Project: House Prices - Advanced Regression Techniques on Kaggle

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Load Packages

In [1]:
```
#basic libs
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
import time
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Model selection
from sklearn.model_selection import StratifiedKFold
```

In [2]:
```
# all the regressors
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import SGDRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import GradientBoostingRegressor
from catboost import CatBoostRegressor
import lightgbm as lgb

import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.graphics.gofplots import ProbPlot
```

In [3]:
```
### data transformation & parameters tuning
#validation & tuning
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

#Stacking
from vecstack import stacking
from mlxtend.regressor import StackingCVRegressor

# preprocessing
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings("ignore")

# Skopt functions
from skopt import BayesSearchCV
from skopt.callbacks import DeadlineStopper, VerboseCallback, DeltaXStopper
from skopt.space import Real, Categorical, Integer
```

Set Path

In [4]:
```
print(os.getcwd())
os.chdir('D:/OneDrive/ASU/2020 Fall/CIS 508/TeamAssignment')
print(os.getcwd())
```

```
C:\Users\Jinhang Jiang
D:\OneDrive\ASU\2020 Fall\CIS 508\TeamAssignment
```

Read Data and Overview

In [33]:
```
house = pd.read_csv('train.csv')
holdout = pd.read_csv('test.csv')
```

In [34]:
```
print(house.shape)
print(holdout.shape)
```

```
(1460, 81)
(1459, 80)
```

In [35]:
```
print(house.dtypes.astype(str).value_counts())
```

```
object     43
int64      35
float64     3
dtype: int64
```

In [36]:
```
house.head()
```

Out[36]:

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

5 rows × 81 columns

In [37]:
```
house.describe()
```

Out[37]:

MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	I
1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	
56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	1984.865753	
42.300571	24.284752	9981.264932	1.382997	1.112799	30.202904	20.645407	
20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	1950.000000	
20.000000	59.000000	7553.500000	5.000000	5.000000	1954.000000	1967.000000	
50.000000	69.000000	9478.500000	6.000000	5.000000	1973.000000	1994.000000	
70.000000	80.000000	11601.500000	7.000000	6.000000	2000.000000	2004.000000	
190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	2010.000000	

s

In [7]:
```
nullvalue=house.isnull().sum()
nullvalue.where((nullvalue/1460)>0.8).dropna().astype(int)
```

Out[7]:
```
Alley          1369
PoolQC         1453
Fence          1179
MiscFeature    1406
dtype: int32
```

In [8]:
```
nullvalue=holdout.isnull().sum()
nullvalue.where((nullvalue/1460)>0.8).dropna().astype(int)
```

Out[8]:
```
Alley          1352
PoolQC         1456
Fence          1169
MiscFeature    1408
dtype: int32
```

Transform the data

One-hot-encoding

In [47]:
```
combined_data = pd.concat([house, holdout], keys=[0,1])
```

In [48]:
```
# drop all the columns with missing values 80% or above
combined_data = combined_data.drop(["Alley","PoolQC","Fence","MiscFeature"],axis=1)
```

In [49]:
```
# standard scale only numeric variables
num_cols = combined_data.columns[combined_data.dtypes.apply(lambda c: np.issubdtype(c, np
num_cols
```

Out[49]:
```
Index(['1stFlrSF', '2ndFlrSF', '3SsnPorch', 'BedroomAbvGr', 'BsmtFinSF1',
       'BsmtFinSF2', 'BsmtFullBath', 'BsmtHalfBath', 'BsmtUnfSF',
       'EnclosedPorch', 'Fireplaces', 'FullBath', 'GarageArea', 'GarageCars',
       'GarageYrBlt', 'GrLivArea', 'HalfBath', 'Id', 'KitchenAbvGr', 'LotArea',
       'LotFrontage', 'LowQualFinSF', 'MSSubClass', 'MasVnrArea', 'MiscVal',
       'MoSold', 'OpenPorchSF', 'OverallCond', 'OverallQual', 'PoolArea',
       'SalePrice', 'ScreenPorch', 'TotRmsAbvGrd', 'TotalBsmtSF', 'WoodDeckSF',
       'YearBuilt', 'YearRemodAdd', 'YrSold'],
      dtype='object')
```

In [50]:
```
combined_data["AgeofHouse"]= combined_data["YrSold"] - combined_data["YearRemodAdd"]
print(combined_data[["AgeofHouse","YrSold","YearRemodAdd","SalePrice"]].head())
```

```
     AgeofHouse  YrSold  YearRemodAdd  SalePrice
0 0           5    2008          2003   208500.0
  1          31    2007          1976   181500.0
  2           6    2008          2002   223500.0
  3          36    2006          1970   140000.0
  4           8    2008          2000   250000.0
```

In [107]:
```
standard = StandardScaler()
combined_data[num_cols] = standard.fit_transform(combined_data[num_cols])
combined_data["SalePrice"]=house["SalePrice"]
```

In [51]:
```
combined_data = combined_data.drop(["YrSold","YearRemodAdd","YearBuilt"],axis=1)
```

In [52]:
```
td=pd.get_dummies(combined_data)
```

In [53]:
```
print(td.shape)
```

```
(2919, 275)
```

In [54]:
```
td["SalePrice"].head()
```

Out[54]:
```
0  0     208500.0
   1     181500.0
   2     223500.0
   3     140000.0
   4     250000.0
Name: SalePrice, dtype: float64
```

In [55]:
```
nullvalue=td.isnull().sum()
nullvalue.where(nullvalue>0).dropna().astype(int)
```

Out[55]:
```
BsmtFinSF1         1
BsmtFinSF2         1
BsmtFullBath       2
BsmtHalfBath       2
BsmtUnfSF          1
GarageArea         1
GarageCars         1
GarageYrBlt      159
LotFrontage      486
MasVnrArea        23
SalePrice       1459
TotalBsmtSF        1
dtype: int32
```

In [56]:
```
td = td.fillna(td.mean())
```

In [57]:
```
nullvalue=td.isnull().sum()
nullvalue.isna().any()
```

Out[57]:
```
False
```

In [58]:
```
# unpack the conbined data
train = td.xs(0)
test = td.xs(1).drop(['SalePrice'],axis=1)
```

In [59]:
```
train["SalePrice"]=np.log(house["SalePrice"])
train["SalePrice"]
```

Out[59]:
```
0       12.247694
1       12.109011
2       12.317167
3       11.849398
4       12.429216
          ...
1455    12.072541
1456    12.254863
1457    12.493130
1458    11.864462
1459    11.901583
Name: SalePrice, Length: 1460, dtype: float64
```

In [60]:
```
print(train.shape)
print(test.shape)
```

```
(1460, 275)
(1459, 274)
```

In [132]:
```
#train.to_csv('train_dummy1.csv',index=False)
#test.to_csv('test_dummy1.csv',index=False)
```

