



Predicting Housing Prices in King County, WA

NOVEMBER 2020
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Context

“Helping good people find affordable homes.”

M3 Consulting

Working with several non-profit groups in King County, WA:

- 1) What features help predict home price (under \$500K)?
- 2) What features can be minimized to bring down home price?
- 3) Where in King County should new buyers look for affordable homes?



Understanding the Context

King County, WA:

- Population (2010): 1.9 million
- HH Income (2014): \$75K
- Median home value (2014-2018): \$494K
- Tech boom of the 2000 has created one of the most expensive housing markets in the country
- In a recent survey, the top feature buyers said they want most:
 - “a home that is within my initial budget” (89%)



Meet the Salazar family

Currently renting an apartment

Looking to buy their first home

HH Income of \$75K

Assuming a \$10K down payment,
they can afford a **\$316K** home*

**based on an affordability calculator*

“We want a home we can afford, and that will be a safe place for our kids to grow.”

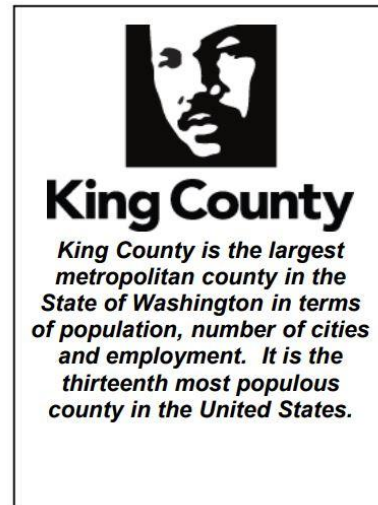


Data

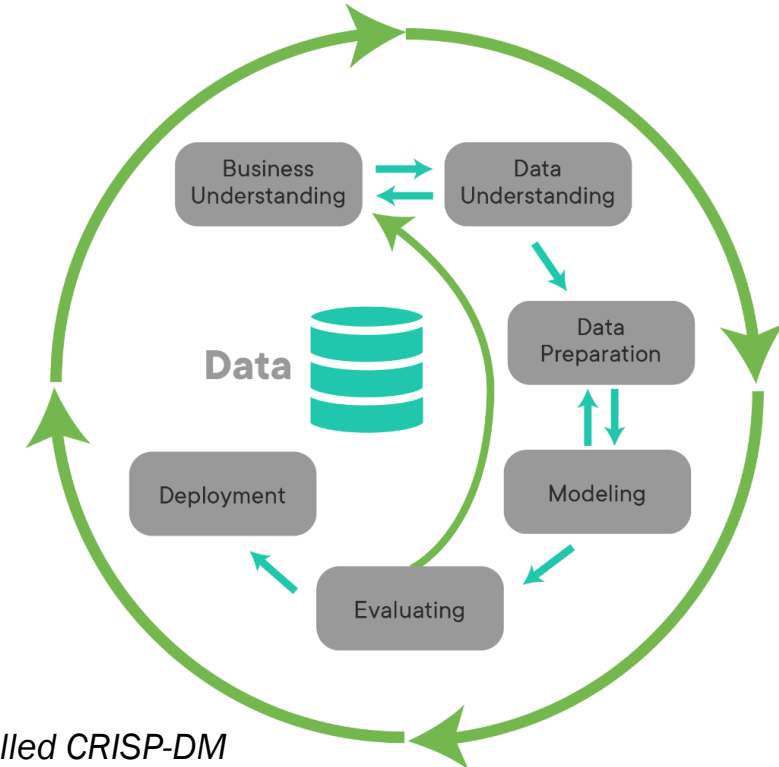
Exploring the Data

Housing Sales Data:

- Data provided by King County Assessors Office
- Home sales: May 2014 to May 2015
- ~ 21,000 records
- 21 variables



Our Process*:



