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Introduction

An accurate prediction on the house price is important to prospective homeowners, developers, investors, appraisers, tax assessors and other real estate market participants, such as, mortgage lenders and insurers.

Dataset

Dataset consists of historical house prices of residential homes in Ames, Iowa, with a total of 81 exploratory features and 1460 observations. The dataset is extracted from Kaggle website.

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

The data set contains every minute detail of the house. Some of the major features in this data set are:

1. Lot Area
2. Neighborhood
3. House Style
4. Quality of the house
5. Overall condition of the house
6. Year built
7. Year remodeled
8. Foundation
9. Basement Condition
10. Total basement square feet
11. 1st floor square feet
12. 2nd floor square feet
13. Above ground living area in square feet
14. Full bathrooms above ground
15. Bedrooms above grade
16. Total rooms above grade
17. Garage size in square feet
18. Garage quality

However, it is good idea to explore the data set from Kaggle to get good idea on the data.

Data Wrangling

Data Wrangling is an extremely important step for any data analysis. It is very crucial for data to be organized. This process typically includes manually converting/mapping data from one raw form into another format to allow for more convenient consumption and organization of the data.

Data Cleaning steps carried out in this project are:

1. Handling missing data
2. Handling inconsistent data in a few variables

House Prices data set information:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
Id               1460 non-null int64
MSSubClass       1460 non-null int64
MSZoning         1460 non-null object
LotFrontage      1201 non-null float64
LotArea          1460 non-null int64
Street           1460 non-null object
Alley            91 non-null object
LotShape         1460 non-null object
LandContour      1460 non-null object
Utilities        1460 non-null object
LotConfig        1460 non-null object
LandSlope        1460 non-null object
Neighborhood     1460 non-null object
Condition1       1460 non-null object
Condition2       1460 non-null object
BldgType         1460 non-null object
HouseStyle       1460 non-null object
OverallQual      1460 non-null int64
OverallCond      1460 non-null int64
YearBuilt        1460 non-null int64
YearRemodAdd     1460 non-null int64
RoofStyle        1460 non-null object
RoofMatl         1460 non-null object
Exterior1st      1460 non-null object
Exterior2nd      1460 non-null object
MasVnrType       1452 non-null object
MasVnrArea       1452 non-null float64
ExterQual        1460 non-null object
ExterCond        1460 non-null object
Foundation       1460 non-null object
BsmtQual         1423 non-null object
BsmtCond         1423 non-null object
BsmtExposure     1422 non-null object
BsmtFinType1     1423 non-null object
BsmtFinSF1       1460 non-null int64
BsmtFinType2     1422 non-null object
BsmtFinSF2       1460 non-null int64
BsmtUnfSF        1460 non-null int64
TotalBsmtSF      1460 non-null int64
Heating          1460 non-null object
HeatingQC        1460 non-null object
CentralAir       1460 non-null object
Electrical       1459 non-null object
1stFlrSF         1460 non-null int64
2ndFlrSF         1460 non-null int64
LowQualFinSF     1460 non-null int64
GrLivArea        1460 non-null int64
BsmtFullBath     1460 non-null int64
BsmtHalfBath     1460 non-null int64
```

```
FullBath         1460 non-null int64
HalfBath         1460 non-null int64
BedroomAbvGr     1460 non-null int64
KitchenAbvGr     1460 non-null int64
KitchenQual      1460 non-null object
TotRmsAbvGrd     1460 non-null int64
Functional       1460 non-null object
Fireplaces       1460 non-null int64
FireplaceQu      770 non-null object
GarageType       1379 non-null object
GarageYrBlt      1379 non-null float64
GarageFinish     1379 non-null object
GarageCars       1460 non-null int64
GarageArea       1460 non-null int64
GarageQual       1379 non-null object
GarageCond       1379 non-null object
PavedDrive       1460 non-null object
WoodDeckSF       1460 non-null int64
OpenPorchSF      1460 non-null int64
EnclosedPorch    1460 non-null int64
3SsnPorch        1460 non-null int64
ScreenPorch      1460 non-null int64
PoolArea         1460 non-null int64
PoolQC           7 non-null object
Fence            281 non-null object
MiscFeature      54 non-null object
MiscVal          1460 non-null int64
MoSold           1460 non-null int64
YrSold           1460 non-null int64
SaleType         1460 non-null object
SaleCondition    1460 non-null object
SalePrice        1460 non-null int64
dtypes: float64(3), int64(35), object(43)
```

The output above is produced from **info()** function. There are a few categorical and numerical variables with missing values.

1. **Handling Missing Data:**
    - **Categorical Data:** The categorical variables with missing values are ‘MasVnrType’ and ‘Electrical’. Python provides many methods like fillna, forward/ backward filling, dropna etc. for handling missing data. I introduced another category called ‘**missing**’ to all the null values. This way I am retaining the original information of the data and not guessing anything.
    - **Numerical Data:** The most popular method to handle missing numerical data is **Mean Imputation**. I applied the same on my numerical data. Mean imputation is a method in which the missing value on a certain variable is replaced by the mean of the available cases. This is a reliable method for handling missing numerical data.

2. Handling inconsistent data:

There are a few null values in the data set which are not actually nulls but are entered wrongly as nulls. Referring to the actual data set description file (data_description.txt) from Kaggle, a few values were coded as ‘NA’ if a feature was not present in the house, but these NA values were entered as Nan in the .csv file. I decoded these misinterpreted values as ‘No feature_name’ (feature_name being name of the feature not present in the house).