

House Flippers



Pricing which suits you

Project 1

September 11th, 2019



Agenda



**Exploratory
Analysis**

Data Cleaning

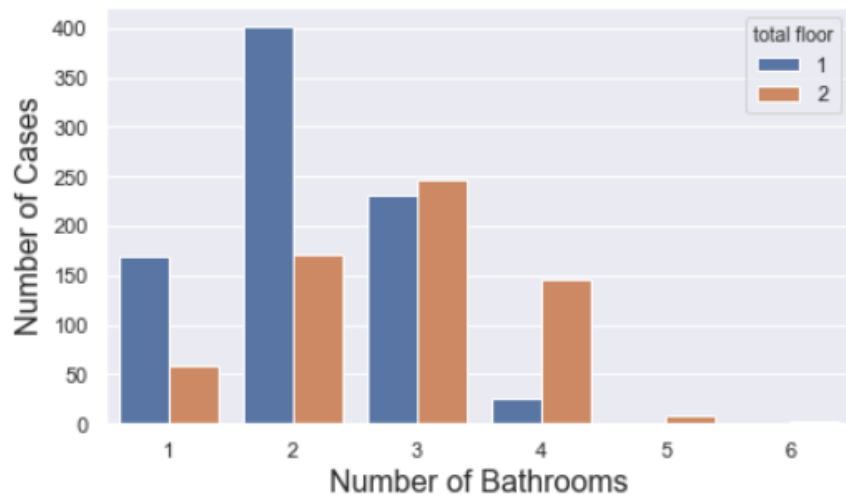
Model

Model Details

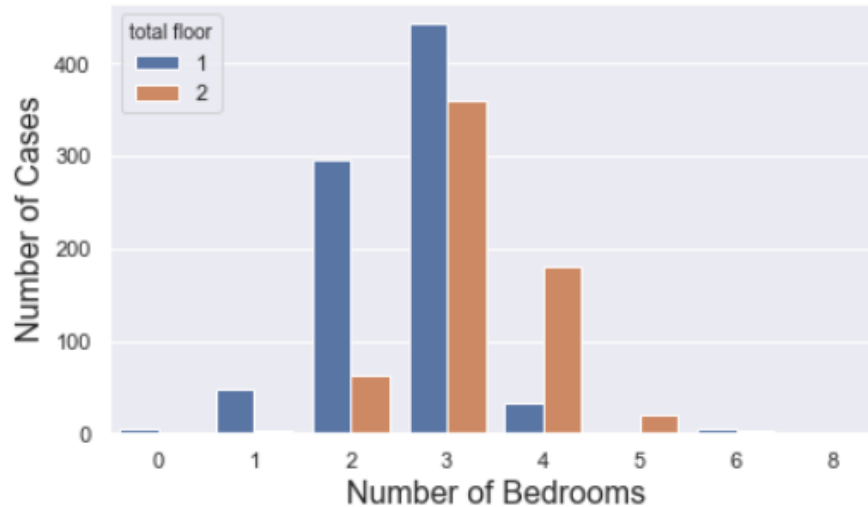
Conclusion

Most of the properties have between 2 and 3 bathrooms and the majority has 3 bedrooms

Total Bathrooms and Total Floor

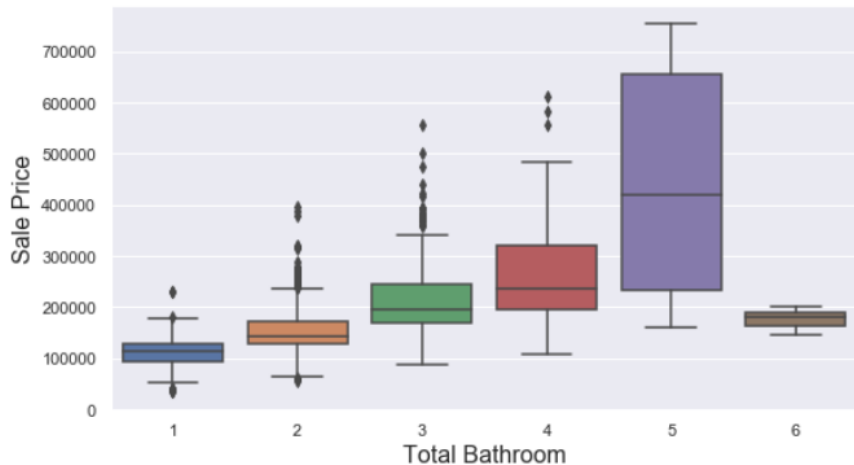


Bedrooms and Total Floor

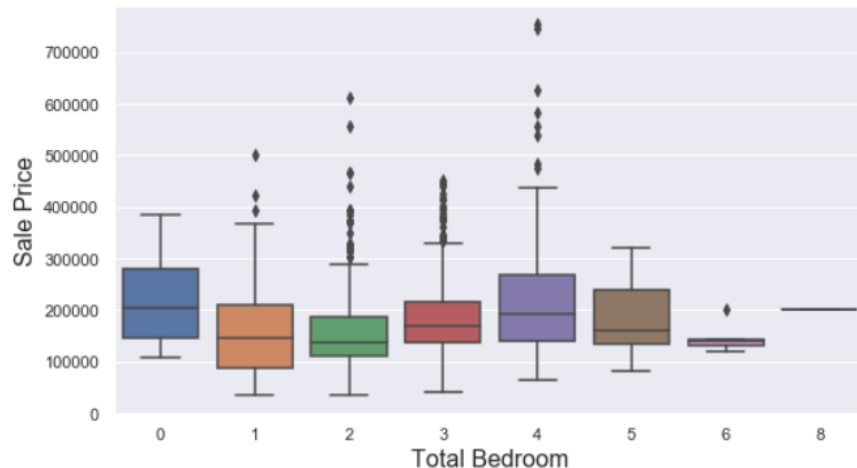


The highest variation of prices occurs when we compare Sale Price with Number of Bathrooms