Plot Variables

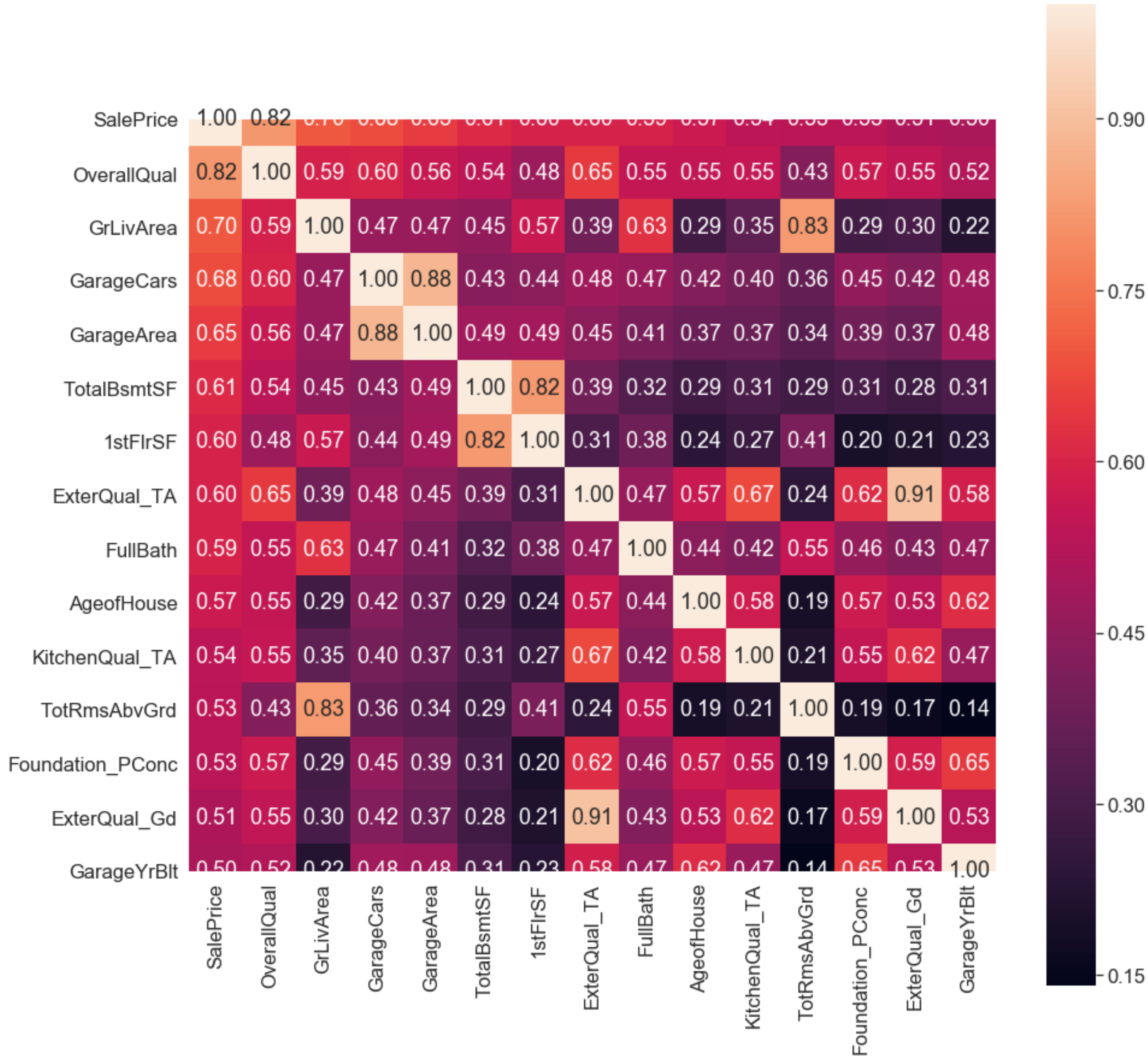
Top 10 correlated

In [133]:
```
correlation = np.abs(train.corr(method='pearson'))
columns = correlation.nlargest(15, 'SalePrice').sort_values(by=["SalePrice"],ascending=Fa

columns = columns["SalePrice"].index
columns
```

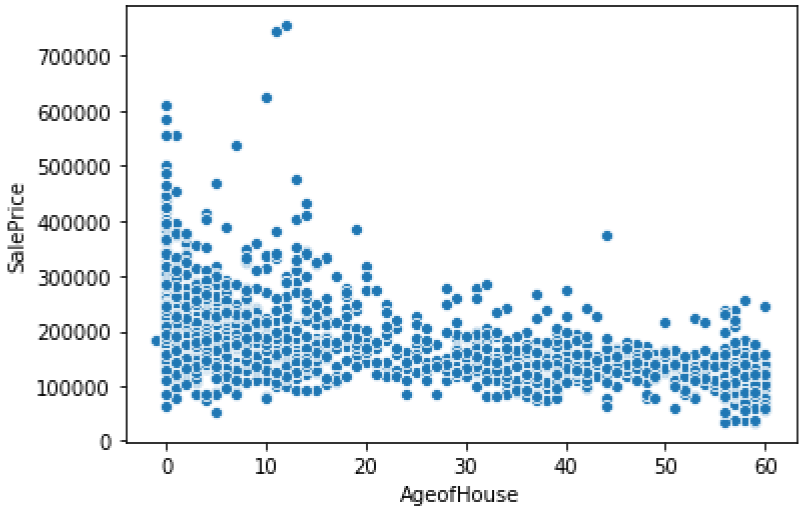
Out[133]:
```
Index(['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea',
       'TotalBsmtSF', '1stFlrSF', 'ExterQual_TA', 'FullBath', 'AgeofHouse',
       'KitchenQual_TA', 'TotRmsAbvGrd', 'Foundation_PConc', 'ExterQual_Gd',
       'GarageYrBlt'],
      dtype='object')
```

In [134]:
```
correlation_map = np.abs(np.corrcoef(train[columns].values.T))
sns.set(font_scale=1.5)
fig, ax = plt.subplots(figsize=(15,15))
heatmap = sns.heatmap(correlation_map,
                      cbar=True,
                      annot=True,
                      square=True,
                      fmt='.2f',
                      yticklabels=columns.values,
                      xticklabels=columns.values)
plt.show()
```



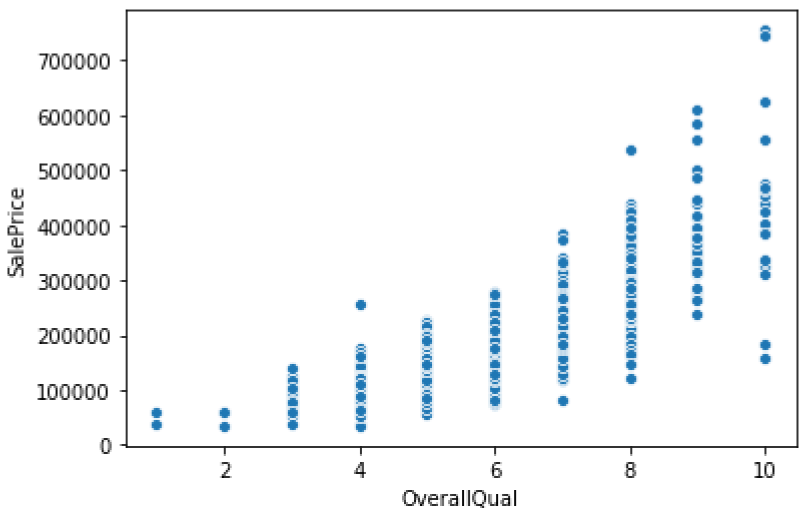
In [29]:
```
sns.scatterplot(train["AgeofHouse"],train["SalePrice"],ci=99)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x25df53e4208>



In [30]:
```
sns.scatterplot(train["OverallQual"],train["SalePrice"], ci=99)
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x25df5455388>



