In [1]: import pandas as pd import math import statsmodels.api as sm import numpy as np import scipy import seaborn as sns from matplotlib import pyplot as plt from scipy.stats import pearsonr from sklearn.decomposition import PCA from sklearn.linear_model import LinearRegression from sklearn.metrics import mean squared error as MSE from sklearn.metrics import mean absolute error as MAE from sklearn.model_selection import train test split Note that the first 1460 samples in cleaned_data.csv are training and cleaned_data.csv does not have sale price in it. In [2]: cleaned_data = pd.read_csv('E:/projects/housing_price/data/cleaned_data.csv',index_col=0) Isolate the response vector 'SalePrice' In [3]: house_price = pd.read_csv('E:/projects/housing_price/data/train.csv',index_col=0)['SalePrice'] Examine correlations among variables In [4]: sns.heatmap(cleaned_data.corr()) plt.show() LotFrontage HeatingQC 0.8 Fireplaces 3SsnPorch gabble roof ExterScore 0.4 MSZoning RM Neighborhood Blmngtn Neighborhood_Gilbert Neighborhood_NridgHt 0.0 Neighborhood_Veenker Condition1_RRNe Condition2_RRAn HouseStyle 1.5Unf MasVnrType None Functional Maj1 GarageType_Detchd SaleType_New SaleCondition_Partial It can be seen that there are highly correlated variables In [5]: correlation = cleaned data.corr() significantly_correlated = set() In [6]: for var1 in set(correlation): for var2 in set(correlation): if correlation.loc[var1][var2]>0.8 and var1!=var2: significantly_correlated.add(tuple(sorted([var1,var2]))) In [7]: print("The highly correlated couples are: {}".format(significantly_correlated)) The highly correlated couples are: {('OverallCond*OverallQual*GrLivArea', 'OverallQual*GrLivArea'), ('GrLivArea', 'OverallCond*GrLivArea'), ('GrLivArea', 'OverallQual*GrLivArea'), ('OverallQual', 'Over allQual*GrLivArea'), ('OverallCond*GrLivArea', 'OverallCond*OverallQual*GrLivArea'), ('FireplaceQu', 'Fireplaces'), ('SaleCondition Partial', 'SaleType New'), ('GrLivArea', 'OverallCond*OverallQual*GrLi vArea') } As is said in readme.txt file, SaleCondition_Partial means when the house is sold, the house is only partially completed which also means that the house is a new house! So we can safely delete one of these categorical variables. In [8]: cleaned data = cleaned data.drop(columns=['SaleCondition Partial']) Take a look at the other pair of high correlation correlation.loc['FireplaceQu']['Fireplaces'] Out[9]: 0.8617353520998596 We should remove one of the two, lets remove 'Fireplaces' In [10]: cleaned_data = cleaned_data.drop(columns=['Fireplaces']) Check again for highly correlated pairs In [11]: significantly_correlated = set() for var1 in set(cleaned data.corr()): for var2 in set(cleaned_data.corr()): if correlation.loc[var1][var2]>0.8 and var1!