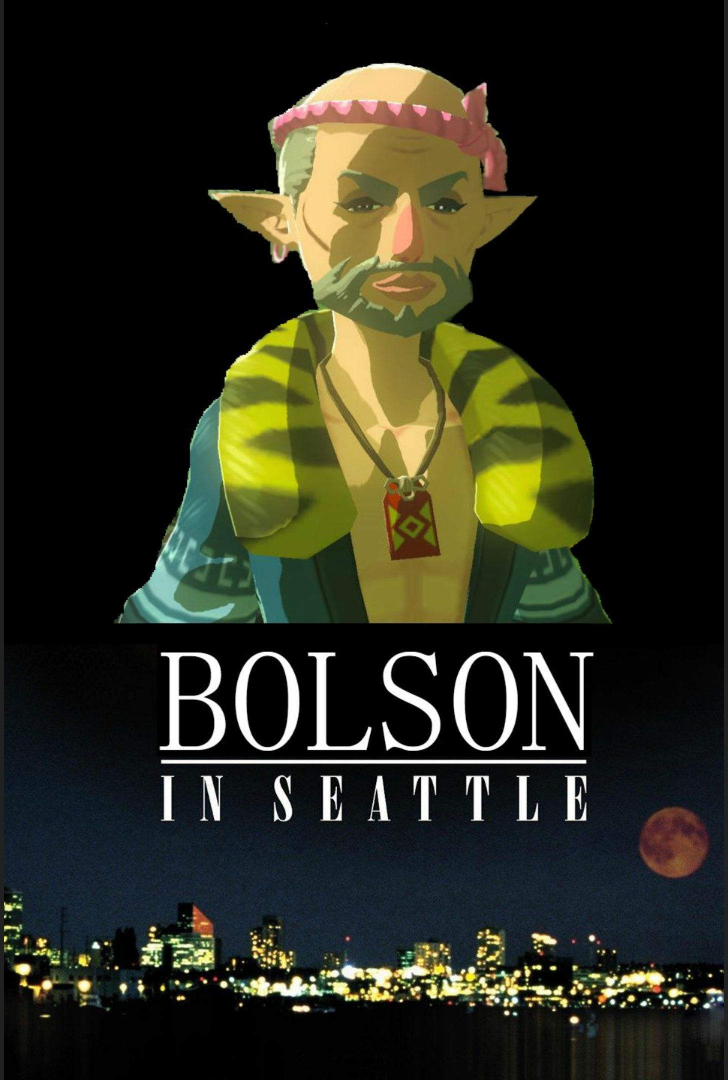
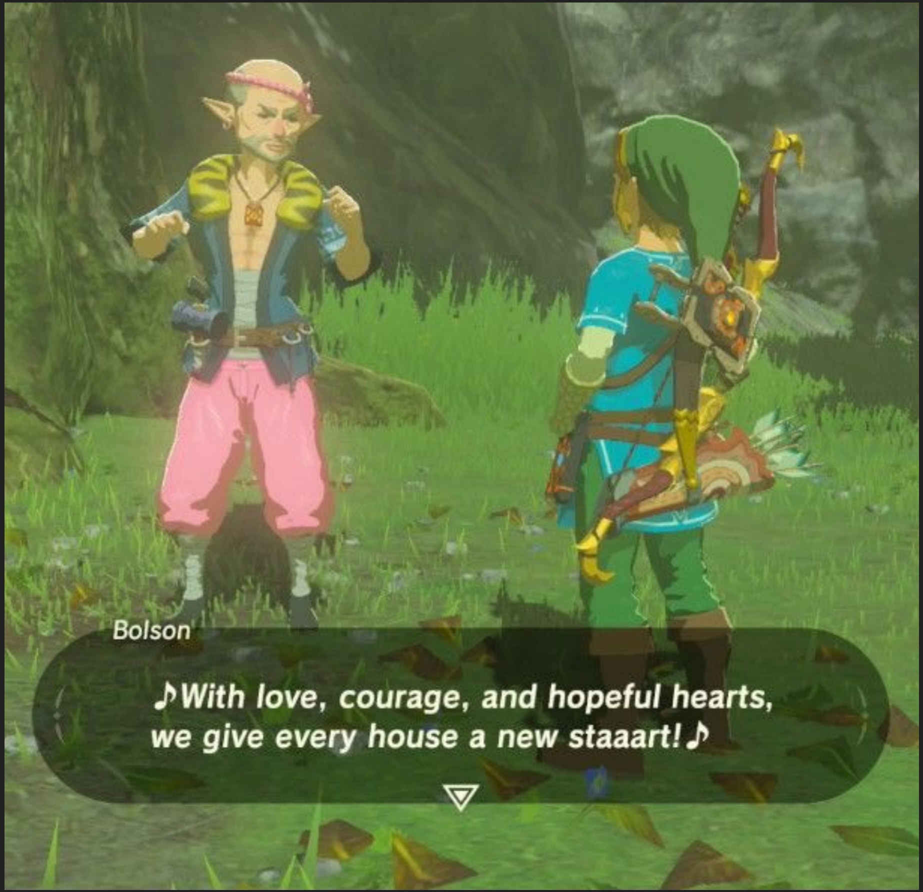
Analyzing the KC House Sales Dataset to Model Sale Price

