Predicting Home Prices in Vancouver and Seattle

Web Scraping and Regression Project

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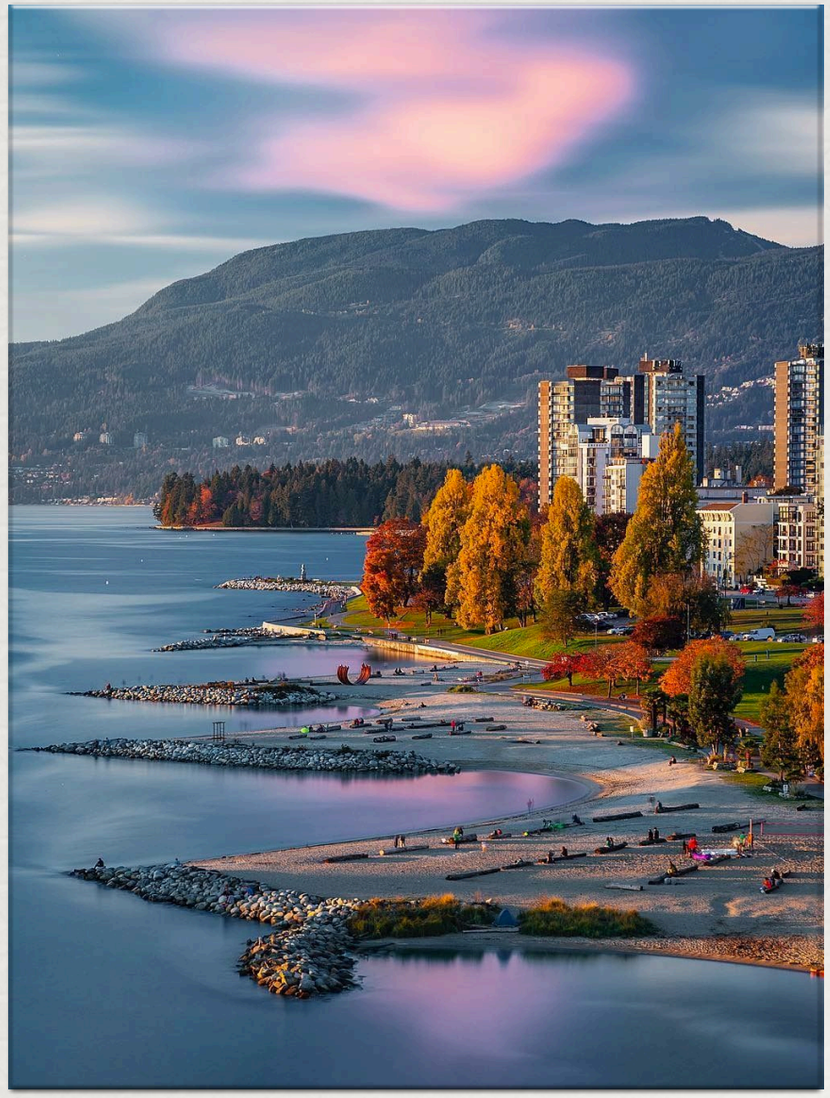
Bridges
GRANVILLE ISLAND PUBLIC MARKET

Objectives

- Web API to compare predictions based on filters — can expand to more cities
- How much does a certain categorical variable increase the home price?
- How far can we go with a simple linear regression model?



Methodology

- Data
  - Scraped Vancouver data from redfin.ca
  - Obtained Seattle data from redfin.com
- Tools
  - Python, Scikit-learn, Pandas, NumPy, Seaborn
  - HTML, Selenium for web scraping
  - JupyterNotebook, Visual Studio Code

Data

- 450 rows, 27 unique features combined
- Also scraped URLs for each individual listing for Vancouver
- Vancouver median price ~900k USD
- Seattle median price ~700k USD

REDFIN

Vancouver Real Estate

Price No min to No max More Filters

Showing 20 of 3456 Homes · Sort Photos **Table**

Address	Location	Price	Beds	Baths	Sq.Ft.	$/Sq.Ft.	On Redfin
2770 Burrard S...	Fairview VW	$849,000	2	1.5	958	$886	64 days
MLS# R2379412 Listed by: Redfin							
3939 Knight St...	Knight	$448,000	1	1	592	$757	64 days
MLS# R2395281 Listed by: Redfin							
838 W Hasting...	Downtown V...	$5,350,000	3	2.5	2,368	$2,259	33 hrs
MLS# R2412257 Listed by: Angell, Hasman & Associates Realty Ltd.							
2640 Point Gre...	Kitsilano	$1,488,000	2	2	1,212	$1,228	31 hrs
MLS# R2412070 Listed by: RE/MAX Treeland Realty							
939 Expo Blvd ...	Yaletown	$808,800	2	1	715	$1,131	2 days
MLS# R2412083 Listed by: Oakwyn Realty Downtown Ltd.							

