

AMES IOWA HOUSING

MODELLING FOR PRICE PREDICTION

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Business Objective

- Deciding on the price of a house is a very subjective matter, that varies from person to person.
- Our team is tasked to create a model that *objectively* and *reproducibly* predicts the price of housing in Ames, Iowa, USA, from past transaction data obtained in 2006-2010

Data Set

Descriptive Abstract:

- Data set contains information from the Ames Assessor's Office used in computing assessed values for individual residential properties sold in Ames, IA from 2006 to 2010.

Sources:

- Ames, Iowa Assessor's Office

Files:

- train.csv (2051 rows, 81 columns)
- test.csv (879 rows, 80 columns)

Technical Overview

1. EDA / Data Cleaning → to get a good dataset to work with
2. EDA / Feature Engineering → to make features as balanced as possible for the model to train on
3. Modelling Process
4. Conclusion

EDA/Cleaning

1. Read and internalize data documentation thoroughly

Understand the different types of variables available and what they mean

2. EDA & Cleaning (original 2051, 81)

a. Drop columns with obvious and extensive (**> 300**) missing values

(5)

b. Drop non-numeric columns whose variation of data is minimal

(occurrence of **SAME category** **> 85%**)

(18)

c. Drop numeric columns whose variation of data is minimal

(occurrence of **SAME category** **> 85%**)

(8)

d. Drop rows with **NA** (184)

→ (1867, 49)

Street	Alley	Lot Shape
Pave	NaN	IR1
Pave	NaN	IR1
Pave	NaN	Reg
Pave	NaN	Reg
Pave	NaN	IR1

1	df['Utilities'].value_counts()
AllPub	2049
NoSeWa	1
NoSewr	1

EDA/Cleaning

CONTINUOUS VARIABLES

- drop weakly correlated variables with SalePrice (< 0.30)
- drop variables strongly corr with each other (> 0.70), keep stronger corr with SalePrice

Other Variables by Observation / Intuition

98.8%
Match!

BsmtFin SF 1	Bsmt Unf SF	Total Bsmt SF
0	533.0	192.0
1st Flr SF	2nd Flr SF	Gr Liv Area
0	725	754
1	913	1209
2	1057	0
3	744	700
4	831	614

drop!

drop!

Year Built vs Year Remod/Add

MS Subclass similar to House Style

drop!

Corr with SalePrice

Gr Liv Area	0.707080
Garage Cars	0.653924
Garage Area	0.646488
1st Flr SF	0.626024
Total Bsmt SF	0.623269
Full Bath	0.551443
TotRms AbvGrd	0.536021
Mas Vnr Area	0.504794
Fireplaces	0.444809
BsmtFin SF 1	0.401466
Open Porch SF	0.332883
Wood Deck SF	0.311658

drop!

Lot Area	0.296810
Bsmt Full Bath	0.268839
Half Bath	0.264706
Bedroom AbvGr	0.139310
Enclosed Porch	-0.128909

drop!



drop!

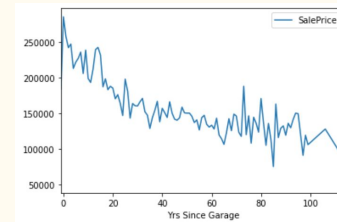
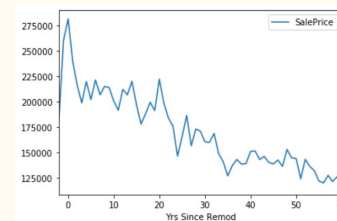
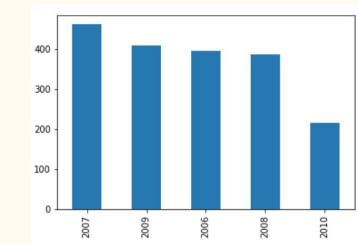
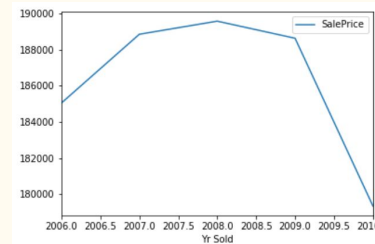
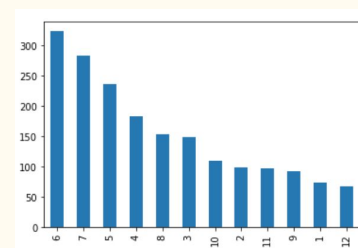
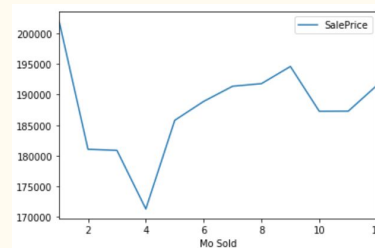
Data Transformations