* This process is called CRISP-DM

Our Data Journey

Researched features

Visualized and looked at descriptive statistics

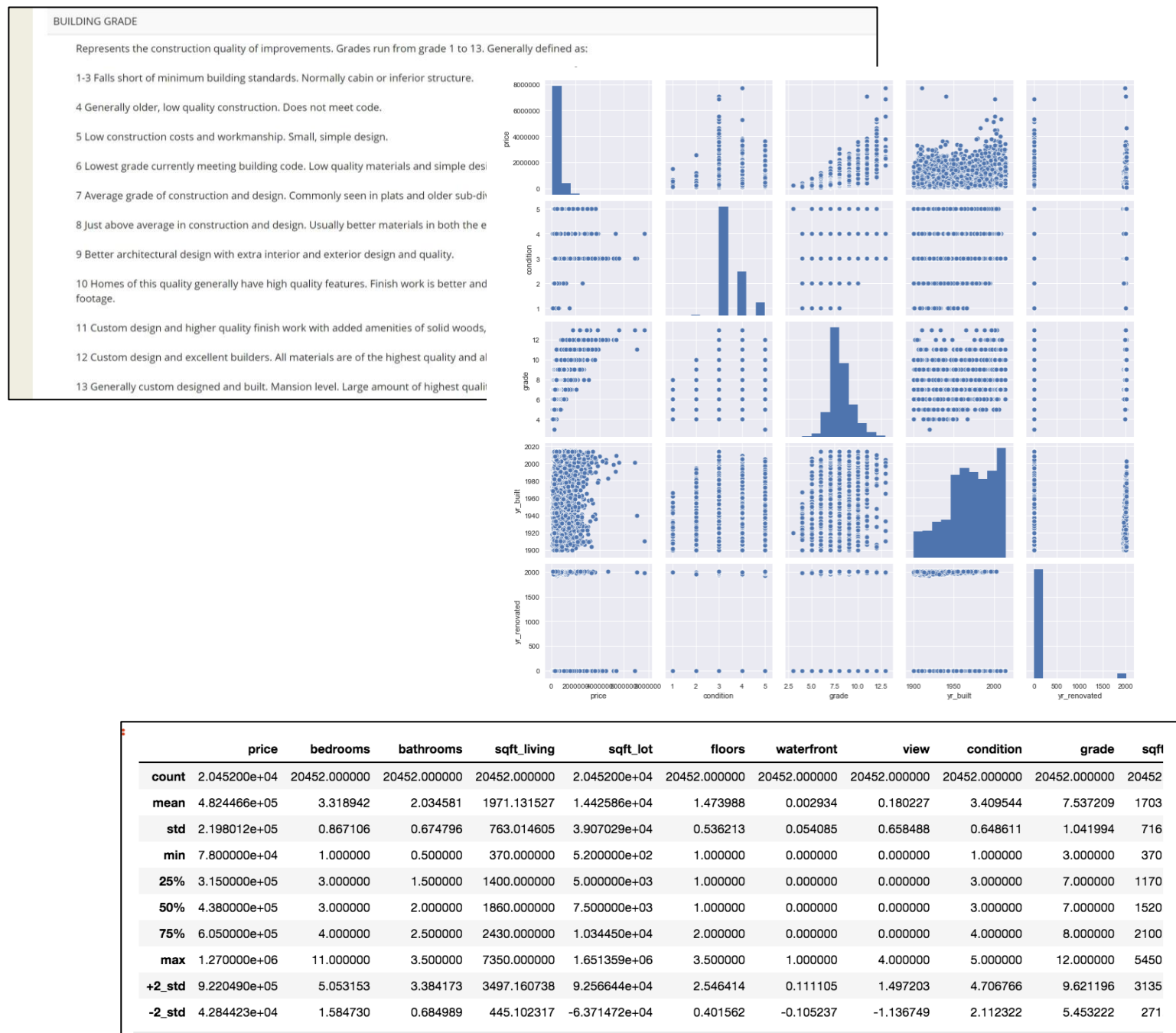
Examined distributions

Looked for linear relationships

Formatted features as numbers; null values turned into 0's

Removed un-used features
(zip code, date, longitude)

Checked for duplicates



Modeling

Our Modeling Journey



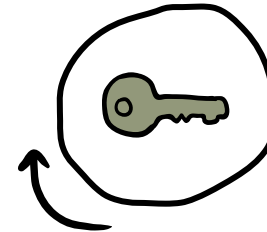
A) Mid-priced

Limited price:
\$315K to \$605K
(7 models; $r^2 \sim 0.10$)