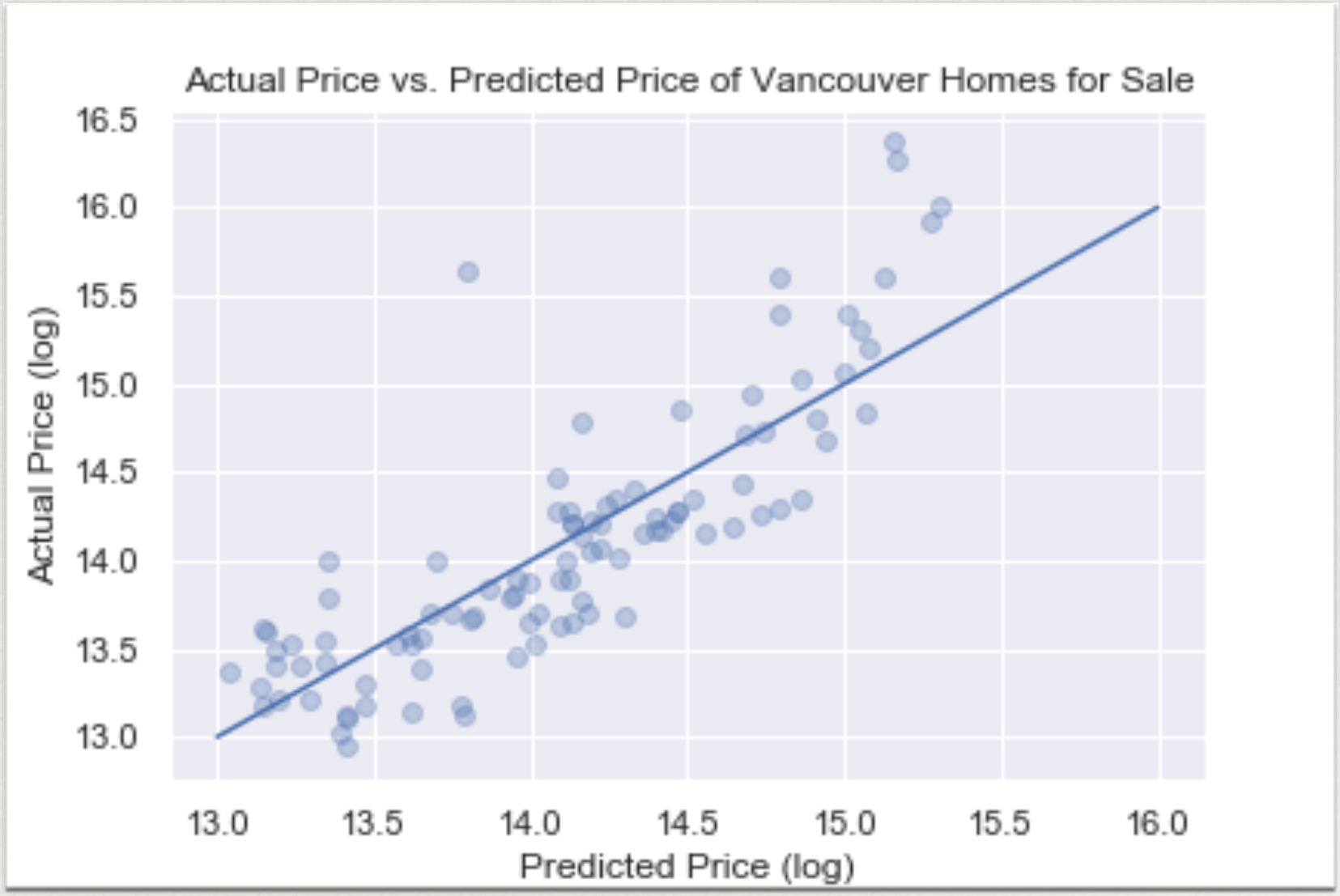
Results - Vancouver

Small dataset

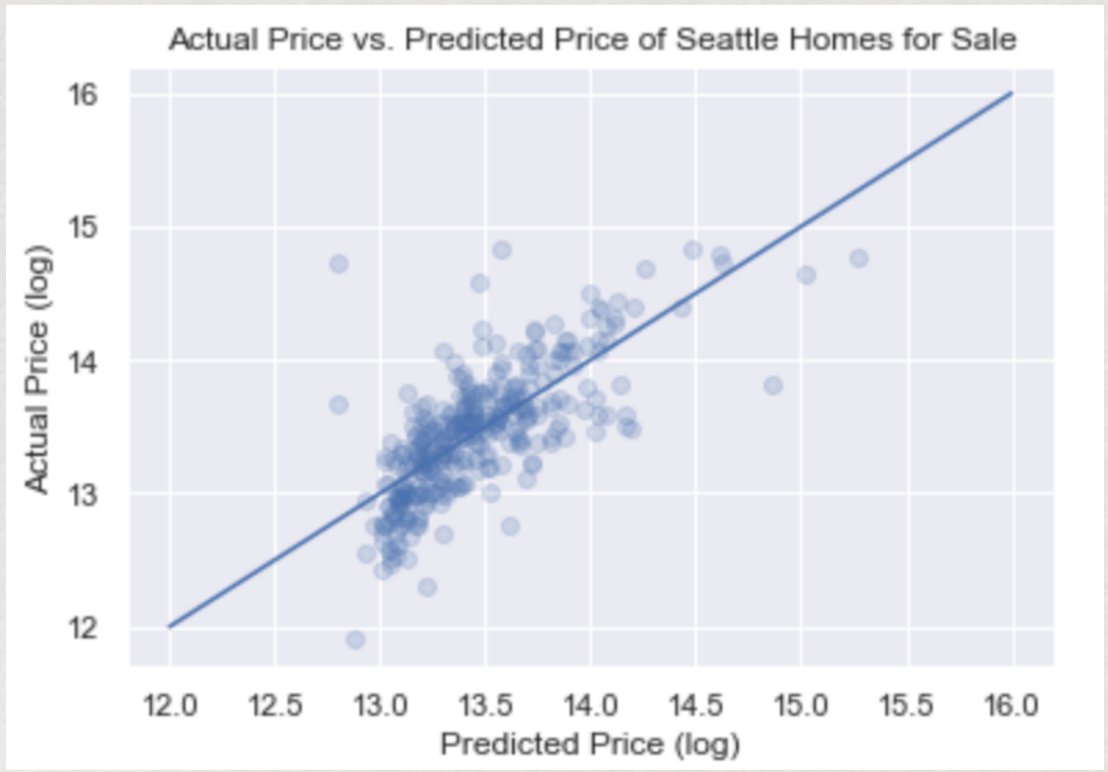
RidgeCV

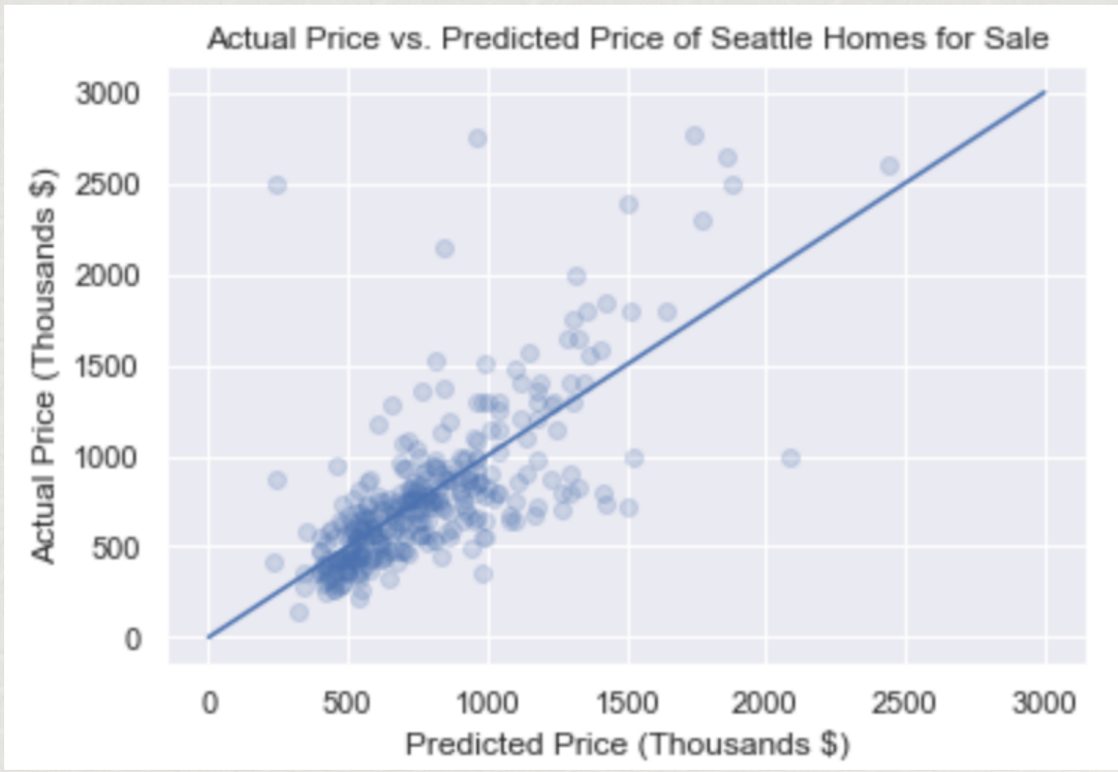
Kf = 5

$R^2 = 0.713$



Results - Seattle





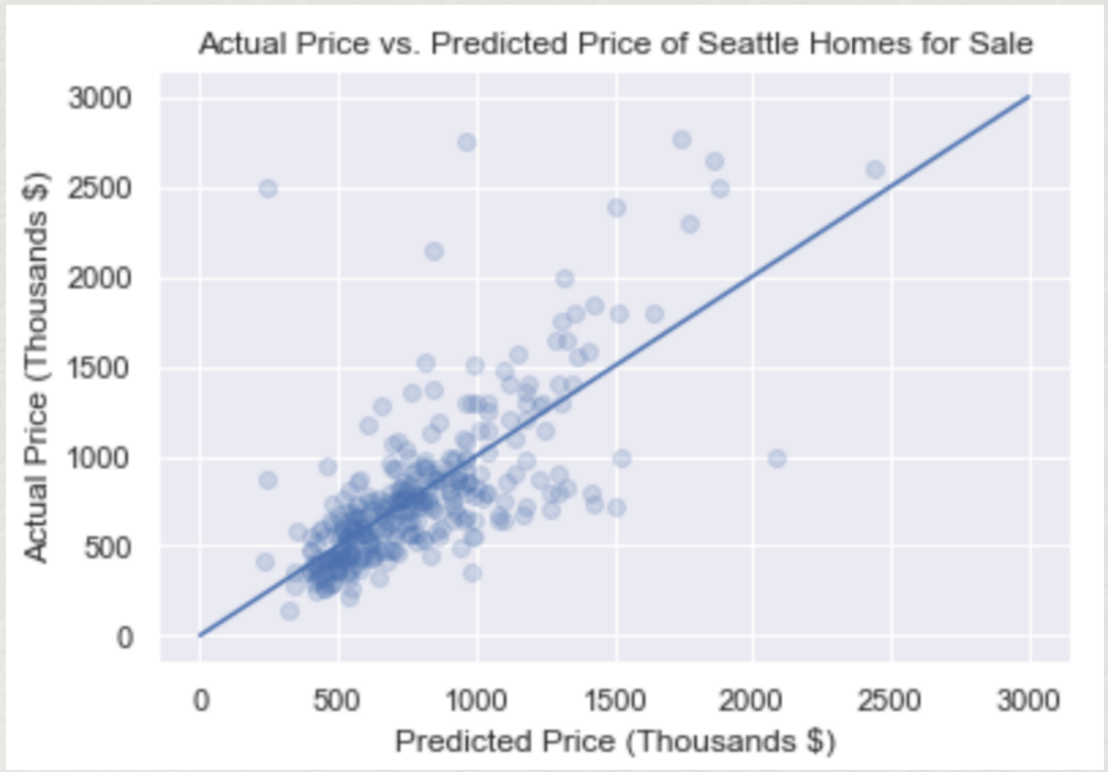
RidgeCV

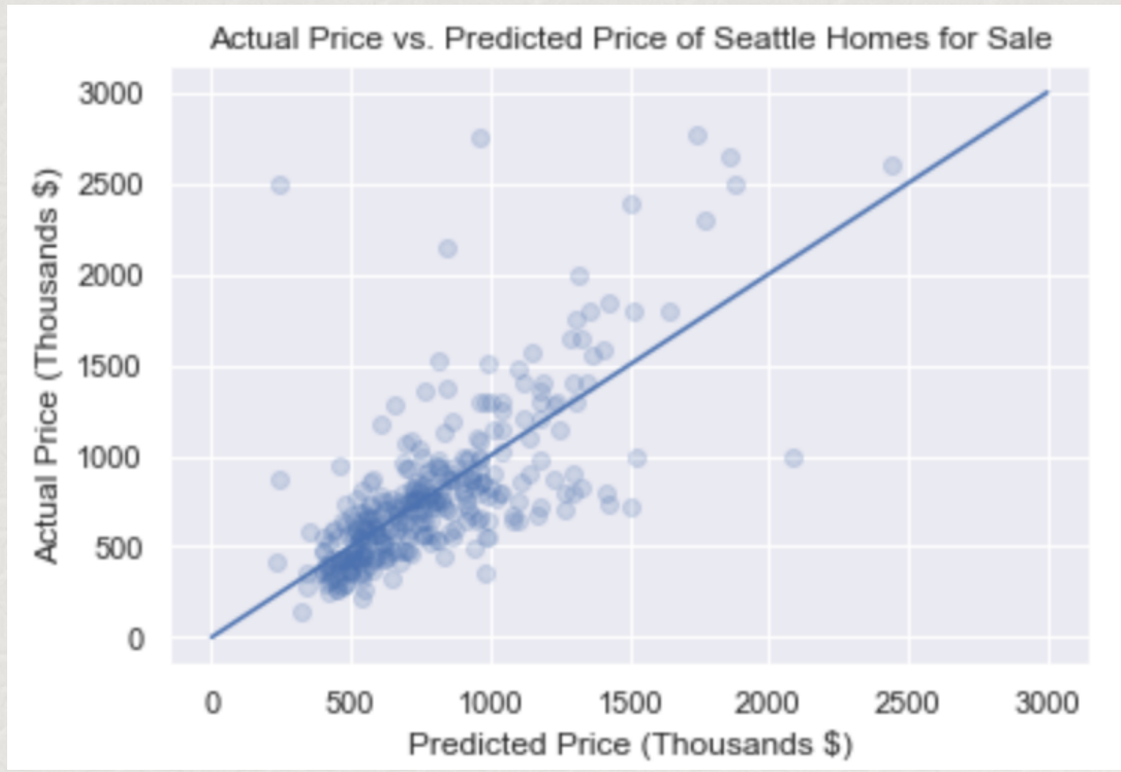