TIME VARIABLES

- Reengineer to continuous with respect to sale price
- Keep 'mo sold' as categorical and created dummy
 - Keep 'yr sold' as continuous

```
def remake_remod(df):  
    df = df.copy()  
    df['Yrs Since Remod'] = df['Yr Sold'] - df['Year Remod/Add']
```

```
def remake_garageyrblt(df):  
    df = df.copy()  
    df['Yrs Since Garage'] = df['Yr Sold'] - df['Garage Yr Blt']
```

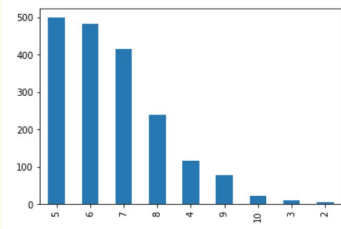


Data Transformations

CATEGORICAL VARIABLES

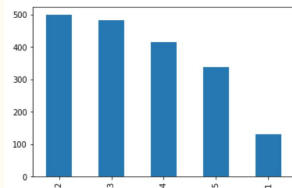
- balance & encode/create dummies

Overall Qual 1867

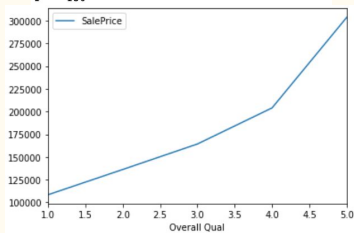


5 499
6 483
7 416
8 240
9 115
10 77
11 22
12 10
13 5

Overall Qual 1867



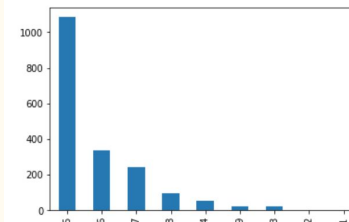
2 499
3 483
4 416
5 240
6 115



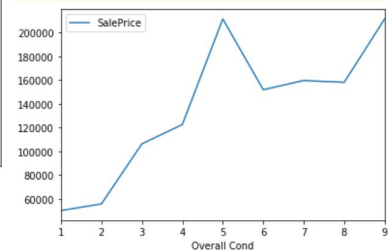
ORDINAL VARIABLES

- check relations, re-balance

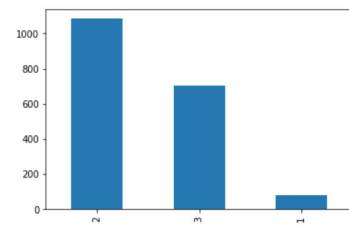
Overall Cond 1867



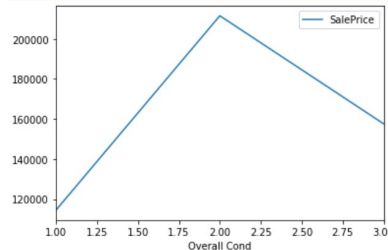
5 1084
6 339
7 244
8 95
9 53
10 25
11 23
12 3
13 1



Overall Cond 1867



2 1084
3 703
4 80



EDA/Cleaning/Engg (55) → 19 → 17 (ALL adjR2 = 0.826)

FINAL VARIABLES

‘Exter Qual’,
‘Bsmt Qual’, ‘Overall Qual’,
‘Overall Cond’, ‘Kitchen Qual’,
‘Gr Liv Area’, ‘Mas Vnr Area’,
‘Fireplaces’, ‘BsmtFin SF 1’,
‘Bldg Type’, ‘House Style_1+’,
‘Garage Area’, ‘Garage Cars’,
‘Garage Type_BuiltIn’,
‘Mo Sold_7’, ‘Roof Style’,
‘MS Zoning_RM’,

