Modeling Real Estate by Predicting Residential Property Prices

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How are residential property prices calculated?

- For sale by owner
- Tax-assessed value
- Official appraisal
- Predictive models (public like Zillow and private like Realist)

Value Proposition

- 1. Identify undervalued properties
- 2. Identify opportunities to increase property value

Dataset Description

- 21,613 houses in King County (Washington State) sold between 2014-2015
- Physical properties about the homes
 - # Beds/Baths
 - Sqft. Living Space & Lot
 - Waterfront, View booleans
 - Condition & Grade (assessed by the King Country Grading System) factors
 - Year Built & Renovated (if applies)
 - Location Data (Zipcode, Latitude, Longitude)



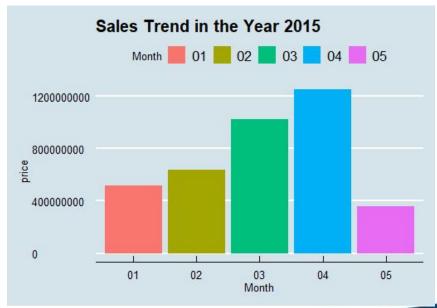
Dataset Description

```
> str(hprice.df)
'data.frame':
               21613 obs. of 22 variables:
 $ id
               : num 7.13e+09 6.41e+09 5.63e+09 2.49e+09 1.95e+09 ...
 $ date
               : Factor w/ 372 levels "20140502T000000",..: 165 221 291 221 284 11 57
 $ price
               : num 221900 538000 180000 604000 510000 ...
 $ bedrooms
               : int 3 3 2 4 3 4 3 3 3 3 ...
 $ bathrooms
               : num 1 2.25 1 3 2 4.5 2.25 1.5 1 2.5 ...
 $ saft living : int 1180 2570 770 1960 1680 5420 1715 1060 1780 1890 ...
 $ sqft_lot
               : int 5650 7242 10000 5000 8080 101930 6819 9711 7470 6560 ...
 $ floors
               : num 1 2 1 1 1 1 2 1 1 2 ...
 $ waterfront
               : int 00000000000...
 $ view
               : int 0000000000...
 $ condition
               : int 3 3 3 5 3 3 3 3 3 3 ...
 $ grade
 $ sqft_above
               : int 1180 2170 770 1050 1680 3890 1715 1060 1050 1890 ...
 $ sqft basement: int 0 400 0 910 0 1530 0 0 730 0 ...
 $ yr_built
               : int 1955 1951 1933 1965 1987 2001 1995 1963 1960 2003 ...
 $ yr_renovated : int  0 1991 0 0 0 0 0 0 0 0 ...
               : int 98178 98125 98028 98136 98074 98053 98003 98198 98146 98038 ...
 $ zipcode
 $ lat
               : num 47.5 47.7 47.7 47.5 47.6 ...
 $ long
               : num -122 -122 -122 -122 -122 ...
 $ sqft_living15: int 1340 1690 2720 1360 1800 4760 2238 1650 1780 2390 ...
 $ sqft_lot15 : int 5650 7639 8062 5000 7503 101930 6819 9711 8113 7570 ...
```



