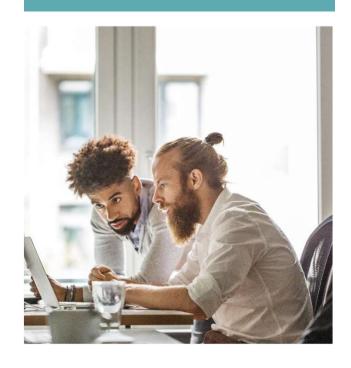
Analysis of Property Sales

Ryan Chung





Introduction

Business Problem

Data & Methods Used

Results & Conclusion

Final Thoughts

Outline

Project Introduction

Business Problem

A local real estate agency is looking to identify features of house listings that act as accurate predictors of their selling prices to take into consideration when purchasing and selling residential property.



Data Used

For this project, the real estate agency provided a data set which was comprised of residential property listings with various features.

Some of the features in the data set include housing aspects such as number of bedrooms, bathrooms, and floors.







Methods



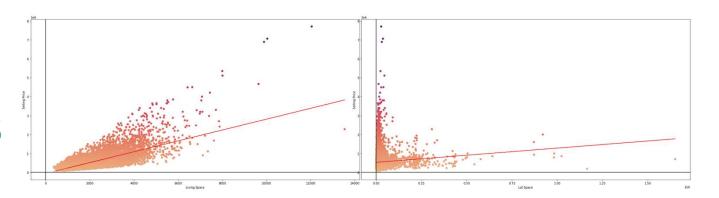
Initial Steps

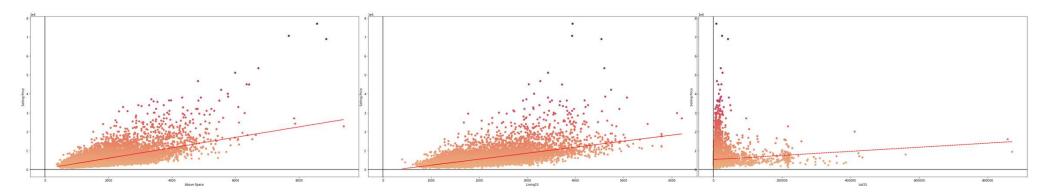
- Upon receiving the data set, it was cleaned and checked for null values.
- After cleaning the data, basic visualizations were created for several housing features.
- Three simple linear regression models were created based upon the insights from the basic visualizations.
- After looking at various housings features and their impact on their selling prices, the decision to make a multiple linear regression was made.

Final Model

- The multiple regression model encompassed all housing features and was created using an iterative approach.
- A train test split approach was utilized, features were scaled, and the model was then checked for multicollinearity along with its distribution of error terms.
- Upon the completion of the finalized model, R2 values were compared and the RMSE was evaluated.
- Several housing features were identified to be accurate predictors of a house's selling price.

Initial Visualizations





Initial MLR OLS Summary + VIF Values

LR_1.summary()