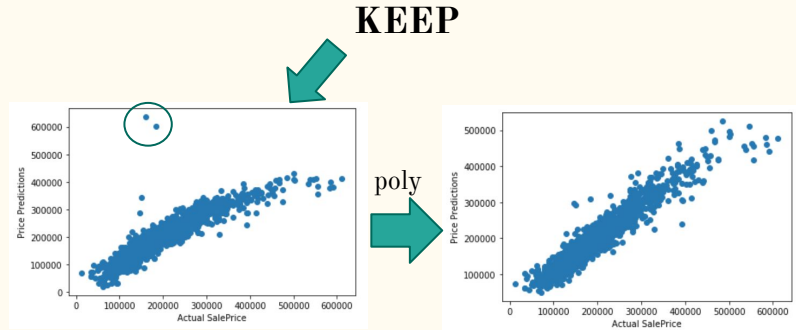
Create ‘Pipeline’ of
transformation functions done
on train set to apply on test set
and modelling later

Dep. Variable:	SalePrice	R-squared:	0.831
Model:	OLS	Adj. R-squared:	0.826
Method:	Least Squares	F-statistic:	178.7
Date:	Sun, 24 Nov 2019	Prob (F-statistic):	0.00
Time:	19:06:56	Log-Likelihood:	-22036.
No. Observations:	1867	AIC:	4.417e+04
DF Residuals:	1816	BIC:	4.446e+04
DF Model:	50		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	1.871e+05	758.721	246.540	0.000	1.86e+05	1.89e+05
x1	882.4270	1122.607	0.786	0.432	-1319.310	3084.164
x2	716.8367	1008.418	0.709	0.478	-1245.945	2692.619
x3	8477.2801	1248.686	6.789	0.000	6028.268	1.09e+04
x4	1.099e+04	1390.021	7.906	0.000	8263.048	1.37e+04
x5	1.116e+04	1324.777	8.427	0.000	8565.691	1.38e+04
x6	1.194e+04	1368.924	8.724	0.000	9257.696	1.46e+04
x7	4409.4884	895.571	4.924	0.000	2653.032	6165.945
x8	-1176.6176	786.640	-1.496	0.135	-2719.432	366.197
x9	-2078.127	1283.525	-1.617	0.106	-4592.514	442.168
x10	3328.4664	1521.151	2.188	0.029	345.077	6311.856
x11	2.008e+04	2227.182	9.017	0.000	1.57e+04	2.45e+04
x12	6475.7612	1658.710	3.904	0.000	3222.581	9729.942
x13	5116.3030	1644.231	3.074	0.002	1852.295	8380.311
x14	620.6696	2419.764	0.257	0.798	-4125.145	5366.484
x15	2360.7268	1969.375	1.199	0.231	-1501.751	6223.205
x16	-401.0821	893.985	-0.449	0.652	-2699.663	1897.499
x17	2527.2501	1412.382	1.789	0.074	-242.814	5297.315
x18	6234.0027	923.749	6.749	0.000	4422.280	8045.725
x19	4598.0225	942.604	4.878	0.000	2749.350	6446.755
x20	7200.4488	985.256	7.308	0.000	5268.094	9132.804
x21	-414.4853	860.498	-0.482	0.630	-2102.155	1273.185
x22	1512.0740	833.269	1.815	0.070	-122.192	3146.340
x23	558.6934	800.318	0.698	0.485	-1010.948	2128.335
x24	5672.6902	887.261	6.393	0.000	3932.531	7412.849
x25	-3047.5508	843.930	-3.611	0.000	-4702.726	-1392.376
x26	-1210.5248	849.293	-1.423	0.153	-2875.219	355.181
x27	-987.3533	768.021	-1.286	0.199	-2493.650	518.944
x28	1179.9300	741.110	1.592	0.112	-273.588	2633.448
x29	103.5481	763.603	0.136	0.892	-1394.085	1601.181
x30	621.7910	499.217	1.246	0.213	-357.308	1600.890
x31	-1249.1237	601.015	-2.078	0.038	-2427.877	-70.370
x32	2801.3284	741.198	3.779	0.000	1347.638	4255.019
x33	-2417.9927	889.861	-2.713	0.007	-4163.252	-672.734
x34	-942.0044	772.201	-1.220	0.223	-2456.501	572.492
x35	-1334.6303	840.175	-1.589	0.112	-2982.441	313.180
x36	-28.6085	642.508	-0.045	0.964	-1288.740	1231.523
x37	860.8367	751.638	1.145	0.253	-613.332	2335.005
x38	-1305.6603	795.929	-1.640	0.101	-2866.693	255.372
x39	-163.3471	552.263	-0.296	0.767	-1246.485	919.791
x40	786.2033	698.567	1.126	0.259	-1746.630	1339.634
x41	2132.4565	807.373	2.641	0.008	548.979	3715.934
x42	-36.1087	777.124	-0.046	0.963	-1560.260	1488.042
x43	-684.3806	687.691	-0.995	0.320	-2033.129	664.368
x44	303.6845	735.584	0.413	0.680	-1746.363	1138.994
x45	-753.5535	723.084	-1.042	0.297	-2171.718	664.611
x46	136.8354	702.115	0.195	0.846	-1240.202	1513.873
x47	-446.6520	698.567	-0.639	0.523	-1816.732	923.428
x48	360.7650	706.926	0.538	0.591	-955.102	1676.632
x49	-224.2597	649.118	-0.345	0.730	-1497.356	1048.837
x50	1635.8042	661.156	2.474	0.013	339.099	2932.510
x51	217.3407	701.802	0.310	0.751	-1159.067	1593.764
x52	-236.0728	732.086	-0.322	0.747	-1671.891	1199.746
x53	-1117.3720	722.050	-1.548	0.122	-2533.507	298.763
x54	-277.0694	725.779	-0.382	0.703	-1700.518	1146.379
x55	95.3494	737.269	0.129	0.897	-1350.635	1541.334