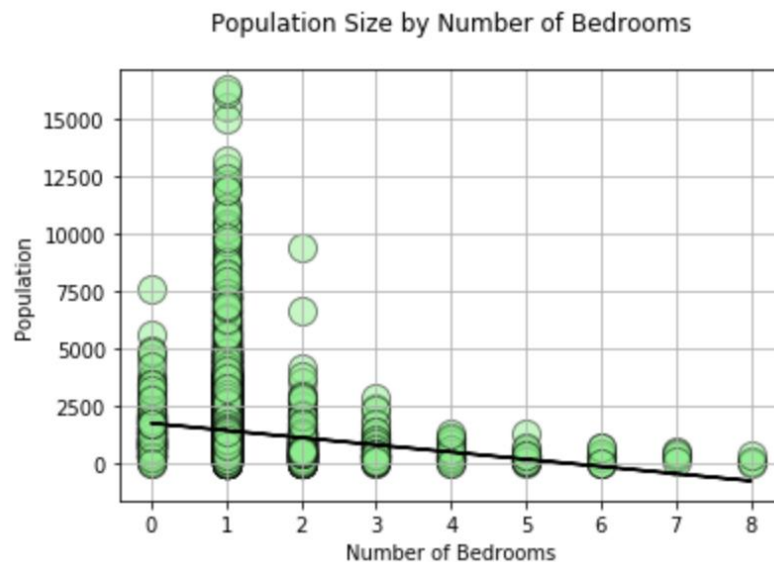
Box-Plot Chart Sale Price vs Total Bathroom



Box-Plot Chart Sale Price vs Total Bedroom



Trends in Sales Price and Population by Number of Bedrooms

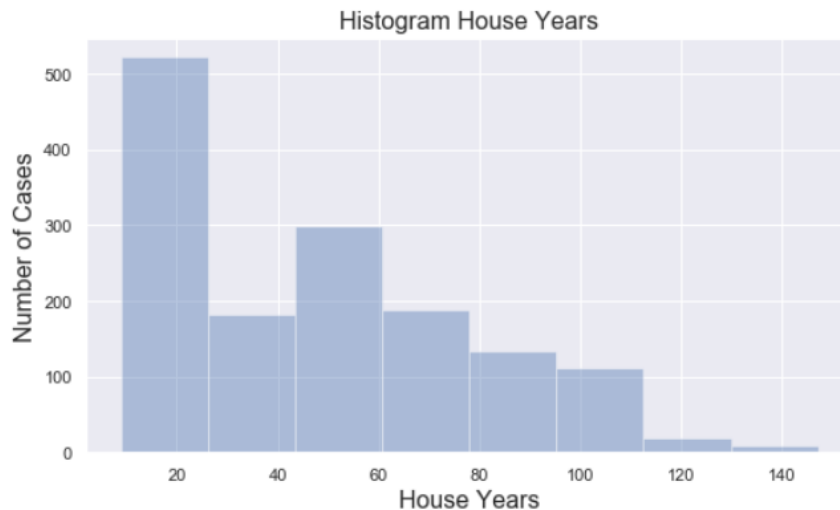


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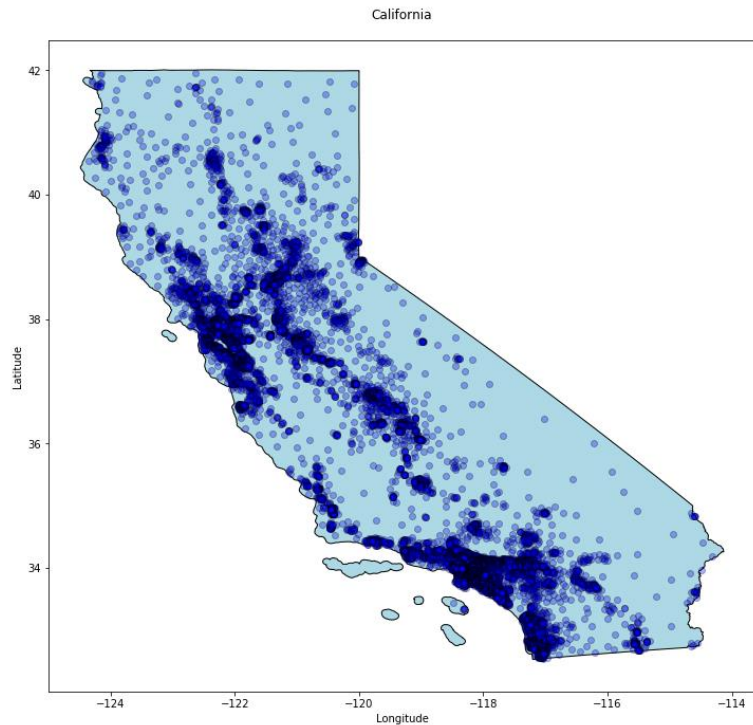
Source: train1 dataset Ames, Iowa, Kaggle

As we expected the older the property, the lower the price will be

	Count Sale Price	Avg Sale Price	Std Sale Price
Year Built			
0 to 15	275	248,398	88,616
16 to 30	278	228,168	80,565
31 to 45	166	172,229	48,086
46 to 60	281	148,860	43,246
61 to 75	185	135,350	37,856
76 to 90	93	138,966	62,535
91 to 105	129	127,834	43,988
>105	52	137,238	70,245