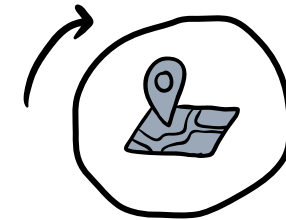
B) Low-priced

Limited price:
\$154K to \$315K
(8 models; $r^2 \sim 0.19$)



C) Adjust features

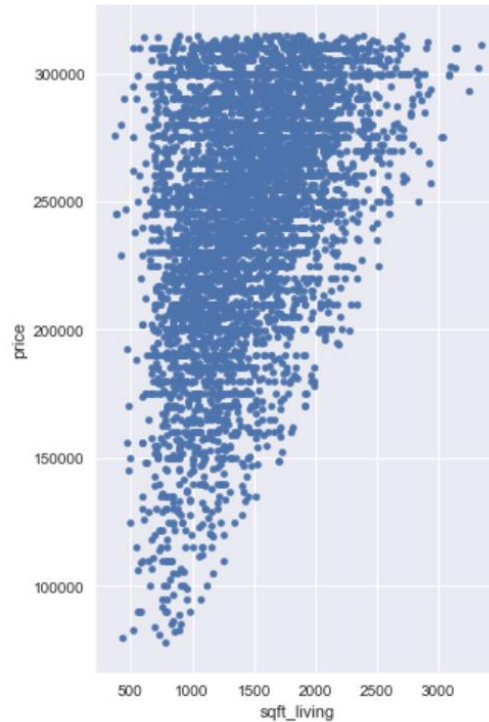
Tried adjusting scales of
most features (min-max)
and logged grade.
(3 models; $r^2 \sim 0.20$)



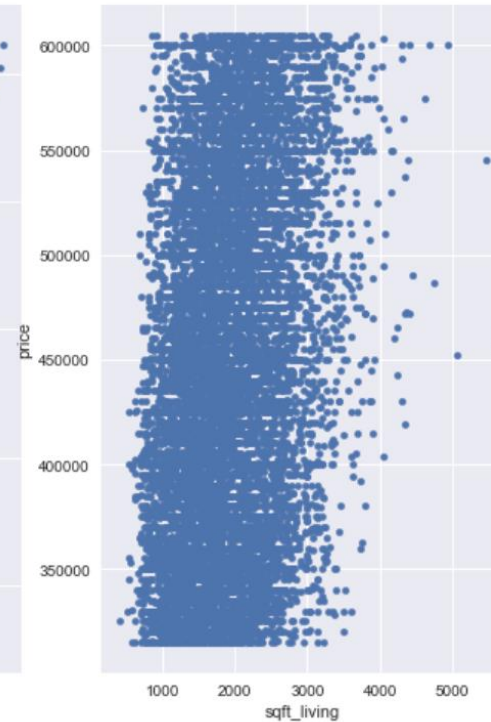
D) Add latitude

Added in latitude (bands)
and this helped.
Broadened price to \$453K.
(4 models; $r^2 \sim 0.492$)

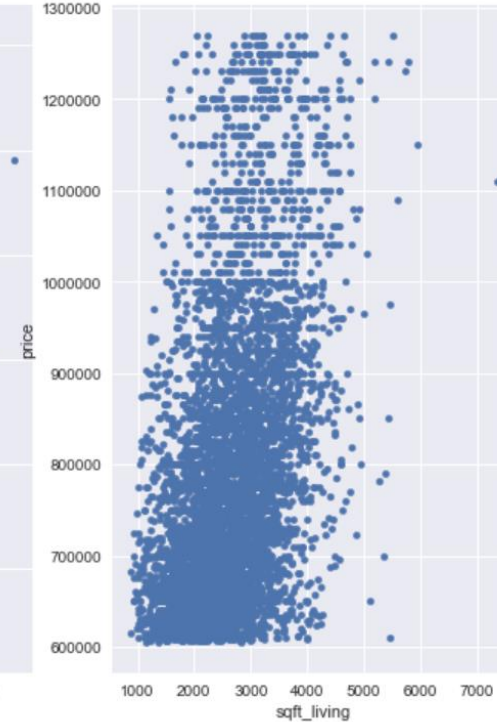
Low-priced
(up to \$314K)



