House Prices : Data cleaning, visualization and modeling

In [1]:

```
# Import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from lightgbm import LGBMRegressor
from xgboost import XGBRegressor
import sklearn.metrics as metrics
import math
```

Importing **train** and **test** datasets

In [2]:

```
sample_submission = pd.read_csv("../input/house-prices-advanced-regression-techniques/sample_submiss
test = pd.read_csv("../input/house-prices-advanced-regression-techniques/test.csv")
train = pd.read_csv("../input/house-prices-advanced-regression-techniques/train.csv")
#Creating a copy of the train and test datasets
c_test  = test.copy()
c_train  = train.copy()
```

- Getting information about train dataset

In [3]:

```
c_train.head()
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	/
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	/
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	/
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	/
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	/

5 rows × 81 columns

- Getting information about test dataset

In [4]:

```
c_test.head()
```

Out[4]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS

5 rows × 80 columns

1. We have 81 columns. 2. Our target variable is SalePrice. 3. Id is just an index that we can drop but we will need it in the final submission.

1. We have many missing values

* * * * we have 79 features in our dataset.

- Concat Train and Test datasets

In [5]:

```
c_train['train']  = 1
c_test['train']  = 0
df = pd.concat([c_train, c_test], axis=0,sort=False)
```

Data preprocessing

- Calculating the percentage of missing values of each feature

In [6]:

```
#Percentage of NAN Values
NAN = [(c, df[c].isna().mean()*100) for c in df]
NAN = pd.DataFrame(NAN, columns=["column_name", "percentage"])
```

- Features with more than 50% of missing values.

In [7]:

```
NAN = NAN[NAN.percentage > 50]
NAN.sort_values("percentage", ascending=False)
```

Out[7]:

	column_name	percentage
72	PoolQC	99.657417
74	MiscFeature	96.402878
6	Alley	93.216855
73	Fence	80.438506

- We can drop PoolQC, MiscFeature, Alley and Fence features because they have more than 80% of missing values.

In [8]:

```
#Drop PoolQC, MiscFeature, Alley and Fence features
df = df.drop(['Alley','PoolQC','Fence','MiscFeature'],axis=1)
```

- Now we will select numerical and categorical features

In [9]:

```
object_columns_df = df.select_dtypes(include=['object'])
numerical_columns_df =df.select_dtypes(exclude=['object'])
```

- **Categorical Features** :

In [10]:

```
object_columns_df.dtypes
```

Out[10]:

```
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
dtype: object
```

- **Numerical Features** :

In [11]:

```
numerical_columns_df.dtypes
```

Out[11]:

```
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
train             int64
dtype: object
```

- Deeling with **categorical** feature

In [12]:

```
#Number of null values in each feature
null_counts = object_columns_df.isnull().sum()
print("Number of null values in each column:\n{}".format(null_counts))
```

```
Number of null values in each column:
MSZoning            4
Street              0
LotShape            0
LandContour         0
Utilities           2
LotConfig           0
LandSlope           0
Neighborhood        0
Condition1          0
Condition2          0
BldgType            0
HouseStyle          0
RoofStyle           0
RoofMatl            0
Exterior1st         1
Exterior2nd         1
MasVnrType         24
ExterQual           0
ExterCond           0
Foundation          0
BsmtQual           81
BsmtCond           82
BsmtExposure       82
BsmtFinType1       79
BsmtFinType2       80
Heating             0
HeatingQC           0
CentralAir          0
Electrical          1
KitchenQual         1
Functional          2
FireplaceQu      1420
GarageType        157
GarageFinish      159
GarageQual        159
GarageCond        159
PavedDrive          0
SaleType            1
SaleCondition       0
dtype: int64
```

- We will fill -- **BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, GarageType, GarageFinish, GarageQual, FireplaceQu, GarageCond** -- with "None" (Take a look in the data description).
- We will fill the rest of features with th most frequent value (using its own most frequent value).

In [13]:

```
columns_None = ['BsmtQual','BsmtCond','BsmtExposure','BsmtFinType1','BsmtFinType2','GarageType','Gar
object_columns_df[columns_None]= object_columns_df[columns_None].fillna('None')
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/frame.py:3509: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  self[k1] = value[k2]
```

In [14]:

```
columns_with_lowNA = ['MSZoning','Utilities','Exterior1st','Exterior2nd','MasVnrType','Electrical','
#fill missing values for each column (using its own most frequent value)
object_columns_df[columns_with_lowNA] = object_columns_df[columns_with_lowNA].fillna(object_columns_
```

- Now we have a clean categorical features
- In the next step we will deal with the **numerical** features black

In [15]:

```
#Number of null values in each feature
null_counts = numerical_columns_df.isnull().sum()
print("Number of null values in each column:\n{}".format(null_counts))
```

```
Number of null values in each column:
Id                  0
MSSubClass          0
LotFrontage       486
LotArea             0
OverallQual         0
OverallCond         0
YearBuilt           0
YearRemodAdd        0
MasVnrArea         23
BsmtFinSF1          1
BsmtFinSF2          1
BsmtUnfSF           1
TotalBsmtSF         1
1stFlrSF            0
2ndFlrSF            0
LowQualFinSF        0
GrLivArea           0
BsmtFullBath        2
BsmtHalfBath        2
FullBath            0
HalfBath            0
BedroomAbvGr        0
KitchenAbvGr        0
TotRmsAbvGrd        0
Fireplaces          0
GarageYrBlt       159
GarageCars          1
GarageArea          1
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
MiscVal             0
MoSold              0
YrSold              0
SalePrice        1459
train               0
dtype: int64
```

1. Fill GarageYrBlt and LotFrontage
2. Fill the rest of columns with 0

In [16]:

```
print((numerical_columns_df['YrSold']-numerical_columns_df['YearBuilt']).median())
print(numerical_columns_df["LotFrontage"].median())
```

```
35.0
68.0
```

So we will fill the year with 1979 and the Lot frontage with 68

In [17]:

```
numerical_columns_df['GarageYrBlt'] = numerical_columns_df['GarageYrBlt'].fillna(numerical_columns_d
numerical_columns_df['LotFrontage'] = numerical_columns_df['LotFrontage'].fillna(68)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  """Entry point for launching an IPython kernel.
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
```

Fill the rest of columns with 0

In [18]:

```
numerical_columns_df= numerical_columns_df.fillna(0)
```

- We finally end up with a clean dataset

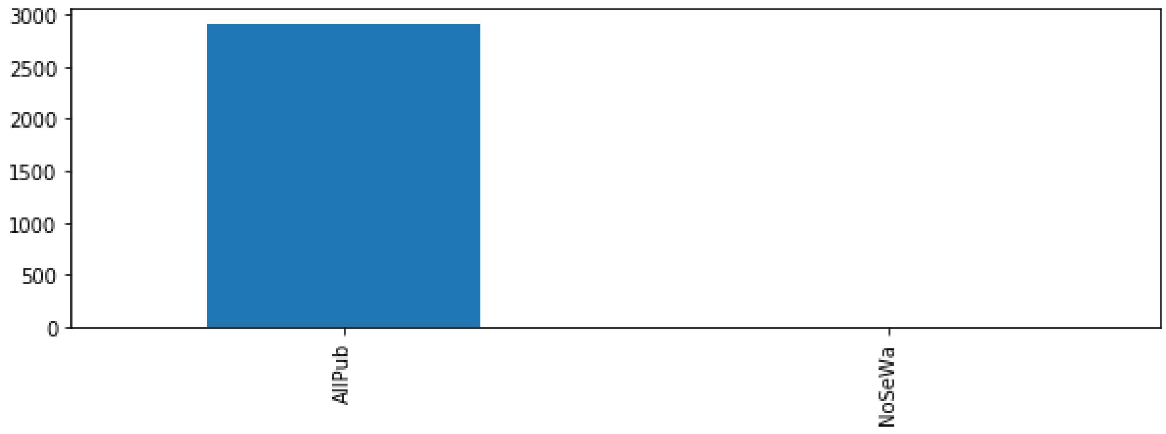
- After making some plots we found that we have some colums with low variance so we decide to delete them

In [19]:

```
object_columns_df['Utilities'].value_counts().plot(kind='bar',figsize=[10,3])
object_columns_df['Utilities'].value_counts()
```

Out[19]:

```
AllPub    2918
NoSeWa       1
Name: Utilities, dtype: int64
```

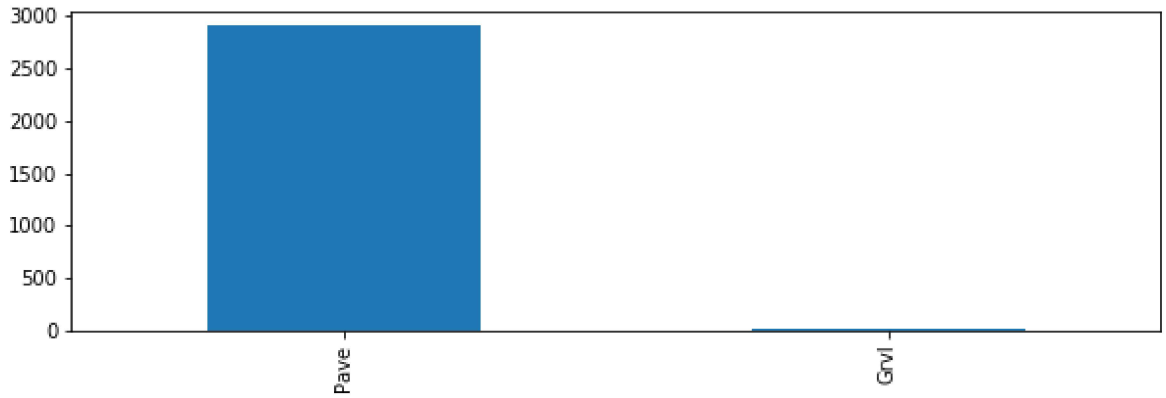


In [20]:

```
object_columns_df['Street'].value_counts().plot(kind='bar',figsize=[10,3])
object_columns_df['Street'].value_counts()
```

Out[20]:

```
Pave    2907
Grvl      12
Name: Street, dtype: int64
```

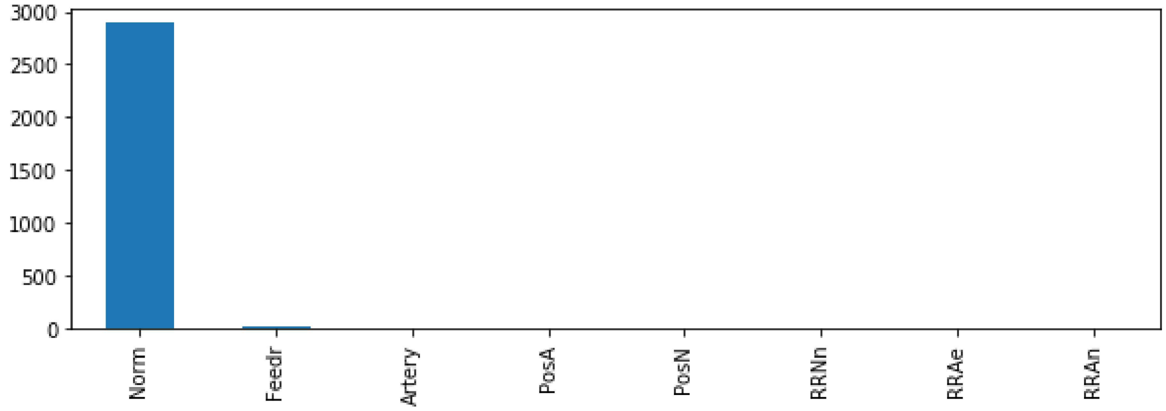


In [21]:

```
object_columns_df['Condition2'].value_counts().plot(kind='bar',figsize=[10,3])
object_columns_df['Condition2'].value_counts()
```

Out[21]:

```
Norm      2889
Feedr       13
Artery       5
PosA         4
PosN         4
RRNn         2
RRAe         1
RRAn         1
Name: Condition2, dtype: int64
```

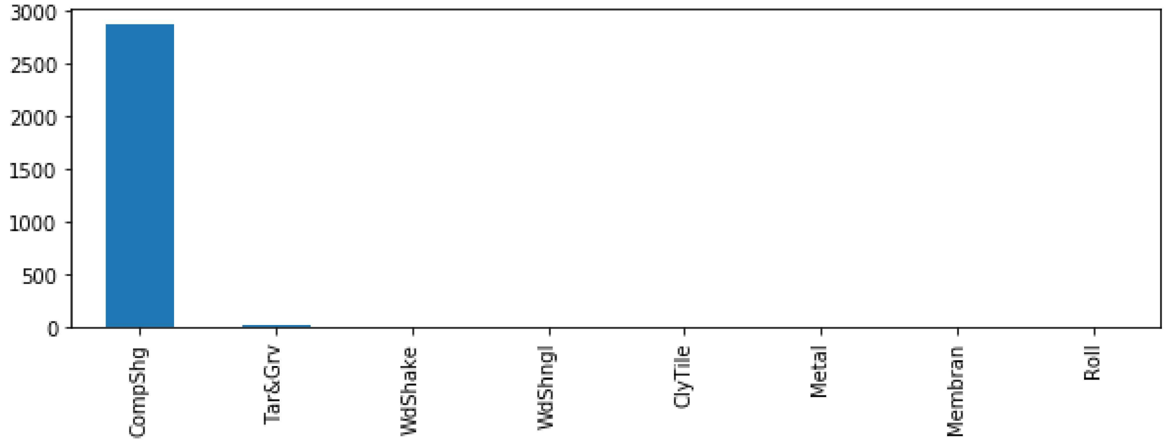


In [22]:

```
object_columns_df['RoofMatl'].value_counts().plot(kind='bar',figsize=[10,3])
object_columns_df['RoofMatl'].value_counts()
```

Out[22]:

```
CompShg    2876
Tar&Grv      23
WdShake       9
WdShngl       7
ClyTile       1
Metal         1
Membran       1
Roll          1
Name: RoofMatl, dtype: int64
```

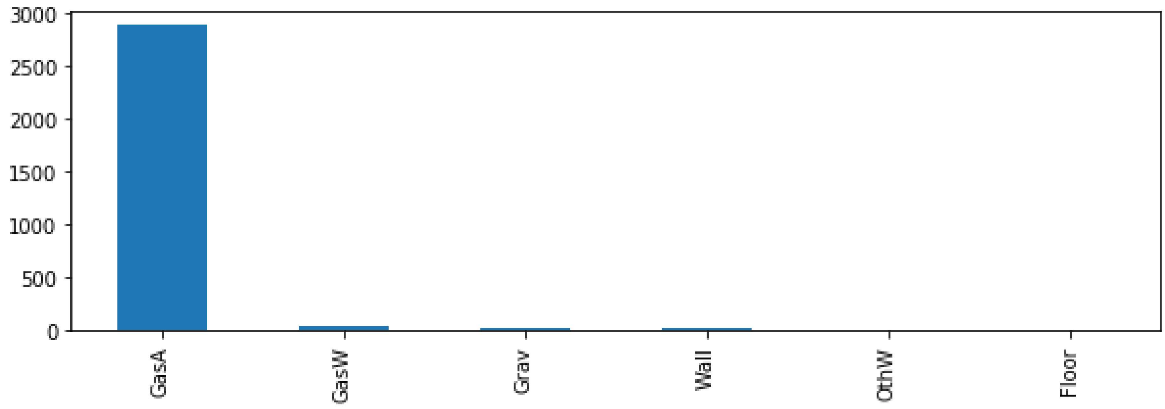


In [23]:

```
object_columns_df['Heating'].value_counts().plot(kind='bar',figsize=[10,3])
object_columns_df['Heating'].value_counts() #======> Drop feature one Type
```

Out[23]:

```
GasA    2874
GasW      27
Grav       9
Wall       6
OthW       2
Floor      1
Name: Heating, dtype: int64
```



In [24]:

```
object_columns_df = object_columns_df.drop(['Heating','RoofMatl','Condition2','Street','Utilities'],
```

- **Now we will create some new features**

In [25]:

```
numerical_columns_df['Age_House']= (numerical_columns_df['YrSold']-numerical_columns_df['YearBuilt']
numerical_columns_df['Age_House'].describe()
```

Out[25]:

```
count    2919.000000
mean       36.479959
std        30.336182
min        -1.000000
25%         7.000000
50%        35.000000
75%        54.500000
max       136.000000
Name: Age_House, dtype: float64
```

In [26]:

```
Negatif = numerical_columns_df[numerical_columns_df['Age_House'] < 0]
Negatif
```

Out[26]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemo
1089	2550	20	128.0	39290	10	5	2008	

1 rows × 40 columns

- Like we see here tha the minimun is -1 ???
- It is strange to find that the house was sold in 2007 before the YearRemodAdd 2009.

  So we decide to change the year of sold to 2009

In [27]:

```
numerical_columns_df.loc[numerical_columns_df['YrSold'] < numerical_columns_df['YearBuilt'],'YrSold'
numerical_columns_df['Age_House']= (numerical_columns_df['YrSold']-numerical_columns_df['YearBuilt']
numerical_columns_df['Age_House'].describe()
```

Out[27]:

```
count    2919.000000
mean       36.480644
std        30.335358
min         0.000000
25%         7.000000
50%        35.000000
75%        54.500000
max       136.000000
Name: Age_House, dtype: float64
```

* TotalBsmtBath : Sum of : BsmtFullBath and 1/2 BsmtHalfBath

- TotalBath : Sum of : FullBath and 1/2 HalfBath
- TotalSA : Sum of : 1stFlrSF and 2ndFlrSF and basement area

In [28]:

```
numerical_columns_df['TotalBsmtBath'] = numerical_columns_df['BsmtFullBath'] + numerical_columns_df[
numerical_columns_df['TotalBath'] = numerical_columns_df['FullBath'] + numerical_columns_df['HalfBat
numerical_columns_df['TotalSA']=numerical_columns_df['TotalBsmtSF'] + numerical_columns_df['1stFlrSF
```

In [29]:

```
numerical_columns_df.head()
```

Out[29]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd
0	1	60	65.0	8450	7	5	2003	2003
1	2	20	80.0	9600	6	8	1976	1976
2	3	60	68.0	11250	7	5	2001	2002
3	4	70	60.0	9550	7	5	1915	1970
4	5	60	84.0	14260	8	5	2000	2000

5 rows × 43 columns

- Now the next step is to encode categorical features

- **Ordinal categories features** - Mapping from 0 to N

In [30]:

```
bin_map  = {'TA':2,'Gd':3, 'Fa':1,'Ex':4,'Po':1,'None':0,'Y':1,'N':0,'Reg':3,'IR1':2,'IR2':1,'IR3':0
           "No" : 2, "Mn" : 2, "Av": 3,"Gd" : 4,"Unf" : 1, "LwQ": 2, "Rec" : 3,"BLQ" : 4, "ALQ" : 5
           }
object_columns_df['ExterQual'] = object_columns_df['ExterQual'].map(bin_map)
object_columns_df['ExterCond'] = object_columns_df['ExterCond'].map(bin_map)
object_columns_df['BsmtCond'] = object_columns_df['BsmtCond'].map(bin_map)
object_columns_df['BsmtQual'] = object_columns_df['BsmtQual'].map(bin_map)
object_columns_df['HeatingQC'] = object_columns_df['HeatingQC'].map(bin_map)
object_columns_df['KitchenQual'] = object_columns_df['KitchenQual'].map(bin_map)
object_columns_df['FireplaceQu'] = object_columns_df['FireplaceQu'].map(bin_map)
object_columns_df['GarageQual'] = object_columns_df['GarageQual'].map(bin_map)
object_columns_df['GarageCond'] = object_columns_df['GarageCond'].map(bin_map)
object_columns_df['CentralAir'] = object_columns_df['CentralAir'].map(bin_map)
object_columns_df['LotShape'] = object_columns_df['LotShape'].map(bin_map)
object_columns_df['BsmtExposure'] = object_columns_df['BsmtExposure'].map(bin_map)
object_columns_df['BsmtFinType1'] = object_columns_df['BsmtFinType1'].map(bin_map)
object_columns_df['BsmtFinType2'] = object_columns_df['BsmtFinType2'].map(bin_map)

PavedDrive =   {"N" : 0, "P" : 1, "Y" : 2}
object_columns_df['PavedDrive'] = object_columns_df['PavedDrive'].map(PavedDrive)
```

- Will we use One hot encoder to encode the rest of categorical features

In [31]:

```
#Select categorical features
rest_object_columns = object_columns_df.select_dtypes(include=['object'])
#Using One hot encoder
object_columns_df = pd.get_dummies(object_columns_df, columns=rest_object_columns.columns)
```

In [32]:

```
object_columns_df.head()
```

Out[32]:

	LotShape	ExterQual	ExterCond	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	Bsmt
0	3	4	2	4	2	2	6	
1	3	2	2	4	2	4	5	
2	2	4	2	4	2	2	6	
3	2	2	2	2	4	2	5	
4	2	4	2	4	2	3	6	

5 rows × 164 columns

- Concat Categorical (after encoding) and numerical features

In [33]:

```
df_final = pd.concat([object_columns_df, numerical_columns_df], axis=1,sort=False)
df_final.head()
```

Out[33]:

	LotShape	ExterQual	ExterCond	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	Bsmt
0	3	4	2	4	2	2	6	
1	3	2	2	4	2	4	5	
2	2	4	2	4	2	2	6	
3	2	2	2	2	4	2	5	
4	2	4	2	4	2	3	6	

5 rows × 207 columns

In [34]:

```
df_final = df_final.drop(['Id',],axis=1)

df_train = df_final[df_final['train'] == 1]
df_train = df_train.drop(['train',],axis=1)


df_test = df_final[df_final['train'] == 0]
df_test = df_test.drop(['SalePrice'],axis=1)
df_test = df_test.drop(['train',],axis=1)
```

- Separate Train and Targets

In [35]:

```
target= df_train['SalePrice']
df_train = df_train.drop(['SalePrice'],axis=1)
```

Modeling

In [36]:

```
x_train,x_test,y_train,y_test = train_test_split(df_train,target,test_size=0.33,random_state=0)
```

In [37]:

```
xgb =XGBRegressor( booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.6, gamma=0,
             importance_type='gain', learning_rate=0.01, max_delta_step=0,
             max_depth=4, min_child_weight=1.5, n_estimators=2400,
             n_jobs=1, nthread=None, objective='reg:linear',
             reg_alpha=0.6, reg_lambda=0.6, scale_pos_weight=1,
             silent=None, subsample=0.8, verbosity=1)


lgbm = LGBMRegressor(objective='regression',
                                       num_leaves=4,
                                       learning_rate=0.01,
                                       n_estimators=12000,
                                       max_bin=200,
                                       bagging_fraction=0.75,
                                       bagging_freq=5,
                                       bagging_seed=7,
                                       feature_fraction=0.4,
                                       )
```

In [38]:

```
#Fitting
xgb.fit(x_train, y_train)
lgbm.fit(x_train, y_train,eval_metric='rmse')
```

```
/opt/conda/lib/python3.6/site-packages/xgboost/core.py:587: FutureWarning: Series.ba
se is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \

[22:45:26] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is no
w deprecated in favor of reg:squarederror.
```

Out[38]:

```
LGBMRegressor(bagging_fraction=0.75, bagging_freq=5, bagging_seed=7,
              boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              feature_fraction=0.4, importance_type='split', learning_rate=0.01,
              max_bin=200, max_depth=-1, min_child_samples=20,
              min_child_weight=0.001, min_split_gain=0.0, n_estimators=12000,
              n_jobs=-1, num_leaves=4, objective='regression',
              random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

In [39]:

```
predict1 = xgb.predict(x_test)
predict = lgbm.predict(x_test)
```

In [40]:

```
print('Root Mean Square Error test = ' + str(math.sqrt(metrics.mean_squared_error(y_test, predict1))
print('Root Mean Square Error test = ' + str(math.sqrt(metrics.mean_squared_error(y_test, predict)))
```

```
Root Mean Square Error test = 26089.30803984919
Root Mean Square Error test = 26726.198278903514
```

- Fitting With all the dataset

In [41]:

```
xgb.fit(df_train, target)
lgbm.fit(df_train, target,eval_metric='rmse')
```

```
[22:45:47] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is no
w deprecated in favor of reg:squarederror.
```

```
/opt/conda/lib/python3.6/site-packages/xgboost/core.py:587: FutureWarning: Series.ba
se is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
/opt/conda/lib/python3.6/site-packages/xgboost/core.py:588: FutureWarning: Series.ba
se is deprecated and will be removed in a future version
  data.base is not None and isinstance(data, np.ndarray) \
```

Out[41]:

```
LGBMRegressor(bagging_fraction=0.75, bagging_freq=5, bagging_seed=7,
              boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              feature_fraction=0.4, importance_type='split', learning_rate=0.01,
              max_bin=200, max_depth=-1, min_child_samples=20,
              min_child_weight=0.001, min_split_gain=0.0, n_estimators=12000,
              n_jobs=-1, num_leaves=4, objective='regression',
              random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

In [42]:

```
predict4 = lgbm.predict(df_test)
predict3 = xgb.predict(df_test)
predict_y = ( predict3*0.45 + predict4 * 0.55)
```

In [43]:

```
submission = pd.DataFrame({
        "Id": test["Id"],
        "SalePrice": predict_y
    })
submission.to_csv('submission.csv', index=False)
```