Fit models, Tuning, and Diagnosis check

Split data

In [285]:
```
#top 79 variable by correlation
#correlation = train.corr(method='pearson').abs()
#columns_80 = correlation.nlargest(80, 'SalePrice').index
columns_79=['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea',
       'TotalBsmtSF', '1stFlrSF', 'ExterQual_TA', 'FullBath', 'BsmtQual_Ex',
       'TotRmsAbvGrd', 'YearBuilt', 'KitchenQual_TA', 'AgeofHouse',
       'YearRemodAdd', 'KitchenQual_Ex', 'Foundation_PConc', 'MasVnrArea',
       'GarageYrBlt', 'Fireplaces', 'ExterQual_Gd', 'BsmtQual_TA',
       'ExterQual_Ex', 'BsmtFinType1_GLQ', 'HeatingQC_Ex', 'GarageFinish_Fin',
       'GarageFinish_Unf', 'Neighborhood_NridgHt', 'BsmtFinSF1',
       'MasVnrType_None', 'SaleType_New', 'GarageType_Detchd',
       'SaleCondition_Partial', 'Foundation_CBlock', 'FireplaceQu_Gd',
       'GarageType_Attchd', 'LotFrontage', 'MasVnrType_Stone',
       'Neighborhood_NoRidge', 'WoodDeckSF', 'KitchenQual_Gd', '2ndFlrSF',
       'OpenPorchSF', 'HeatingQC_TA', 'BsmtExposure_Gd', 'Exterior2nd_VinylSd',
       'Exterior1st_VinylSd', 'MSZoning_RM', 'HalfBath', 'GarageCond_TA',
       'LotShape_Reg', 'LotArea', 'BsmtExposure_No', 'FireplaceQu_Ex',
       'CentralAir_Y', 'CentralAir_N', 'GarageQual_TA', 'MSZoning_RL',
       'HouseStyle_2Story', 'SaleType_WD', 'Electrical_SBrkr', 'RoofStyle_Hip',
       'GarageType_BuiltIn', 'BsmtQual_Gd', 'PavedDrive_Y', 'BsmtFullBath',
       'RoofStyle_Gable', 'LotShape_IR1', 'Neighborhood_StoneBr', 'BsmtUnfSF',
       'PavedDrive_N', 'Foundation_BrkTil', 'MasVnrType_BrkFace',
       'Electrical_FuseA', 'Neighborhood_OldTown', 'Neighborhood_NAmes',
       'Neighborhood_Edwards', 'GarageFinish_RFn', 'RoofMatl_WdShngl',
       'BedroomAbvGr']
```

In [286]:
```
#label = train["SalePrice"]
#data = train[columns_79].fillna(house.mean())
```

In [365]:
```
#train=pd.read_csv('train_dummy.csv')
#test=pd.read_csv('test_dummy.csv')
```

In [63]:
```
label = train["SalePrice"]
data = train.drop(["Id","SalePrice"],axis=1).fillna(train.mean())
```

In [73]:
```
data
```

Out[73]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	Bs
0	856	854	0	3	706.0	0.0	1.0	
1	1262	0	0	3	978.0	0.0	0.0	
2	920	866	0	3	486.0	0.0	1.0	
3	961	756	0	3	216.0	0.0	1.0	
4	1145	1053	0	4	655.0	0.0	1.0	
...	...	...	...	...	...	...	...	
1455	953	694	0	3	0.0	0.0	0.0	
1456	2073	0	0	3	790.0	163.0	1.0	
1457	1188	1152	0	4	275.0	0.0	0.0	
1458	1078	0	0	2	49.0	1029.0	1.0	
1459	1256	0	0	3	830.0	290.0	1.0	

1460 rows × 273 columns

In [65]:
```
X_train, X_test, y_train, y_test = train_test_split (data, label,
                                                     test_size = 0.2,
                                                    random_state = 42)
```

In [42]:
```
X_train, y_train = data, label
```

statsmodels

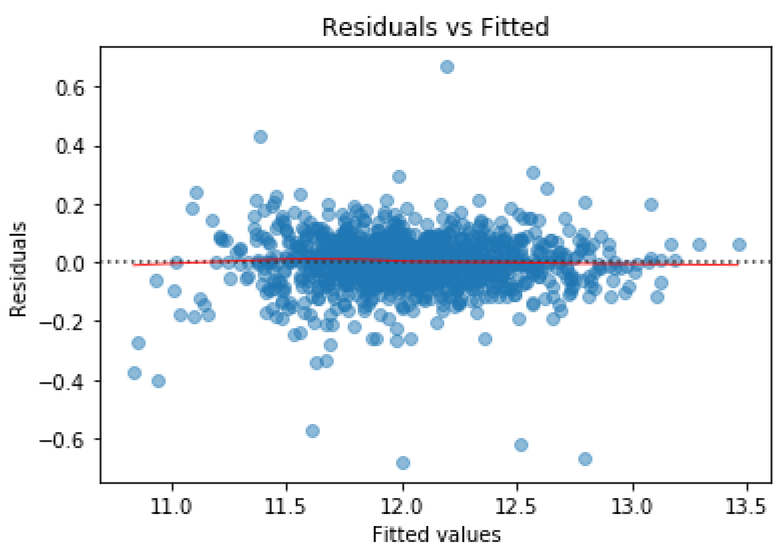
In [81]:
```
#original
# generate OLS model
sm_model = sm.OLS(y_train, sm.add_constant(X_train))
sm_model_fit = sm_model.fit()

# create dataframe from X, y for easier plot handling
dataframe = pd.concat([pd.DataFrame(X_train), pd.DataFrame(y_train)], axis=1)
```

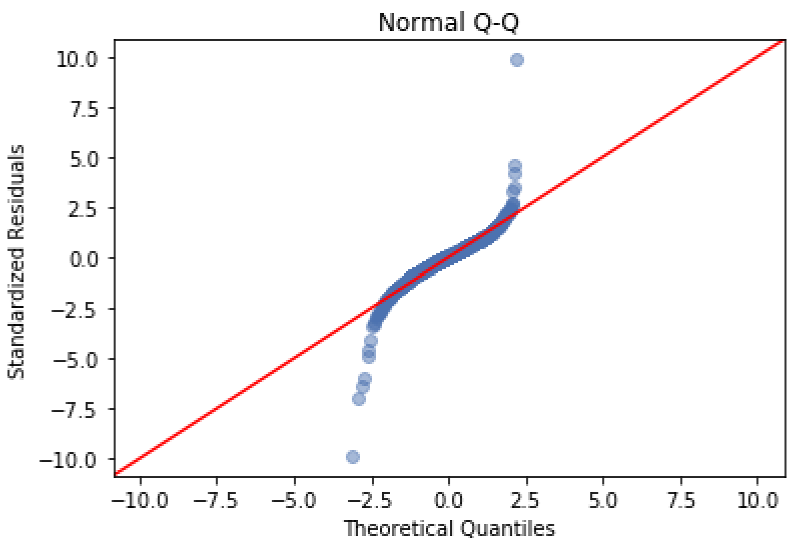
In [74]:
```
# model values
model_fitted_y = sm_model_fit.fittedvalues
# model residuals
model_residuals = sm_model_fit.resid
# normalized residuals
model_norm_residuals = sm_model_fit.get_influence().resid_studentized_internal
# absolute squared normalized residuals
model_norm_residuals_abs_sqrt = np.sqrt(np.abs(model_norm_residuals))
# absolute residuals
model_abs_resid = np.abs(model_residuals)
# leverage, from statsmodels internals
model_leverage = sm_model_fit.get_influence().hat_matrix_diag
# cook's distance, from statsmodels internals
model_cooks = sm_model_fit.get_influence().cooks_distance[0]

plot_lm_1 = plt.figure()
plot_lm_1.axes[0] = sns.residplot(model_fitted_y, dataframe.columns[-1], data=dataframe,
                          lowess=True,
                          scatter_kws={'alpha': 0.5},
                          line_kws={'color': 'red', 'lw': 1, 'alpha': 0.8})

plot_lm_1.axes[0].set_title('Residuals vs Fitted')
plot_lm_1.axes[0].set_xlabel('Fitted values')
plot_lm_1.axes[0].set_ylabel('Residuals');
```