=var2: significantly_correlated.add(tuple(sorted([var1,var2]))) if len(significantly_correlated) == 0: print("There is no more highly correlated variables") else: print("The highly correlated couples are: {}".format(significantly_correlated)) The highly correlated couples are: {('OverallCond*OverallQual*GrLivArea', 'OverallQual*GrLivArea'), ('GrLivArea', 'OverallCond*GrLivArea'), ('GrLivArea', 'OverallQual*GrLivArea'), ('OverallQual', 'Over allQual*GrLivArea'), ('OverallCond*GrLivArea', 'OverallCond*OverallQual*GrLivArea'), ('GrLivArea', 'O verallCond*OverallQual*GrLivArea')} Now there is no more highly correlated pairs (other than interaction terms). **Splitting Train and Test Data** In [12]: train_data = cleaned_data.head(1460) test_data = cleaned_data.tail(1459) **Outliers** It is a common sense that the lot area and the living area of the house are usually the most important factors for housing price, so we can plot the area against sale price to see if there is anything unusual. Lot Area vs Sale Price lot_area = train_data['LotArea'] plt.scatter(lot_area, house_price) plt.xlabel('lot area') plt.ylabel('house price') Out[13]: Text(0, 0.5, 'house price') 700000 600000 500000 house price 400000 300000 200000 100000 50000 100000 150000 200000 lot area There are four outliers with high leverage. We need to remove them. # First, to identify the ID's of the houses with the 4 largest lot area, we sort the data frame by lot In [14]: print(train data.sort values('LotArea', ascending=False)['LotArea'][:6]) 314 215245 336 164660 250 159000 707 115149 452 70761 1299 63887 Name: LotArea, dtype: int64 In [15]: # Now, drop them train data = train data.drop(index=[314,336,250,707,452,1299]) house price = house price.drop(index=[314,336,250,707,452,1299]) In [16]: Look at the lot again In [17]: lot area = train data['LotArea'] plt.scatter(lot_area, house_price) plt.xlabel('lot area') plt.ylabel('house price') Out[17]: Text(0, 0.5, 'house price') 700000 600000 500000 house price 400000 300000 200000 100000 30000 40000 lot area Living Area vs Sale Price In [18]: living_area = train_data['GrLivArea'] plt.scatter(living area, house price) plt.xlabel('living area') plt.ylabel('house price') Out[18]: Text(0, 0.5, 'house price') 700000 600000 500000 400000 300000 200000 100000 1000 3000 4000 2000 living area It is very clear that there are three outliers. Identify and remove them. # the one with large area but low sale price In [19]: print(living area.sort values(ascending=False)[:1]) 524 4676 Name: GrLivArea, dtype: int64 In [20]: # the two with very high sale price print(house_price.sort_values(ascending=False)[:2]) Ιd 692 755000 1183 745000 Name: SalePrice, dtype: int64 In [21]: train data = train data.drop(index=[524,692,1183]) house price = house price.drop(index=[524,692,1183]) Plot again In [22]: living_area = train_data['GrLivArea'] plt.scatter(living area, house price) plt.xlabel('living area') plt.ylabel('house price') Out[22]: Text(0, 0.5, 'house price') 600000 500000 400000 300000 200000 100000 1000 1500 3000 3500 500 2000 living area Due to the main effect of living_area on SalePrice, this plot here shows heterscedesticity. We should be using weighted least square instead of ordinary least square as the data encodes homoscedestic. But anyhow, lets still get the baseline model out as a basic benchmark. The basic residuals of ordinary least square will also help us determine the weights of weighted least square. Distribution of Y In linear regression, we assumed normality of Y, we need to verify this. In [23]: sns.distplot(house price) plt.title('House Price Distribution') plt.show() House Price Distribution 8 6 4 100000 200000 