Predicting Housing Prices in the Bay Area

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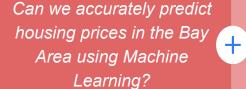
Current Issues Concerning Machine Learning in Real Estate

- Too many systems, collect data in different ways
- Timely and complete data is the biggest barrier to entry



Problem Statement





Is there a day of the week that is best to list your property?

Business Case

BUYER

Allows buyers to gain confidence around the list price of their property



SELLER

 Enable sellers to feel comfortable with pricing estimates regarding their investment

INVESTORS

- what goes in to pricing a real investment
- Helps appraisers appraise true value of properties for taxes

Data Source and Suggested Approach

- Collected data from SF MLS
- Predict prices of residential properties in SF, sold in the year 2020.
- Use this finding to predict prices on currently active homes in San Francisco.



Model - Data Cleansing

```
df.describe(include = 'all') #Listing all columns with various datatypes
                                                                                            Walnut
                                          San
         # of Rooms
                      # of Units
                                                                              Oakland
                                                  San Jose
                                                             Sacramento
                                    Francisco
                                                                                             Creek
                                               14174.000000
       14174.000000
                    14174.000000
                                  14174.000000
                                                            14174.000000
                                                                         14174.000000
```

MAPE	*	lower	12.87551	0
GINI		higher	0.9728788	0
MAE		lower	77558.6	0.0078125
MER		lower	8.298738	0
MSE		lower	2.443724e+ 10	4096
R2		higher	0.8961563	2.220446e- 16

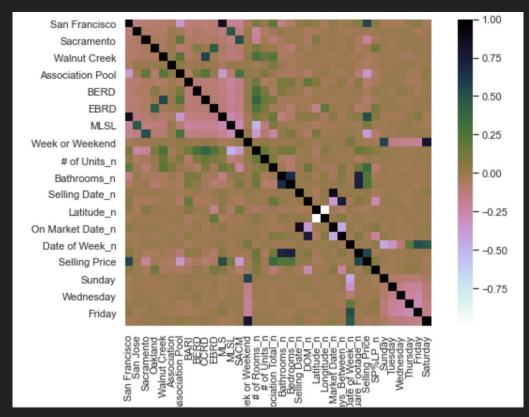
Normalizing non-binary columns (Continuous 0 to 1)
 Normalized columns will have '_n' appended to name

```
X = np.array(df['# of Rooms']).reshape(-1,1)
scaler = MinMaxScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
df['# of Rooms_n'] = X_scaled.reshape(1,-1)[0]

X = np.array(df['# of Units']).reshape(-1,1)
scaler = MinMaxScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
df['# of Units_n'] = X_scaled.reshape(1,-1)[0]
```

Correlation Heat Map

	Selling Price
San Francisco	0.56
San Jose	-0.01
Sacramento	-0.22
Oakland	-0.01
Walnut Creek	-0.05
Association	-0.07
Association Pool	-0.35
BARI	-0.10
BERD	-0.04
CCRD	-0.10
EBRD	-0.06
MLS	0.52
MLSL	0.10
SACM	-0.38
Week or Weekend	-0.04
# of Rooms n	0.11
# of Units n	-0.01
Association Total n	0.34
Bathrooms n	0.24
Bedrooms_n	0.25
Selling Date n	0.02
DOM_n	0.02
Latitude_n	-0.04
Longitude_n	-0.01
On Market Date_n	0.03
Days_Between_n	-0.02
Date of Week_n	-0.01
Square Footage_n	0.54
Selling Price	1.00
SP%LP_n	0.08
Sunday	-0.01
Tuesday	-0.02
Wednesday	-0.01
Thursday	0.01
Friday	0.02
Saturday	-0.04