AKA


BOLSON
IN SEATTLE

Who is Bolson?

- CEO Bolson Construction
- Specializes in:
  - Building Homes
  - Renovating Homes
  - Tearing Down Houses
- Not from around here!
- Needs your business advice!



What does Bolson want to know?

- How much does a house sell for? What drives that price?
- Where are the newest housing developments? Where's the market?
- Is price a function of n bedrooms? N bathrooms? N floors?

To answer these questions Bolson needs:

Data analysis! A working price model!

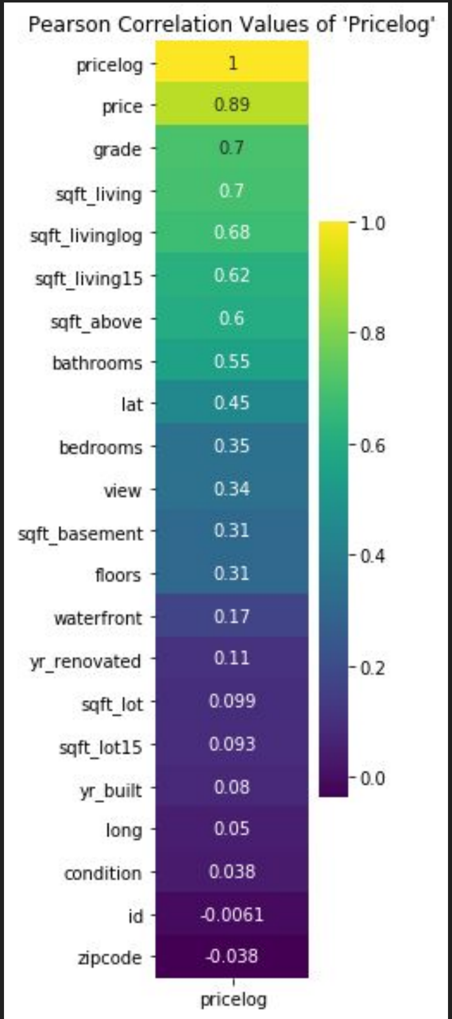
Let’s get started:

Where are the newest developments?

- Plot all sales on a scatterplot using ‘lat’ and ‘long’ data
- Filter all sales for just those that occured in most recent two years (2014, 2015 for this dataset)
- Plot ‘most recent sales` over top all sales, look for trends
- Find mean price:
  - $687K
- Find median price:
  - $599K

What drives the price of houses?

- Pricelog is normalized distribution of Price
- Higher correlation implies better predictor
- Looking at Grade, SQFT Living, Bathrooms, LAT, etc
- How do we clarify?
  - Run a test model
  - R^2 w/ only one variable:
  - Grade
- ‘Grade’ can explain almost 50% of the data on its own! Definitely the biggest driver!