Kf = 10

R2 = 0.501

Reduced RMSE by ~25% after removing outliers

Results - Seattle





RidgeCV

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R2 = 0.501

Reduced RMSE by ~25% after removing outliers

Conclusion

- We can get a decent prediction of home sale price with just a few features and a simple linear model
- Lots of tools to choose from even when dealing with a small dataset; room for improvement
- Possible bias in dataset

Future Work

- Get more data - from other websites; both numerical and categorical features
- Transform different features with different methods
- Compare effects of *individual features* on prediction
- More feature engineering - dummy variables
- Evaluate using metrics such as adjusted-R^2

"All models are wrong,

but some are useful."

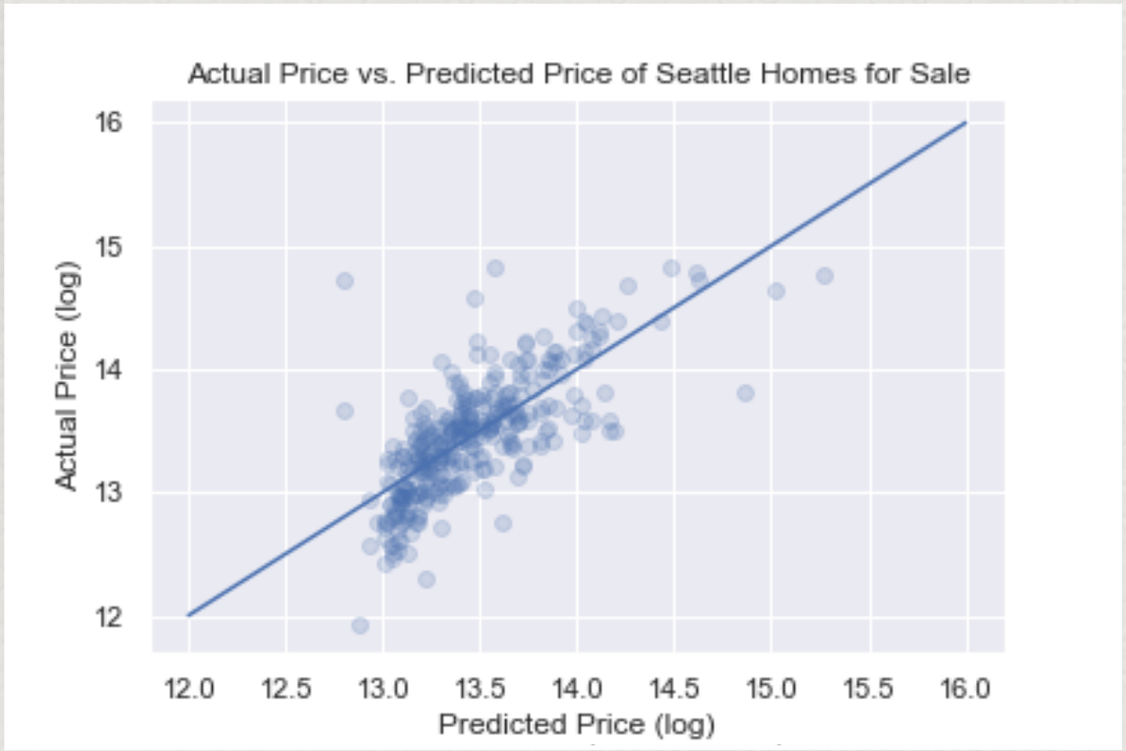
– George E. P. Box (1919 - 2013)