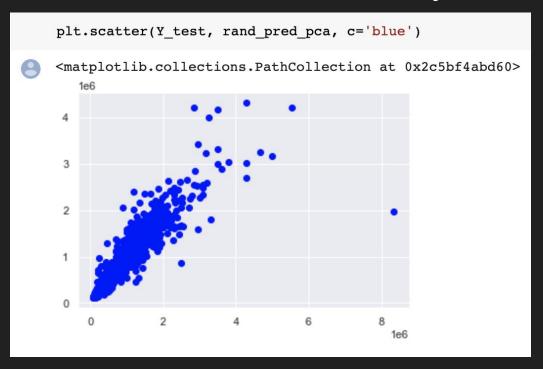
Model - Using Linear Regression

OLS Regression Results						
Dep. Variable:	Selling Price_n	R-squared:	0.716			
Model:	OLS	Adj. R-squared:	0.715			
Method:	Least Squares	F-statistic:	1272.			
Date:	Thu, 02 Dec 2021	Prob (F-statistic):	0.00			
Time:	15:05:27	Log-Likelihood:	34940.			
No. Observations:	14174	AIC:	-6.982e+04			
Df Residuals:	14145	BIC:	-6.960e+04			
Df Model:	28					
Covariance Type:	nonrobust					

Key Takeaways:

- R2 = 0.716
- Adj. R2 = 0.715
- LR fits 72% of data

Model - Random Forest on Days of the Week



Key Takeaways:

- Train Score: 0.986
- Test Score: 0.869
- Prediction Accuracy 86%
- Higher Variance with prediction of higher Selling Prices

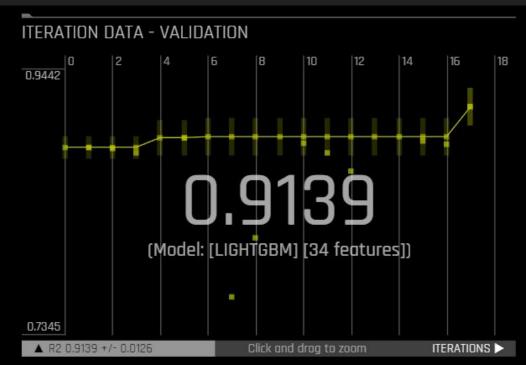
```
Best parameters: {}
Score on test set: 0.8687344674001293
```

Train score: 0.9862530715568794

Test score: 0.8687344674001293

MSE 30344061244.803455

H20.Al Results



VARIABLE IMPORTANCE	
14_Latitude_n	1.00
27_Square Footage_n	0.77
23_San Francisco	0.76
15_Longitude_n	0.50
7_Bathrooms_n	0.11
4_Association Total_n	0.10
16_MLS	0.08
20_SACM	0.06
8_Bedrooms_n	0.06
1_# of Units_n	0.04
17_MLSL	0.03
19_On Market Date_n	0.03
21_SP%LP_n	0.03
10_DOM_n	0.02

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Your Takeaway

- The price of a listing is heavily dependent on the location and square footage of the property.
- The day of the week a property is listed has a small, but noticeable, effect on the sale price, with Sunday being the best day of the week to list a property.

	coef	std err	t	P> t	[0.025	0.975]
Sunday Tuesday Wednesday Thursday Friday Saturday	6.715e+04 -2.254e+04 -3.717e+04 -8.222e+04 -1.099e+05 -1.028e+05	1.25e+04 9097.542 1.1e+04 1.4e+04 1.79e+04 1.63e+04	5.393 -2.477 -3.379 -5.858 -6.133 -6.306	0.000 0.013 0.001 0.000 0.000	4.27e+04 -4.04e+04 -5.87e+04 -1.1e+05 -1.45e+05	9.16e+04 -4705.252 -1.56e+04 -5.47e+04 -7.48e+04 -7.09e+04

Our GitHub Links

Project's:

https://github.com/panderson-scu/FNCE-2431-Final-Project

Patrick's:

https://github.com/panderson-scu

Amanda's:

https://github.com/adelfino22/RealEstateProjections

Mario's:

https://github.com/mcmorales415/FNCE-2431-Final-Project

Thank You!

If you have further ideas, reach out at: panderson@scu.edu, adelfino@scu.edu, and mcmorales@scu.edu.