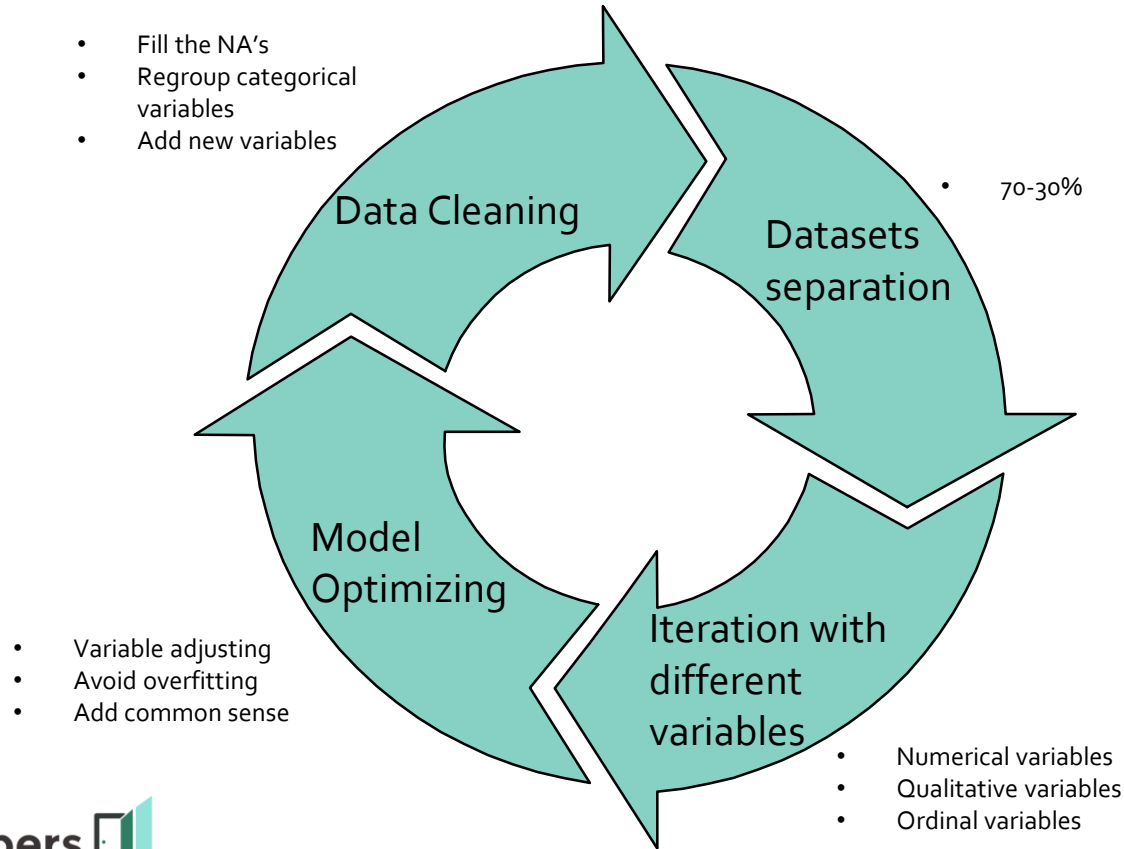


California Population Density and Sales Price by Population

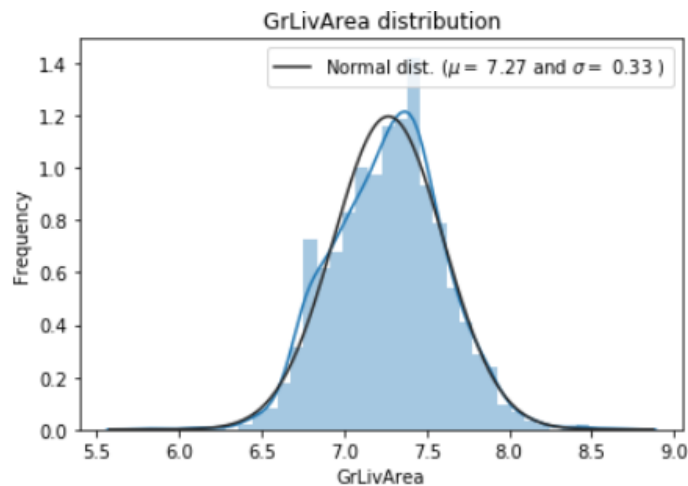
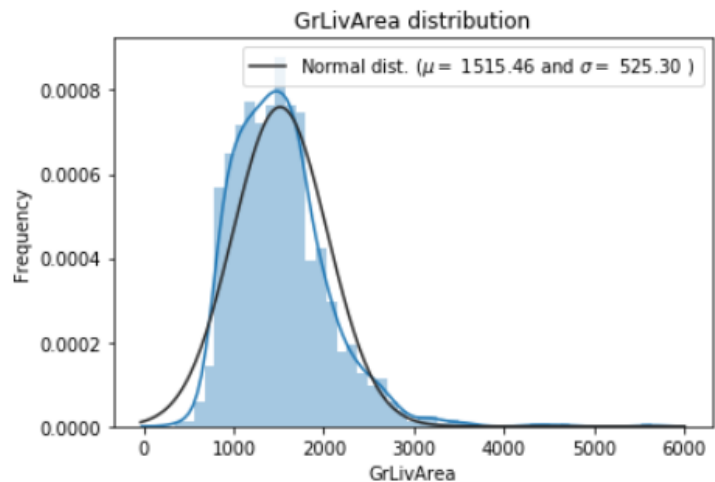


Source: train1 dataset Ames, Iowa, Kaggle

The price prediction model was built through an iterative process applying analytics tools...



Validating data and transforming it was the majority part of the work



```
kitqual = []
for x in train1["KitchenQual"]:
    if x == 'Ex':
        kitqual.append(5)
    elif x == 'Gd':
        kitqual.append(4)
    elif x == 'TA':
        kitqual.append(3)
    elif x == 'Fa':
        kitqual.append(2)
    else:
        kitqual.append(1)
```

kit_qual	
0	4
1	3
2	4
3	4
4	4

We found 15 significant variables that explained 89% of the prices in the dataset...

