

Identifying Real Estate Opportunities

In San Francisco

Through Big Data Analysis

Methodology



Establish Business Case

- Are we at the peak of a RE cycle?
- Even if you get a “bargain” property, will the market crash as a whole?
- What are the rental yields like?

EDA and modelling

Setting the context to identify “bargains”

- What does our data set look like?
- What should I further study?
- What variables should I use to estimate value?

Shortlist Opportunities

Fine tuning and putting the model to use

- Assessing coefficients (ridge, lasso)
- Testing assumptions
- Translate model into practical insights

Establish Business Case

Real Estate Prices & Returns:


Peer Comparison against
other cities

Most Expensive Homes in The World



City	90 sqm apartment price	price to household income	Gross Rental Yield	Price To Rent Ratio City Centre
Hong Kong, Hong Kong	\$2,765,065	47.5	1.8%	56.5
Singapore, Singapore	\$1,788,108	22.3	2.3%	43.0
London, United Kingdom	\$1,544,135	21.2	2.9%	34.7
Seoul, South Korea	\$1,409,990	24.0	1.4%	72.8
Beijing, China	\$1,352,845	44.2	1.7%	60.4
New York, NY, United States	\$1,325,715	10.8	4.9%	20.4
Shenzhen, China	\$1,239,971	44.9	1.3%	77.6
Shanghai, China	\$1,217,843	41.5	2.0%	50.8
Geneva, Switzerland	\$1,191,403	10.5	3.4%	29.4
Taipei, Taiwan	\$1,183,366	33.1	1.0%	96.7
San Francisco, CA, United States	\$1,170,781	7.8	5.9%	17.1
Zurich, Switzerland	\$1,134,909	8.2	3.3%	30.6

