBath | int64 |
| BedroomAbvGr | int64 |
| KitchenAbvGr | int64 |
| TotRmsAbvGrd | int64 |
| Fireplaces | int64 |
| GarageYrBlt | float64 |
| GarageCars | float64 |
| GarageArea | float64 |
| WoodDeckSF | int64 |
| OpenPorchSF | int64 |
| EnclosedPorch | int64 |
| 3SsnPorch | int64 |
| ScreenPorch | int64 |
| PoolArea | int64 |
| MiscVal | int64 |
| MoSold | int64 |
| YrSold | int64 |
| SalePrice | float64 |

| | |
|---|---|
| MSZoning | object |
| Street | object |
| LotShape | object |
| LandContour | object |
| Utilities | object |
| LotConfig | object |
| LandSlope | object |
| Neighborhood | object |
| Condition1 | object |
| Condition2 | object |
| BldgType | object |
| HouseStyle | object |
| RoofStyle | object |
| RoofMatl | object |
| Exterior1st | object |
| Exterior2nd | object |
| MasVnrType | object |
| ExterQual | object |
| ExterCond | object |
| Foundation | object |
| BsmtQual | object |
| BsmtCond | object |
| BsmtExposure | object |
| BsmtFinType1 | object |
| BsmtFinType2 | object |
| Heating | object |
| HeatingQC | object |
| CentralAir | object |
| Electrical | object |
| KitchenQual | object |
| Functional | object |
| FireplaceQu | object |
| GarageType | object |
| GarageFinish | object |
| GarageQual | object |
| GarageCond | object |
| PavedDrive | object |
| SaleType | object |
| SaleCondition | object |

# DATA CLEANING

### Data Encoding for object type columns

```
# label encoding
encoders = {}

# Label encode each categorical column
for column in non_num_cols:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    encoders[column] = le
```

Now lets first deal with the large null columns mentioned earlier

```
# Fill missing values in 'MasVnrType' with the mode
mas_vnr_type_mode = df['MasVnrType'].mode()[0]
df['MasVnrType'].fillna(mas_vnr_type_mode)

# Fill missing values in 'FireplaceQu' with the mean
fireplacequ_mean = df['FireplaceQu'].mean()
df['FireplaceQu'].fillna(fireplacequ_mean)
```

Rest of the null values in other columns are not significantly bigger. So we can use 'mean' to fill the rest.

```
# fill null values with mean for all columns except 'SalePrice'
def fill_na_with_mean(df, col):
    df[col] = df[col].fillna(df[col].mean())
    return df

# Apply the function to each column except 'SalePrice'
for col in df.columns:
    if col != 'SalePrice':
        df = fill_na_with_mean(df, col)
```

# DATA EXPLORATION

**WE ARE VERY INTERESTED TO SEE THE LOCATIONS OF THE PROPERTIES IN A MAP. WE HAVE TO DECODE THE ENCODED VALUES IN THE NEIGHBORHOOD COLUMN. THEN WE WILL USE FOLIUM AND GEOPY LIBRARIES TO GET THE COORDINATES OF THE LOCATIONS AND THEN WE WILL SEE THEM ON THE MAP.**

**THE GEOPY LIBRARY WAS SUCCESSFULL FILLING IN THE CO-ORDINATES OF THE LOCATIONS. HOWEVER, IT COULD NOT FIND SOME OF THEM. WE WILL BE DOING SOME RESEARCH ON OUR OWN ON GOOGLE MAP TO FIND OUT THOSE LOCATIONS AND MANUALLY FILL IN THE CO-ORDINATES. FINALLY WE WERE ABLE TO FILL IN ALL THE NULL VALUES IN COORDINATES**

```python
# Function to geocode neighborhood
def geocode_neighborhood(neighborhood):
    try:
        location = geolocator.geocode(neighborhood + ', Ames, IA')
        if location:
            return location.latitude, location.longitude
        else:
            return None, None
    except Exception as e:
        print(f"Error geocoding {neighborhood}: {e}")
        return None, None
```

```python
# Apply geocoding to full form neighborhoods
df[['Latitude', 'Longitude']] = df['Neighborhood_Full'].apply(lambda x: pd.Series(geocode_neighborhood(x)))
```

```
# Sample error messages
error_messages = """
Error geocoding College Creek: Non-successful status code 403
Error geocoding North Ames: Non-successful status code 403
Error geocoding South & West of Iowa State University: Non-successful status code 403
Error geocoding South & West of Iowa State University: Non-successful status code 403
Error geocoding Northwest Ames: Non-successful status code 403
Error geocoding Edwards: Non-successful status code 403
Error geocoding Mitchell: HTTPSConnectionPool(host='nominatim.openstreetmap.org', port=443):
Error geocoding Old Town: Non-successful status code 403
Error geocoding South & West of Iowa State University: Non-successful status code 403
Error geocoding South & West of Iowa State University: Non-successful status code 403
Error geocoding South & West of Iowa State University: Non-successful status code 403
Error geocoding Clear Creek: Non-successful status code 403
```

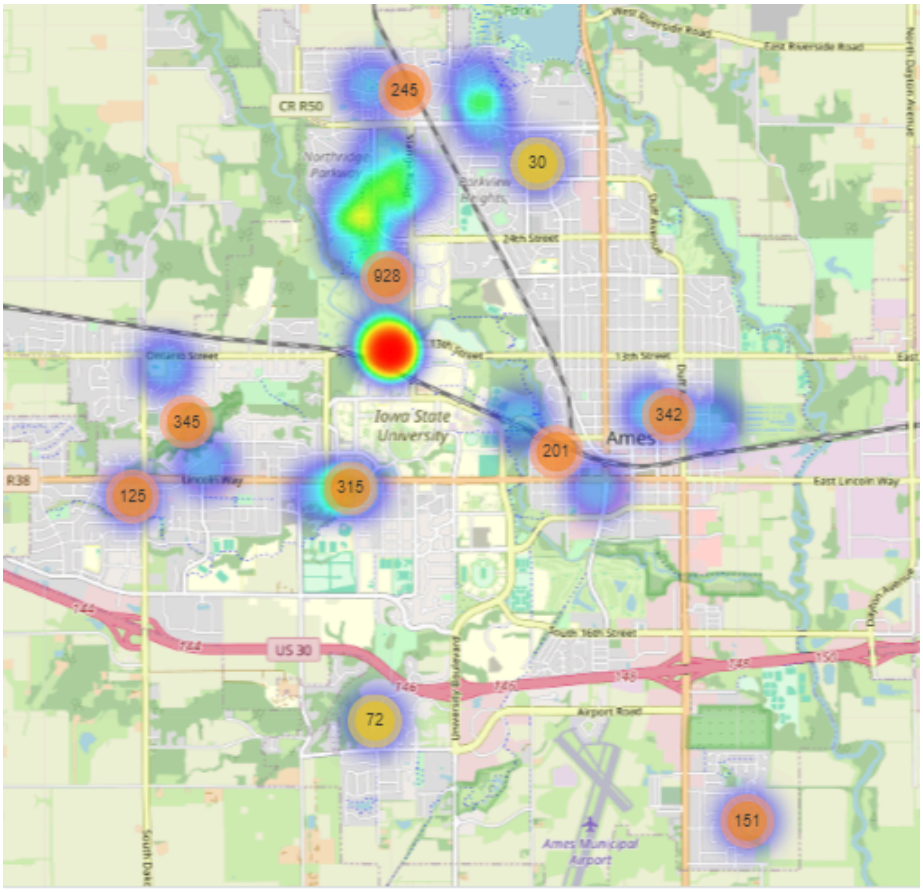
```python
# Use regex to extract the location names from the error messages
pattern = r"Error geocoding ([\w\s&]+):"
locations_not_found = re.findall(pattern, error_messages)

# Remove duplicates
locations_not_found = list(set(locations_not_found))

# Display the list
print(locations_not_found)
```

```python
# Check for NaN values in Latitude and Longitude
nan_coords = df[df['Latitude'].isna() | df['Longitude'].isna()]

# Print the rows with NaN values in Latitude and Longitude along with Neighborhood_Full
unique_nan_neighborhoods = nan_coords['Neighborhood_Full'].unique()
print(unique_nan_neighborhoods)
```

```python
coordinates = {
    'Gilbert' : '42.107339, -93.650046',
    'Timberland' : '42.000054, -93.649546',
    'Edwards' : '42.024238, -93.671078',
    'South & West of Iowa State University' : '42.021641, -93.656344',
    'Old Town' : '42.029275, -93.614412',
    'North Ames': '42.034866, -93.647473',
    'Clear Creek' : '42.036081, -93.648845',
    'Brookside' : '42.028438, -93.631153',
    'Somerset' : '42.050756, -93.644471'
}

# Split coordinates and assign to respective columns
for neighborhood, coord in coordinates.items():
    lat, lon = map(float, coord.split(', '))
    df.loc[df['Neighborhood_Full'] == neighborhood, 'Latitude'] = lat
    df.loc[df['Neighborhood_Full'] == neighborhood, 'Longitude'] = lon
```

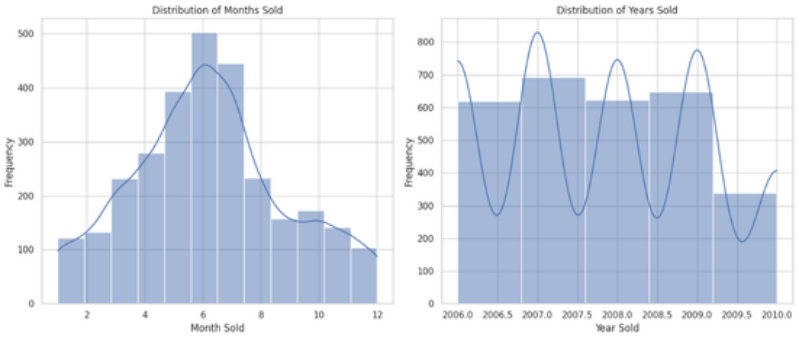
```python
# checking again for the null values in the coordinates
nan_coords = df[df['Latitude'].isna() | df['Longitude'].isna()]

# Print the rows with NaN values in Latitude and Longitude along with Neighborhood_Full
unique_nan_neighborhoods = nan_coords['Neighborhood_Full'].unique()
print(unique_nan_neighborhoods)
```

# PROPERTY LOCATIONS




The most number of listed properties in the dataset belong to the central, northern side and south west side of the region. Next we will see the yearly and monthly sales of each property.