And 7 variables that can be exploited to increase housing value



Building Age



Building Age



of Bathrooms



of Bedrooms



of Floors



Overall Condition



Type of Property



Zoning Classification

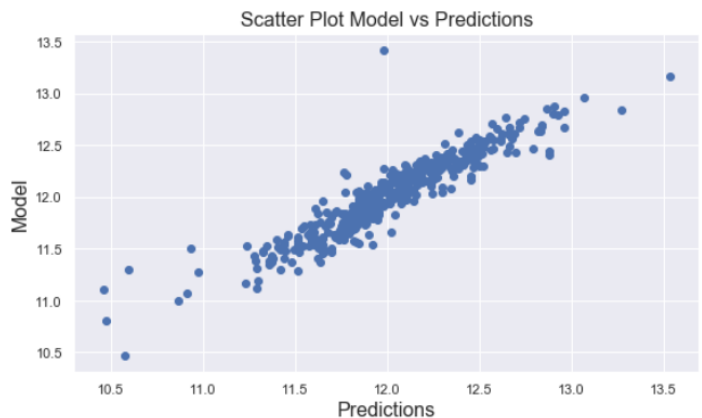


Garage Condition

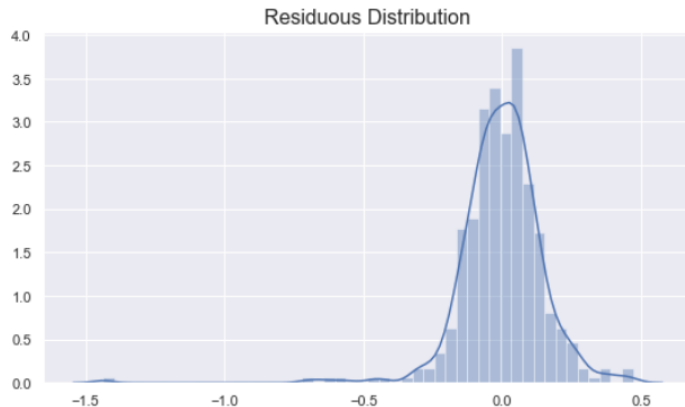


Heating Quality

The residuals are normally distributed, and the scatter plot shows a clear straight-line, however we must remove outliers.



Mean Squared Error (MSE): **0.103**
Root Mean Squared Error (RMSE): **0.153**



Numerical

Categorical

	Features	Coefs	P[>]
0	Intercept	6.696	0.000
1	LN_LotArea	0.107	0.000
2	LN_GrLivArea	0.491	0.000
3	LN_YearBuilt_Adj	-0.103	0.000
4	LN_Total_Bath	0.103	0.000
5	LN_total floor	-0.152	0.000
6	BedroomAbvGr	-0.024	0.001
7	OverallQual	0.078	0.000
8	OverallCond	0.052	0.000
9	2fmCon	-0.053	0.098
10	Duplex	-0.102	0.000
11	Twnhs	0.013	0.682
12	TwnhsE	0.005	0.816
13	FV	0.143	0.019
14	RH	0.187	0.010
15	RL	0.124	0.028
16	RM	0.062	0.276
17	GarageCars	0.046	0.000
18	kit_qual	0.041	0.000
19	heat_qual	0.011	0.058
20	g_cond	0.012	0.115

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Source: train1 dataset Ames, Iowa, Kaggle

To wrap up: improving this model is possible using more sophisticated techniques and obtaining geographic data



Designing a model takes time: understanding, organizing, cleaning the data



Improvement opportunities for this model are related to additional information such as living nearby the ocean, ocean view, economy shocks, new big projects (Amazon), create additional dummy variables, so forth



Location is very important for the price, however with this data set we cannot validate this assumption



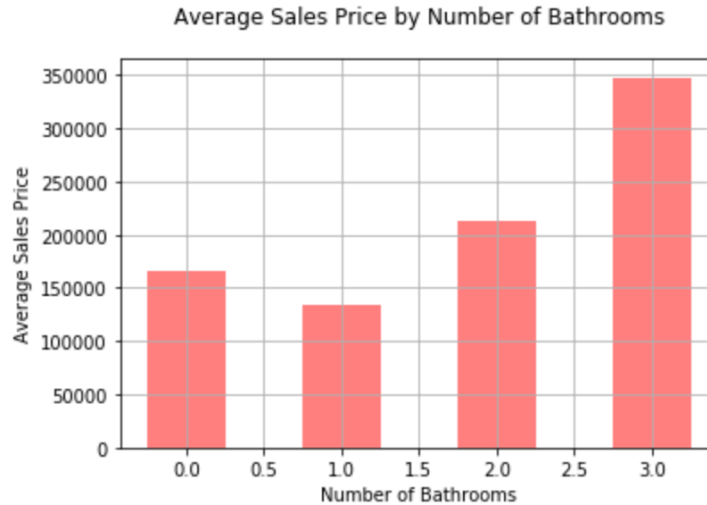
Removing Outliers will reduce the error of the model