Mid-priced
(\$315K to \$605K)

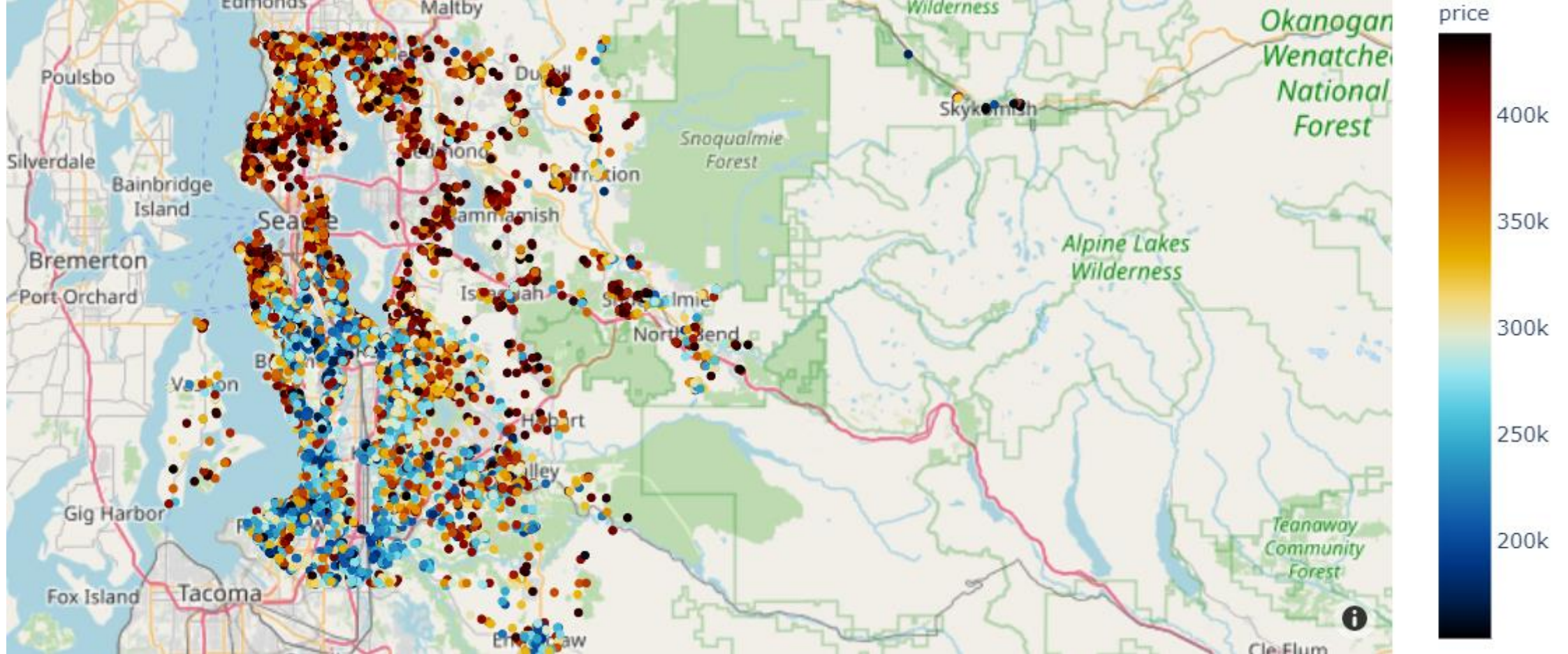


High-priced
(\$606K and up)