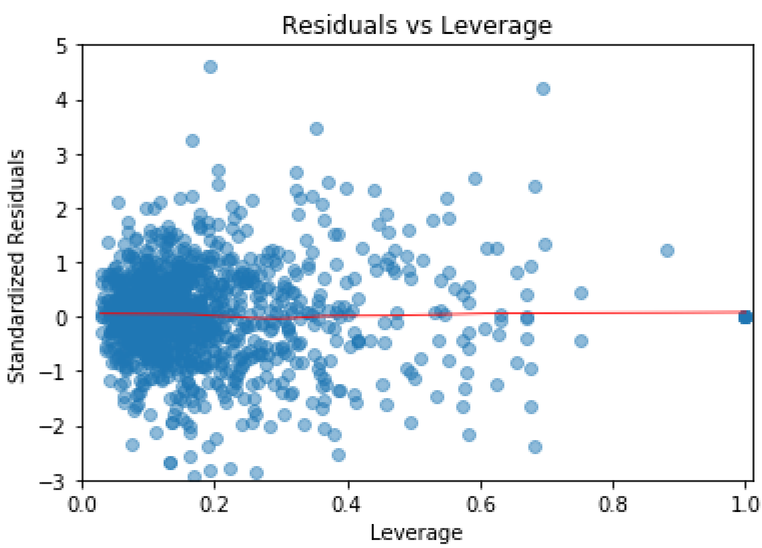


In [75]:
```
QQ = ProbPlot(model_norm_residuals)
plot_lm_2 = QQ.qqplot(line='45', alpha=0.5, color='#4C72B0', lw=1)
plot_lm_2.axes[0].set_title('Normal Q-Q')
plot_lm_2.axes[0].set_xlabel('Theoretical Quantiles')
plot_lm_2.axes[0].set_ylabel('Standardized Residuals');
# annotations
abs_norm_resid = np.flip(np.argsort(np.abs(model_norm_residuals)), 0)
abs_norm_resid_top_3 = abs_norm_resid[:3]
for r, i in enumerate(abs_norm_resid_top_3):
    plot_lm_2.axes[0].annotate(i,
                               xy=(np.flip(QQ.theoretical_quantiles, 0)[r],
                                   model_norm_residuals[i]));
```



In [76]:
```
plot_lm_4 = plt.figure();
plt.scatter(model_leverage, model_norm_residuals, alpha=0.5);
sns.regplot(model_leverage, model_norm_residuals,
            scatter=False,
            ci=False,
            lowess=True,
            line_kws={'color': 'red', 'lw': 1, 'alpha': 0.8});
plot_lm_4.axes[0].set_xlim(0, max(model_leverage)+0.01)
plot_lm_4.axes[0].set_ylim(-3, 5)
plot_lm_4.axes[0].set_title('Residuals vs Leverage')
plot_lm_4.axes[0].set_xlabel('Leverage')
plot_lm_4.axes[0].set_ylabel('Standardized Residuals');

# annotations
leverage_top_3 = np.flip(np.argsort(model_cooks), 0)[:3]
for i in leverage_top_3:
      plot_lm_4.axes[0].annotate(i,
                                 xy=(model_leverage[i],
                                     model_norm_residuals[i]));
```



In [77]:
```
print(sm_model_fit.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.928
Method:                 Least Squares   F-statistic:                     65.64
Date:                Sun, 25 Oct 2020   Prob (F-statistic):               0.00
Time:                        18:15:09   Log-Likelihood:                 1111.4
No. Observations:                1168   AIC:                            -1753.
Df Residuals:                     933   BIC:                            -563.1
Df Model:                         234
Covariance Type:            nonrobust
=====================================================================================
====
                            coef    std err          t      P>|t|      [0.025      0.
975]
-------------------------------------------------------------------------------------
----
const                     1.5082      0.095     15.820      0.000       1.321
1.695
```

In [88]:
```
sm_prediction=sm_model_fit.predict(sm.add_constant(test.drop(["Id"],axis=1)))
```

In [89]:
```
sm_prediction
```

Out[89]:
```
0       11.728774
1       11.991745
2       12.122877
3       12.195325
4       12.206700
          ...
1454    11.283007
1455    11.425600
1456    12.078040
1457    11.653754
1458    12.290807
Length: 1459, dtype: float64
```

In [90]:
```
sm_DATA = pd.DataFrame({"ID":holdout["Id"],"SalePrice":np.exp(sm_prediction)})
sm_DATA.head()
```

Out[90]:

	ID	SalePrice
0	1461	124091.476956
1	1462	161416.857428
2	1463	184034.226946
3	1464	197861.995501
4	1465	200125.507353

In [91]:
```
sm_DATA.to_csv("sm.csv",index=False)
```

XGBRegressor

In [91]:
```
xgb = XGBRegressor()
```

In [412]:
```
model = xgb.fit(X_train, y_train)
```

In [413]:
```
y_pred = model.predict(X_test)
```

In [415]:
```
print(mean_squared_error(y_test,y_pred))
```

```
0.024557546111597647
```

In [95]:
```
### Tuning
cv=KFold(n_splits = 5, random_state=2020)
```

In [147]:
```
xgb_param = { 'objective':['reg:linear'],
              'learning_rate': [0.01,.03, 0.05], #so called `eta` value
              'max_depth': [2,3,4,5],
              'min_child_weight': [2,4,6],
              'subsample': [0.7,0.8,0.3],
              'colsample_bytree': [0.7,0.3],
              'n_estimators': [1300,2000,3000]}
```

In [148]:
```
xgb_grid = GridSearchCV(xgb,
                        xgb_param,
                        cv = cv,
                        n_jobs = 5,
                        verbose=True)
```

In [149]:
```
xgb_grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 648 candidates, totalling 3240 fits

[Parallel(n_jobs=5)]: Using backend LokyBackend with 5 concurrent workers.
[Parallel(n_jobs=5)]: Done  40 tasks      | elapsed:  1.7min
[Parallel(n_jobs=5)]: Done 190 tasks      | elapsed:  8.6min
[Parallel(n_jobs=5)]: Done 440 tasks      | elapsed: 25.0min
[Parallel(n_jobs=5)]: Done 790 tasks      | elapsed: 46.7min
[Parallel(n_jobs=5)]: Done 1240 tasks      | elapsed: 76.7min
[Parallel(n_jobs=5)]: Done 1790 tasks      | elapsed: 113.8min
[Parallel(n_jobs=5)]: Done 2440 tasks      | elapsed: 150.1min
[Parallel(n_jobs=5)]: Done 3190 tasks      | elapsed: 192.6min
[Parallel(n_jobs=5)]: Done 3240 out of 3240 | elapsed: 196.4min finished

[22:18:55] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
[22:19:02] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
```

Out[149]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=XGBRegressor(base_score=None, booster=None,
                                    colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None, gamma=None,
                                    gpu_id=None, importance_type='gain',
                                    interaction_constraints=None,
                                    learning_rate=None, max_delta_step=None,
                                    max_depth=None, min_child_weight=None,
                                    missing=nan, mo...
                                    reg_alpha=None, reg_lambda=None,
                                    scale_pos_weight=None, subsample=None,
                                    tree_method=None, validate_parameters=None,
                                    verbosity=None),
             n_jobs=5,
             param_grid={'colsample_bytree': [0.7, 0.3],
                         'learning_rate': [0.01, 0.03, 0.05],
                         'max_depth': [2, 3, 4, 5],
                         'min_child_weight': [2, 4, 6],
                         'n_estimators': [1300, 2000, 3000],
                         'objective': ['reg:linear'],
                         'subsample': [0.7, 0.8, 0.3]},
             verbose=True)
```

In [150]:
```
print(xgb_grid.best_score_)
print(xgb_grid.best_params_)
```