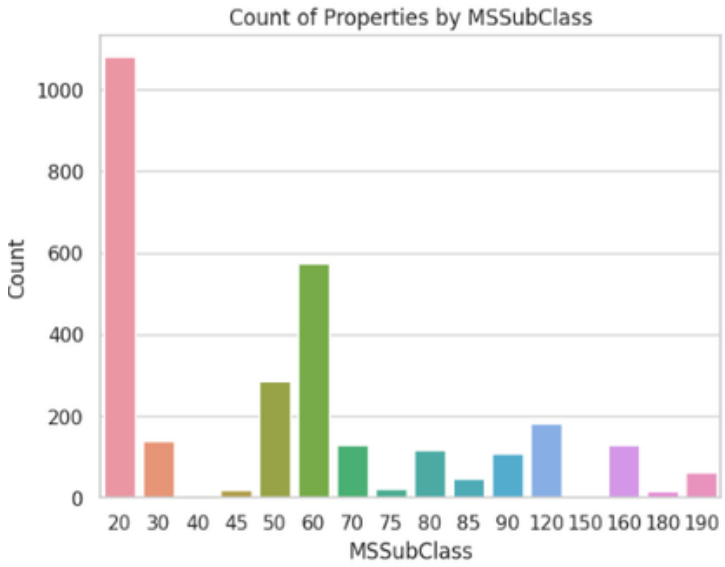
# DISTRIBUTION OF MONTHLY AND YEARLY SALES AND SALE PRICE ANALYSIS




The monthly sell represents a normal distribution which indicates that the highest number of sells happen in the middle of the year. The most number of houses were sold in the years 2007 and 2009.


- Most houses are sold which have prices around 200,000 dollars.
- The count is extremely high comparing to other price ranges.
- Next highest count is for the price range between '100k- 200k'.
- More expensive houses beyoind 200k are least sold.
- It gives us an idea about the earning capacity of the population of Ames Iowa. Looking at the plot, this is our assumption that mostly the higher middle class people live in that area followed by the middle class, lower middle class and extremely rich people.

# BUILDING CHARACTERISTICS



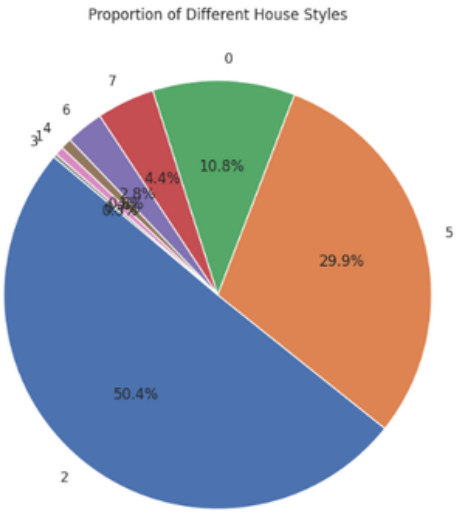

MOST TYPES OF HOUSES IN THE DATASET ARE :

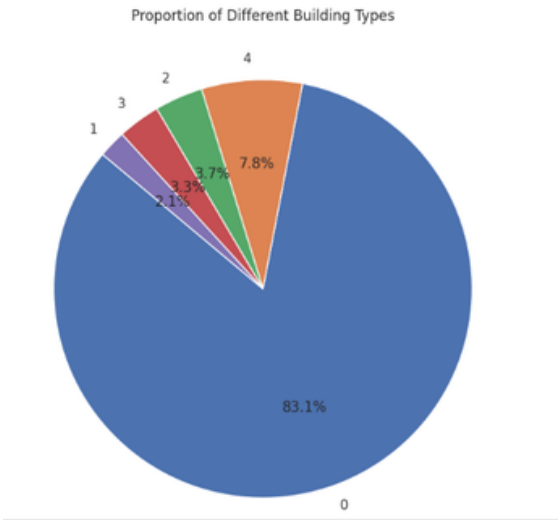
1-STORY 1946 & NEWER ALL STYLES
2-STORY 1946 & NEWER
1-1/2 STORY FINISHED ALL AGES
1-STORY PUD (PLANNED UNIT DEVELOPMENT) - 1946 & NEWER

LEAST TYPES OF HOUSES IN THE DATASET ARE :

1-1/2 STORY - UNFINISHED ALL AGES
2-1/2 STORY ALL AGES
PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
SPLIT FOYER

# PROPORTION OF DIFFERENT TYPES IN THE DATASET

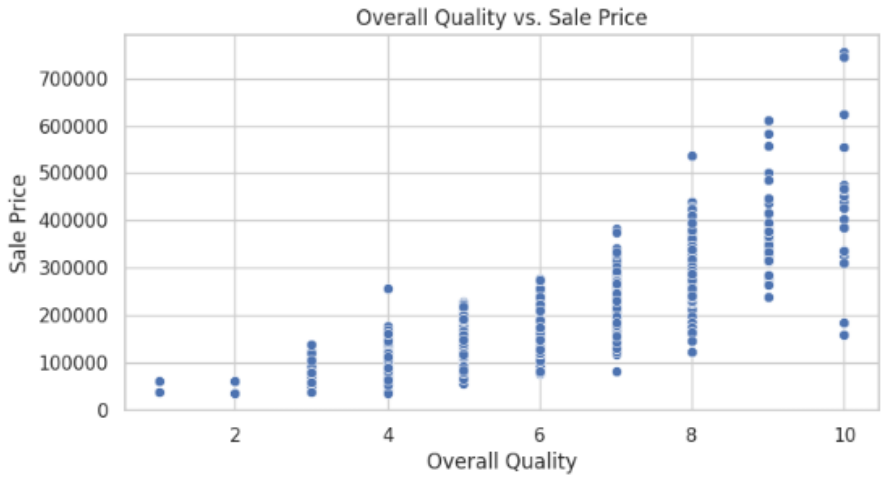



**CLASS 2 REPRESENTS "1STORY" HOUSES WHICH ACCOUNT FOR MORE THAN 50% IN THE DATASET. FOLLOWED BY CLASS 5 WHICH REPRESENTS '2STORY' HOUSES.**

**THE ABOVE VISUALIZATION SHOWS THAT CLASS 0 THAT MEANS SINGLE-FAMILY DETACHED BUILDINGS ARE MOSTLY IN THE DATASET WHICH IS EXTREMELY HIGH IN NUMBER FOLLOWED BY CLASS 4 - TOWNHOUSE INSIDE UNIT TYPES OF BUILDINGS.**

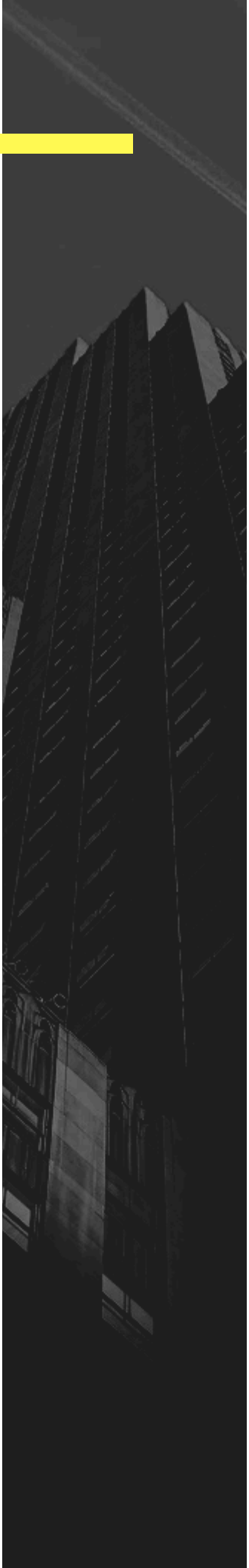
# OVERALL QUALITY VS SALES PRICE




1. Properties ranging from 100K - 200K include most various quality. Extremely good quality houses can be found as well within that range. That makes sense why most properties cost that range.
2. The properties above 200k dollars are extremely good quality properties.

# HOW LOT SIZE INFLUENCES PROPERTY PRICES

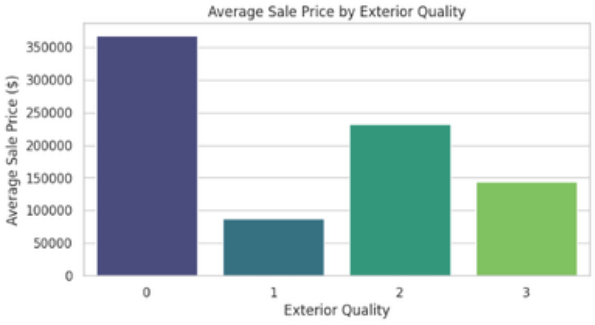

1. The plot represents the relationship between the size of a property's lot (measured in square feet) and its sale price (in dollars).
2. Most data points cluster at the lower end, indicating smaller lots with lower prices.
3. Larger lots show a slight trend toward higher prices