Appendix

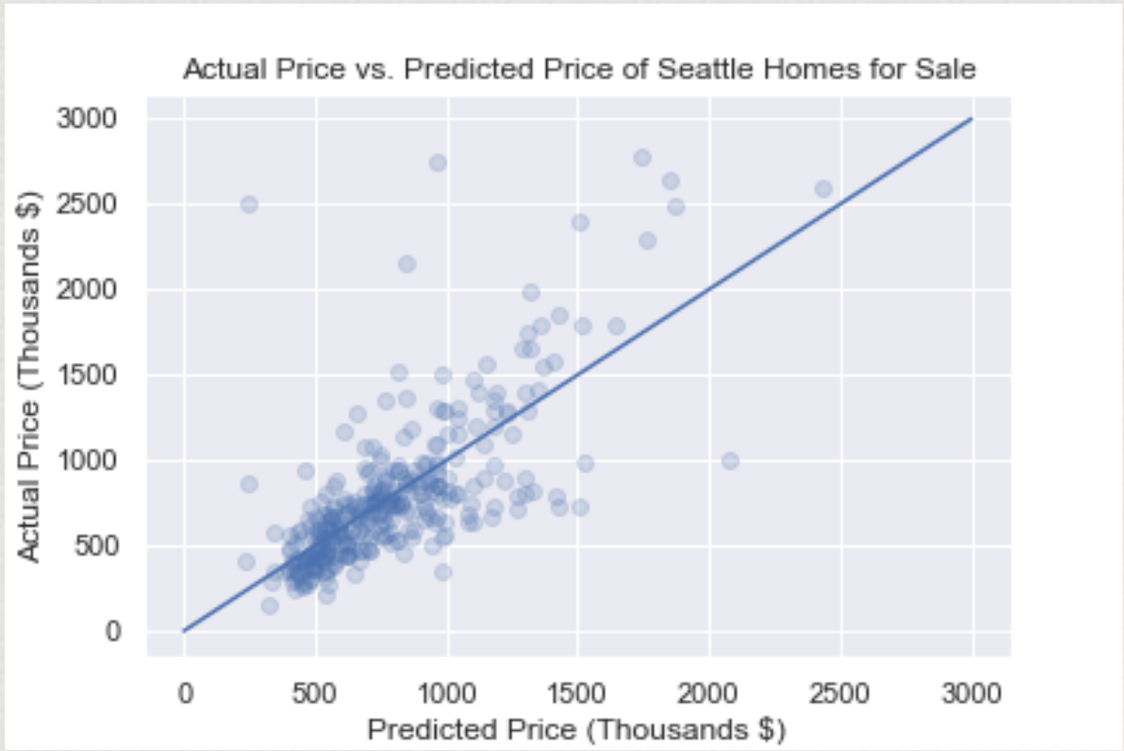
- Standardization of data:
  - Tried different scalers (Standard, MinMax, Robust, QuantileTransform, PowerTransform)
    - Also plan to transform different features in X differently
- Feature engineering:
  - Adding polynomial terms (degrees 2 and 3)
  - Adding interaction terms (ratio of number of bathrooms to bedrooms)

Appendix

- Removing outliers
  - Seattle Dataset (filtered out prices > 3 million USD)



Before: RMSE 411k (~57% of median)



After: RMSE 298k (~40% of median)

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- Removing outliers
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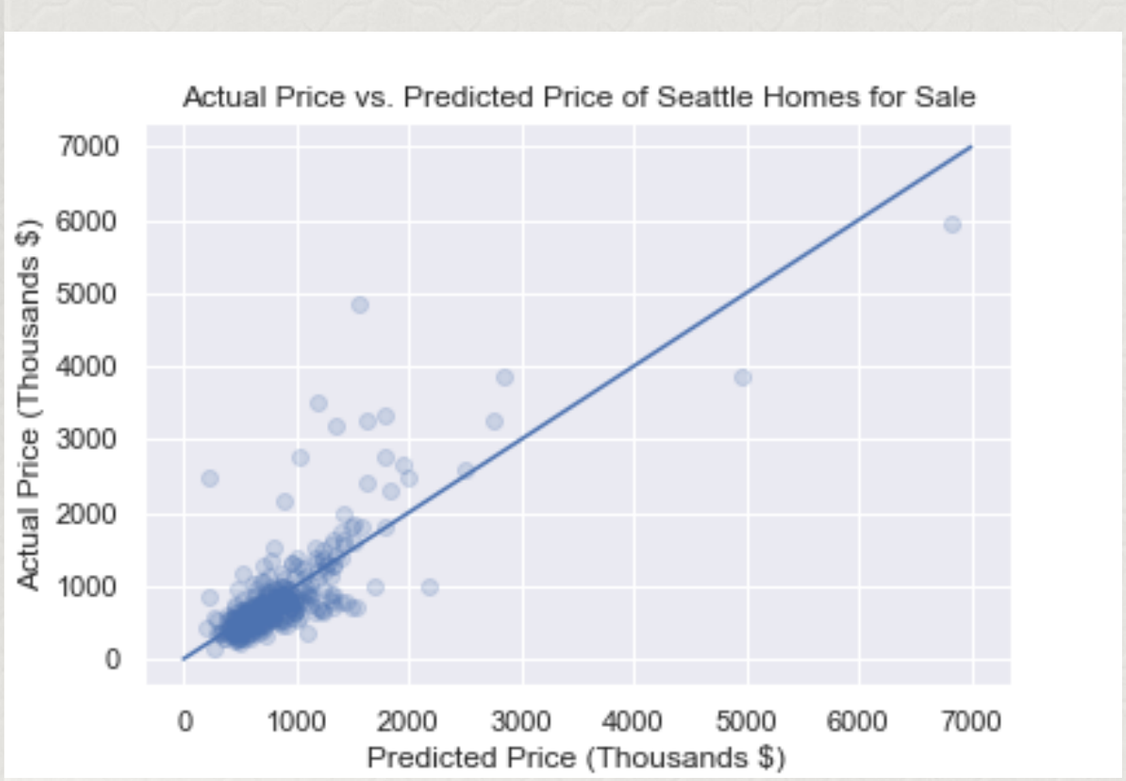