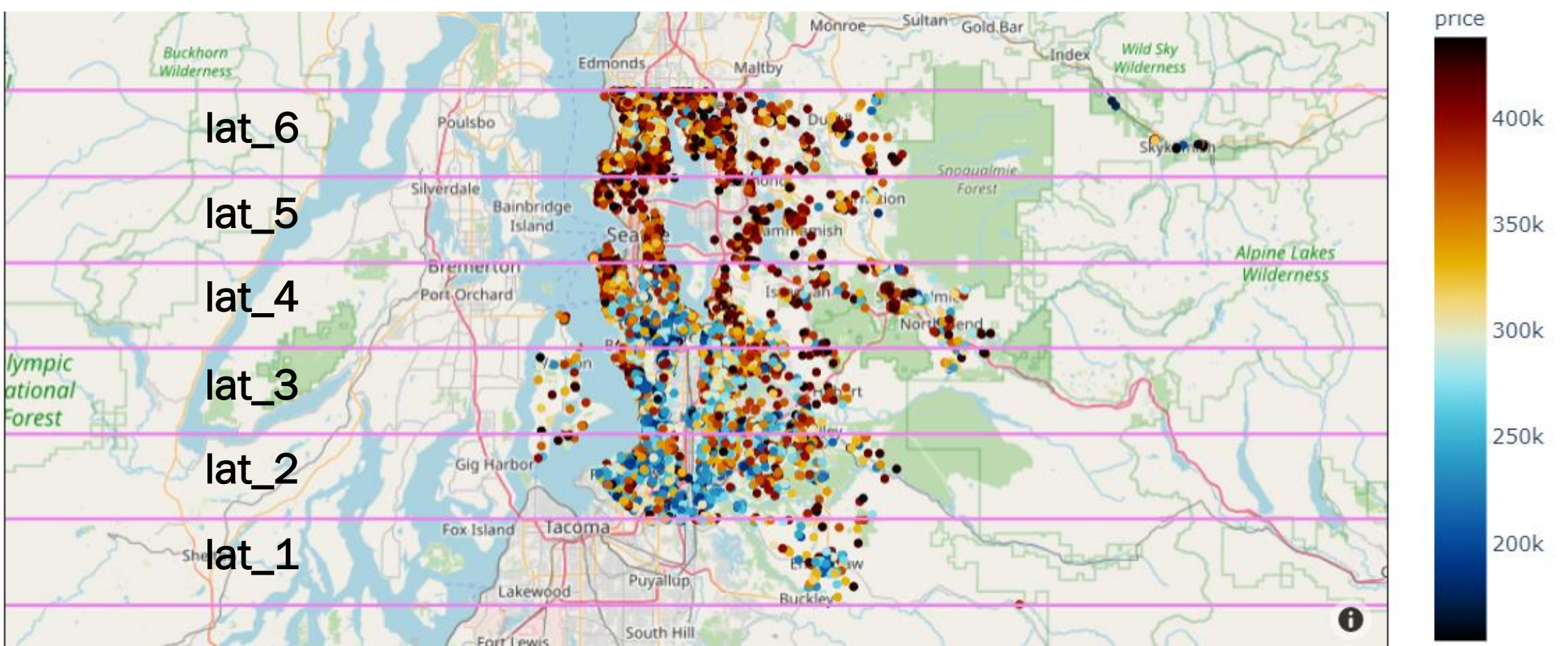
Low-priced shows clearer linear relationship

Re-examining scatter plots led us to shift from mid-priced homes to low-priced homes



Location, location, location...

Plotting home sales on a map revealed an important pattern in our data
(latitude more pronounced differences than longitude)



Created 6 bands for latitude

From the bands, created separate “dummy” features (lat_1 to lat_6)*.

* Note that lat_1 was “dropped” from the predictor set.