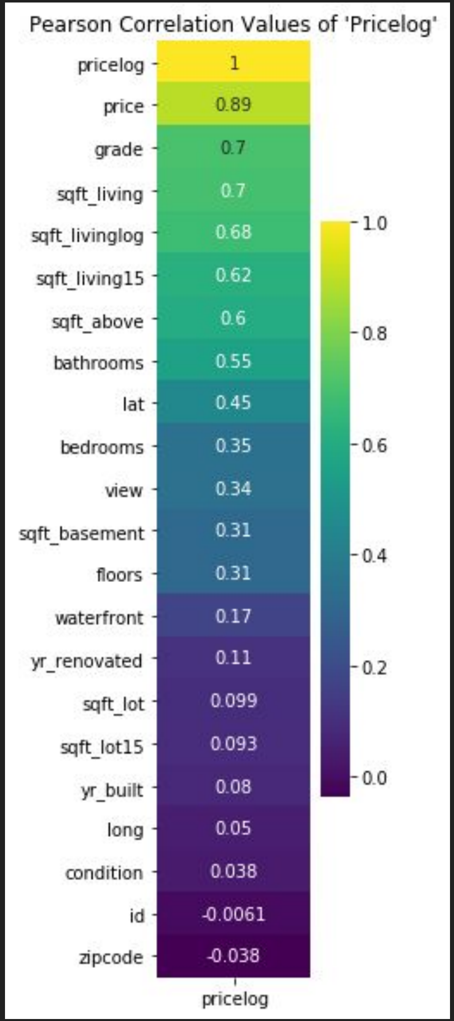
Dep. Variable:	pricelog	**R-squared:**	0.495
Model:	OLS	**Adj. R-squared:**	0.495
Method:	Least Squares	**F-statistic:**	2.066e+04
Date:	Fri, 21 Jun 2019	**Prob (F-statistic):**	0.00
Time:	18:22:48	**Log-Likelihood:**	-9172.9
No. Observations:	21054	**AIC:**	1.835e+04
Df Residuals:	21052	**BIC:**	1.837e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	10.6321	0.017	624.993	0.000	10.599	10.665
grade	0.3156	0.002	143.752	0.000	0.311	0.320

Omnibus:	133.048	**Durbin-Watson:**	1.965
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	136.615
Skew:	0.186	**Prob(JB):**	2.16e-30
Kurtosis:	3.132	**Cond. No.**	52.0

What about beds, baths, and extra floors?

- High correlation with n bathrooms helps, but still explains much less of Price - even with three variables!



Dep. Variable:	pricelog	R-squared:	0.311
Model:	OLS	Adj. R-squared:	0.311
Method:	Least Squares	F-statistic:	3171.
Date:	Fri, 21 Jun 2019	Prob (F-statistic):	0.00
Time:	18:22:48	Log-Likelihood:	-12447.
No. Observations:	21054	AIC:	2.490e+04
Df Residuals:	21050	BIC:	2.493e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	12.1041	0.013	911.436	0.000	12.078	12.130
bathrooms	0.3268	0.005	61.880	0.000	0.316	0.337
bedrooms	0.0523	0.004	13.230	0.000	0.045	0.060
floors	0.0515	0.007	7.918	0.000	0.039	0.064

Omnibus:	192.663	Durbin-Watson:	1.962
Prob(Omnibus):	0.000	Jarque-Bera (JB):	197.773
Skew:	0.236	Prob(JB):	1.13e-43
Kurtosis:	3.054	Cond. No.	20.7

Oh no! There’s no easy answer!

So what do we do?

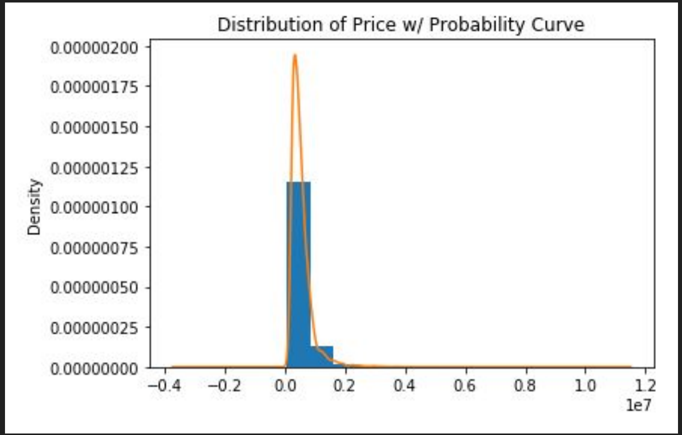
We Build a Model That Examines Multiple Features!

To get a working model we need:

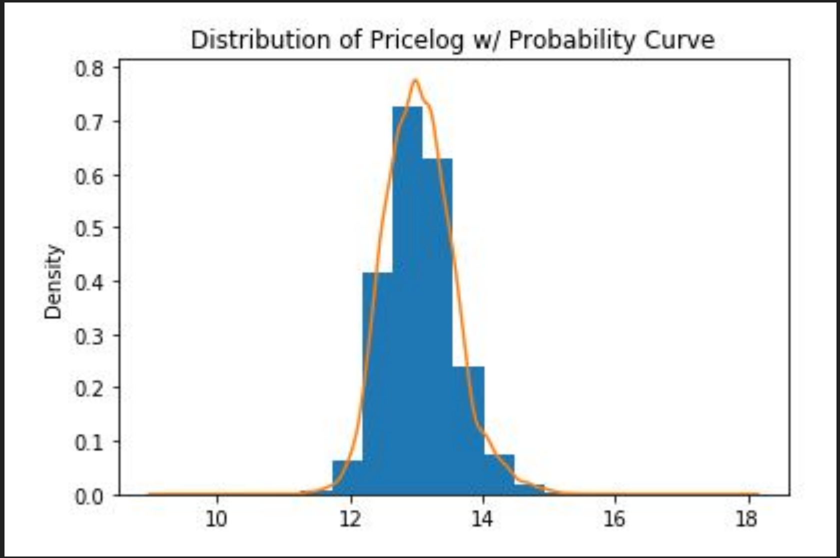
1. Linear relationships
    a. The Pearson correlation tells us this, so we’ve got some options
    b. We can’t include things that strongly correlate to each other!
2. When the model is wrong, it needs to be reliably wrong
    a. i.e. it’s wrongness must be predictable
    b. We need to ‘normalize’ some of our data
3. The model has to be fairly reliable
    a. This is our friendly R^2 variable

Predictably Unpredictable

- Linear models work best when they are ‘normalized’ aka ‘proportionally distributed’
- Pricelog, as seen earlier, is the normalized version of Price
- Transforming it like this will help make sure that the model’s mistakes are ALSO proportionally distributed!



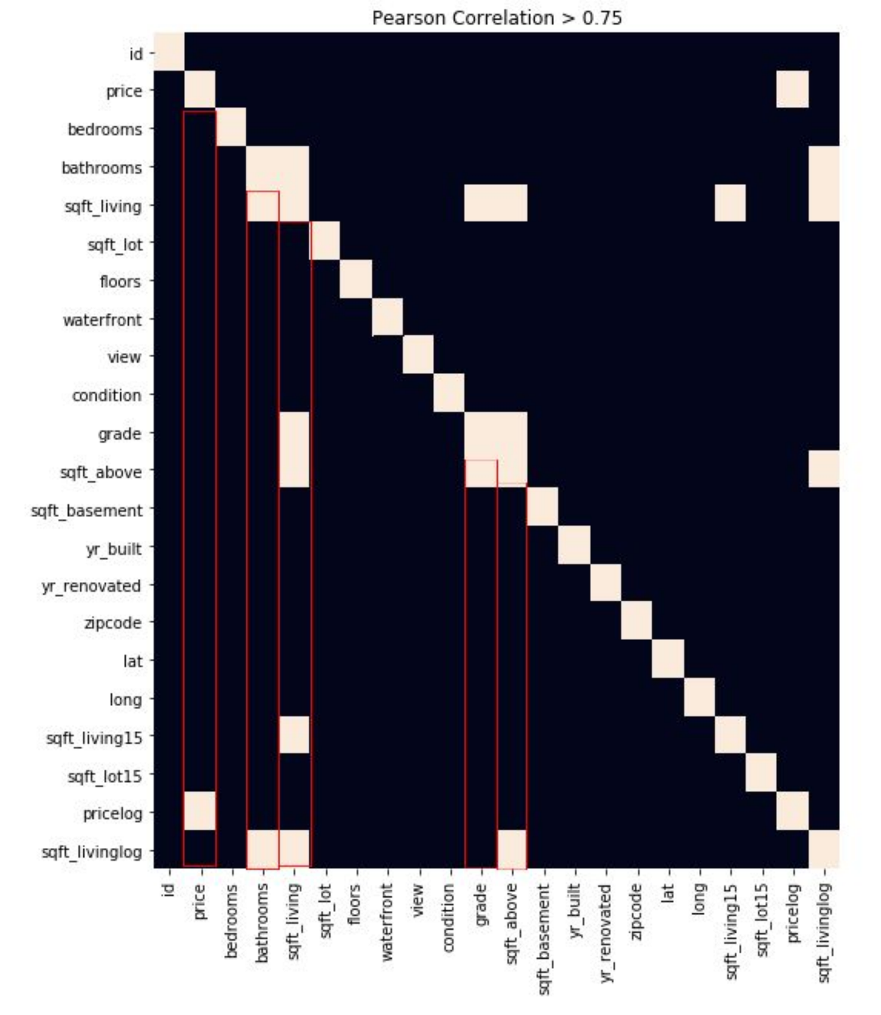
Before



After

Don’t Double-Dip

- If we add in features that are closely related to each other, they can disrupt the Pricelog prediction!
- Think of it like paying off one credit card with another: things are moving, but you aren’t changing your total amount of debt
- Take out things that talk to each other:
    - e.g. Grade talks to sqft_living and sqft_above