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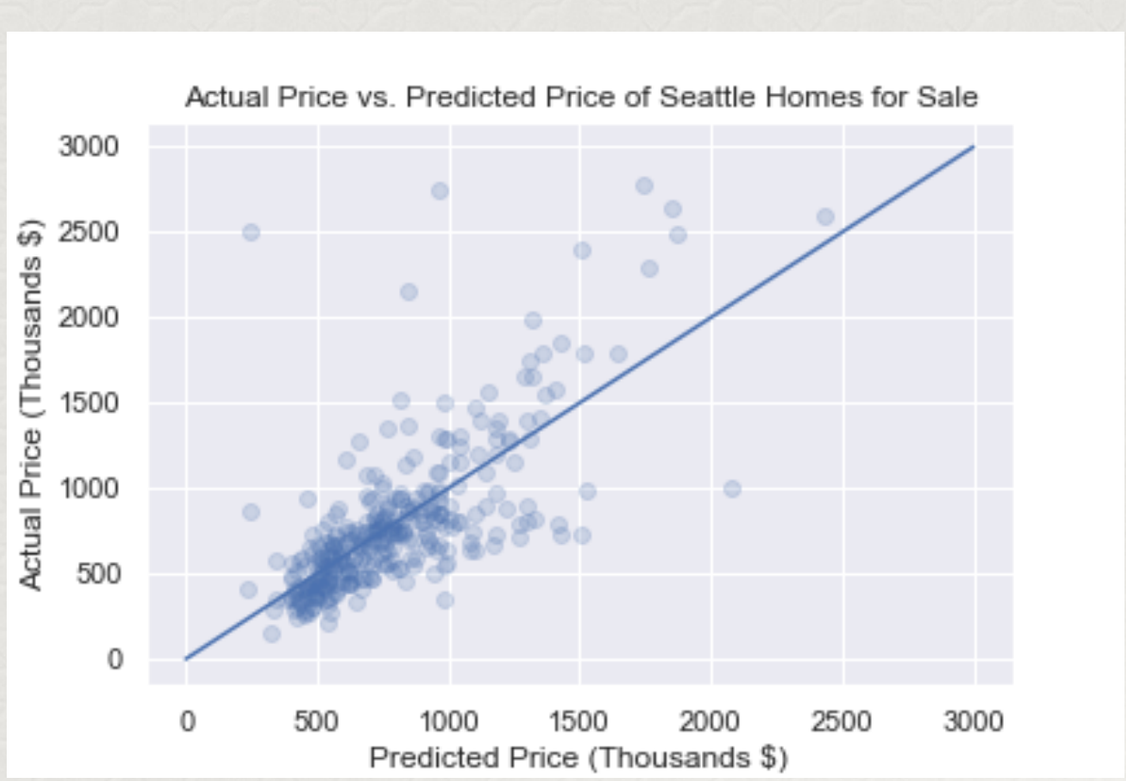


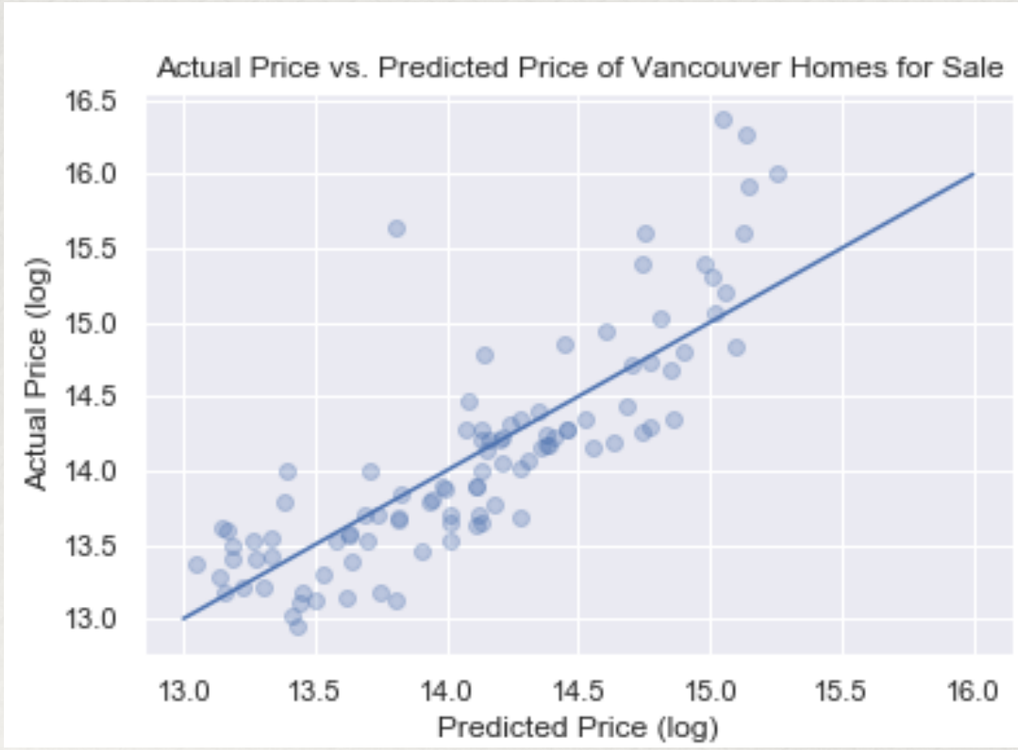
After: RMSE 298k (~40% of median)