```
0.9170237077670726
{'colsample_bytree': 0.7, 'learning_rate': 0.03, 'max_depth': 3, 'min_child_weight': 2,
'n_estimators': 1300, 'objective': 'reg:linear', 'subsample': 0.8}
```

In [151]:
```
xgb_best_params={'colsample_bytree': 0.7,
                 'learning_rate': 0.03,
                 'max_depth': 3,
                 'min_child_weight': 2,
                 'n_estimators': 1300,
#                 'nthread': 4,
                 'objective': 'reg:linear',
#                 'silent': 1,
                 'subsample': 0.8}
```

In [152]:
```
xgb_best_model = XGBRegressor(**xgb_best_params,tree_method='gpu_hist')
```

In [153]:
```
xgb_best_model.fit(X_train,y_train,
#                   eval_set=[(X_train, y_train), (X_test, y_test)],
                   eval_metric='rmse',
                   verbose=True
                  )
```

```
[22:28:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
[22:28:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
```

Out[153]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.7, gamma=0, gpu_id=0,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.03, max_delta_step=0, max_depth=3,
             min_child_weight=2, missing=nan,
             monotone_constraints='(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,...,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0)',
             n_estimators=1300, n_jobs=0, num_parallel_tree=1,
             objective='reg:linear', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, subsample=0.8, tree_method='gpu_hist',
             validate_parameters=1, verbosity=None)
```

In [521]:
```
xgb_pred=xgb_best_model.predict(X_test)


print(mean_squared_error(y_test,xgb_pred))
```

```
0.017949099914394914
```

In [154]:
```
xgb_prediction = xgb_best_model.predict(test)
xgb_DATA = pd.DataFrame({"ID":holdout["Id"],"SalePrice":np.exp(xgb_prediction)})
xgb_DATA.head()
```

Out[154]:

	ID	SalePrice
0	1461	120392.445312
1	1462	160303.812500
2	1463	180038.406250
3	1464	180824.078125
4	1465	172652.843750

In [155]:
```
xgb_DATA.to_csv("xgb_regressor11.csv",index=False)
```

SGDRegressor

In [503]:
```
# SGD gives us super wierd value, so we have to do some transformation of the whole datase
standard = StandardScaler()
data1=standard.fit_transform(data)
```

In [504]:
```
X_train1, X_test1, y_train, y_test = train_test_split (data1, label,
                                                     test_size = 0.2,
                                                    random_state = 42)
```

In [481]:
```
sgd = SGDRegressor()
```

In [482]:
```
sgd_param = {"loss":["squared_loss","huber", "epsilon_insensitive","squared_epsilon_insens
            "penalty":['l1',"l2"],
            "learning_rate":["adaptive","invscaling","optimal"],
            "average":[True,False],
             "l1_ratio":[0.05,0.1,0.15,0.2]
            }
```

In [483]:
```
sgd_grid = GridSearchCV(sgd,
                        sgd_param,
                        cv = cv,
                        n_jobs = 5,
                        verbose=True)
```

In [505]:
```
sgd_grid.fit(X_train1,y_train)
```

```
Fitting 5 folds for each of 192 candidates, totalling 960 fits

[Parallel(n_jobs=5)]: Using backend LokyBackend with 5 concurrent workers.
[Parallel(n_jobs=5)]: Done  40 tasks      | elapsed:    6.1s
[Parallel(n_jobs=5)]: Done 324 tasks      | elapsed:   20.6s
[Parallel(n_jobs=5)]: Done 872 tasks      | elapsed:   46.8s
[Parallel(n_jobs=5)]: Done 960 out of 960 | elapsed:   49.9s finished
```

Out[505]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=SGDRegressor(), n_jobs=5,
             param_grid={'average': [True, False],
                         'l1_ratio': [0.05, 0.1, 0.15, 0.2],
                         'learning_rate': ['adaptive', 'invscaling', 'optimal'],
                         'loss': ['squared_loss', 'huber',
                                  'epsilon_insensitive',
                                  'squared_epsilon_insensitive'],
                         'penalty': ['l1', 'l2']},
             verbose=True)
```

In [506]:
```
print(sgd_grid.best_score_)
print(sgd_grid.best_params_)
```

```
-3.988928802491153
{'average': False, 'l1_ratio': 0.1, 'learning_rate': 'optimal', 'loss': 'huber', 'penal
ty': 'l1'}
```

In [488]:
```
sgd_best_params={'average': False, 'l1_ratio': 0.1, 'learning_rate': 'optimal', 'loss': 'l
```

In [489]:
```
sgd_best_model = SGDRegressor(**sgd_best_params)
```

In [508]:
```
sgd_best_model.fit(X_train1,y_train)
```

Out[508]:
```
SGDRegressor(l1_ratio=0.1, learning_rate='optimal', loss='huber', penalty='l1')
```

In [509]:
```
sgd_pred=sgd_best_model.predict(X_test1)


print(mean_squared_error(y_test,sgd_pred))
```

```
0.45458349035606394
```

In [510]:
```
test1=standard.fit_transform(test.drop(["Id"],axis=1))
```

In [511]:
```
sgd_prediction = sgd_best_model.predict(test1)
sgd_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(sgd_prediction)})
sgd_DATA.head()
```

Out[511]:

	ID	SalePrice
0	1461	117928.852709
1	1462	164215.072130
2	1463	162123.230425
3	1464	161705.959493
4	1465	646652.079468

In [512]:
```
sgd_DATA.to_csv("sgd_regressor2.csv",index=False)
```

MLPRegressor

In [525]:
```
mlp=MLPRegressor(max_iter=200)
```

In [526]:
```
mlp_param = {
    'hidden_layer_sizes': [(50,50,50), (50,100,50), (100,)],
    'activation': ['tanh', 'relu'],
    'solver': ['sgd', 'adam'],
    'alpha': [0.0001, 0.05],
    'learning_rate': ['constant','adaptive'],
}
```

In [529]:
```
mlp_grid = GridSearchCV(mlp,
                        mlp_param,
                        cv = cv,
                        n_jobs = 3,
                        verbose=True)
```

In [531]:
```
mlp_grid.fit(X_train1,y_train)
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits

[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  44 tasks      | elapsed:   47.1s
[Parallel(n_jobs=3)]: Done 194 tasks      | elapsed:  3.9min
[Parallel(n_jobs=3)]: Done 240 out of 240 | elapsed:  5.1min finished
```

Out[531]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=MLPRegressor(), n_jobs=3,
             param_grid={'activation': ['tanh', 'relu'],
                         'alpha': [0.0001, 0.05],
                         'hidden_layer_sizes': [(50, 50, 50), (50, 100, 50),
                                                (100,)],
                         'learning_rate': ['constant', 'adaptive'],
                         'solver': ['sgd', 'adam']},
             verbose=True)
```

In [532]:
```
print(mlp_grid.best_score_)
print(mlp_grid.best_params_)
```

```
0.0511157584189615
{'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 100, 50), 'learning_
rate': 'constant', 'solver': 'sgd'}
```

In [533]:
```
mlp_best_params={'activation': 'tanh',
                 'alpha': 0.0001,
                 'hidden_layer_sizes': (50, 100, 50),
                 'learning_rate': 'constant',
                 'solver': 'sgd'}
```

In [534]:
```
mlp_best_model=MLPRegressor(**mlp_best_params)
```

In [555]:
```
mlp_best_model.fit(X_train1,y_train)
```

Out[555]:
```
MLPRegressor(activation='tanh', hidden_layer_sizes=(50, 100, 50), solver='sgd')
```

In [556]:
```
mlp_pred=mlp_best_model.predict(X_test1)


print(mean_squared_error(y_test,mlp_pred))
```

```
0.08682618465345503
```

In [557]:
```
#test.drop(["Id"],axis=1)
mlp_prediction = mlp_best_model.predict(test1)
mlp_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(mlp_prediction)})
mlp_DATA.head()
```

Out[557]:

	ID	SalePrice
0	1461	106603.498824
1	1462	115823.619146
2	1463	207908.178877
3	1464	211688.654332
4	1465	165892.371563