Model Adjustments

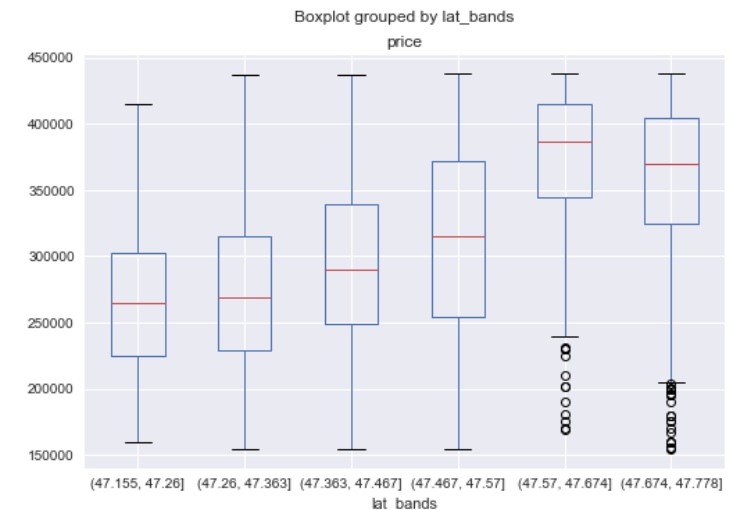
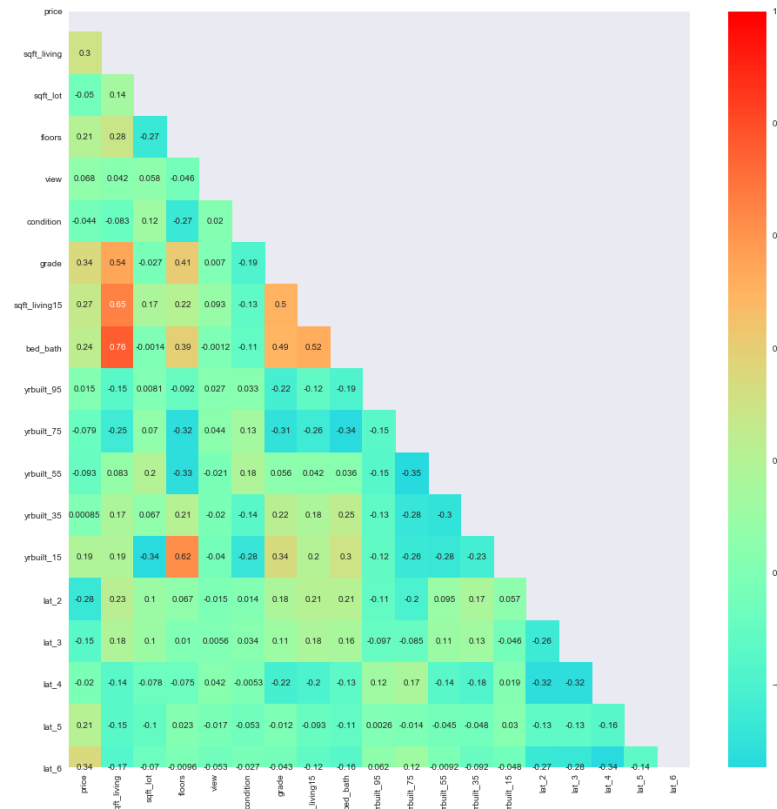
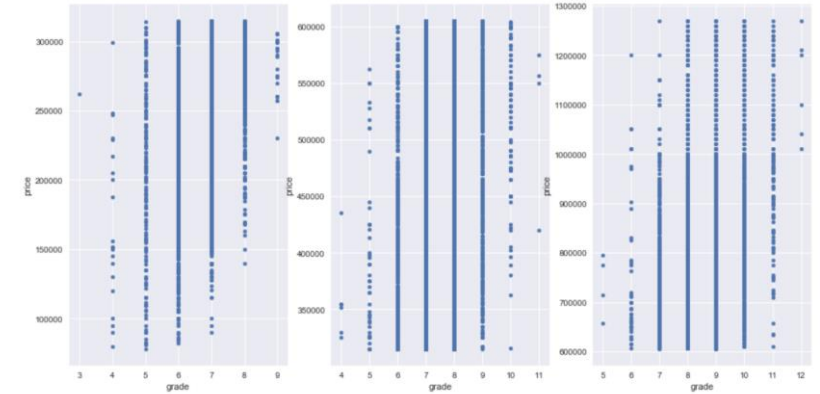
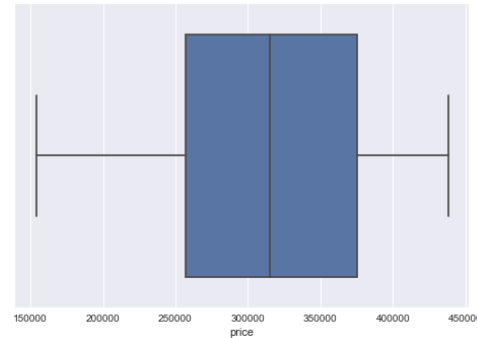
Removed outliers