Most Expensive Homes in The World

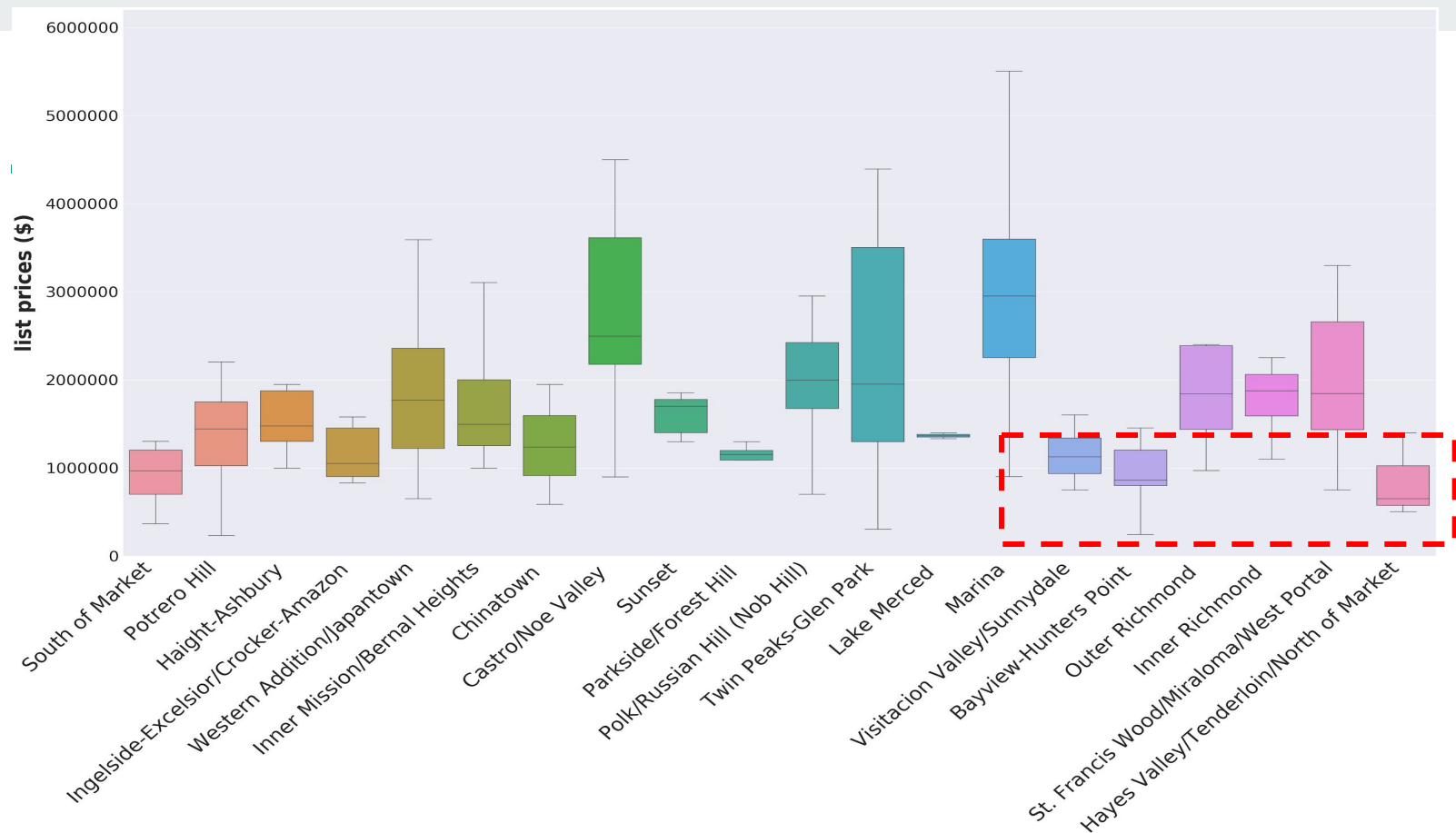


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Comparably valued in terms of price, potential upside in terms of price to income

EDA and Modelling

Understanding the data
and its context to model
effectively



More Data Needed to Determine Best Value for Money

Factors to Home Prices

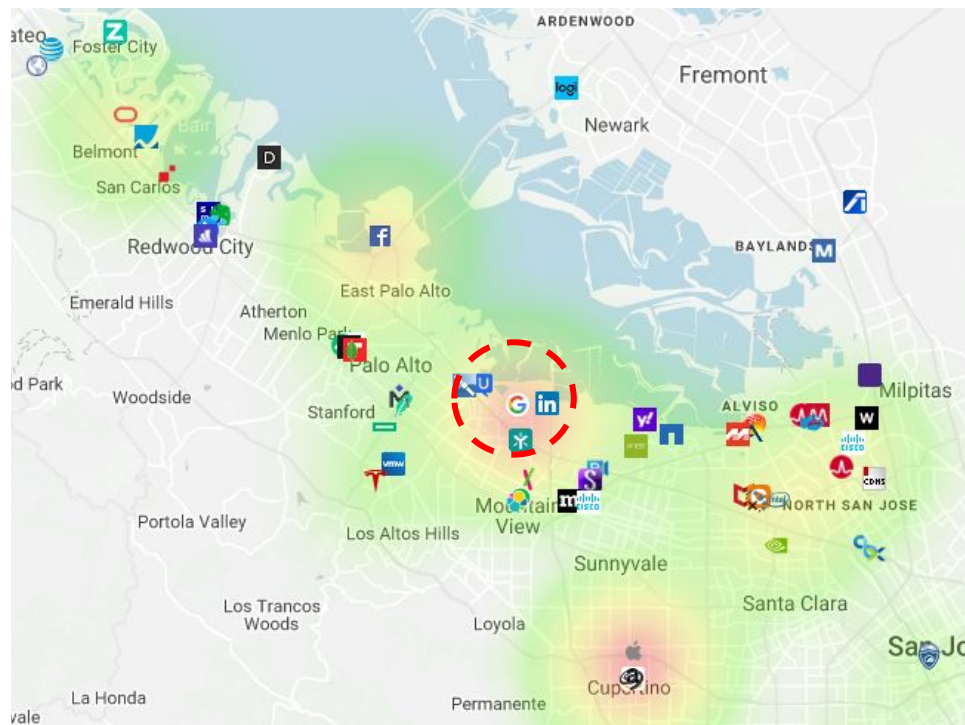
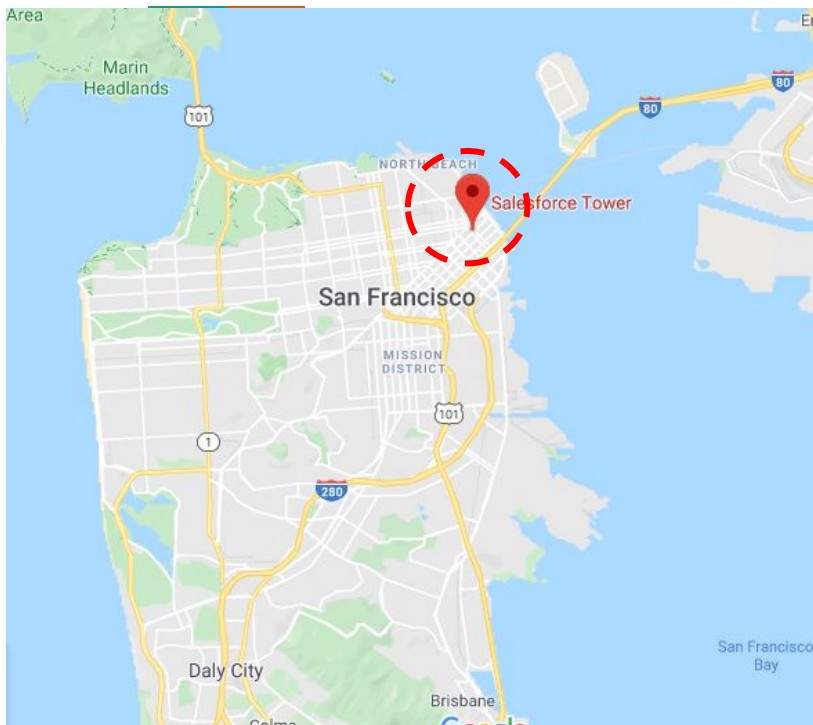