Machine Learning could be a great option to optimize and improve this model

Appendix

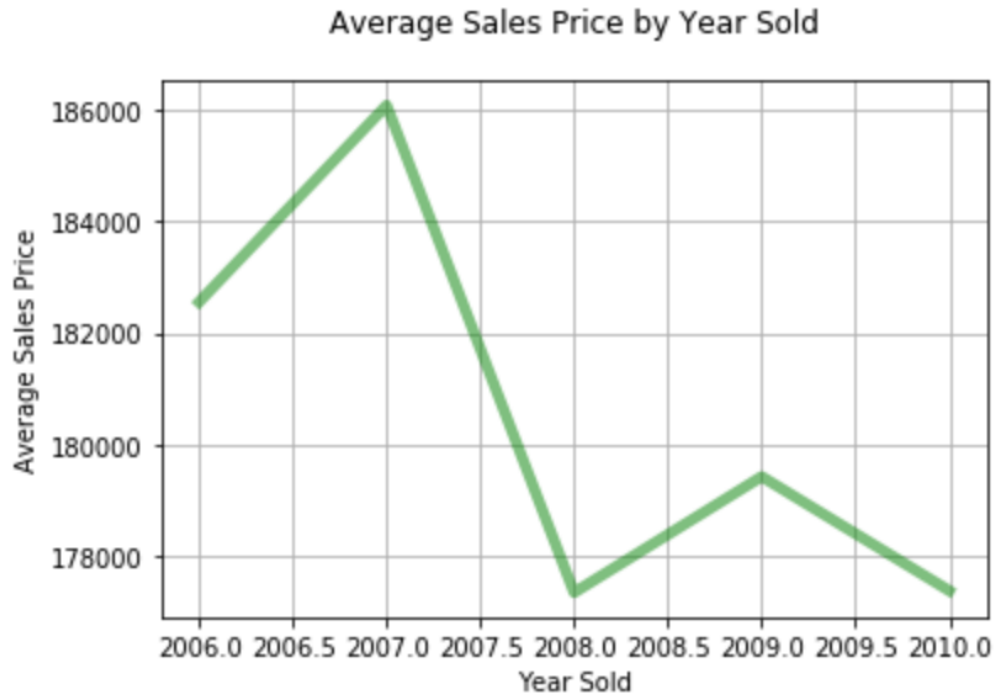
Trends in Sales Price by Number of Bathrooms



FullBath	0	0	0	0	0	0	0	0	0
BsmtFullBath	2	2	1	0	2	1	2	1	2
BsmtHalfBath	0	0	0	2	0	0	0	1	0
HalfBath	1	2	1	2	0	0	2	0	1
BedroomAbvGr	0	2	1	2	0	1	0	0	0