Created banding and "dummy" variables (latitude; year built)

Created new variables (bed and bath combined)

Didn't include highly related features

Removed insignificant features



Our Final Model

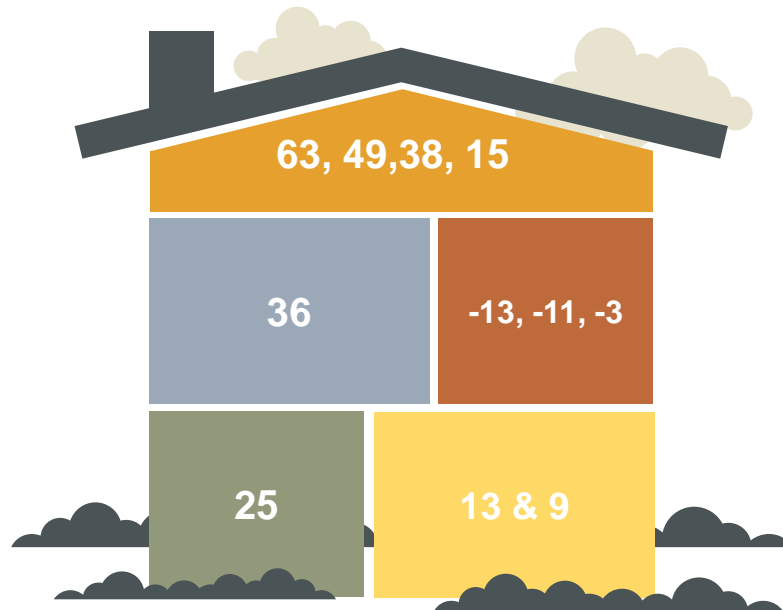
Top features contributing to the model (t-scores*):

Sqft Living Area

From 370 to 3,090 sqft

Grade

Construction quality:
includes grades 5 to 9
(of 13).



Latitude

4 of the 6 latitude bands
(3, 4, 5, 6)

Year built

3 of 6 bands (1940 to
2000)

Other

Condition (5 levels) and
View (4 levels of quality)

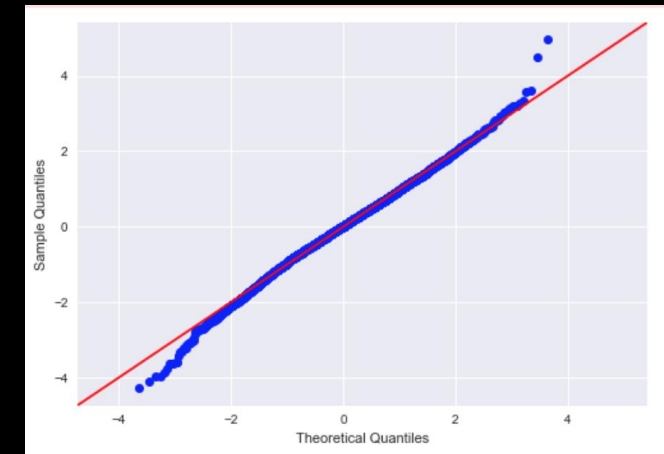
* Higher t-scores mean the feature contributes more to the model.