300000 400000 500000 600000 700000 SalePrice The distribution looks skewed, we consider either take log or take square-root. In [24]: # Taking log log house price = np.log(house price) sns.distplot(log_house_price) plt.title('Log-Transformed House Price Distribution') plt.show() Log-Transformed House Price Distribution 1.2 1.0 0.8 0.6 0.4 0.2 0.0 11.0 12.0 12.5 13.0 13.5 SalePrice In [25]: | sqrt_house_price = np.sqrt(house_price) sns.distplot(sqrt house price) plt.title('Sqrt-Transformed House Price Distribution') plt.show() Sqrt-Transformed House Price Distribution 0.007 0.006 0.005 0.004 0.003 0.002 0.001 0.000 100 200 300 400 500 600 700 800 SalePrice Based on what we see, the log-transformed house price is closer to normal distribution. So we will use log-transformed data, however it seems like there are three exceptionally low sale prices which introduced a little bit of skewness into the distribution. We need to remove them before use. In [26]: print(log house price.sort values()[:3]) 496 10.460242 917 10.471950 969 10.542706 Name: SalePrice, dtype: float64 In [27]: house price = house price.drop(index=[496,917,969]) log house price = log house price.drop(index=[496,917,969]) train_data = train_data.drop(index=[496,917,969]) In [28]: sns.distplot(log house price) plt.title('log-transformed house price after removing outliers') Out[28]: Text(0.5, 1.0, 'log-transformed house price after removing outliers') log-transformed house price after removing outliers 1.2 1.0 0.8 0.6 0.4 0.2 0.0 11.0 11.5 12.0 12.5 13.0 SalePrice **Linear Regression Fit** In [29]: data = sm.add constant(train data) OLS = sm.OLS(log_house_price, train_data) lin_regression = OLS.fit() print(lin_regression.summary()) OLS Regression Results Dep. Variable: SalePrice R-squared: 0.936 OLS Adj. R-squared: Model: 0.929 Least Squares F-statistic: 143.2 Method: Thu, 16 Jul 2020 Prob (F-statistic): 11:44:27 Log-Likelihood: Date: 0.00 Time: 1300.6 No. Observations: 1448 AIC: -2331. 1313 BIC: Df Residuals: -1619. 134 Df Model: Covariance Type: nonrobust coef t P>|t| [0.025 0.975] std err

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 9.92e-05
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 4.574e-06
 8.01e-07
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 3e-06

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0.030 -1.128 0.260 -0.110 Neighborhood IDOTRR 0.036 -2.638 -0.196 Neighborhood MeadowV -0.1121 0.043 0.008 -0.029 Neighborhood Mitchel 0.0198 0.032 0.628 -0.042 0.082 0.530 Neighborhood NAmes 0.0465 1.613 -0.010 0.029 0.107 0.103 Neighborhood NPkVill 0.0932 0.048 1.949 0.052 -0.001 0.187 Neighborhood NWAmes 0.0236 0.770 -0.037 0.031 0.441 0.084 Neighborhood NoRidge 0.035 2.061 0.039 0.003 0.139 0.0713 Neighborhood NridgHt 0.1330 0.033 4.065 0.000 0.069 0.197 0.162 -0.059 Neighborhood OldTown 0.0053 0.033 0.872 0.069 Neighborhood SWISU 0.0662 0.037 1.777 0.076 -0.007 0.139 Neighborhood Sawyer 0.0523 0.030 1.721 -0.007 0.085 0.112 1.381 -0.018 Neighborhood SawyerW 0.0439 0.032 0.168 0.106 Neighborhood Somerst 0.1257 0.034 3.672 0.000 0.059 0.193 Neighborhood StoneBr 0.1797 0.036 4.922 0.000 0.108 0.251 Neighborhood Timber 0.0551 0.033 1.650 0.099 -0.010 0.121 Neighborhood