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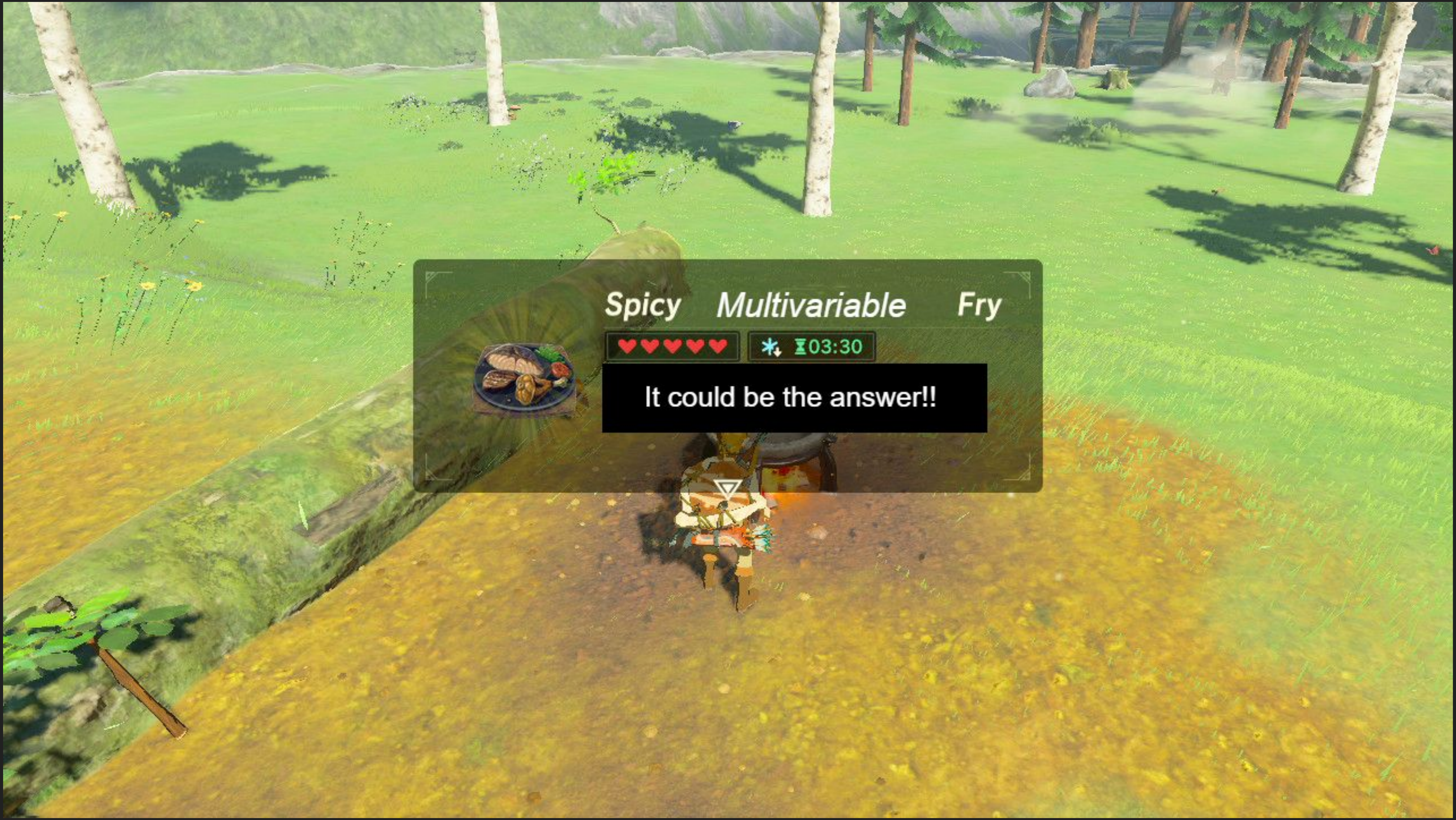
Building a Model With What We Have

- After knocking out variables that correlate to each other, we’re down to about 15 total
- We run combinations of the 15 into the model, and keep the variables that have the largest coeff (ie, really big impact), discard the rest
- Play with some trial and error, adding some variables back in
- Get a nice R^2