# COMPARISON OF THE AVERAGE SALEPRICE ACROSS DIFFERENT LOTSHAPE, LOTCONFIG CATEGORIES AND EXTERIOR QUALITIES

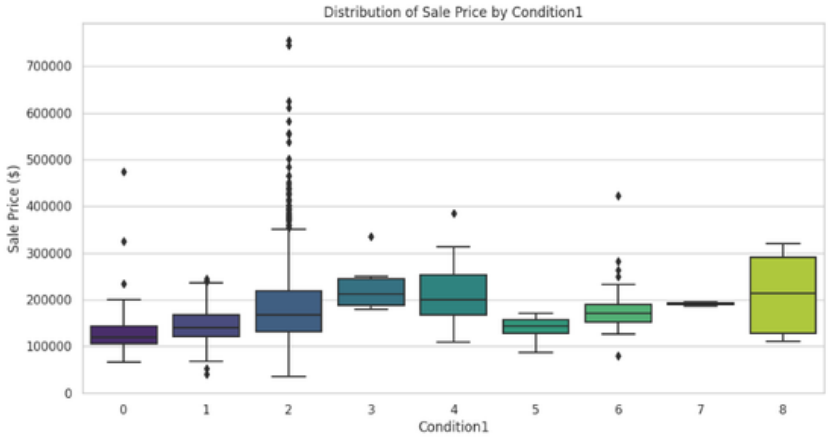

- REGULAR SHAPES REPRESENTING 0 IS COMPARATIVELY CHEAPER
- SLIGHTLY IRREGULAR AND MODERATELY IRREGULAR SHAPES ARE COMPARATIVELY HIGHER IN PRICE


- CUL-DE-SAC HOUSE SITS ON A DEAD-END ROUNDED STREET, FACING OTHER HOUSES AND CREATING A CLOSE-KNIT FEELING BETWEEN NEIGHBORS. THAT REPRESENTS CLASS 1 WHICH ARE HIGHER IN PRICE.
- FRONTAGE ON 3 SIDES OF PROPERTY TYPES HAVE SECOND HIGHEST AVERAGE PRICE.
- OTHER CONFIGURATIONS ARE "FRONTAGE ON 2 SIDES OF PROPERTY", "INSIDE LOT" AND "CORNER LOT" WHICH HAVE A SIMILAR AVERAGE PRICE.




- 0 REPRESENTS THE 'EXCELLENET' QUALITY PROPERTIES WHICH ARE OBVIOUSLY HIGHER IN PRICE.
- 2 IS THE GOOD QUALITY PROPERTIES WHICH COSTS LOWER THAN THE EXCELLENT ONES.
- 3 IS THE TYPICAL OR AVERAGE TYPES WHICH COMES NEXT AND THE LEAST EXPENSIVE PROPERTIES ARE 'FAIR' QUALITY ONES. THERE ARE NO POOR QUALITY PROPERTIES LISTED IN THE DATASET.

# DISTRIBUTION OF SALEPRICE BY CONDITION1 AND CONDITION2

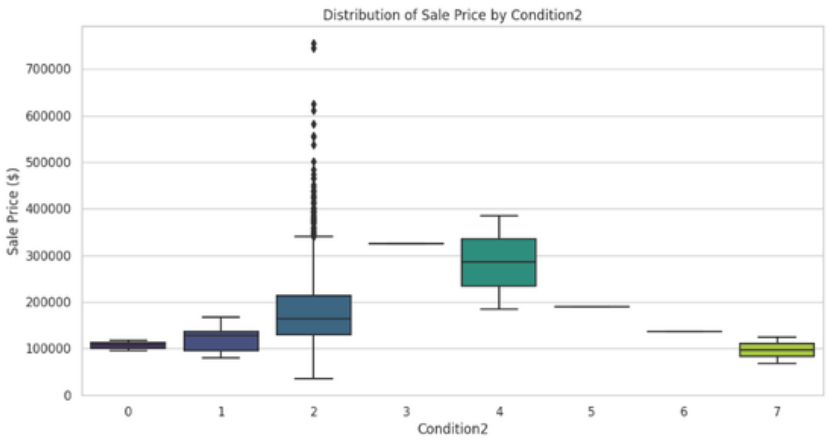



Condition 1 is the Proximity to various conditions as follows :

| | |
|---|---|
| Artery | Adjacent to arterial street |
| Feedr | Adjacent to feeder street |
| Norm | Normal |
| RRNn | Within 200' of North-South Railroad |
| RRAn | Adjacent to North-South Railroad |
| PosN | Near positive off-site feature--park, greenbelt, etc. |
| PosA | Adjacent to postive off-site feature |
| RRNe | Within 200' of East-West Railroad |
| RRAe | Adjacent to East-West Railroad |

- 2 represents the Normal condition properties which have a lot of outliers : extremely minimum and maximum sales price. That means normal type of properties are mostly sold in various price ranges.
- 0 represents the properties which are Adjacent to arterial street. These properties are sold in various prices , sometimes in extremely high prices.

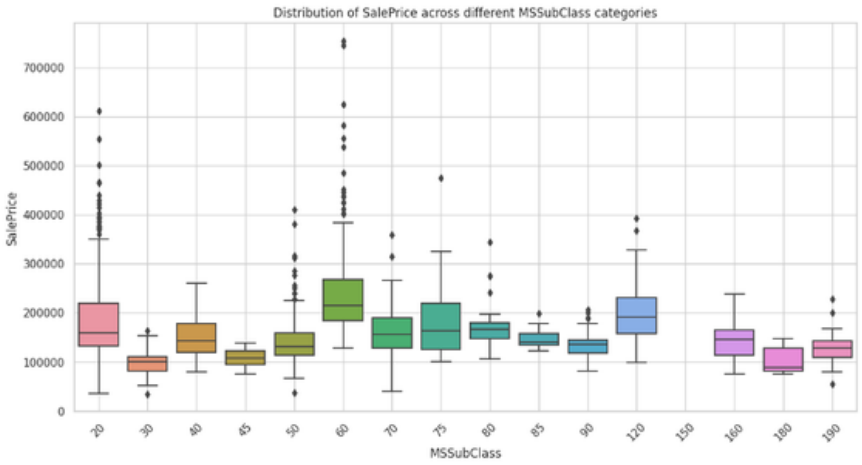
# DISTRIBUTION OF SALEPRICE BY CONDITION1 AND CONDITION2




Condition 2 represents the Proximity to various conditions (if more than one is present). From the plot above, we can observe number of things ;

- Like condition 1, the normal properties are sold in extremely lower and higher prices than average
- For class 0 , the result is similar like condition 1 properties.
- For class 4 , properties near positive off-site feature--park, greenbelt, etc, these are sold in higher prices comparing to having a single condition.
- For properties within 200' of North-South Railroad, if they have multiple conditions present, they are sold in less prices comparing to having a single condition.

# COMPARE SALEPRICE ACROSS DIFFERENT MSSUBCLASS CATEGORIES




- Different building classes (MSSubClass) have significantly different average SalePrices. This suggests that the type of building class is an important factor affecting property prices. Further investigation into which specific classes have higher or lower average SalePrices can provide insights for real estate pricing strategies.
- Skewness, Kurtosis and Normality Tests
- We will assess the distributions and check for normality for few continuous features