Veenker 0.0990 0.041 2.394 0.017 0.018 0.180 0.1105 0.077 -0.041 0.262 Condition1 Artery 1.430 0.153 0.066 -0.009 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0.548 -0.059 0.2071 0.135 BldgType Twnhs 1.529 0.127 0.473 0.2426 BldgType TwnhsE 0.135 1.797 0.073 -0.022 0.507 0.085 2.049 0.041 0.007 HouseStyle 1.5Fin 0.1735 0.340 2.154 HouseStyle 1.5Unf 0.1892 0.088 0.031 0.017 0.361 2.080 0.038 0.010 HouseStyle 1Story 0.1767 0.085 0.343 0.999 0.286 HouseStyle 2.5Fin 0.0964 0.096 0.318 -0.093 HouseStyle 2.5Unf 2.031 0.006 0.1821 0.090 0.042 0.358 0.085 2.007 0.004 HouseStyle 2Story 0.1699 0.045 0.336 HouseStyle SFoyer 0.1716 0.086 1.985 0.047 0.002 0.341 HouseStyle SLvl 0.1780 0.086 2.075 0.038 0.010 0.346 MasVnrType BrkFace 0.4398 1.971 0.049 0.002 0.223 0.878 2.001 0.046 0.009 0.885 MasVnrType None 0.4467 0.223 MasVnrType Others 0.4508 0.045 0.010 0.225 2.007 0.891 Foundation BrkTil 0.2177 0.112 1.944 0.052 -0.002 0.437 0.112 2.146 0.032 0.021 Foundation CBlock 0.2412 0.462 Foundation PConc 2.257 0.024 0.033 0.475 0.2539 0.113 2.109 0.466 Foundation Slab 0.2414 0.114 0.035 0.017 Foundation Stone 0.035 0.2520 0.120 2.105 0.017 0.487 Foundation Wood 0.1311 0.125 1.050 0.294 -0.114 0.376 0.2382 0.099 0.016 0.045 Functional Maj1 2.416 0.432 Functional Maj2 0.107 0.0784 0.730 0.465 -0.132 0.289 0.3017 0.108 0.495 Functional Min1 0.099 3.061 0.002 0.100 0.004 0.095 Functional Min2 0.2905 2.911 0.486 Functional Mod 0.1986 0.102 1.940 0.053 -0.002 0.399 -0.1027 -0.773 Functional Sev 0.133 0.439 -0.363 0.158 0.141 Functional Typ 0.3326 0.097 3.414 0.001 0.524 2.009 0.045 GarageType_Attchd 0.223 0.011 0.887 0.448/ 0.4488 2.008 0.010 GarageType Detchd 0.224 0.045 0.887 0.4398 0.224 1.963 0.050 0.000 0.879 GarageType Others SaleType COD 0.0737 0.079 0.935 0.350 -0.081 0.229 2.074 0.1839 SaleType_CWD 0.089 0.038 0.010 0.358 2.137 0.033 0.018 SaleType_Con 0.105 0.2234 0.429 2.025 0.043 0.005 SaleType ConLD 0.1676 0.083 0.330 0.868 0.385 -0.097 SaleType_ConLI 0.0772 0.089 0.252 -0.091 0.921 0.357 0.088 0.253 SaleType_ConLw 0.0807 0.092 3.002 0.003 0.096 0.459 SaleType_New 0.2776 SaleType Oth 0.1585 0.093 1.704 0.089 -0.024 0.341 1.241 -0.055 SaleType WD 0.0947 0.076 0.215 0.244 SaleCondition_Abnorml 0.0666 0.064 1.040 0.298 -0.059 0.192 -0.021 0.087 1.714 SaleCondition AdjLand 0.1458 0.085 0.313 SaleCondition Alloca 0.0975 0.071 1.363 0.173 -0.043 0.238 SaleCondition Family 0.0671 0.994 0.068 0.321 -0.065 0.200 0.008 2.096 0.036 SaleCondition_Normal 0.1321 0.063 0.256 Exterior HdBoard 0.2082 0.112 1.859 0.063 -0.012 0.428 0.016 Exterior MetalSd 0.2353 0.112 2.105 0.036 0.455 Exterior Others 0.2439 0.112 2.182 0.029 0.025 0.463 0.2157 0.113 1.908 Exterior_Plywood 0.057 -0.006 0.437 0.009 2.042 0.041 Exterior_VinylSd 0.2291 0.112 0.449 0.2051 0.112 1.837 0.066 Exterior Wd Sdng -0.014 0.424 Omnibus: 394.020 Durbin-Watson: 1.886 0.000 Jarque-Bera (JB): 2932.107 Prob(Omnibus): 0.00 -1.060 Prob(JB): Kurtosis: 9.641 Cond. No. 1.25e+16 Warnings: [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. [2] The smallest eigenvalue is 3.61e-20. This might indicate that there are strong multicollinearity problems or that the design matrix is singular. D:\anaconda\lib\site-packages\numpy\core\fromnumeric.py:2542: FutureWarning: Method .ptp is deprecate d and will be removed in a future version. Use numpy.ptp instead. return ptp(axis=axis, out=out, **kwargs) If we were doing a train-validation split on the training data, we can use the second half of the code below to compare the results. But since we have known that the regression model (with our carefully chose features) is very robust, we go ahead without validating. In [40]: train_fitted_log_price = lin_regression.predict(train_data) train_fitted_price = np.exp(train_fitted_log_price) train percentage error = np.abs(house price-train fitted price)/house price print("Average percentage error for training data: {}".format(sum(train_percentage_error)/len(train_per centage_error))) #test fitted log price = lin regression.predict(test data) #test_fitted_price = np.exp(test_fitted_log_price) #test_percentage_error = np.abs(np.exp(test_house_price) -test_fitted_price)/np.exp(test_house_price) #print("Average percentage error for testing data: {}".format(sum(test percentage error)/len(test perce ntage_error))) Average percentage error for training data: 0.07152024776178298 In [31]: sns.distplot(train_percentage_error,color='g',label='train') #sns.distplot(test_percentage_error,color='r',label='test') plt.title("Percentage Error: Training data vs Testing Data"); Percentage Error: Training data vs Testing Data 10 train 8 6 0.4 0.2 0.6 0.8 1.0 Prediction of OLS In [32]: OLS_prediction = pd.DataFrame(np.exp(lin_regression.predict(test_data))) OLS prediction = OLS prediction.rename(columns={0:'SalePrice'}) OLS_prediction.to_csv('E:/projects/housing_price/OLS_prediction.csv',columns=OLS_prediction.columns) **Removing Insignificant Predictors** Based on the summary, there are a few predictors with small t-scores together with large p-values. It means that these predictors are weak predictors and should be taken out. In [33]: weak predictors = ['LotFrontage','CentralAir','FireplaceQu','GarageFinish','RecentRemod','YrSold','MoSo ld','BsmtQual','BsmtCond', 'gabble roof', 'LandContour Lvl', 'Electrical', 'MasVnrArea', 'BedroomAbvGr', 'MiscVal', 'PoolArea', 'has fence', 'LandSlope Gtl', 'ExterScore', 'SaleCondition Abnorml', 'SaleCondition AdjLand', 'SaleCo ndition_Alloca', 'SaleCondition Family', 'SaleCondition Normal', '3SsnPorch', 'LowQualFinSF'] In [34]: weak removed train data = train data.drop(columns=weak predictors) In [35]: weak removed test data = test data.drop(columns=weak predictors) In [36]: weak removed train data = sm.add constant(weak removed train data) weak removed OLS = sm.OLS(log house price, weak removed train data) weak removed lin regression = weak removed OLS.fit() print(weak removed lin regression.summary()) OLS Regression Results ______ Dep. Variable: SalePrice R-squared: 0.932 Model: OLS Adj. R-squared: 0.926 168.9 Method: Least Squares F-statistic: Date: Thu, 16 Jul 2020 Prob (F-statistic): 0.00 11:44:27 Log-Likelihood: 1253.0 1448 AIC: -2288. No. Observations: BIC: Df Residuals: 1339 -1713. Df Model: 108 Covariance Type: nonrobust ______ P>|t| [0.025 0.975] coef std err ______ 4.909e-06 7.98e-07 6.148 0.000 3.34e-06 6.48e-06 LotArea 3.183 0.001 0.032 2.341 0.019 0.010 0.0824 0.026 0.133 