External Factors

Internal or Direct Factors

Factor	Measurable	Factor	Measurable
Distance to Centers of Commerce	Travel times	Home size	Square Feet listed
Crime	Crime Statistics	Age	Year Built /Refurbished
Closeness to amenities	Walk Scores	Layout	1BR, 2BR, # bathrooms
Neighborhood Quality	Zip code household income	Internal Finishings	Descriptors (NLP), pictures (IP)

Computing Distance to Centers of Commerce



~250 Iterations, then
Lowest of Travel Times Between Salesforce Tower and Googleplex Used

Assessing Model Fit

Data set size: ~1600 rows

Variables: Travel times, year built, home size, layout (1BR, 2BR, #bathrooms)

Methodology: Ordinary least square regression applied, standardize data, ridge and lasso used to drop variables

Dep. Variable:	PRICE	R-squared (uncentered):	0.724
Model:	OLS	Adj. R-squared (uncentered):	0.723
Method:	Least Squares	F-statistic:	632.5
Date:	Fri, 24 Jan 2020	Prob (F-statistic):	0.00
Time:	07:59:13	Log-Likelihood:	-18568.
No. Observations:	1211	AIC:	3.715e+04
Df Residuals:	1206	BIC:	3.717e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
SQUARE FEET	893.4146	44.149	20.236	0.000	806.798	980.032
YEAR BUILT	183.2160	53.232	3.442	0.001	78.778	287.654
shortesttime	-1.815e+04	2609.236	-6.955	0.000	-2.33e+04	-1.3e+04
BEDS	-1.617e+05	3.35e+04	-4.828	0.000	-2.27e+05	-9.6e+04
BATHS	1.51e+05	5.41e+04	2.791	0.005	4.49e+04	2.57e+05
Omnibus:	1458.122	Durbin-Watson:	1.950			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	422354.801			
Skew:	5.743	Prob(JB):	0.00			
Kurtosis:	93.766	Cond. No.	5.14e+03			

Test Set



$R^2 = \sim 0.488$

Shortlist Opportunities

Refining the data to provide
sharper insights

Shortlisted Opportunities

ADDRESS	CITY	PRICE (less than \$2M)	SQUARE FEET	\$/psf
2641 Yuba St	El Cerrito	\$899,000	8360	349.54
2637 E 16th St	Oakland	\$850,000	4192	202.77
1725 Estudillo Ave	San Leandro	\$1,449,000	4750	305.05
1112 CHUAUCER #2	Berkeley	\$1,499,000	4800	312.29
915 Grosvenor Pl	Oakland	\$1,250,000	4163	300.26
1225 VIENNA Dr #976	SUNNYVALE	\$525,000	2600	201.92
1985 Tunnel Rd	Berkeley	\$1,495,000	4083	366.15

Mobile Home

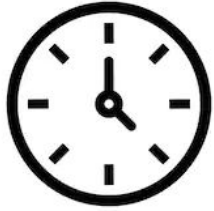


On Redfin for 4 days,
viewed 1,766 times
Redfin Estimate: \$1,016,985



Redfin Estimate: 1,593,751

Further Studies



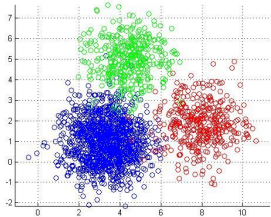
Time series Analysis

- How do prices evolve over time? Do we observe any neighborhoods with high price increases?
- How has demand shifted over time? More need for studios?



Expand Scope

- Include additional parameters like household income, crime rates, school quality, walkability etc.
- Compare trends across cities (LA, NY etc.) - How do we see variables shifting?



Greater Statistical Analysis

- E.g K means clustering - do positive attributes have a tendency to cluster? Do negative attributes compound?
- Points to the effect of “market making”

Acknowledgements



Redfin

```
target_companies_list.remove( 'Zillow' )  
Target_companies_list += [ 'Redfin' ]
```

Michael Boles (ex Metis Student!)

<https://towardsdatascience.com/@michaeladamboles>

John Joo

<https://blog.dominodatalab.com/exploring-us-real-estate-values-with-python/>

Stack Overflow and Google



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