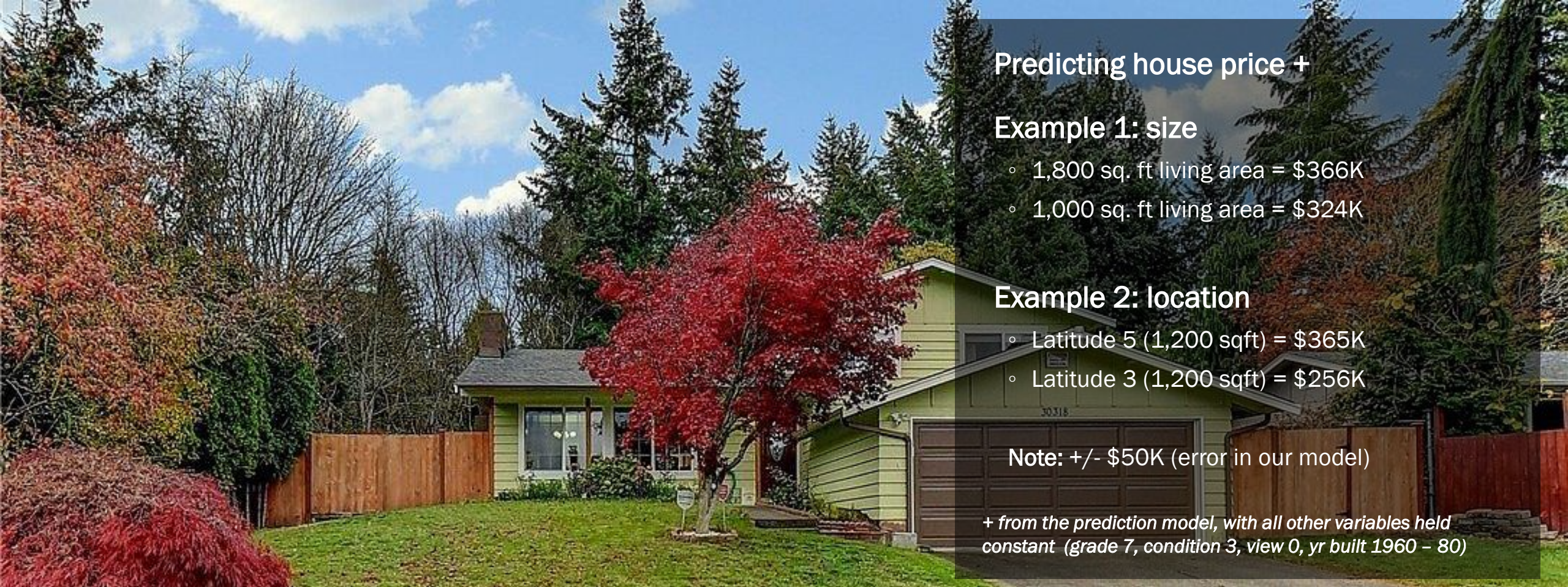
Model Details:

- Price is target feature (\$154K to \$438K)
- 11 predictor features
- $n = 7,212$ (train set)

Success Criteria :

- $r^2 = 0.52$
- RMSE = 50,137 (test)
- Cross Validation (8-folds)
RMSE = 49,932 (mean)





Predicting house price +

Example 1: size

- 1,800 sq. ft living area = \$366K
- 1,000 sq. ft living area = \$324K

Example 2: location

- Latitude 5 (1,200 sqft) = \$365K
- Latitude 3 (1,200 sqft) = \$256K

Note: +/- \$50K (error in our model)

+ from the prediction model, with all other variables held constant (grade 7, condition 3, view 0, yr built 1960 – 80)

Predicting with the Model (The Salazar's \$316K target price)

A) **Size:** Each additional sq. ft of living area will add \$52 to the home price.*

B) **Location:** A home in latitude 5 (Seattle) will add ~\$135K to the home price versus a home in latitude 1 (south).*

** Based on coefficient values for the feature, when all other features are held constant.*

Conclusions

Insights

Key Learnings

- Location is a key factor
- Living space, quality also important
- Iterating is vital to modelling



Limitations of our Model / Approach

- Relatively low predictive power; high margin of error
- Limiting price range may have hurt model
- Data not fulfill all of model assumptions
- Over-reliance on categorical data?
- Linear regression may not be the best modeling approach for the data

Next Steps

More exploration of **location**:

- transit routes
- walkability
- proximity to grocery stores

Examine various **home types**:

- duplex
- town-homes
- condos

Investigate other dwelling / property **features**:

- floor plans
- private yard
- Parking

Explore impact of **Covid-19** on prices and market



Thanks

Many thanks to:

- Flatiron School
- Our fearless instructor: Yish Lim
- Fill-in instructors: Amber Y., Lindesy B., and Abhineet K.
- Our helpful classmates in cohort (onl-ft-092820)

Learn more at: <https://github.com/melfriedman/KingHousing>

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