# STATISTICAL ANALYSIS

## Average, Standard Deviation and Percentiles of the Features

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Id | 2919.000000 | 1460.000000 | 842.787043 | 1.000000 | 730.500000 | 1460.000000 | 2189.500000 | 2919.000000 |
| MSSubClass | 2919.000000 | 57.137718 | 42.517628 | 20.000000 | 20.000000 | 50.000000 | 70.000000 | 190.000000 |
| MSZoning | 2919.000000 | 3.030490 | 0.662386 | 0.000000 | 3.000000 | 3.000000 | 3.000000 | 5.000000 |
| LotFrontage | 2919.000000 | 69.305795 | 21.312345 | 21.000000 | 60.000000 | 69.305795 | 78.000000 | 313.000000 |
| LotArea | 2919.000000 | 10168.114080 | 7886.996359 | 1300.000000 | 7478.000000 | 9453.000000 | 11570.000000 | 215245.000000 |
| Street | 2919.000000 | 0.995889 | 0.063996 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |
| LotShape | 2919.000000 | 1.947585 | 1.409721 | 0.000000 | 0.000000 | 3.000000 | 3.000000 | 3.000000 |
| LandContour | 2919.000000 | 2.776978 | 0.704391 | 0.000000 | 3.000000 | 3.000000 | 3.000000 | 3.000000 |
| Utilities | 2919.000000 | 0.001713 | 0.055510 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 2.000000 |
| LotConfig | 2919.000000 | 3.055841 | 1.604472 | 0.000000 | 2.000000 | 4.000000 | 4.000000 | 4.000000 |
| LandSlope | 2919.000000 | 0.053786 | 0.248750 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 2.000000 |
| Neighborhood | 2919.000000 | 12.437136 | 5.957992 | 0.000000 | 7.000000 | 12.000000 | 17.000000 | 24.000000 |
| Condition1 | 2919.000000 | 2.040425 | 0.874047 | 0.000000 | 2.000000 | 2.000000 | 2.000000 | 8.000000 |
| Condition2 | 2919.000000 | 2.002055 | 0.209431 | 0.000000 | 2.000000 | 2.000000 | 2.000000 | 7.000000 |
| BldgType | 2919.000000 | 0.505653 | 1.206513 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 4.000000 |
| HouseStyle | 2919.000000 | 3.026721 | 1.912937 | 0.000000 | 2.000000 | 2.000000 | 5.000000 | 7.000000 |
| OverallQual | 2919.000000 | 6.089072 | 1.409947 | 1.000000 | 5.000000 | 6.000000 | 7.000000 | 10.000000 |
| OverallCond | 2919.000000 | 5.564577 | 1.113131 | 1.000000 | 5.000000 | 5.000000 | 6.000000 | 9.000000 |
| YearBuilt | 2919.000000 | 1971.312778 | 30.291442 | 1872.000000 | 1953.500000 | 1973.000000 | 2001.000000 | 2010.000000 |
| YearRemodAdd | 2919.000000 | 1984.264474 | 20.894344 | 1950.000000 | 1965.000000 | 1993.000000 | 2004.000000 | 2010.000000 |
| RoofStyle | 2919.000000 | 1.396369 | 0.820906 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 5.000000 |
| RoofMatl | 2919.000000 | 1.063035 | 0.539210 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 7.000000 |
| Exterior1st | 2919.000000 | 9.625214 | 3.200303 | 0.000000 | 8.000000 | 12.000000 | 12.000000 | 15.000000 |
| Exterior2nd | 2919.000000 | 10.337102 | 3.552133 | 0.000000 | 8.000000 | 13.000000 | 13.000000 | 16.000000 |
| MasVnrType | 2919.000000 | 2.286742 | 0.926533 | 0.000000 | 1.000000 | 3.000000 | 3.000000 | 3.000000 |
| MasVnrArea | 2919.000000 | 102.201312 | 178.626089 | 0.000000 | 0.000000 | 0.000000 | 163.500000 | 1600.000000 |
| ExterQual | 2919.000000 | 2.530661 | 0.702245 | 0.000000 | 2.000000 | 3.000000 | 3.000000 | 3.000000 |
| ExterCond | 2919.000000 | 3.708804 | 0.773641 | 0.000000 | 4.000000 | 4.000000 | 4.000000 | 4.000000 |
| Foundation | 2919.000000 | 1.393285 | 0.727061 | 0.000000 | 1.000000 | 1.000000 | 2.000000 | 5.000000 |
| BsmtQual | 2919.000000 | 2.288112 | 0.922771 | 0.000000 | 2.000000 | 2.000000 | 3.000000 | 4.000000 |
| BsmtCond | 2919.000000 | 2.835903 | 0.700631 | 0.000000 | 3.000000 | 3.000000 | 3.000000 | 4.000000 |
| BsmtExposure | 2919.000000 | 2.327509 | 1.151168 | 0.000000 | 2.000000 | 3.000000 | 3.000000 | 4.000000 |
| BsmtFinType1 | 2919.000000 | 2.846865 | 1.862342 | 0.000000 | 2.000000 | 2.000000 | 5.000000 | 6.000000 |
| BsmtFinSF1 | 2919.000000 | 441.423235 | 455.532750 | 0.000000 | 0.000000 | 369.000000 | 733.000000 | 5644.000000 |
| BsmtFinType2 | 2919.000000 | 4.714628 | 1.012141 | 0.000000 | 5.000000 | 5.000000 | 5.000000 | 6.000000 |
| BsmtFinSF2 | 2919.000000 | 49.582248 | 169.176615 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1526.000000 |
| BsmtUnfSF | 2919.000000 | 560.772104 | 439.468337 | 0.000000 | 220.000000 | 467.000000 | 805.000000 | 2336.000000 |
| TotalBsmtSF | 2919.000000 | 1051.777587 | 440.690726 | 0.000000 | 793.000000 | 990.000000 | 1302.000000 | 6110.000000 |
| Heating | 2919.000000 | 1.025351 | 0.245678 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 5.000000 |
| HeatingQC | 2919.000000 | 1.533744 | 1.742548 | 0.000000 | 0.000000 | 0.000000 | 4.000000 | 4.000000 |
| CentralAir | 2919.000000 | 0.932854 | 0.250318 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |
| Electrical | 2919.000000 | 3.685509 | 1.047746 | 0.000000 | 4.000000 | 4.000000 | 4.000000 | 5.000000 |
| 1stFlrSF | 2919.000000 | 1159.581706 | 392.362079 | 334.000000 | 876.000000 | 1082.000000 | 1387.500000 | 5095.000000 |
| 2ndFlrSF | 2919.000000 | 336.483727 | 428.701456 | 0.000000 | 0.000000 | 0.000000 | 704.000000 | 2065.000000 |
| LowQualFinSF | 2919.000000 | 4.694416 | 46.396825 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1064.000000 |
| GrLivArea | 2919.000000 | 1500.759849 | 506.051045 | 334.000000 | 1126.000000 | 1444.000000 | 1743.500000 | 5642.000000 |
| BsmtFullBath | 2919.000000 | 0.429894 | 0.524556 | 0.000000 | 0.000000 | 0.000000 | 1.000000 | 3.000000 |

# STATISTICAL ANALYSIS

## Average, Standard Deviation and Percentiles of the Features

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| BsmtHalfBath | 2919.000000 | 0.061364 | 0.245603 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 2.000000 |
| FullBath | 2919.000000 | 1.568003 | 0.552969 | 0.000000 | 1.000000 | 2.000000 | 2.000000 | 4.000000 |
| HalfBath | 2919.000000 | 0.380267 | 0.502872 | 0.000000 | 0.000000 | 0.000000 | 1.000000 | 2.000000 |
| BedroomAbvGr | 2919.000000 | 2.860226 | 0.822693 | 0.000000 | 2.000000 | 3.000000 | 3.000000 | 8.000000 |
| KitchenAbvGr | 2919.000000 | 1.044536 | 0.214462 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 3.000000 |
| KitchenQual | 2919.000000 | 2.347379 | 0.834847 | 0.000000 | 2.000000 | 3.000000 | 3.000000 | 4.000000 |
| TotRmsAbvGrd | 2919.000000 | 6.451524 | 1.569379 | 2.000000 | 5.000000 | 6.000000 | 7.000000 | 15.000000 |
| Functional | 2919.000000 | 5.760534 | 0.935847 | 0.000000 | 6.000000 | 6.000000 | 6.000000 | 7.000000 |
| Fireplaces | 2919.000000 | 0.597122 | 0.646129 | 0.000000 | 0.000000 | 1.000000 | 1.000000 | 4.000000 |
| FireplaceQu | 2919.000000 | 3.825968 | 1.398569 | 0.000000 | 2.000000 | 4.000000 | 5.000000 | 5.000000 |
| GarageType | 2919.000000 | 2.483727 | 1.932814 | 0.000000 | 1.000000 | 1.000000 | 5.000000 | 6.000000 |
| GarageYrBlt | 2919.000000 | 1978.113406 | 24.867762 | 1895.000000 | 1961.500000 | 1978.113406 | 2001.000000 | 2207.000000 |
| GarageFinish | 2919.000000 | 1.284001 | 0.897327 | 0.000000 | 1.000000 | 1.000000 | 2.000000 | 3.000000 |
| GarageCars | 2919.000000 | 1.766621 | 0.761494 | 0.000000 | 1.000000 | 2.000000 | 2.000000 | 5.000000 |
| GarageArea | 2919.000000 | 472.874572 | 215.357904 | 0.000000 | 320.000000 | 480.000000 | 576.000000 | 1488.000000 |
| GarageQual | 2919.000000 | 3.904762 | 0.692049 | 0.000000 | 4.000000 | 4.000000 | 4.000000 | 5.000000 |
| GarageCond | 2919.000000 | 3.959233 | 0.568221 | 0.000000 | 4.000000 | 4.000000 | 4.000000 | 5.000000 |
| PavedDrive | 2919.000000 | 1.830764 | 0.537299 | 0.000000 | 2.000000 | 2.000000 | 2.000000 | 2.000000 |
| WoodDeckSF | 2919.000000 | 93.709832 | 126.526589 | 0.000000 | 0.000000 | 0.000000 | 168.000000 | 1424.000000 |
| OpenPorchSF | 2919.000000 | 47.486811 | 67.575493 | 0.000000 | 0.000000 | 26.000000 | 70.000000 | 742.000000 |
| EnclosedPorch | 2919.000000 | 23.098321 | 64.244246 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1012.000000 |
| 3SsnPorch | 2919.000000 | 2.602261 | 25.188169 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 508.000000 |
| ScreenPorch | 2919.000000 | 16.062350 | 56.184365 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 576.000000 |
| PoolArea | 2919.000000 | 2.251799 | 35.663946 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 800.000000 |
| MiscVal | 2919.000000 | 50.825968 | 567.402211 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 17000.000000 |
| MoSold | 2919.000000 | 6.213087 | 2.714762 | 1.000000 | 4.000000 | 6.000000 | 8.000000 | 12.000000 |
| YrSold | 2919.000000 | 2007.792737 | 1.314964 | 2006.000000 | 2007.000000 | 2008.000000 | 2009.000000 | 2010.000000 |
| SaleType | 2919.000000 | 7.491607 | 1.593719 | 0.000000 | 8.000000 | 8.000000 | 8.000000 | 9.000000 |
| SaleCondition | 2919.000000 | 3.779034 | 1.078241 | 0.000000 | 4.000000 | 4.000000 | 4.000000 | 5.000000 |
| SalePrice | 1460.000000 | 180921.195890 | 79442.502883 | 34900.000000 | 129975.000000 | 163000.000000 | 214000.000000 | 755000.000000 |
| Latitude | 2919.000000 | 42.036187 | 0.023631 | 41.990092 | 42.022005 | 42.033483 | 42.049205 | 42.107339 |
| Longitude | 2919.000000 | -93.644576 | 0.020378 | -93.680265 | -93.652025 | -93.648429 | -93.635387 | -93.601829 |

- HIGH STANDARD DEVIATION FOR FEATURES LIKE LOTAREA,MISCVAL, WOODDECKSF, GRLIVAREA, 2NDFLRSF, 1STFLRSF INDICATE THAT THEY HAVE A VERY WIDE RANGE WHICH MEANS THESE PROPERTY FEATURES HAVE A GREAT VARIETY IN THE MARKET.
- IN FEATURES LIKE LOTAREA, MASVNRAREA, BSMTFINSF1 AND TOTALBSMTSF ETC THE IQR RANGE IS VERY HIGH WHICH INDICATES THAT THERE COULD BE OUTLIERS.