OLS Regression Results									
Dep. Variable:	SalePrice	R-squared:	0.828						
Model:	OLS	Adj. R-squared:	0.826						
Method:	Least Squares	F-statistic:	522.6						
Date:	Sun, 24 Nov 2019	Prob (F-statistic):	0.00						
Time:	19:06:57	Log-Likelihood:	-22054.						
No. Observations:	1867	AIC:	4.414e+04						
DF Residuals:	1849	BIC:	4.424e+04						
DF Model:	17								
Covariance Type:	nonrobust								
	coef	std err	t	P> t	[0.025	0.975]			
const	1.871e+05	759.420	246.313	0.000	1.86e+05	1.89e+05			
Kitchen Qual	9044.5450	1193.867	7.576	0.000	6703.076	1.14e+04			
Exter Qual	1.149e+04	1328.505	8.650	0.000	8886.697	1.41e+04			
Bsmt Qual	1.198e+04	1194.701	10.029	0.000	9638.581	1.43e+04			
Overall Qual	1.284e+04	1285.319	9.909	0.000	1.03e+04	1.54e+04			
Overall Cond	4522.7676	834.677	5.419	0.000	2885.759	6159.776			
Gr Liv Area	2.321e+04	1149.860	20.186	0.000	2.1e+04	2.55e+04			
Garage Cars	6959.8478	1578.466	4.408	0.000	3863.301	1.01e+04			
Mas Vnr Area	6440.0474	899.379	7.161	0.000	4676.143	8203.952			
Fireplaces	4993.3644	902.456	5.533	0.000	3223.424	6763.305			
BsmtFin SF 1	8181.5638	889.090	9.204	0.000	6439.838	9927.289			
Bldg Type	6073.6798	821.518	7.393	0.000	4462.479	7684.880			
Roof Style	-3364.7259	814.691	-4.130	0.000	-4962.536	-1766.915			
House Style_1+	6018.0506	901.243	6.678	0.000	4250.491	7785.610			
Garage Area	4167.6170	1550.527	2.688	0.007	1126.648	7208.586			
Garage Type_BuiltIn	2123.1981	834.341	2.545	0.011	486.848	3759.548			
Mo Sold_7	1926.8344	763.615	2.523	0.012	429.195	3424.474			
MS Zoning_RM	-2615.9747	823.211	-3.178	0.002	-4230.496	-1001.453			
Omnibus:	1050.173	Durbin-Watson:	1.964						
Prob(Omnibus):	0.000	Jarque-Bera	134804.00						
Skewness:	-1.644	Prob(JB):	0.00						
Kurtosis:	44.510	Cond. No.	6.39						