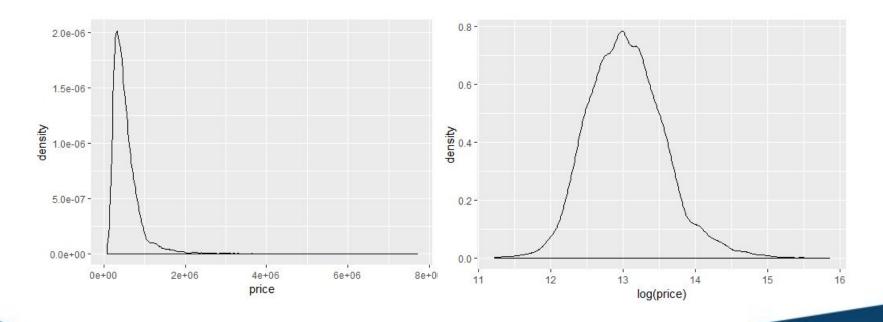
Sales trend from May 2014 to May 2015





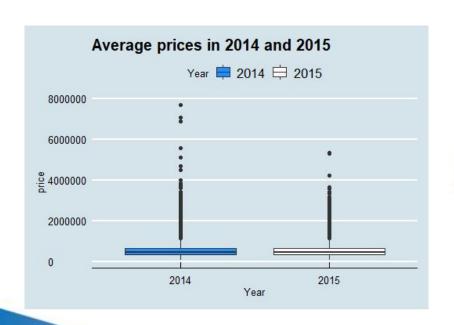


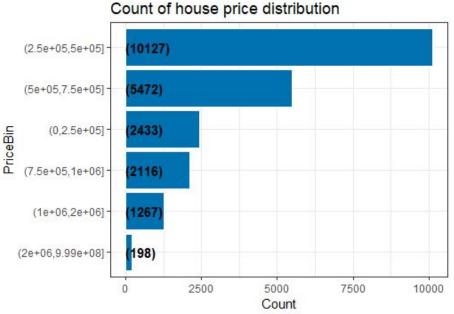
Price distribution in 2014 and 2015





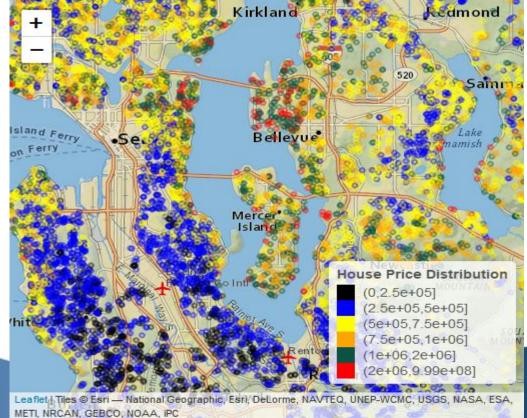
Price distribution in 2014 and 2015





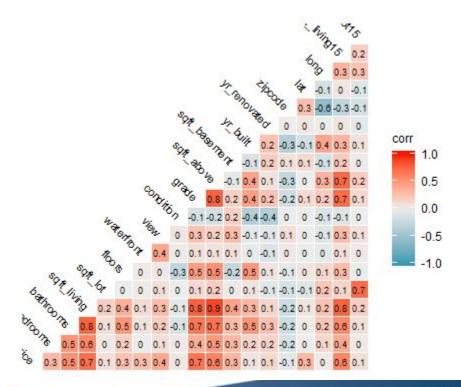


Houses location Map





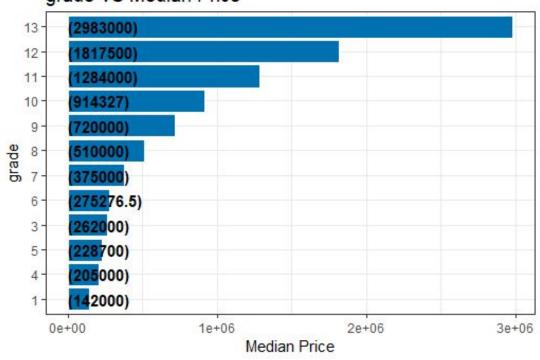
Dataset Visualization - Correlation





Dataset Visualization

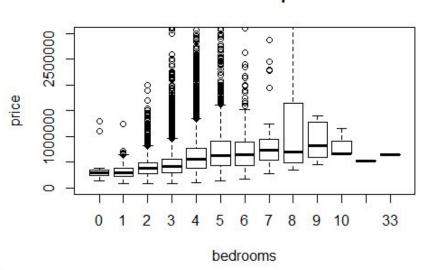




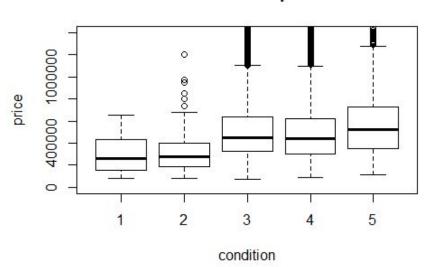


Dataset Visualization

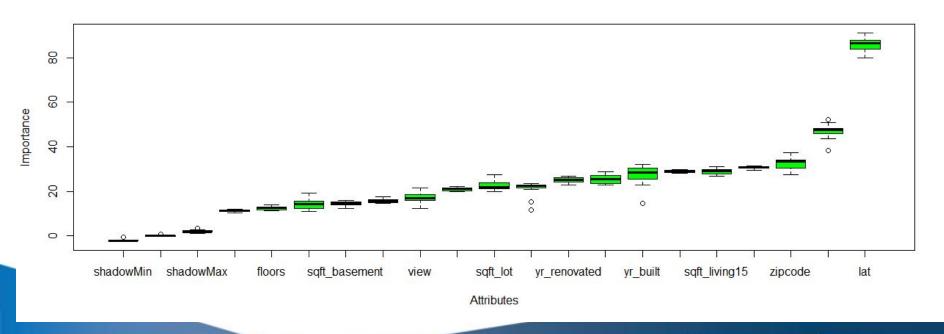
bedrooms vs price



condition vs price



Dataset Visualization - Boruta Feature Selection





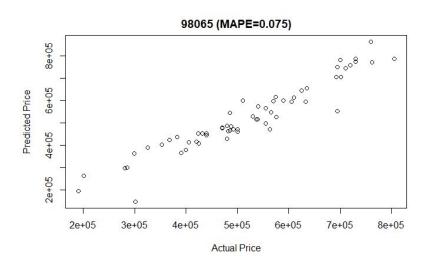
Comparison of Models

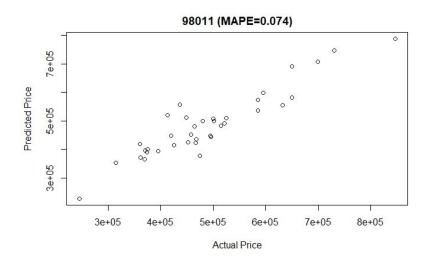
Model	Mean Absolute % Error
Multi-variate Linear Regression	21.192%
Random Forest	19.538%