Appendix

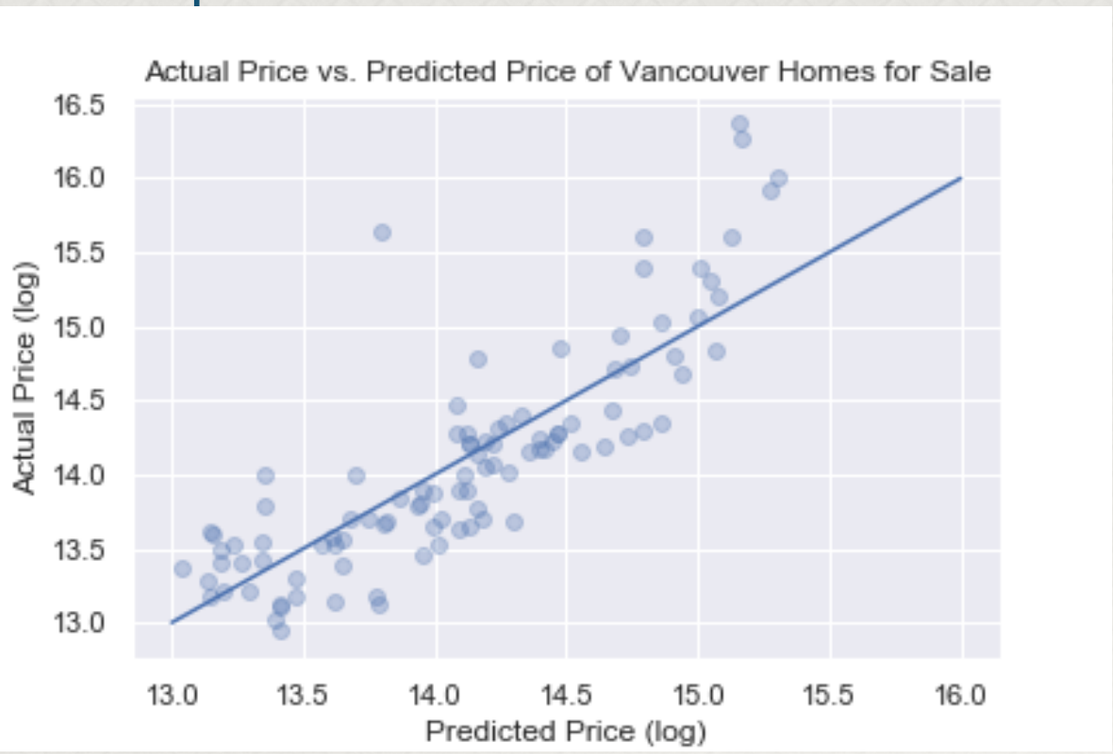
- Evaluation metrics
  - Used **R^2** (coefficient of determination) and **RMSE** (root mean squared error)
  - Problem: if new features are added to our model, R^2 only increases or remains constant but it never decreases
  - The **Adjusted R^2** is the modified form of R^2 that has been adjusted for the number of predictors in the model. The adjusted R-Square *only increases if the new term improves the model accuracy*

Appendix

- Regularization: Ridge vs. LASSO
  - Have a small number of features in our dataset, decided to use Ridge, despite similar R^2 values for certain alpha values. Lasso would eliminate some features we want to keep.



RidgeCV, alpha = 10, R^2 = 0.698



LassoCV, alpha = 0.05, R^2 = 0.712

Appendix

- Regularization: Ridge vs. LASSO
  - Ridge regularization:
  - Minimizes cost function: changing alpha is controlling the penalty term. The higher the values of alpha, the larger the penalty and the magnitude of coefficients are reduced.
  - It shrinks the parameters, therefore it is mostly used to prevent multicollinearity.
  - It reduces the model complexity by coefficient shrinkage.
  - If our model is overfit (variance too high), regularization can often improve generalization error by reducing variance