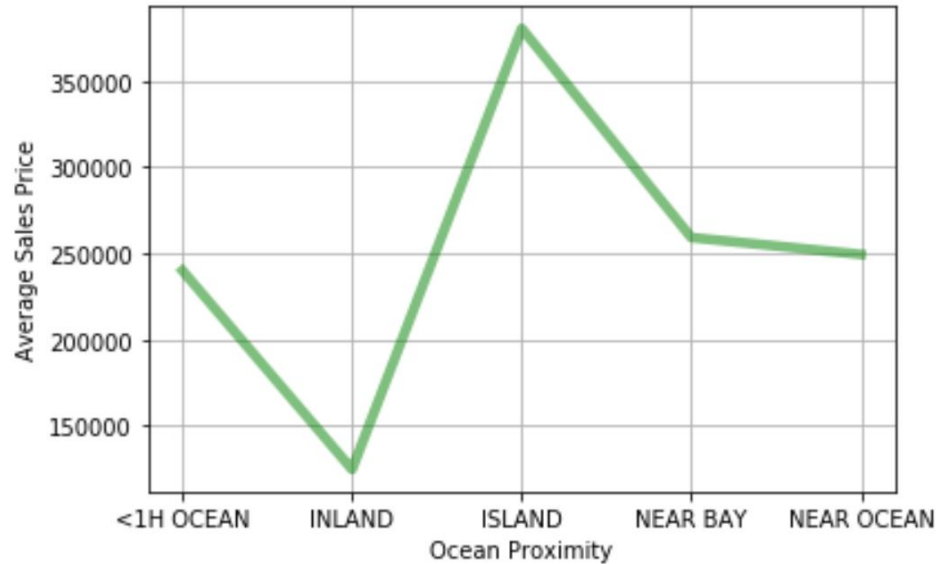


Annual Trends in Sales Price

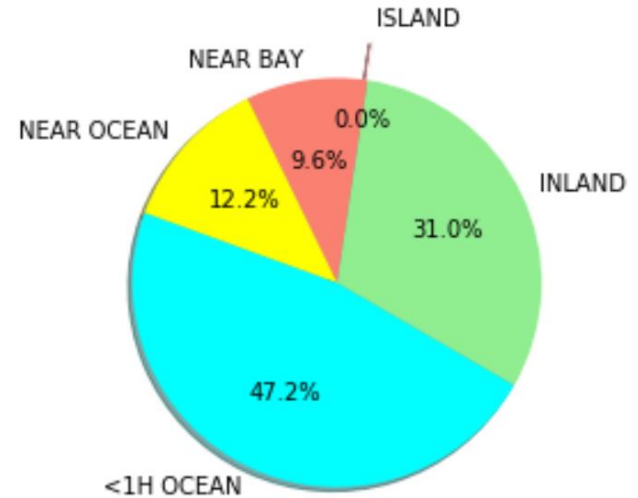


Trends in Sales Price and Population Size by Ocean Proximity

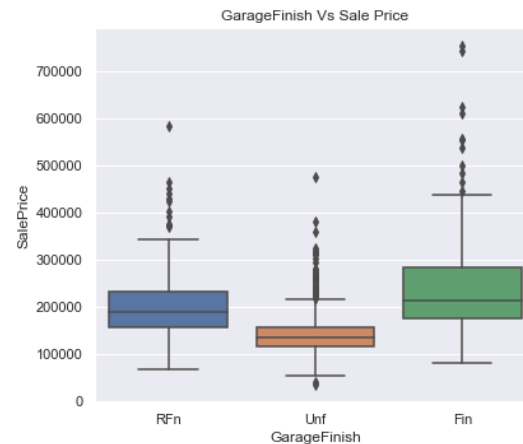
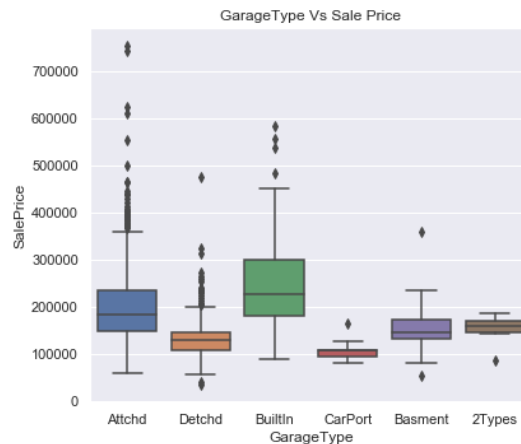
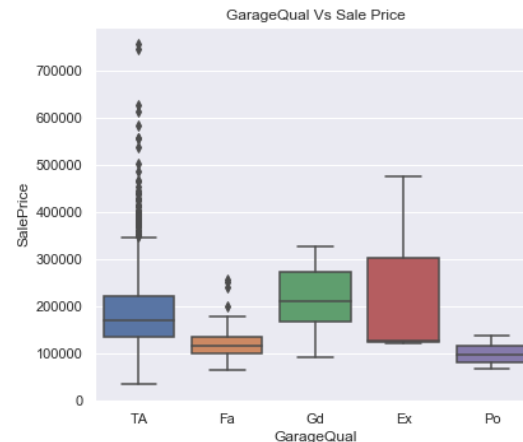
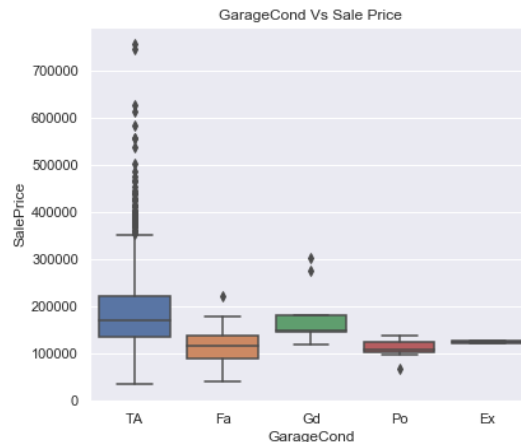
Average Sales Price by Ocean Proximity