# SKEWNESS ANALYSIS

**Skewness**:

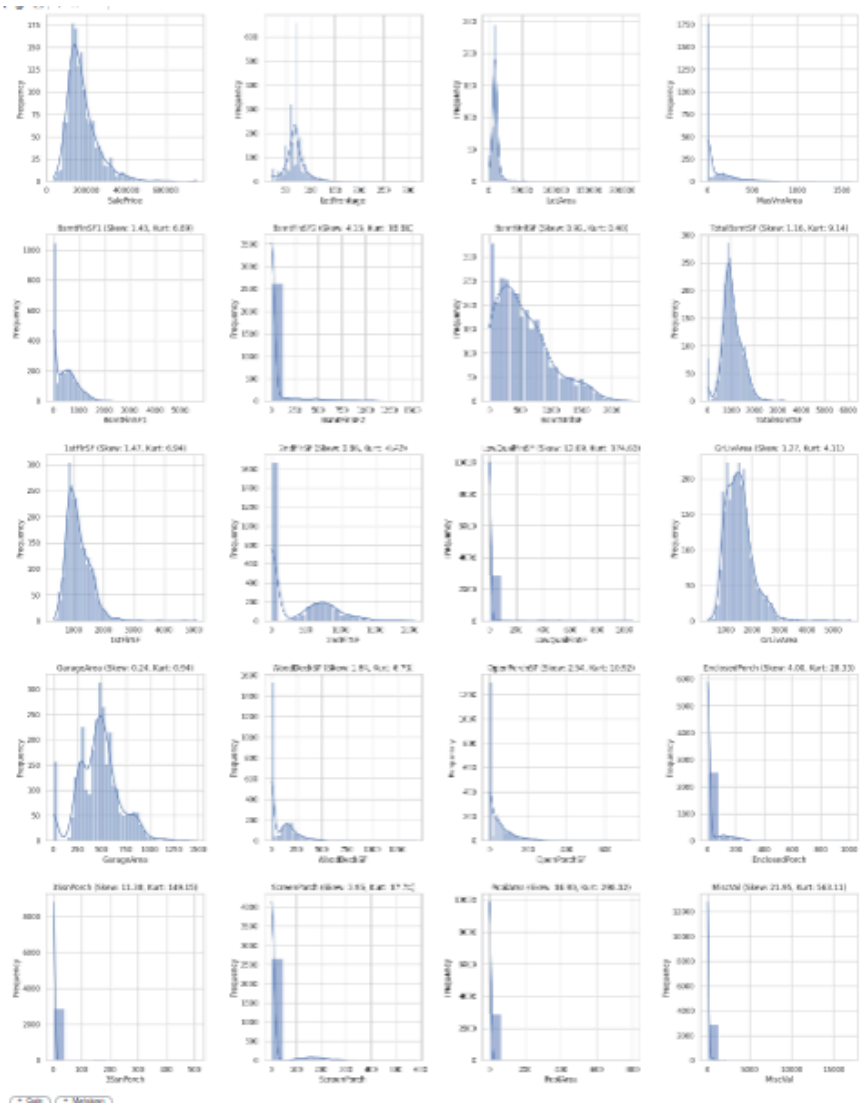
- A skewness value greater than 1 indicates a highly skewed distribution.
- Most variables have high skewness values, indicating that their distributions are not symmetrical.
- 'LotArea', 'LowQualFinSF', 'PoolArea', and 'MiscVal' have extremely high skewness values, indicating severe skewness.

**Kurtosis**:

- A kurtosis value greater than 3 indicates a leptokurtic distribution (heavy-tailed).
- Most variables have high kurtosis values, indicating that their distributions have heavy tails.
- 'LotArea', 'LowQualFinSF', 'PoolArea', and 'MiscVal' have extremely high kurtosis values, indicating extremely heavy-tailed distributions.

**Shapiro-Wilk Test Results:**

- The Shapiro-Wilk test is a normality test that checks if the data follows a normal distribution.
- The test produces a statistic (W) and a p-value.
- A p-value less than 0.05 indicates that the data does not follow a normal distribution.
- Most variables have p-values very close to 0, indicating that they do not follow a normal distribution.
- Only 'GarageArea' has a p-value greater than 0.05, indicating that it may follow a normal distribution.



# OUTLIER DETECTION AND HANDLING

WE WILL CREATE FEW FUNCTIONS TO HANDLE OUTLIERS. INSTEAD OF REMOVING THE DATAPOINTS COMPLETELY, WE WILL REPLACE THEM WITH LOWER AND HIGHER THRESHOLD VALUES. WE WILL KEEP SOME FEATURES OUT FROM THIS PROCESS. FOR EXAMPLE, ID, LATITUDE, LONGITUDE ETC.

```
# List of columns to exclude from outlier handling
excluded_columns = ['Id', 'Neighborhood', 'MoSold', 'YrSold', 'Neighborhood_Decoded', 'Neighborhood_Full', 'Latitude', 'Longitude']

# Selecting all numeric columns
numeric_vars = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Filtering out the excluded columns
numeric_vars = [col for col in numeric_vars if col not in excluded_columns]

# Function to calculate lower and upper thresholds
def outlier_thresholds(dataframe, col_name, q1=0.1, q3=0.9):
    quartile1 = dataframe[col_name].quantile(q1)
    quartile3 = dataframe[col_name].quantile(q3)
    interquantile_range = quartile3 - quartile1
    up_limit = quartile3 + 1.5 * interquantile_range
    low_limit = quartile1 - 1.5 * interquantile_range
    return low_limit, up_limit

# Function to check for outliers in a specific column
def check_outlier(dataframe, col_name):
    if pd.api.types.is_numeric_dtype(dataframe[col_name]):
        low_limit, up_limit = outlier_thresholds(dataframe, col_name)
        return dataframe[(dataframe[col_name] > up_limit) | (dataframe[col_name] < low_limit)][col_name]
    else:
        return pd.Series([])

# Function to replace outliers with defined thresholds
def replace_with_thresholds(dataframe, variable, q1=0.1, q3=0.9):
    low_limit, up_limit = outlier_thresholds(dataframe, variable, q1, q3)

    # Get the current dtype of the column
    col_dtype = dataframe[variable].dtype

    # Cast thresholds to the appropriate dtype
    if pd.api.types.is_integer_dtype(col_dtype):
        low_limit = int(low_limit)
        up_limit = int(up_limit)

    dataframe.loc[(dataframe[variable] < low_limit), variable] = low_limit
    dataframe.loc[(dataframe[variable] > up_limit), variable] = up_limit

# Iterating through each numeric column to check and handle outliers
for col in numeric_vars:
    outliers = check_outlier(df, col)
    if not outliers.empty:
        print(f"Outliers found in {col}. Handling outliers...")
        replace_with_thresholds(df, col)

print("Outlier handling completed.")
```

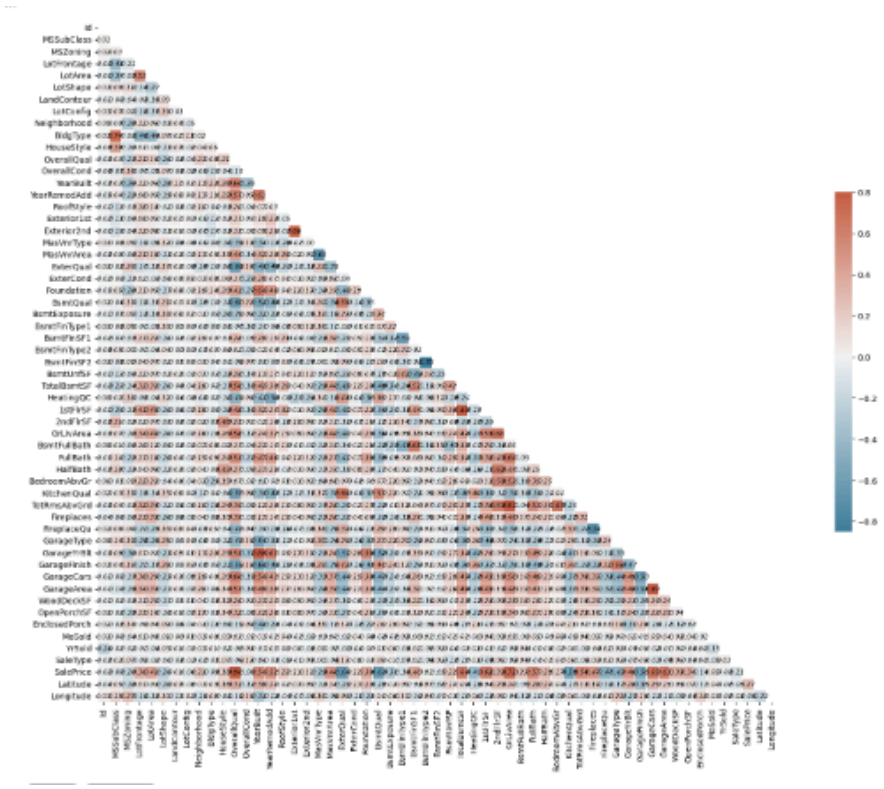
# CORRELATION MATRIX

WE WILL PERFORM CORRELATION MATRIX TO IDENTIFY THE FEATURES WHICH HAVE HIGH CORRELATION WITH SALESPRICE BUT BEFORE THAT WE NEED TO REMOVE THOSE FEATURES WHICH HAVE ONLY ONE UNIQUE VALUE.

```
unique_value_counts = df.nunique()
variables_with_one_unique_value = unique_value_counts[unique_value_counts == 1].index.tolist()

print('Variables with unique value count of 1:')
print(variables_with_one_unique_value)
```

```
Variables with unique value count of 1:
['Street', 'Utilities', 'LandSlope', 'Condition1', 'Condition2', 'RoofMatl', 'BsmtCond', 'Heating', 'CentralAir', 'Electrical', 'LowQualFinSF', 'BsmtH
alfBath', 'KitchenAbvGr', 'Functional', 'GarageQual', 'GarageCond', 'PavedDrive', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'SaleCondition']
```

```
# dropping the features which have only one unique value
df.drop(variables_with_one_unique_value, axis=1, inplace=True)
```



FEW FEATURES HAVE HIGH CORRELATION PAIR. WE WILL DROP THOSE FEATURES TO AVOID DATA LEAKAGE. WE WILL DO THAT AFTER WE CREATE NEW FEATURES WHICH WILL HAVE HIGH CORRELATION.