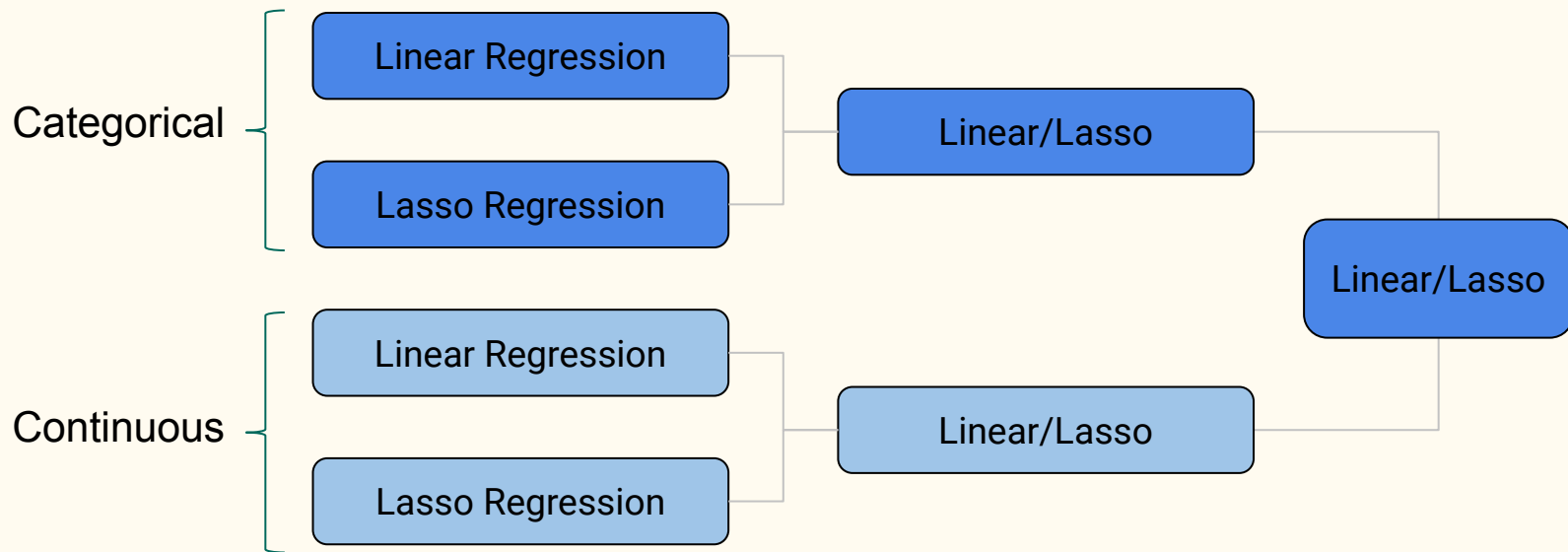
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



R2 = 0.826

R2 = 0.863

Modelling Process:



Stage 1:

- Train-test-split
- Feat. Eng
- Dum.Var

Stage 2:

- Cross-val
- R2-score

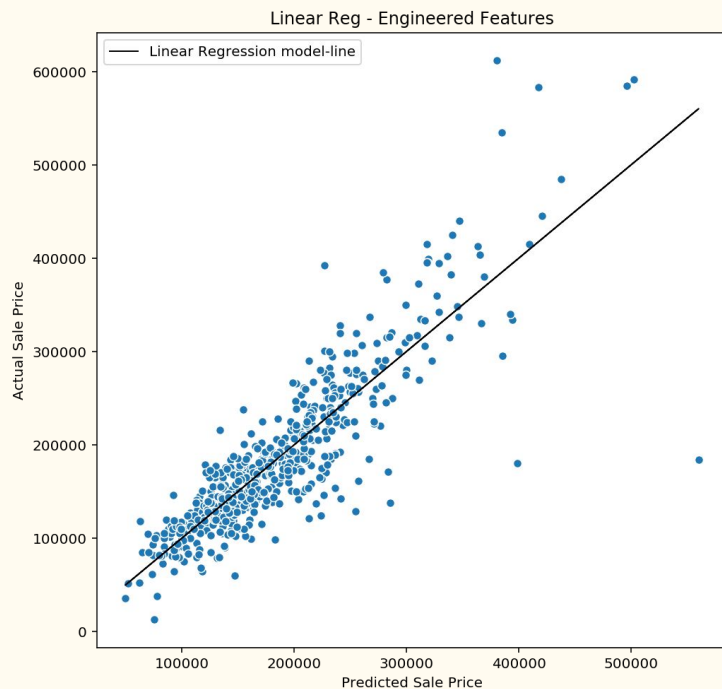
Stage 3:

- Combine Feat
- R2-score

Stage 4:

- Final
- Kaggle Test

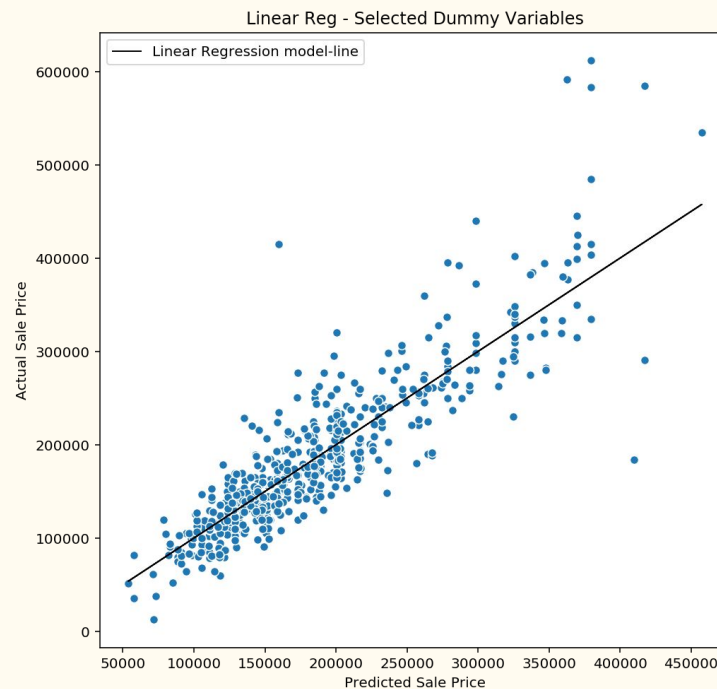
Model Evaluation (Individual)