OverallQual 0.0621 0.027 0.114 OverallCond 2.9550.0033.7260.0003.2970.001 0.004 0.004 0.018 BsmtExposure 0.0107 0.007 0.004 HeatingQC 0.0151 0.023 0.000 0.0004 0.000 0.001 GrLivArea -0.107 0.023 -2.723 0.007 KitchenAbvGr -0.0622 -0.017 KitchenQual 0.0189 0.007 2.806 0.005 0.006 0.032 4.646 GarageArea 0.0001 2.3e-05 0.000 6.16e-05 0.000 3.0384 0.048 2.945 63.860 0.000 3.132 PavedDrive 0.001 3.62e-05 8.696e-05 2.59e-05 3.362 0.000 WoodDeckSF 2.845 0.005 4.54e-05 OpenPorchSF 0.0001 5.14e-05 0.000 0.109 EnclosedPorch 8.648e-05 5.4e-05 1.603 -1.94e-05 0.000 5.33e-05 0.0003 4.749 0.000 0.000 0.000 ScreenPorch 0.007 0.0286 4.399 0.000 0.016 0.041 Bath 0.004 0.017 0.0105 0.003 3.208 0.001 2.71e-06 1.003 -2.6e-06 OverallCond*OverallQual*GrLivArea 2.722e-06 0.316 8.04e-06 OverallQual*GrLivArea -1.939e-05 1.57e-05 -1.235 0.217 -5.02e-05 1.14e-05 OverallCond*GrLivArea -8.965e-06 -0.483 0.629 -4.54e-052.74e-05 1.86e-05 OverallCond*OverallQual -0.0048 -1.045 -0.014 0.005 0.296 0.004 0.0001 1.46e-05 6.960 0.000 7.32e-05 0.000 BsmtLowQArea 7.980 0.000 0.000 0.0001 1.69e-05 0.000 BsmtAvgQArea 1.67e-05 10.837 0.000 BsmtHiQArea 0.0002 0.000 0.000 -0.0023 0.000 -7.745 0.000 -0.003 -0.002 HouseAge 31.085 0.4720 0.015 0.000 0.442 0.502 MSZoning Others 0.5280 0.012 44.243 0.000 0.505 0.551 MSZoning RL 0.492 0.5192 0.014 37.702 0.000 0.546 MSZoning RM LotShape IR1 0.3786 0.013 30.238 0.000 0.354 0.403 0.000 0.354 LotShape IR2 0.3890 0.018 21.791 0.424 LotShape IR3 0.3744 0.031 12.205 0.000 0.314 0.435 0.3772 0.013 29.480 0.000 0.352 0.402 LotShape Reg 0.5096 0.010 52.493 0.000 0.491 0.529 LotConfig Corner LotConfig Inside 0.4991 0.009 53.851 0.000 0.481 0.517 LotConfig_Others 0.5105 0.011 47.712 0.000 0.489 0.531 Neighborhood Blmngtn 0.0922 0.031 3.022 0.003 0.032 0.152 Neighborhood Blueste -0.096 0.0511 0.075 0.680 0.496 0.199 Neighborhood BrDale -0.0063 0.033 -0.190 0.849 -0.072 0.059 Neighborhood BrkSide 0.0763 0.020 3.824 0.000 0.037 0.115 Neighborhood ClearCr 0.0651 0.024 2.770 0.006 0.019 0.111 0.0379 0.013 2.976 0.003 0.013 0.063 Neighborhood CollgCr Neighborhood Crawfor 0.1807 0.018 10.257 0.000 0.146 0.215 -0.019 Neighborhood Edwards 0.0077 0.013 0.573 0.567 0.034 Neighborhood Gilbert 0.0561 0.017 3.375 0.001 0.023 0.089 -0.0409 -1.646 -0.090 Neighborhood IDOTRR 0.025 0.100 0.008 Neighborhood MeadowV -0.0994 0.032 -3.095 0.002 -0.162 -0.036 Neighborhood Mitchel 0.0244 0.017 1.448 0.148 -0.009 0.058 0.0523 0.011 4.764 0.000 0.031 0.074 Neighborhood NAmes Neighborhood NPkVill 0.1038 0.039 2.666 0.008 0.027 0.180 Neighborhood NWAmes 0.0287 0.015 1.852 0.064 -0.002 0.059 Neighborhood NoRidge 0.0731 0.021 3.474 0.001 0.032 0.114 Neighborhood NridgHt 0.1545 0.018 8.728 0.000 0.120 0.189 Neighborhood OldTown -0.036 0.0038 0.020 0.191 0.849 0.043 Neighborhood SWISU 0.0625 0.026 2.433 0.015 0.012 0.113 Neighborhood_Sawyer 0.015 3.597 0.000 0.025 0.084 0.0541 Neighborhood SawyerW 0.0447 0.016 2.763 0.006 0.013 0.076 Neighborhood Somerst 0.1398 0.021 6.685 0.000 0.099 0.181 0.138 Neighborhood StoneBr 0.1858 0.024 7.653 0.000 0.233 0.028 Neighborhood_Timber 0.0669 0.020 3.362 0.001 0.106 Neighborhood_Veenker 0.1042 0.034 3.089 0.002 0.038 0.170 Condition1 Artery 0.1297 0.021 6.301 0.000 0.089 