# FEATURE ENGINEERING

We have created few features based on the context

```
# 1. TotalLivingArea
df['TotalLivingArea'] = df['GrLivArea'] + df['TotalBsmtSF'] + df['1stFlrSF']

# 2. TotalBathroom
df['TotalBathroom'] = df['FullBath'] + df['HalfBath']

# 3. TotalPorchArea
df['TotalPorchArea'] = df['OpenPorchSF'] + df['EnclosedPorch']

# 4. AvgLotSize
df['AvgLotSize'] = df['LotArea'] / df['LotFrontage']

# 5. HouseAge
df['HouseAge'] = df['YrSold'] - df['YearBuilt']

# 6. YearsSinceRemodel
df['YearsSinceRemodel'] = df['YrSold'] - df['YearRemodAdd']

# 7. TotalOutdoorSpace
df['TotalOutdoorSpace'] = df['WoodDeckSF'] + df['OpenPorchSF'] + df['EnclosedPorch']

# 8. BsmtFinRatio
df['BsmtFinRatio'] = (df['BsmtFinSF1'] + df['BsmtFinSF2']) / df['TotalBsmtSF']

# 9. AboveGradeLivingRatio
df['AboveGradeLivingRatio'] = df['GrLivArea'] / df['TotalLivingArea']
```

```
# 10. BathroomPerBedroom
df['BathroomPerBedroom'] = df['TotalBathroom'] / df['BedroomAbvGr']

# 11. FireplaceQuality
df['FireplaceQuality'] = df['FireplaceQu'].apply(lambda x: 1 if x == 'Ex' else 0)

# 12. GarageSize
df['GarageSize'] = df['GarageCars'] * df['GarageArea']

# 13. NeighborhoodQuality
df['NeighborhoodQuality'] = df['Neighborhood_Decoded'].apply(lambda x: 1 if x == 'High' else 0)

# 14. HouseStyleQuality
df['HouseStyleQuality'] = df['HouseStyle'].apply(lambda x: 1 if x in ['2Story', '1.5Fin'] else 0)

# 15. TotalRoomDensity
df['TotalRoomDensity'] = df['TotRmsAbvGrd'] / df['TotalLivingArea']
```

WE NEED TO FIND HIGH CORRELATION FEATURE PAIRS SO THAT WE CAN REMOVE ONE FROM EACH PAIR SO THAT OUR MODEL CAN AVOID OVERFITTING

WE WILL ALSO REMOVE THE CATEGORICAL FEATURES WHICH WERE USED FOR DATA ANALYSIS. FOR MODELLING WE DO NOT NEED THEM NOW. WE WILL ALSO REMOVE THE ID COLUMN.

# REMOVING HIGH CORRELATED FEATURE AND OTHER CATEGORICAL FEATURES

```python
def find_high_correlation_features(df, threshold=0.95):
    # Select only numerical columns
    numerical_df = df.select_dtypes(exclude=['object', 'datetime'])

    # Remove the Id column (assuming it's named 'Id')
    numerical_df = numerical_df.drop('Id', axis=1)

    # Calculate the correlation matrix
    corr_matrix = numerical_df.corr()

    # Get the upper triangle of the correlation matrix (excluding the diagonal)
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

    # Find the features with high correlation (above the threshold)
    high_corr_features = [(column, row) for column in upper.columns for row in upper.index if abs(upper.loc[row, column]) > threshold]

    return high_corr_features
```

```python
high_corr_features = find_high_correlation_features(df, threshold=0.95)
print(high_corr_features)
```

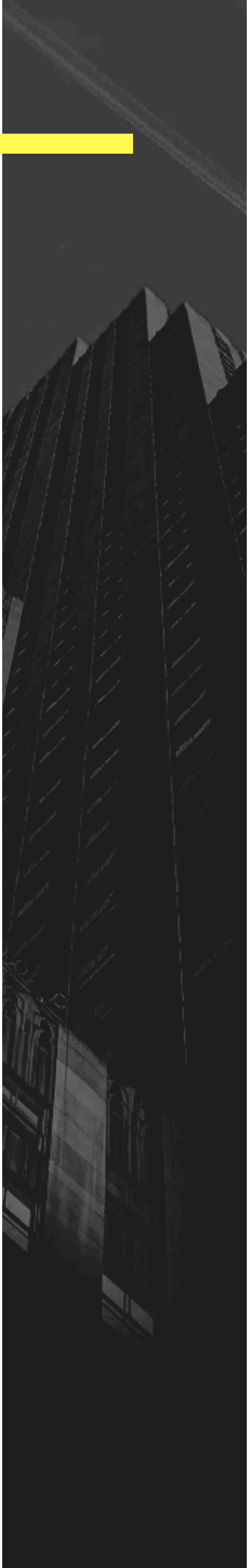
```
[('HouseAge', 'YearBuilt'), ('YearsSinceRemodel', 'YearRemodAdd')]
```

## NOW THAT WE HAVE GOT THE HIGH CORRELATION PAIRS, WE WILL REMOVE SOME OF THE FEATURES ALONG WITH ID, AND TWO OBJECT FEATURES THAT WE HAVE

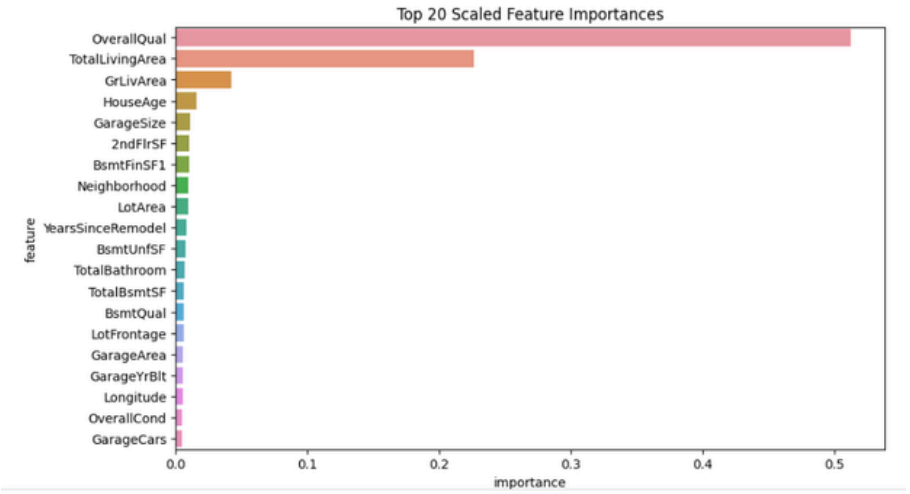
```python
# removing
df = df.drop(['YearBuilt', 'YearRemodAdd' , 'Id', 'Neighborhood_Decoded', 'Neighborhood_Full'   ], axis=1)
```

# FEATURE IMPORTANCE AND FEATURE SELECTION

*We tried different techniques for extracting important features.*



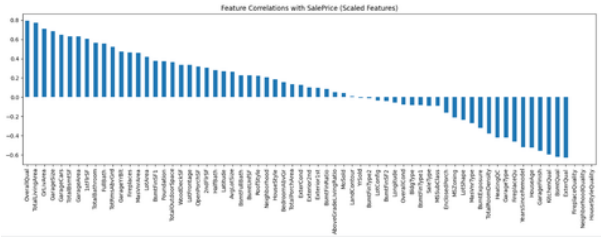
# FEATURE IMPORTANCE FROM RANDOM FOREST



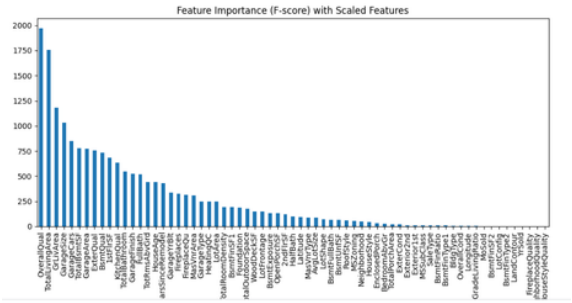

*We wanted to try other feature importance techniques and finally take the decision after comparing one to another.*

# OTHER TECHNIQUES TO GET FEATURE IMPORTANCE

### USING CORRELATION FOR FEATURE IMPORTANCE




### F-SCORE FOR FEATURE IMPORTANCE

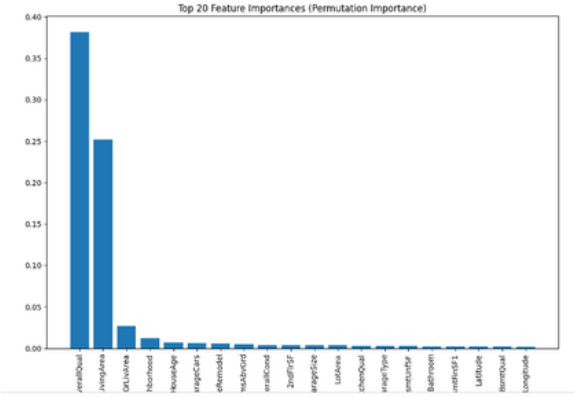



### WE TRIED TO FIND OUT THE COMMON FEATURES IN THESE TWO TECHNIQUES

```
common_features = set(top_correlated.index).intersection(set(f_scores.index))

# Convert the result to a list if needed
common_features_list = list(common_features)

# Print the common features
print("Common features:", common_features_list)
```

```
Common features: ['Foundation', 'LotShape', 'BedroomAbvGr', 'TotalBsmtSF', 'HasVnrArea', 'GarageType', 'HasVnrType', 'HouseAge', 'TotalRoomDensity', 'ExterQual', 'BsmtExp
osure', 'AvgLotSize', 'ExterCond', 'HalfBath', 'FullBath', 'Neighborhood', 'TotalPorchArea', 'MSZoning', 'TotalBathroom', 'LotArea', 'BsmtFullBath', 'KitchenQual', 'Garag
eCars', 'TotalLivingArea', 'GarageYrBlt', 'OpenPorchSF', 'EnclosedPorch', '2ndFlrSF', 'BsmtUnfSF', 'GarageArea', 'LotFrontage', 'Fireplaces', 'FireplaceQu', 'Latitude',
'1stFlrSF', 'YearsSinceRemodel', 'WoodDeckSF', 'TotRmsAbvGrd', 'BsmtFinSF1', 'Exterior2nd', 'BsmtQual', 'OverallQual', 'GarageFinish', 'GarageSize', 'HeatingQC', 'GrLivAr
ea', 'HouseStyle', 'RoofStyle', 'TotalOutdoorSpace']
```