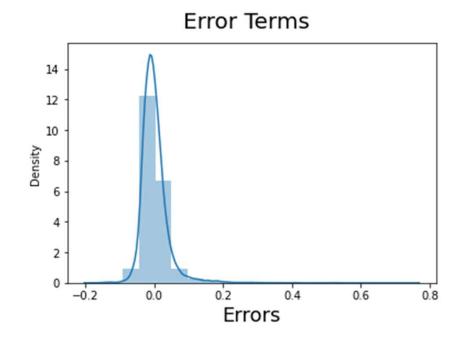
OLS Regression Results

Dep. Variable:		price		R-sc	0.610		
Model:		OLS		Adj. R-sc	uared:	0.610	
Method: Lea		st Squares		F-st	140	7	
Dat	e: Mon, 0	9 Aug 2	021 Pro	ob (F-sta	tistic):	0.	00
Time:		20:40	0:09 L	Log-Likelihood:		22072	
No. Observations:		10	800		AIC:	-4.412e+	04
Df Residuals:		10	787	BIC		-4.402e+	04
Df Mode	el:		12				
Covariance Typ	e:	nonro	bust				
	coef	std err		Dollar	10.025	0.0751	
			191		[0.025	0.975]	
const	-0.0495	0.002	-24.282		-0.054	-0.046	
bedrooms	-0.1571	0.013	-12.159	0.000	-0.182	-0.132	
bathrooms	-0.0098	0.005	-1.941	0.052	-0.020	9.6e-05	
sqft_living	0.1354	0.003	38.861	0.000	0.129	0.142	
sqft_lot	0.0107	0.017	0.615	0.538	-0.023	0.045	
floors	-0.0038	0.002	-1.972	0.049	-0.008	-2.2e-05	
waterfront	0.0838	0.004	21.758	0.000	0.076	0.091	
view	0.0337	0.002	18.119	0.000	0.030	0.037	
condition	0.0279	0.002	14.345	0.000	0.024	0.032	
grade	0.1250	0.005	27.239	0.000	0.116	0.134	
sqft_above	0.1613	0.005	34.035	0.000	0.152	0.171	
sqft_basement	0.0786	0.003	24.002	0.000	0.072	0.085	
sqft_living15	-0.0024	0.004	-0.576	0.564	-0.011	0.006	
sqft_lot15	-0.0887	0.014	-6.516	0.000	-0.115	-0.062	
Omnibus:	0500 000	D.,	-l-i- 18/-4		2.00		
	8500.808		rbin-Wat		2.00		
Prob(Omnibus):	0.000		ue-Bera	1 - 1 - 1 - 1 - 1	61410.47		
Skew:				Prob(JB): 0.			
Kurtosis:	40.798		Cond	. No.	2.42e+1	6	

vif

VIF	Features	
inf	sqft_living	2
inf	sqft_above	9
inf	sqft_basement	10
31.62	grade	8
16.67	sqft_living15	11
15.90	bathrooms	1
10.62	bedrooms	0
9.73	condition	7
3.45	floors	4
2.70	sqft_lot15	12
2.53	sqft_lot	3
1.48	view	6
1.20	waterfront	5

Final
MLR OLS
Summary
+ VIF
Values



	Features	VIF
6	sqft_lot15	2.65
0	sqft_lot	2.52
4	condition	2.37
5	sqft_basement	1.66
1	floors	1.63
3	view	1.42
2	waterfront	1.20

Final MLR OLS Summary

print(LR_7.summary())

OLS R	legres	sion F	lesult
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						======	
Dep. Variable:	price		R-squared:		0.330		
Model:	OLS		Adj. R-sq	Adj. R-squared:		0.329	
Method:	Le	Least Squares		F-statistic:		758.3	
Date:	Mon,			Prob (F-statistic):		0.00	
Time:		21:11:11		Log-Likelihood:		19146.	
No. Observations:		10800		AIC:		-3.828e+04	
Df Residuals:		10792	BIC:		-3.822e+04		
Df Model:		7					
Covariance Type:		nonrobust					
		std err			[0.025	0.975]	
const		0.002			0 016	0.023	
sqft lot					0.030		
_		0.002			0.075		
waterfront				0.000			
		0.002	26.988	0.000	0.059	0.069	
condition	0.0165	0.003	6.509	0.000	0.012	0.021	
sqft_basement	0.1438	0.004	36.260	0.000	0.136	0.152	
sqft_lot15	0.0497	0.018	2.813	0.005	0.015	0.084	
Omnibus:	9602.168		Durbin-Watson:		2.039		
Prob(Omnibus):	0.000		Jarque-Bera (JB):		793601.084		
Skew:		3.911	Prob(JB):		0.00		
Kurtosis:		44.260	Cond. No.			81.2	

Notes

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

Check R2 values to confirm if final predicted model is best fitted or not.

```
from sklearn.metrics import r2_score

r2_score(y_true = y_test, y_pred = y_pred_M7)
0.33375961922542563

# With R2 values almost equal the model is best fitted!!!
```

Check RMSE

```
import sklearn
import math

mse = sklearn.metrics.mean_squared_error(y_test, y_pred_M7)

rmse = math.sqrt(mse)

print(rmse)

0.03750663037047103
```

Confirmation of R2 Values and RMSE Value

Images from JYNB

When comparing the two computed R2 values, the final model was confirmed to be best fitted.

Using the sklearn library, the RMSE value was found to be 0.0375.

Results & Conclusions

Reviewing the final multiple regression OLS summary, the features indicated to be accurate predictors of a house's selling price include the following: Square footage of property's lot, number of floors, waterfront, view, condition of property, square footage of basement, & square footage of nearest 15 neighbor's lot.

Returning to the initial business problem, it can be said that the local real estate agency should look at these features of residential housing listings when purchasing and selling property.



Data Cleaned + Visualized (EDA)



Initial Model Checked for Multicollinearity + Error Term Distribution



R2 Values of Model Compared + RMSE Calculated



Features Identified as Accurate Predictors for Business Recommendations.

Thank You!