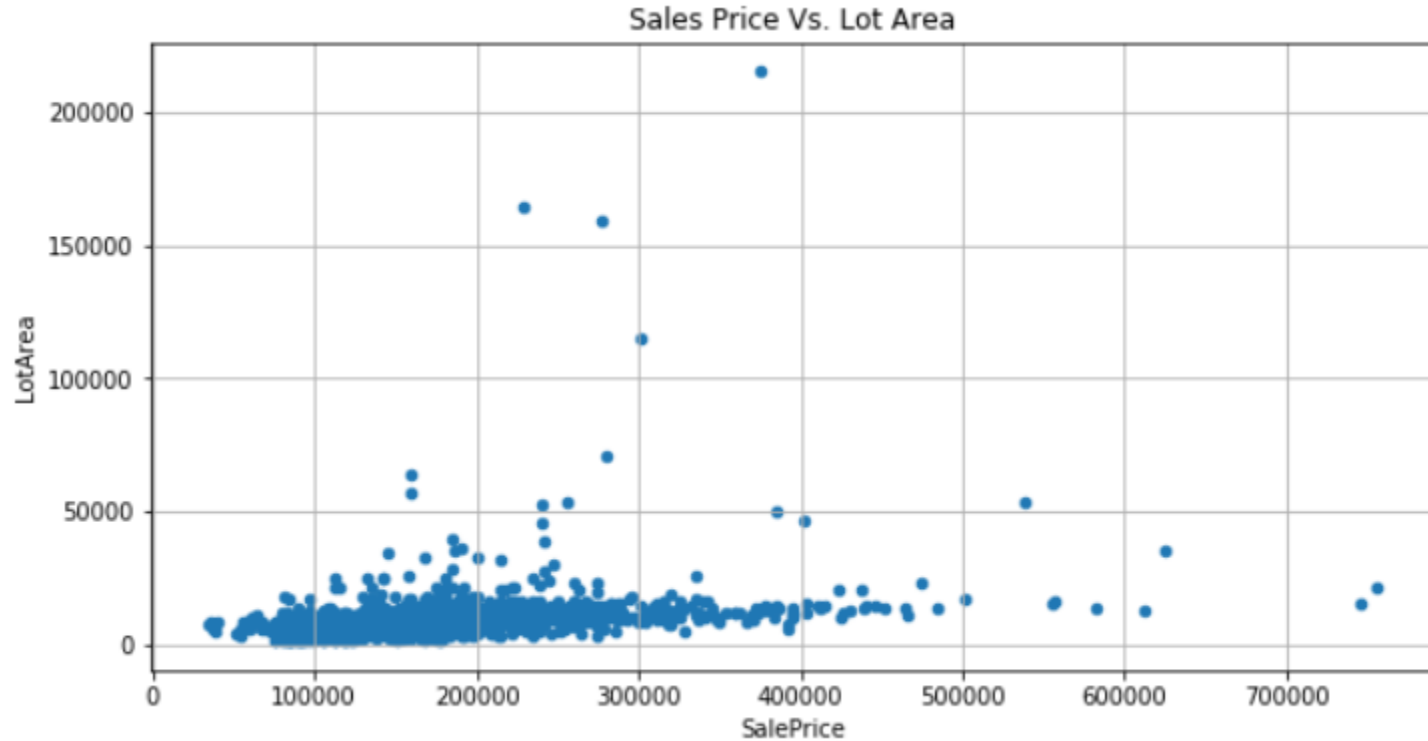
Population Size by Ocean Proximity



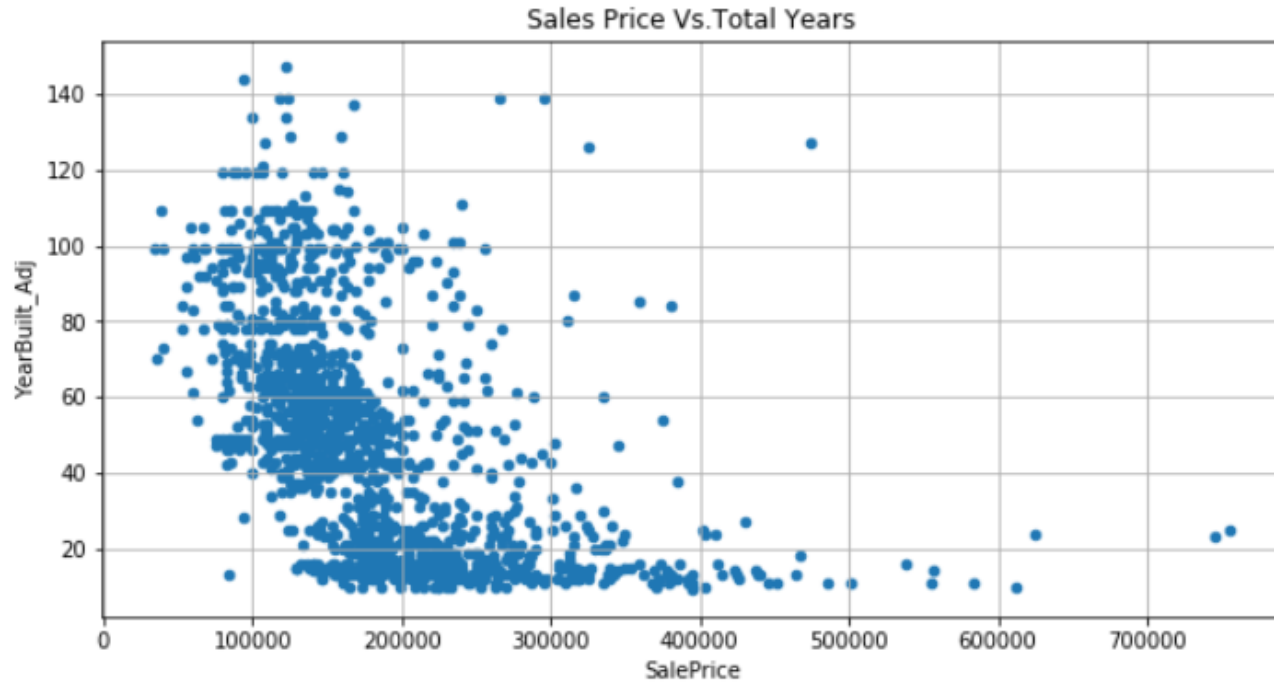
Trends in Sales Price and Population Size by Ocean Proximity