### WE ALSO TRIED A TECHNIQUE CALLED PERMUTATION FEATURE IMPORTANCE



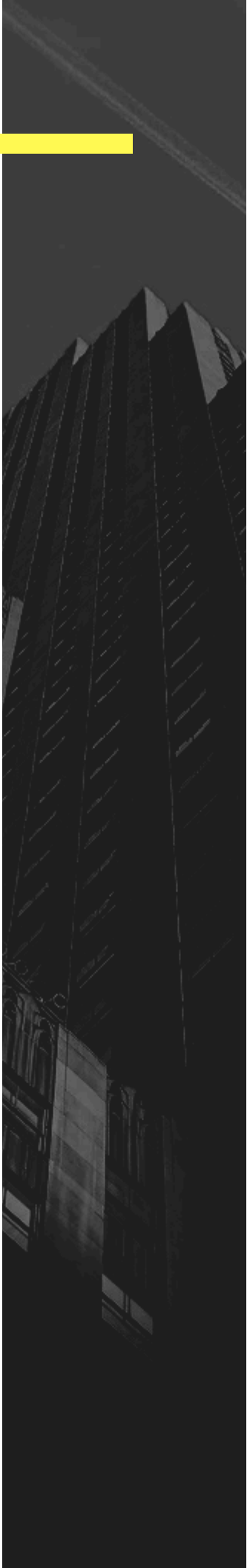
# FEATURE IMPORTANCE DECISION

we had extracted features using different kinds methods. Seeing the results, using top correlated features made more sense to us.

*Using top correlated features*
*gave us the opportunity to use*
*all high correlated features*
*which were recommended by other techniques too.*

# MODELLING

**For modelling, we tried different methodologies**



- **Baseline 1 :** At this stage, we used all the features in three models : Linear Regression, Decision Tree and Neural Network
- **Baseline 2 :** Here we have used selected features which we got from our correlation features. Then we have applied **log transformation** and **scaling.** Then we applied the models below :
  - Linear Regression
  - Ridge Regression
  - Lasso Regression
  - ElasticNet,
  - Decision Tree
  - Random Forest
  - Gradient Boosting
  - SVR
  - KNN
  - XGBoost
  - LightGBM
  - Neural Network
- **Final Model :** At this stage, we applied hyperparameter tuning to the best two machine learning models that we got in baseline 2 - **Gradient Boosting and Random Forest**. We evaluated the results of these two models along with the **Neural Network** model. Finally the result of the Gradient Boosting model was the best.

# HYPERPARAMETER TUNING

## APPLIED HYPERPARAMETER TUNING AFTER BASELINE 2 USING GRIDSEARCHCV

## Tuning  Gradient Boosting

```python
# tuning gradient boosting

def tune_gradient_boosting(X_train, y_train):
    param_grid = {
        'n_estimators': [100, 200, 300],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 4, 5],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    }
    gb = GradientBoostingRegressor(random_state=42)
    grid_search = GridSearchCV(gb, param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
    grid_search.fit(X_train, y_train)
    return grid_search.best_params_
```

```
Best Gradient Boosting parameters: {'learning_rate': 0.1, 'max_depth': 4, 'min_samples_leaf': 1, 'min_samples_split': 10, 'n_estimators': 200}
```

## Tuning  Random Forest

```python
# tuning random forest

def tune_random_forest(X_train, y_train):
    param_grid = {
        'n_estimators': [100, 200, 300],
        'max_depth': [None, 10, 20, 30],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4],
        'max_features': [1.0, 'sqrt', 'log2']  # Changed 'auto' to 1.0
    }

    rf = RandomForestRegressor(random_state=42)

    grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
    grid_search.fit(X_train, y_train)

    return grid_search.best_params_
```

```
Best Random Forest parameters: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
```

# MODEL EVALUATION

## Baseline 1

*With 5 fold cross validation*

EVALUATING LINEAR REGRESSION:
CROSS-VALIDATION RMSE: 29073.4837 (+/- 6090.6673)
CROSS-VALIDATION R2 SCORE: 0.8558 (+/- 0.0456)
VALIDATION RMSE: 27536.1105
VALIDATION R2 SCORE: 0.8870

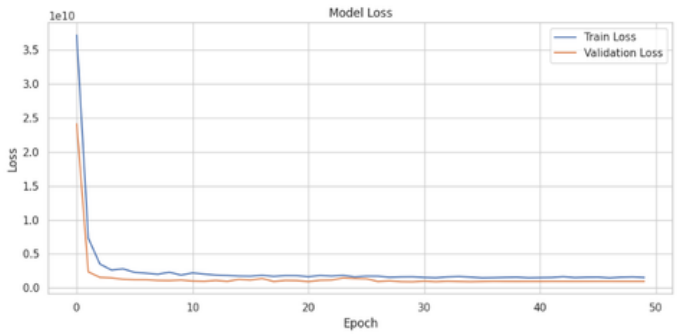
EVALUATING DECISION TREE:
CROSS-VALIDATION RMSE: 37708.3540 (+/- 7471.5025)
CROSS-VALIDATION R2 SCORE: 0.7556 (+/- 0.0922)
VALIDATION RMSE: 37209.4743
VALIDATION R2 SCORE: 0.7936

EVALUATING NEURAL NETWORK
TEST LOSS: 943303104.0000
TEST MAE: 21773.9258

## Baseline 2

| Model | Train RMSE | Train R2 | Validation RMSE | Validation R2 |
|---|---|---|---|---|
| Gradient Boosting | 16802.865097 | 0.950413 | 25725.422160 | 0.901334 |
| Random Forest | 10826.503980 | 0.979414 | 26046.141330 | 0.898859 |
| LightGBM | 12208.428742 | 0.973823 | 27086.585549 | 0.890617 |
| XGBoost | 1462.162601 | 0.999625 | 27739.142647 | 0.885283 |
| Linear Regression | 31209.603918 | 0.828928 | 31251.098562 | 0.854396 |
| Lasso Regression | 31209.611482 | 0.828928 | 31251.423325 | 0.854393 |
| Ridge Regression | 31211.332498 | 0.828909 | 31253.878490 | 0.854370 |
| ElasticNet | 32651.597633 | 0.812755 | 32930.519558 | 0.838326 |
| KNN | 27640.195598 | 0.865821 | 32989.866727 | 0.837743 |
| Decision Tree | 171.728222 | 0.999995 | 34021.001562 | 0.827441 |
| SVR | 77101.362465 | -0.044061 | 82823.164384 | -0.022695 |

{'Model': 'Deep Learning (TensorFlow)', 'Train RMSE': 30390.47702245533, 'Train R2': 0.8377902525300349,
'Validation RMSE': 32910.75214965297, 'Validation R2': 0.8385202175947031,




*Deep Learning Model Training and Validation Loss*

# METRICS AFTER TUNING

## Gradient Boosting

- 'MODEL': 'GRADIENT BOOSTING (BEST PARAMETERS)',
- 'TRAIN RMSE': 9635.141982088855,
- 'TRAIN R2': 0.9836950995468902,
- 'VALIDATION RMSE': 25395.863406245982,
- 'VALIDATION R2': 0.903845745552171

## Random Forest

- TRAINING MSE: 109816240.0885
- TRAINING RMSE: 10479.3244
- TRAINING R-SQUARED: 0.9807

- VALIDATION MSE: 661492876.6941
- VALIDATION RMSE: 25719.5038
- VALIDATION R-SQUARED: 0.9014

# PACKAGING THE BEST MODEL WITH PICKLE

Using Pickle, we saved the model, selected features, skewed features and scaler to use for inference.

```
# Save the model
with open('gradient_boosting_model.pkl', 'wb') as f:
    pickle.dump(gb_model, f)

# Save the scaler
with open('scaler.pkl', 'wb') as f:
    pickle.dump(scaler, f)

# Save the list of selected features
with open('selected_features.pkl', 'wb') as f:
    pickle.dump(top_cor_features_list, f)

# Save the list of skewed features
with open('skewed_features.pkl', 'wb') as f:
    pickle.dump(skewed_features, f)
```

# DEPLOYMENT USING FLASK AND STREAMLIT

At this stage we had the best model saved and wanted to deploy our model using flask and streamlit. Streamlit creates an UI and pushes the input to the Flask server and returns the output. The codes for flask and streamlit are below.

```python
# flask app.py

from flask import Flask, request, jsonify
import pandas as pd
import pickle
import numpy as np

app = Flask(__name__)

# Load the model and other necessary components
with open('gradient_boosting_model.pkl', 'rb') as f:
    model = pickle.load(f)
with open('scaler.pkl', 'rb') as f:
    scaler = pickle.load(f)
with open('selected_features.pkl', 'rb') as f:
    selected_features = pickle.load(f)
with open('skewed_features.pkl', 'rb') as f:
    skewed_features = pickle.load(f)
```