Continuous Features

R2-score: 0.687

RMSE: 39647.45

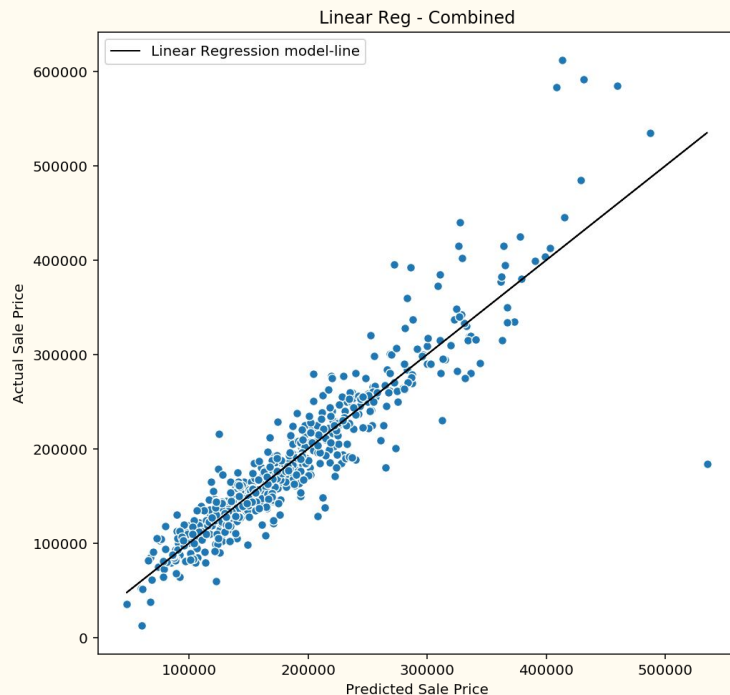


Categorical Features

R2-score: 0.698

RMSE: 37771.02

Model Evaluation (Combined)



Combined Features

R2-score: 0.824

RMSE: 30864.89

Predictors Coeffs.

47	Overall Qual_10	131754.019070
29	Neighborhood_GrnHill	102370.455690
55	Overall Qual_9	92271.974348
54	Overall Qual_8	70048.499174
53	Overall Qual_7	53156.259879
52	Overall Qual_6	41775.848841
51	Overall Qual_5	32727.480697
44	Neighborhood_StoneBr	30685.501542
23	Neighborhood_ClearCr	27874.277119
50	Overall Qual_4	26069.262578
3	Gr Liv Area	22631.793502
25	Neighborhood_Crawfor	20651.731751
49	Overall Qual_3	20641.100360
37	Neighborhood_NoRidge	20020.889372

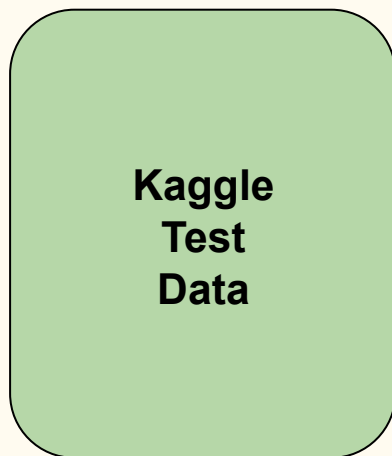
Top 15 positive
predictors

Predictors Coeffs.

28	Neighborhood_Greens	-14513.151549
60	Bsmt Qual_Gd	-14693.750663
35	Neighborhood_NPKvill	-15319.336894
57	Exter Qual_Gd	-15925.999486
30	Neighborhood_IDOTRR	-16326.259845
39	Neighborhood_OldTown	-16601.759971
64	Bsmt Qual_UnKn	-16992.136110
59	Bsmt Qual_Fa	-19490.351089
58	Exter Qual_TA	-21061.428090
63	Bsmt Qual_TA	-21206.505257
32	Neighborhood_MeadowV	-22788.035580
66	Kitchen Qual_Gd	-26383.688639
56	Exter Qual_Fa	-32661.475977
67	Kitchen Qual_TA	-35635.269316
65	Kitchen Qual_Fa	-41310.676463

Top 15 negative
predictors

Test data preprocessing & Kaggle Submission



1. Linear Reg
2. Lasso Reg

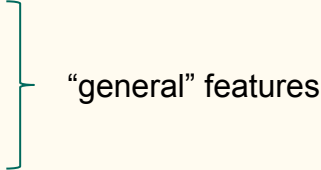


Cleaning
Pre-processing
Prediction

Kaggle scores:

1. Linear Regression (RMSE)
 - Private: 30262.80
 - Public: 28869.88
2. Lasso Regression (RMSE)
 - Private: 31505.63
 - Public: 30562.34

Conclusion

1. The model is sufficiently robust to predict housing prices in Ames, IA.
 - Area of the house (sq-feet)
 - Condition of the house
 - Neighbourhood

“general” features
2. Ability for the model to be applied in future housing predictions.
 - Property evaluation
 - Housing development projects

Future Recommendations

- Train on 2006-2009 data, test on 2010 data
- Income bracket of the person buying/ selling
- Crime rate of area
- Distance to offices/ amenities around the neighbourhood

Thanks!