0.170 Condition1_Feedr 0.1599 0.017 9.372 0.000 0.126 0.193 0.000 0.185 Condition1_Norm 0.2111 0.013 15.846 0.237 Condition1 PosA 0.1593 0.037 4.314 0.000 0.087 0.232 Condition1 PosN 0.2177 0.027 8.057 0.000 0.165 0.271 0.018 Condition1 RRAe 0.0825 0.033 2.502 0.012 0.147 Condition1_RRAn 0.1844 0.024 7.616 0.000 0.137 0.232 Condition1_RRNe 0.1700 0.069 2.446 0.015 0.034 0.306 Condition1 RRNn 0.2046 0.046 4.430 0.000 0.114 0.295 0.006 Condition2_Artery 0.2224 0.080 2.777 0.065 0.380 0.054 0.000 0.082 Condition2_Feedr 0.1870 3.494 0.292 Condition2 Norm 0.2372 0.032 7.339 0.000 0.174 0.301 Condition2 PosA 0.3365 0.116 2.906 0.004 0.109 0.564 Condition2 PosN 0.0569 0.103 0.554 0.580 -0.145 0.259 0.272 -0.088 Condition2_RRAe 0.1118 0.102 1.099 0.311 -0.029 Condition2 RRAn 0.1686 0.101 1.672 0.095 0.366 Condition2 RRNn 0.1987 0.075 2.659 0.008 0.052 0.345 BldgType_1Fam 0.3402 0.012 29.456 0.000 0.318 0.363 BldgType_2fmCon 0.3392 0.021 16.405 0.000 0.299 0.380 BldgType_Duplex 0.3083 0.021 14.549 0.000 0.267 0.350 BldgType_Twnhs 0.2427 0.020 12.041 0.000 0.203 0.282 0.260 BldgType_TwnhsE 0.2887 0.015 19.550 0.000 0.318 0.2019 0.012 0.000 0.178 HouseStyle_1.5Fin 16.677 0.226 HouseStyle_1.5Unf 0.2267 0.028 7.978 0.000 0.171 0.282 HouseStyle_1Story 0.2031 0.012 17.406 0.000 0.180 HouseStyle_2.5Fin 0.0864 0.040 2.146 0.032 0.007 0.165 5.994 0.1983 0.033 0.000 0.133 HouseStyle_2.5Unf 0.263 0.011 17.466 0.000 HouseStyle 2Story 0.1926 0.171 0.214 0.021 9.833 0.016 12.687 HouseStyle SFoyer 0.2056 0.000 0.165 0.247 HouseStyle SLvl 0.2047 0.000 0.173 0.236 0.009 53.264 0.5042 0.000 0.486 MasVnrType_BrkFace 0.523 0.009 53.886 0.011 45.475 0.017 14.516 0.015 18.172 0.016 18.024 0.026 10.619 0.040 6.475 0.054 2.977 0.032 8.695 0.046 2.465 0.009 53.886 0.000 0.485 0.5037 0.522 MasVnrType_None 0.489 0.217 0.249 0.258 0.5113 0.2504 0.000 MasVnrType Others 0.000 0.000 0.000 Foundation BrkTil 0.284 Foundation_CBlock 0.309 0.2793 0.2895 Foundation PConc 0.321 Foundation Slab 0.2796 0.000 0.228 0.331 0.2601 0.000 Foundation Stone 0.181 0.339 0.1604 0.003 0.055 0.266 Foundation_Wood 0.2746 0.000 0.213 0.337 Functional_Maj1 2.465 13.578 0.023 0.1128 0.014 0.203 Functional Maj2 0.025 0.3363 Functional Min1 0.385 0.281 0.000 0.378 Functional_Min2 0.3292 0.025 13.265 0.031 7.666 0.094 -1.467 Functional Mod 0.2346 0.000 0.175 0.295 Functional Sev -0.1384 0.143 -0.323 0.047 Functional Typ 0.3701 0.019 19.415 0.000 0.333 0.408 0.010 50.636 0.000 0.492 GarageType_Attchd 0.5121 0.532 0.486 0.5069 0.000 0.011 47.646 0.528 GarageType_Detchd 0.479 0.000 GarageType_Others 0.5002 0.011 47.111 0.521 0.051 0.091 0.135 0.000 4.313 0.000 0.000 0.000 SaleType_COD 0.0942 0.022 0.137 0.1901 3.770 0.050 0.289 SaleType_CWD 0.2734 0.070 3.889 SaleType_Con 0.411 0.119 SaleType ConLD 0.1919 0.037 5.179 0.000 0.265 0.046 0.046 SaleType_ConLI 0.1217 2.653 0.008 0.032 0.212 0.1341 2.893 0.004 0.225 0.043 SaleType_ConLw

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7]: WLS_prediction = pd.DataFrame(np.exp(weighted_lin_regression.predict(test_data))) 8]: WLS_prediction = WLS_prediction.rename(columns={0:'SalePrice'}) 1]: WLS_prediction.to_csv('E:/projects/housing_price/WLS_prdiction.csv',columns=WLS_prediction.columns)