In [558]:
```
mlp_DATA.to_csv("mlpstandard.csv",index=False)
```

Decision Tree

In [559]:
```
dt=DecisionTreeRegressor()
```

In [579]:
```
criterion = ['mse','mae','friedman_mse']
splitter = ['best']
max_depth = [6,8,10,13]
min_samples_split = [30,33,35,37,39]
min_samples_leaf = [9,13,15,17]

max
#cross validation
dt_params = {'criterion': criterion,
        'splitter': splitter,
        'max_depth': max_depth,
        'min_samples_split': min_samples_split,
        'min_samples_leaf': min_samples_leaf
       }
```

In [580]:
```
dt_grid = GridSearchCV(dt, dt_params,cv=cv, n_jobs=3,verbose=True)
```

In [581]:
```
dt_grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 240 candidates, totalling 1200 fits

[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done 120 tasks      | elapsed:    3.7s
[Parallel(n_jobs=3)]: Done 568 tasks      | elapsed:   20.5s
[Parallel(n_jobs=3)]: Done 821 tasks      | elapsed:   40.3s
[Parallel(n_jobs=3)]: Done 1200 out of 1200 | elapsed:   44.5s finished
```

Out[581]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=DecisionTreeRegressor(), n_jobs=3,
             param_grid={'criterion': ['mse', 'mae', 'friedman_mse'],
                         'max_depth': [6, 8, 10, 13],
                         'min_samples_leaf': [9, 13, 15, 17],
                         'min_samples_split': [30, 33, 35, 37, 39],
                         'splitter': ['best']},
             verbose=True)
```

In [606]:
```
print(dt_grid.best_params_)
```

```
{'criterion': 'mse', 'max_depth': 13, 'min_samples_leaf': 13, 'min_samples_split': 30,
'splitter': 'best'}
```

In [607]:
```
dt_best_params={'criterion': 'mse', 'max_depth': 13, 'min_samples_leaf': 13, 'min_samples_
```

In [612]:
```
dt_best_model=DecisionTreeRegressor(**dt_best_params)
```

In [613]:
```
dt_best_model.fit(X_train,y_train)
```

Out[613]:
```
DecisionTreeRegressor(max_depth=13, min_samples_leaf=13, min_samples_split=30)
```

In [614]:
```
dt_pred=dt_best_model.predict(X_test)
print(mean_squared_error(y_test,dt_pred))
```

```
0.036820079392524 85
```

In [615]:
```
dt_prediction=dt_best_model.predict(test.drop(["Id"],axis=1))
dt_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(dt_prediction)})
dt_DATA.head()
```

Out[615]:

	ID	SalePrice
0	1461	134147.548966
1	1462	141774.712588
2	1463	167677.135798
3	1464	168149.679258
4	1465	193160.120840

In [592]:
```
dt_DATA.to_csv("dtregressor.csv",index=False)
```

RandomForestRegressor

In [593]:
```
rdr=RandomForestRegressor()
```

In [603]:
```
# Number of trees in random forest
n_estimators = [100,500]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(2, 50, num = 5)]
#max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [int(x) for x in np.linspace(2, 50, num = 5)]
# Minimum number of samples required at each leaf node
min_samples_leaf = [int(x) for x in np.linspace(2, 50, num = 5)]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Criterion
criterion = ['mse','mae']
# Create the random grid
rdr_params = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap,
               'criterion':criterion}
```

In [604]:
```
rdr_grid = GridSearchCV(rdr, rdr_params,cv=cv, n_jobs=-1,verbose=True)
```

In [605]:
```
rdr_grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 2000 candidates, totalling 10000 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   12.5s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   50.1s
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed:  4.0min
[Parallel(n_jobs=-1)]: Done 1234 tasks      | elapsed:  6.8min
[Parallel(n_jobs=-1)]: Done 1784 tasks      | elapsed: 10.3min
[Parallel(n_jobs=-1)]: Done 2434 tasks      | elapsed: 13.5min
[Parallel(n_jobs=-1)]: Done 3184 tasks      | elapsed: 51.6min
[Parallel(n_jobs=-1)]: Done 4034 tasks      | elapsed: 90.0min
[Parallel(n_jobs=-1)]: Done 4984 tasks      | elapsed: 136.5min
[Parallel(n_jobs=-1)]: Done 6034 tasks      | elapsed: 142.9min
[Parallel(n_jobs=-1)]: Done 7184 tasks      | elapsed: 153.2min
[Parallel(n_jobs=-1)]: Done 8434 tasks      | elapsed: 246.2min
[Parallel(n_jobs=-1)]: Done 9784 tasks      | elapsed: 401.1min
[Parallel(n_jobs=-1)]: Done 10000 out of 10000 | elapsed: 404.1min finished
```

Out[605]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=RandomForestRegressor(), n_jobs=-1,
             param_grid={'bootstrap': [True, False],
                         'criterion': ['mse', 'mae'],
                         'max_depth': [2, 14, 26, 38, 50],
                         'max_features': ['auto', 'sqrt'],
                         'min_samples_leaf': [2, 14, 26, 38, 50],
                         'min_samples_split': [2, 14, 26, 38, 50],
                         'n_estimators': [100, 500]},
             verbose=True)
```

In [616]:
```
print(rdr_grid.best_params_)
```

```
{'bootstrap': False, 'criterion': 'mse', 'max_depth': 38, 'max_features': 'sqrt', 'min_
samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 500}
```

In [638]:
```
rdr_best_params={'bootstrap': False,
                 'criterion': 'mse',
                 'max_depth': 38,
                 'max_features': 'sqrt',
                 'min_samples_leaf': 2,
                 'min_samples_split': 2,
                 'n_estimators': 1000}
```

In [639]:
```
rdr_best_model=RandomForestRegressor(**rdr_best_params)
```

In [640]:
```
rdr_best_model.fit(X_train,y_train)
```

Out[640]:
```
RandomForestRegressor(bootstrap=False, max_depth=38, max_features='sqrt',
                      min_samples_leaf=2, n_estimators=1000)
```

In [641]:
```
rdr_pred=rdr_best_model.predict(X_test)
print(mean_squared_error(y_test,rdr_pred))
```

```
0.024680508434331112
```

In [642]:
```
rdr_prediction=rdr_best_model.predict(test.drop(["Id"],axis=1))
rdr_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(rdr_prediction)})
rdr_DATA.head()
```

Out[642]:

	ID	SalePrice
0	1461	123935.210335
1	1462	151565.423184
2	1463	182647.432118
3	1464	190596.601881
4	1465	197232.594484

In [643]:
```
rdr_DATA.to_csv("rdrregressor3.csv",index=False)
```

SVR

In [692]:
```
svr = SVR()
```

In [ ]:
```
parameters={'cache_size': range(100,200,10),'degree':range(1,10,2),'kernel':['linear']}
svr_grid = GridSearchCV(svr,parameters,cv=3, n_jobs=-1, verbose=2)
svr_grid.fit(X_train, y_train)
#grid_parm=svr_random.best_params_print(svr_predict_Test)
print(svr_random.best_parmas_)
```

In [703]:
```
svr_best_params={'cache_size':110,'degree':3,'kernel':'linear'}
svr_best_model=SVR(**svr_best_params)
svr_best_model.fit(X_train1,y_train)
```

Out[703]:
```
SVR(cache_size=110, kernel='linear')
```

In [704]:
```
svr_pred=svr_best_model.predict(test1)
```

In [705]:
```
svr_pred
```

Out[705]:
```
array([11.77316633, 11.95321119, 12.15007822, ..., 12.13288317,
       11.68715218, 12.30549477])
```

In [706]:
```
svr_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(svr_pred)})
print(svr_DATA.head())
svr_DATA.to_csv("svr.csv",index=False)
```

```
     ID      SalePrice
0  1461  129724.250813
1  1462  155315.093197
2  1463  189108.881514
3  1464  198682.251301
4  1465  197319.159645
```