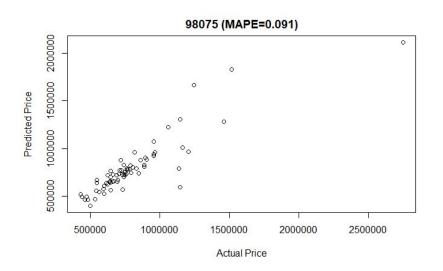
-	numberOfHouses *	zipcode [‡]	medianPrice *	mape ‡	19	282	98040	993750.0	0.15800295
63	195	98011	470000.0	0.07366011	61	446	98155	375000.0	0.15891846
11	141	98007	555000.0	0.08079399	23	269	98112	915000.0	0.15915241
64	274	98031	288200.0	0.08332194	40	317	98004	1150000.0	0.15942827
56	321	98029	575000.0	0.08563075	32	118	98070	463750.0	0.15967694
55	310	98065	500000.0	0.08591979	2	410	98125	425000.0	0.16242839
43	359	98075	739999.0	0.09129048	58	109	98109	736000.0	0.16364033
21	256	98030	282255.0	0.09147443	39	343	98144	450000.0	0.16946033
20	351	98092	309780.0	0.09353712	53	269	98168	235000.0	0.17342132
17	199	98002	235000.0	0.09624872	8	280	98198	265000.0	0.17465579
3	283	98028	445000.0	0.10123318	9 57	288 498	98146 98006		0.17733070
					69	268	98055		0.17636094
6	405	98053	635000.0	0.10128134	67	136	98188		0.18356069
5	441	98074	642000.0	0.10219683	50	105	98102		0.19291454
10	590	98038	342000.0	0.10445080	30	254	98166		0.19821252
15	190	98019	401250.0	0.10664537	38	290	98122		0.20161103
27	455	98058	335000.0	0.11035906	54	255	98177	554000.0	0.20290650
34	229	98105	675000.0	0.11079546	46	508	98118	367500.0	0.20292465
59	234	98022	279500.0	0.11264953	70	50	98039	1892500.0	0.20394688
33	57	98148	278000.0	0.11449169	68	124	98014	415000.0	0.20479676
35	548	98042	292000.0	0.11569475	62	81	98024	460000.0	0.20624120
48	125	98032	249000.0	0.11685478	22	184	98119	744975.0	0.21449782
18	494	98133	375000.0	0.11912783	45	100	98010	359999.5	0.23035717 HFFE

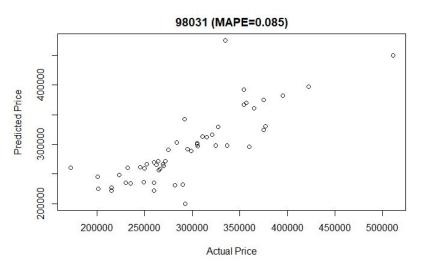
Best Predicted Zip Codes





Works on High & Low Value Homes





Potential Value in Purchase

- Our model shows that houses have sold below the predicted value
- The difference between our predicted price and the actual list price could be used to identify unrealized value
- The sum of \$ in our best predicted Zip Code (98011) alone is \$650,857.39

Summary of Potential Values

 In our best predicted Zip Codes the potential value is several million dollars in real estate

-	zipcode ‡	potentialValue [©]
63	98011	650875.3923
56	98029	1019592.4962
24	98052	3242726.5204
6	98053	2555147.7926
55	98065	1392058.7915
64	98031	585143.4562
21	98030	585342.3603
17	98002	397962.2161
5	98074	3863813.4041
35	98042	1905701.3597
66	98072	1494259.6215
11	98007	1024022.5294
43	98075	4529958.6631
31	98023	1745144.3642
3	98028	1592410.5536
10	98038	3225895.6846
4	98136	1770939.2377
26	98117	3816846.1176
67	98188	394570.1002
7	98003	1323621.9835

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Renovation Suggestions

• LR Coefficients tell us the value of each variable in terms of price (Zip:98011)

Bedrooms	\$554.09	
Bathrooms	\$13328.65	
Sqft Living	\$34.208	
Sqft Basement	\$65.85	
Years Old	-\$1594.40	
Years Since Renovation	-\$19.76	
Sqft Above Ground	\$104.29	
Base Value	\$238257.51	

Conclusion

- Major assumption: consistency of resources within a zip code
- Location is the most important predictor
- Consistency of comparable sales matters (i.e., consistency of the market)

Possibilities for future research: Combining traditional (what sellers can control) and non-traditional data (what sellers cannot control)

Nearly 60 percent of predictive power can come from nontraditional variables.