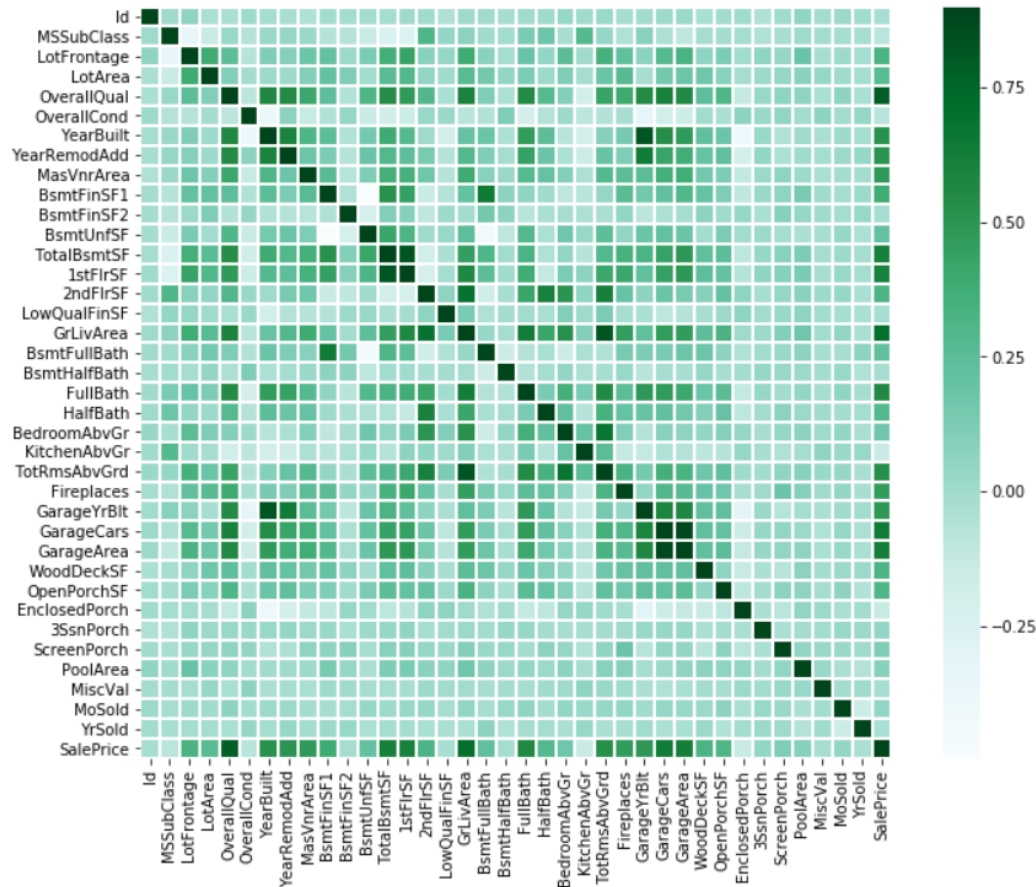
Removing Outliers is a MUST



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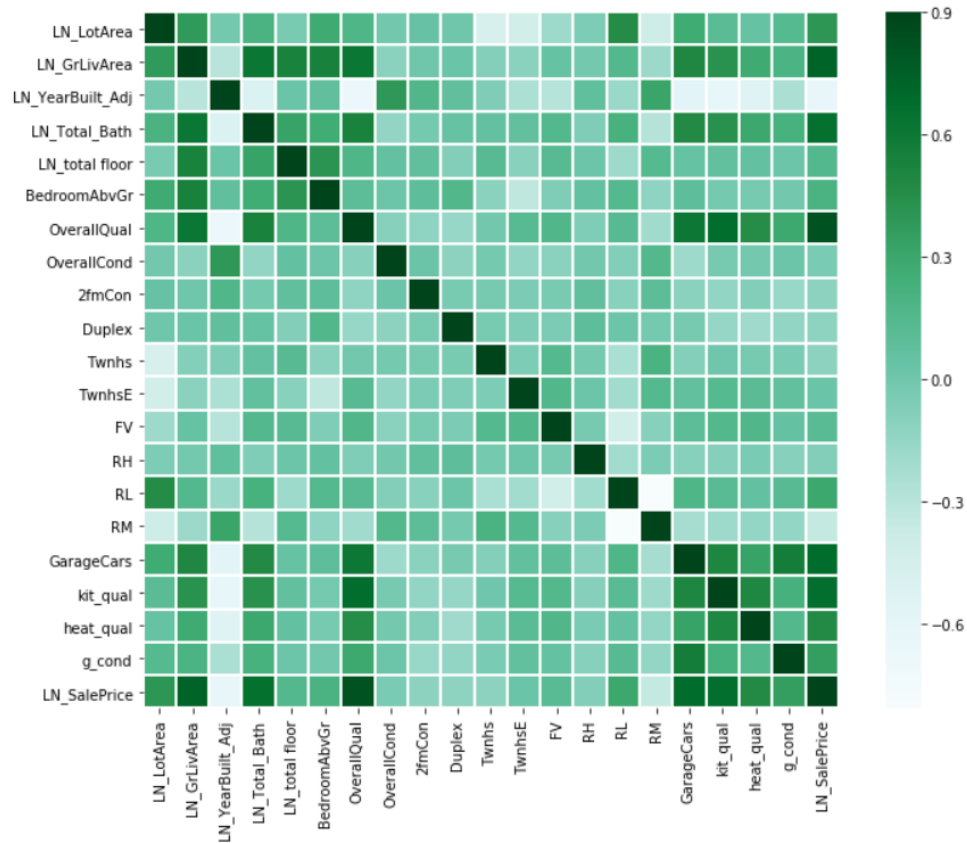
Correlation Matrix



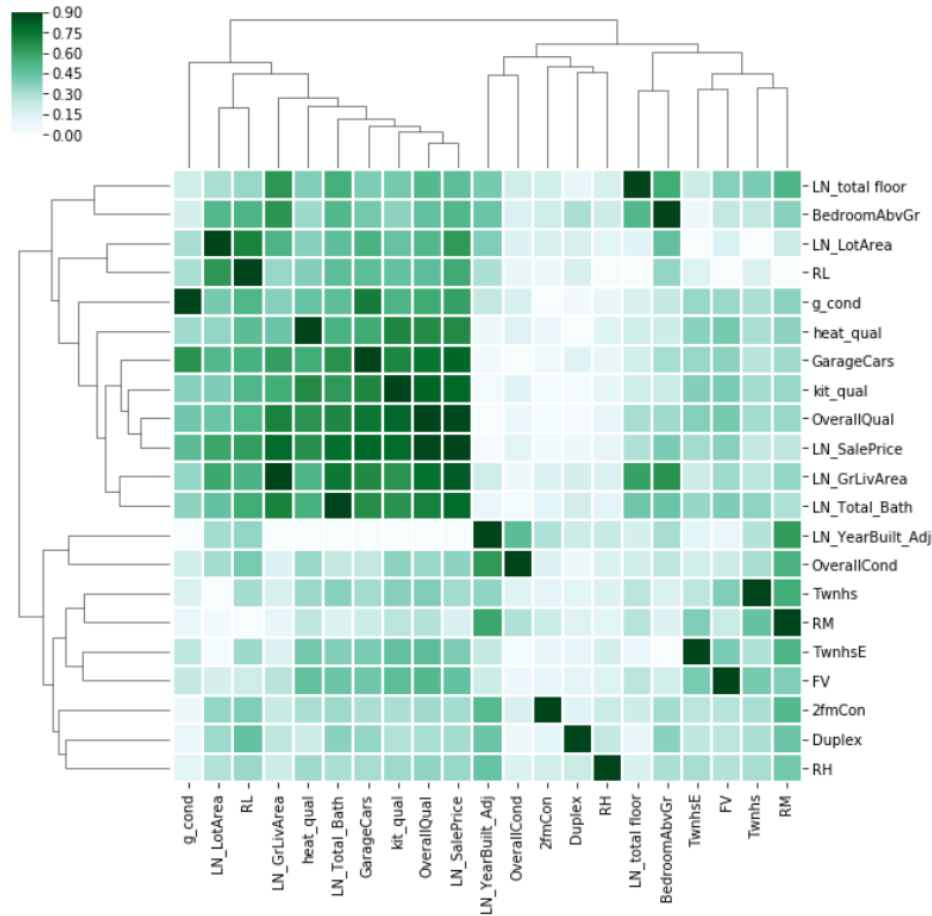
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Correlation Matrix



Correlation Matrix



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