Catboost Regressor

In [108]:
```
cat=CatBoostRegressor()
cat.fit(X_train,y_train,plot=True)
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

In [110]:
```
#Base model - Prediction
cat_prediction=cat.predict(test)
cat_DATA = pd.DataFrame({"ID":holdout["Id"],"SalePrice":np.exp(cat_prediction)})
print(cat_DATA.head())
cat_DATA.to_csv("cat9.csv",index=False)
```

```
     ID      SalePrice
0  1461  119229.117194
1  1462  163924.658264
2  1463  187254.013619
3  1464  195871.969510
4  1465  183441.244376
```

In [112]:
```
cat_grid_params={'bagging_temperature': [0,0.3],
                 'border_count': [1,10,50,100],
                 'depth': [2,4,6],
                 'iterations': [1000,1200,1500],
                 'learning_rate': [0.01,0.05,0.1]}
```

In [113]:
```
cat=CatBoostRegressor()
cat_grid_result = cat.grid_search(cat_grid_params, X=X_train,y=y_train,plot=True)
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

In [114]:
```
print(cat_grid_result)
```

```
{'params': {'border_count': 50, 'bagging_temperature': 0, 'depth': 2, 'iterations': 1
000, 'learning_rate': 0.05}, 'cv_results': defaultdict(<class 'list'>, {'iterations':
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 2
3, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 4
4, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 6
5, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 8
6, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105,
106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122,
123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139,
140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156,
157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173,
174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190,
191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207,
208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224,
225, 226, 227, 228, 229, 230, 231, 232, 233, 234, 235, 236, 237, 238, 239, 240, 241,
242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258,
259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273, 274, 275,
276, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286, 287, 288, 289, 290, 291, 292,
293, 294, 295, 296, 297, 298, 299, 300, 301, 302, 303, 304, 305, 306, 307, 308, 309,
```

In [115]:
```
cat_best_params={
    'bagging_temperature': 0,
    'border_count': 50,
    'depth': 2,
    'iterations': 1000,
    'learning_rate': 0.05
            }
```

In [116]:
```
cat_best_model = CatBoostRegressor(**cat_best_params,task_type = "GPU",early_stopping_rour
cat_best_model.fit(X_train,y_train,plot=True)
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

In [118]:
```
cat_prediction=cat_best_model.predict(test)
```

In [119]:
```
cat_DATA = pd.DataFrame({"ID":holdout["Id"],"SalePrice":np.exp(cat_prediction)})
print(cat_DATA.head())
cat_DATA.to_csv("cat10.csv",index=False)
```

```
     ID      SalePrice
0  1461  111302.257559
1  1462  165148.222086
2  1463  178981.921808
3  1464  190765.222287
4  1465  192037.941917
```

LightGBM

In [372]:
```
# set params
params = {'objective': 'gamma',
          'metric': 'rmse',
#          'num_class': 1,
          'is_unbalance': True,
          'boosting_type': 'gbdt',
          'learning_rate': 0.01,
          'max_depth':20,
#          'num_leaves': 84,
#          'feature_fraction':  0.7134122385103637,
 #         'lambda_l1': 516,
#          'lambda_l2': 212,
#          'max_bin':812,
#          'subsample': 0.246039627411813l2,
          'num_iterations':15000,
#          'min_data_in_leaf':79,
          'tree_learner':'serial'
         }
```

In [373]:
```
train_data = lgb.Dataset(X_train, label=y_train)
valid_data = lgb.Dataset(X_test, label=y_test)
```

In [374]:
```
lgb1 = lgb.train(params,
                 train_data,
#                 num_boost_round = 1000,
                 valid_sets=[train_data, valid_data],
                 early_stopping_rounds=200 )
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't set num_leaves and 2^max_de
pth > num_leaves
[LightGBM] [Warning] Find whitespaces in feature_names, replace with underlines
[LightGBM] [Warning] Accuracy may be bad since you didn't set num_leaves and 2^max_de
pth > num_leaves
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.001539 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 3258
[LightGBM] [Info] Number of data points in the train set: 1168, number of used featur
es: 181
[LightGBM] [Warning] Accuracy may be bad since you didn't set num_leaves and 2^max_de
pth > num_leaves
[LightGBM] [Warning] Find whitespaces in feature_names, replace with underlines
[LightGBM] [Info] Start training from score 2.487458
[1]     training's rmse: 0.387228       valid_1's rmse: 0.430018
Training until validation scores don't improve for 200 rounds
[2]     training's rmse: 0.384046       valid_1's rmse: 0.426795
[3]     training's rmse: 0.380899       valid_1's rmse: 0.423633
```

In [376]:
```
names=X_train.columns
lgb_pred = lgb1.predict(test[names])
```

In [378]:
```
lgb_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(lgb_pred)})
print(lgb_DATA.head())
```

```
     ID      SalePrice
0  1461  124638.445004
1  1462  155500.444705
2  1463  184243.636455
3  1464  178248.449213
4  1465  193055.825040
```

In [379]:
```
lgb_DATA.to_csv("lgb1.csv",index=False)
```

Stacking Models

In [662]:
```
models = [
    RandomForestRegressor(bootstrap= False,
                 criterion='mse',
                 max_depth= 38,
                 max_features='sqrt',
                 min_samples_leaf=2,
                 min_samples_split=2,
                 n_estimators= 1000),

    DecisionTreeRegressor(criterion='mse',
                          max_depth=13,
                          min_samples_leaf= 13,
                          min_samples_split= 30,
                          splitter= 'best'),

#    MLPRegressor(activation= 'tanh',
#                 alpha=0.0001,
#                 hidden_layer_sizes=(50, 100, 50),
#                 learning_rate= 'constant',
#                 solver= 'sgd'),

    XGBRegressor(colsample_bytree=0.7,
                 learning_rate= 0.03,
                 max_depth=4,
                 min_child_weight= 4,
                 n_estimators=1300,
                 nthread= 4,
                 objective= 'reg:linear',
                 silent=1,
                 subsample= 0.7,
                 tree_method='gpu_hist')
]
```

In [663]:
```
S_train, S_test = stacking(models,
                           data, label, test.drop(["Id"],axis=1),
                           regression=True,

                           mode='oof_pred_bag',

                           needs_proba=False,

                           save_dir=None,

                           metric=mean_squared_error,

                           n_folds=5,

                           stratified=True,

                           shuffle=True,

                           random_state=0,

                           verbose=2)
```

```
task:         [regression]
metric:       [mean_squared_error]
mode:         [oof_pred_bag]
n_models:     [3]

model  0:     [RandomForestRegressor]
    fold  0:  [0.01946940]
    fold  1:  [0.01545666]
    fold  2:  [0.03312323]
    fold  3:  [0.01857182]
    fold  4:  [0.01673297]
    ----
    MEAN:     [0.02067082] + [0.00638131]
    FULL:     [0.02067082]

model  1:     [DecisionTreeRegressor]
    fold  0:  [0.03397764]
    fold  1:  [0.03298931]
    fold  2:  [0.04459972]
```

stacking with the model in the first layer

In [664]:
```
stacking_model=XGBRegressor(colsample_bytree=0.7,
                 learning_rate= 0.03,
                 max_depth=4,
                 min_child_weight= 4,
                 n_estimators=1300,
                 nthread= 4,
                 objective= 'reg:linear',
                 silent=1,
                 subsample= 0.7,
                 tree_method='gpu_hist')
stacking_model.fit(S_train,label)
```

```
[22:21:54] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
[22:21:54] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\le
arner.cc:516:
Parameters: { silent } might not be used.