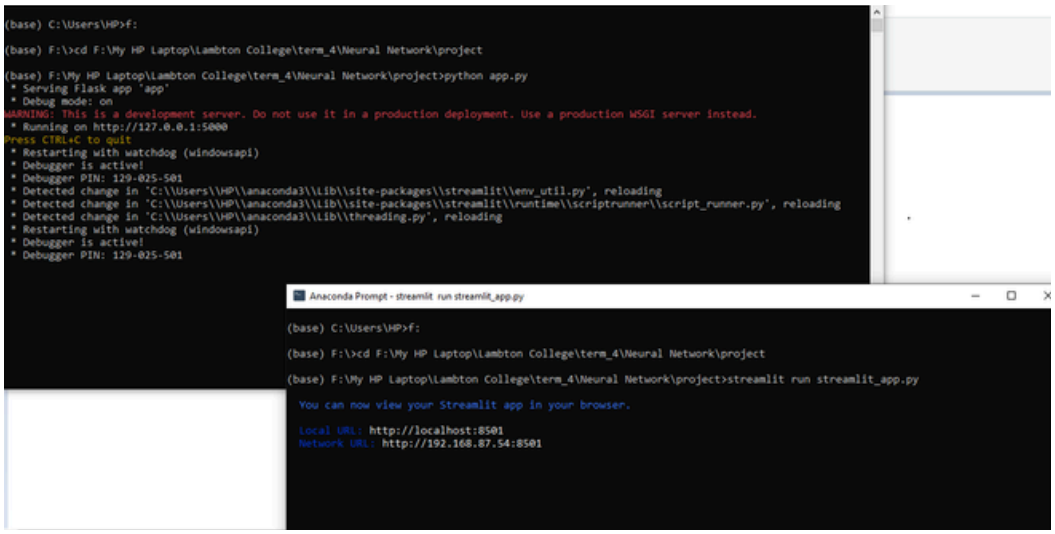
```python
def preprocess_input(input_data):
    # Select features
    input_selected = input_data[selected_features]

    # Log transform skewed features
    for feat in skewed_features:
        input_selected[feat] = np.log1p(input_selected[feat])

    # Handle infinite values
    input_selected = input_selected.replace([np.inf, -np.inf], np.nan)
    input_selected = input_selected.fillna(input_selected.mean())

    # Scale features
    input_scaled = pd.DataFrame(scaler.transform(input_selected),
                                columns=input_selected.columns,
                                index=input_selected.index)

    return input_scaled

@app.route('/predict', methods=['POST'])
def predict():
    data = request.json
    input_df = pd.DataFrame(data, index=[0])
    processed_input = preprocess_input(input_df)
    prediction = model.predict(processed_input)[0]
    return jsonify({'prediction': prediction})

if __name__ == '__main__':
    app.run(debug=True)
```

# DEPLOYMENT USING FLASK AND STREAMLIT

THE STREAMLIT APP DECODES THE CATEGORICAL FEATURE INPUTS AS PER THE ENCODING BY LABEL ENCODER AND THEN IT PUSHES THE INPUT BARIABLES TO THE FLASK SERVER.

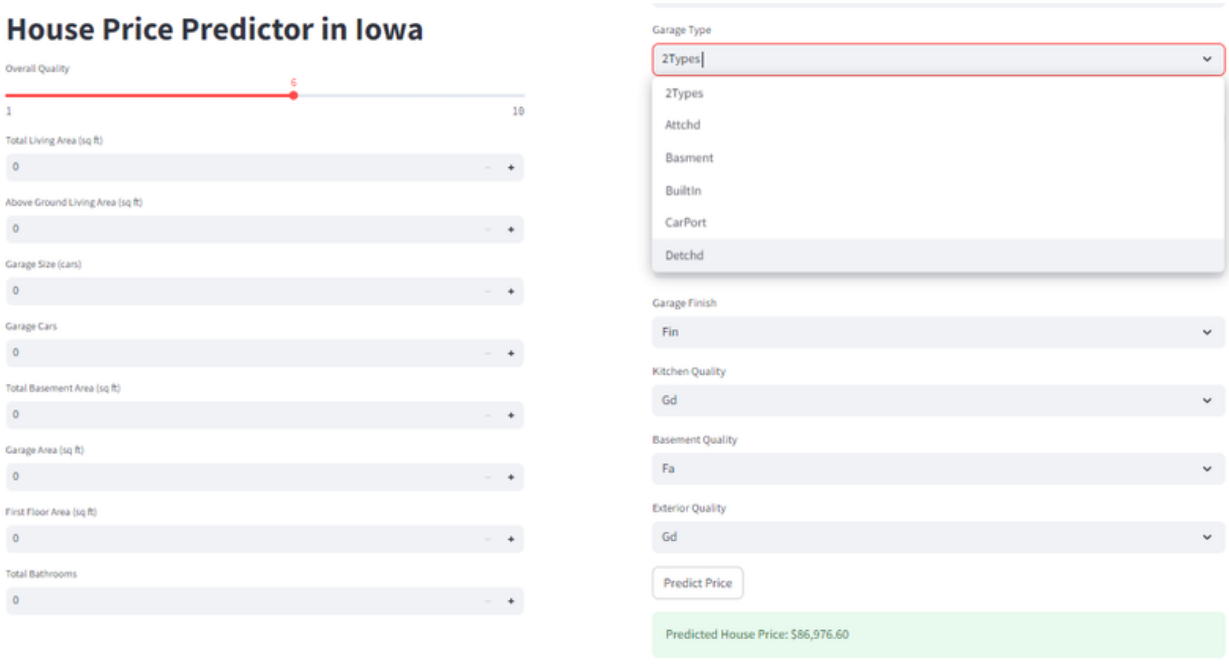
```python
# streamlit_app.py

import streamlit as st
import pandas as pd
import requests

# Define the encoding dictionaries
encodings = {
    'ExterQual': {'Ex': 0, 'Fa': 1, 'Gd': 2, 'TA': 3},
    'HeatingQC': {'Ex': 0, 'Fa': 1, 'Gd': 2, 'Po': 3, 'TA': 4},
    'GarageType': {'2Types': 0, 'Attchd': 1, 'Basment': 2, 'BuiltIn': 3, 'CarPort': 4, 'Detchd': 5},
    'FireplaceQu': {'Ex': 0, 'Fa': 1, 'Gd': 2, 'Po': 3, 'TA': 4},
    'GarageFinish': {'Fin': 0, 'RFn': 1, 'Unf': 2},
    'KitchenQual': {'Ex': 0, 'Fa': 1, 'Gd': 2, 'TA': 3},
    'BsmtQual': {'Ex': 0, 'Fa': 1, 'Gd': 2, 'TA': 3}
}

st.title('House Price Predictor in Iowa')

# Create input fields for each feature
overall_qual = st.slider('Overall Quality', 1, 10, 5)
total_living_area = st.number_input('Total Living Area (sq ft)', min_value=0)
gr_liv_area = st.number_input('Above Ground Living Area (sq ft)', min_value=0)
garage_size = st.number_input('Garage Size (cars)', min_value=0)
garage_cars = st.number_input('Garage Cars', min_value=0)
total_bsmt_sf = st.number_input('Total Basement Area (sq ft)', min_value=0)
garage_area = st.number_input('Garage Area (sq ft)', min_value=0)
first_flr_sf = st.number_input('First Floor Area (sq ft)', min_value=0)
total_bathroom = st.number_input('Total Bathrooms', min_value=0)
full_bath = st.number_input('Full Bathrooms', min_value=0)
tot_rms_abv_grd = st.number_input('Total Rooms Above Ground', min_value=0)
garage_yr_blt = st.number_input('Garage Year Built', min_value=1900, max_value=2023)
fireplaces = st.number_input('Number of Fireplaces', min_value=0)
mas_vnr_area = st.number_input('Masonry Veneer Area (sq ft)', min_value=0)
lot_area = st.number_input('Lot Area (sq ft)', min_value=0)
heating_qc = st.selectbox('Heating Quality', list(encodings['HeatingQC'].keys()))
garage_type = st.selectbox('Garage Type', list(encodings['GarageType'].keys()))
fireplace_qu = st.selectbox('Fireplace Quality', list(encodings['FireplaceQu'].keys()))
years_since_remodel = st.number_input('Years Since Remodel', min_value=0)
house_age = st.number_input('House Age (years)', min_value=0)
garage_finish = st.selectbox('Garage Finish', list(encodings['GarageFinish'].keys()))
kitchen_qual = st.selectbox('Kitchen Quality', list(encodings['KitchenQual'].keys()))
bsmt_qual = st.selectbox('Basement Quality', list(encodings['BsmtQual'].keys()))
exter_qual = st.selectbox('Exterior Quality', list(encodings['ExterQual'].keys()))

if st.button('Predict Price'):
    # Prepare the input data
    input_data = {
        'OverallQual': overall_qual,
        'TotalLivingArea': total_living_area,
        'GrLivArea': gr_liv_area,
        'GarageSize': garage_size,
        'GarageCars': garage_cars,
        'TotalBsmtSF': total_bsmt_sf,
        'GarageArea': garage_area,
        '1stFlrSF': first_flr_sf,
        'TotalBathroom': total_bathroom,
        'FullBath': full_bath,
        'TotRmsAbvGrd': tot_rms_abv_grd,
        'GarageYrBlt': garage_yr_blt,
        'Fireplaces': fireplaces,
        'MasVnrArea': mas_vnr_area,
        'LotArea': lot_area,
        'HeatingQC': encodings['HeatingQC'][heating_qc],
        'GarageType': encodings['GarageType'][garage_type],
        'FireplaceQu': encodings['FireplaceQu'][fireplace_qu],
        'YearsSinceRemodel': years_since_remodel,
        'HouseAge': house_age,
        'GarageFinish': encodings['GarageFinish'][garage_finish],
        'KitchenQual': encodings['KitchenQual'][kitchen_qual],
        'BsmtQual': encodings['BsmtQual'][bsmt_qual],
        'ExterQual': encodings['ExterQual'][exter_qual]
    }

    # Send a POST request to the Flask API
    response = requests.post('http://localhost:5000/predict', json=input_data)

    if response.status_code == 200:
        prediction = response.json()['prediction']
        st.success(f'Predicted House Price: ${prediction:,.2f}')
    else:
        st.error('An error occurred while making the prediction.')
```

# USER INTERFACE OF THE APPLICATION




*First we run our Flask app in a terminal. Then we run the Streamlit app in another terminal*

# USER INTERFACE OF THE APPLICATION




After running both the apps, we will be able to see  the application in our browser which will be able to take inputs provide the predicted price based on out Gradient Boosting model.

# CONCLUSION

This project has enabled us to experiment and build a robust data product. We started from the scratch and went through the steps of data exploration, analysis, feature enginnering, feature selection, hyperparameter tuning, modelling and deployment. Each in step we have learnt new things and we have tried to push oursdelves to reach out to better results. We hope to continue to learn more and make better AI products in the future.

# APPENDIX

## Github Repository

https://www.github.com/farsim-hossain/house_price_prediction_ames_iowa.git

## Dataset

https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data