  This may not be accurate due to some parameters are only used in language bindings bu
t
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[22:21:57] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.2.0/src/ob
jective/regression_obj.cu:174: reg:linear is now deprecated in favor of reg:squarederro
r.
```

Out[664]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.7, gamma=0, gpu_id=0,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.03, max_delta_step=0, max_depth=4,
             min_child_weight=4, missing=nan, monotone_constraints='(0,0,0)',
             n_estimators=1300, n_jobs=4, nthread=4, num_parallel_tree=1,
             objective='reg:linear', random_state=0, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, silent=1, subsample=0.7,
             tree_method='gpu_hist', validate_parameters=1, verbosity=None)
```

stakcing_model with new regressor

In [669]:
```
stacking_model=GradientBoostingRegressor()
```

Out[669]:
```
GradientBoostingRegressor()
```

In [673]:
```
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(2, 50, num = 5)]
#max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [int(x) for x in np.linspace(2, 50, num = 3)]
# Minimum number of samples required at each leaf node
min_samples_leaf = [int(x) for x in np.linspace(2, 50, num = 3)]
# Criterion
criterion = ['mse','mae','friedman_mse']
# Create the random grid
stakcing_params = {'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'criterion':criterion}
```

In [676]:
```
stacking_grid = GridSearchCV(stacking_model, stakcing_params,cv=cv, n_jobs=-1,verbose=Tru
```

In [677]:
```
stacking_grid.fit(S_train,label)
```

```
Fitting 5 folds for each of 135 candidates, totalling 675 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    4.0s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   12.6s
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  3.4min
[Parallel(n_jobs=-1)]: Done 675 out of 675 | elapsed:  3.7min finished
```

Out[677]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2020, shuffle=False),
             estimator=GradientBoostingRegressor(), n_jobs=-1,
             param_grid={'criterion': ['mse', 'mae', 'friedman_mse'],
                         'max_depth': [2, 14, 26, 38, 50],
                         'min_samples_leaf': [2, 26, 50],
                         'min_samples_split': [2, 26, 50]},
             verbose=True)
```

In [678]:
```
print(stacking_grid.best_params_)
```

```
{'criterion': 'mae', 'max_depth': 2, 'min_samples_leaf': 2, 'min_samples_split': 2}
```

In [679]:
```
stacking_best_params={'criterion': 'mae', 'max_depth': 2, 'min_samples_leaf': 2, 'min_samp
```

In [680]:
```
stacking_model=GradientBoostingRegressor(**stacking_best_params)
```

In [681]:
```
stacking_model.fit(S_train,label)
```

Out[681]:
```
GradientBoostingRegressor(criterion='mae', max_depth=2, min_samples_leaf=2)
```

In [682]:
```
stacking_prediction=stacking_model.predict(S_test)
```

In [683]:
```
stacking_DATA = pd.DataFrame({"ID":test["Id"],"SalePrice":np.exp(stacking_prediction)})
stacking_DATA.head()
```

Out[683]:

	ID	SalePrice
0	1461	126458.963326
1	1462	161341.302407
2	1463	187398.503172
3	1464	192598.884133
4	1465	181948.623489

In [684]:
```
stacking_DATA.to_csv("stacking4.csv",index=False)
```

Stacking with StackingCVRegressor

In [120]:
```
from sklearn.ensemble import VotingRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.svm import SVR
from sklearn.linear_model import Ridge
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import GradientBoostingRegressor
from lightgbm import LGBMRegressor
from xgboost import XGBRegressor
```

In [ ]:
```
lasso = Lasso(alpha = 0.0005)
ridge = Ridge(alpha = 11.9)
elasticnet = ElasticNet(alpha = 0.001)
gbr = GradientBoostingRegressor(learning_rate = 0.1, loss = 'huber', max_depth = 1, max_fe
                                min_samples_leaf = 15, min_samples_split = 10, n_estimator
lightgbm = LGBMRegressor(learning_rate = 0.01, n_estimators = 5000, num_leaves = 4)
xgboost = XGBRegressor(learning_rate = 0.01, max_depth = 3, n_estimators = 3500)
scvr = StackingCVRegressor(regressors=(rdr_best_model, lasso, elasticnet, gbr, xgboost, li
                           meta_regressor=xgboost,
                           use_features_in_secondary=True)
```

In [132]:
```
stdSc=StandardScaler()
num_features = X_train.select_dtypes(exclude = ["object"]).columns

X_train.loc[:, num_features] = stdSc.fit_transform(X_train.loc[:, num_features])
scvr.fit(np.array(X_train),np.array(y_train))
```

Out[132]:
```
StackingCVRegressor(meta_regressor=XGBRegressor(base_score=None, booster=None,
                                                colsample_bylevel=None,
                                                colsample_bynode=None,
                                                colsample_bytree=None,
                                                gamma=None, gpu_id=None,
                                                importance_type='gain',
                                                interaction_constraints=None,
                                                learning_rate=0.01,
                                                max_delta_step=None,
                                                max_depth=3,
                                                min_child_weight=None,
                                                missing=nan,
                                                monotone_constraints=None,
                                                n_estimators=3500, n_...
                                             min_child_weight=None, missing=nan,
                                             monotone_constraints=None,
                                             n_estimators=3500, n_jobs=None,
                                             num_parallel_tree=None,
                                             random_state=None, reg_alpha=None,
                                             reg_lambda=None,
                                             scale_pos_weight=None,
                                             subsample=None, tree_method=None,
                                             validate_parameters=None,
                                             verbosity=None),
                                LGBMRegressor(learning_rate=0.01,
                                              n_estimators=5000,
                                              num_leaves=4)),
                    use_features_in_secondary=True)
```

In [135]:
```
scvr_pred=scvr.predict(np.array(test.fillna(test.mean())))
```

In [137]:
```
scvr_DATA = pd.DataFrame({"ID":holdout["Id"],"SalePrice":np.exp(scvr_pred)})
scvr_DATA.head()
```

Out[137]:

	ID	SalePrice
0	1461	128010.148438
1	1462	160763.093750
2	1463	189990.406250
3	1464	205336.171875
4	1465	186763.609375

In [139]:
```
scvr_DATA.to_csv("scvr1.csv",index=False)
```

In [ ]:

```

```

Average

average ensemble

In [688]:

```
Average=pd.DataFrame({"ID":test["Id"],"SalePrice":(np.exp(dt_prediction)+
                                                    np.exp(mlp_prediction)+
                                                    np.exp(rdr_prediction)+
                                                    np.exp(xgb_prediction))/4})
Average
```

Out[688]:

	ID	SalePrice
0	1461	123056.722734
1	1462	142497.813729
2	1463	186566.444511
3	1464	190947.897930
4	1465	186010.810784
...	...	...
1454	2915	86293.440743
1455	2916	85348.386581
1456	2917	164322.386546
1457	2918	129475.698070
1458	2919	246635.266413

1459 rows × 2 columns

In [689]:

```
Average.to_csv("average1.csv", index=False)
```

weighted average ensemble

In [690]:
```
WeightedAverage=pd.DataFrame({"ID":test["Id"],"SalePrice":(0.2*np.exp(dt_prediction)+
                                                          0.1*np.exp(mlp_prediction)+
                                                          0.3*np.exp(rdr_prediction)+
                                                          0.4*np.exp(xgb_prediction))})

WeightedAverage
```

Out[690]:

	ID	SalePrice
0	1461	125686.676682
1	1462	149737.931387
2	1463	184333.685620
3	1464	189320.445912
4	1465	189494.305294
...	...	...
1454	2915	85935.875363
1455	2916	86572.695459
1456	2917	160486.926951
1457	2918	122972.780341
1458	2919	232518.836631

1459 rows × 2 columns

In [691]:
```
WeightedAverage.to_csv("WeightedAverage.csv",index=False)
```

In [ ]:
```
```