Dep. Variable:	pricelog	R-squared:	0.723
Model:	OLS	Adj. R-squared:	0.723
Method:	Least Squares	F-statistic:	9175.
Date:	Fri, 21 Jun 2019	Prob (F-statistic):	0.00
Time:	18:22:53		
No. Observations:	21054		
Df Residuals:	21047		
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-42.6515	0.733	-58.172	0.000	-44.089	-41.214
grade	0.2666	0.002	118.485	0.000	0.262	0.271
lat	1.2965	0.014	90.746	0.000	1.268	1.324
waterfront	0.6487	0.023	27.993	0.000	0.603	0.694
condition	0.0617	0.003	19.478	0.000	0.055	0.068
bathrooms	0.1874	0.004	53.282	0.000	0.181	0.194
yr_built	-0.0044	8.38e-05	-52.113	0.000	-0.005	-0.004


Spicy Multivariable Fry
03:30
It could be the answer!!

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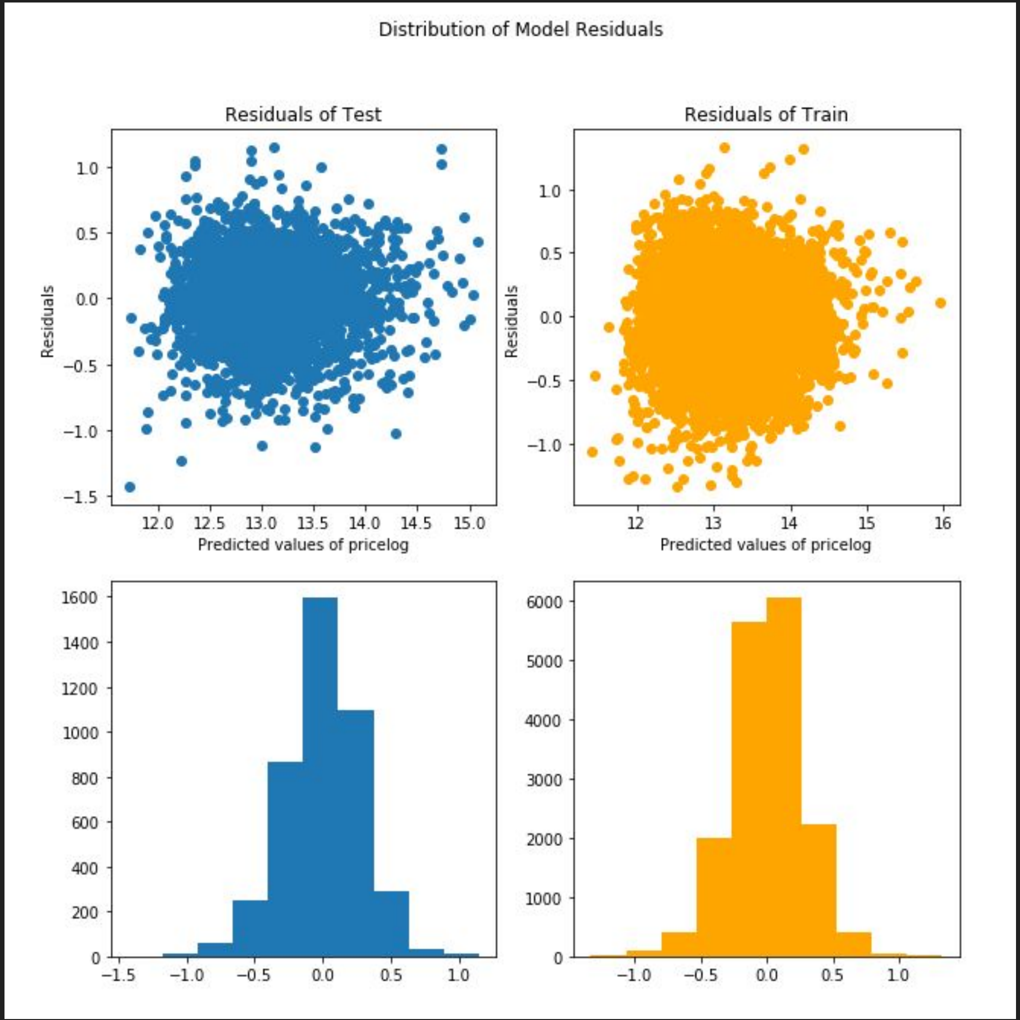
Wrong in the Right Way

- We randomly split the data into two sets:
  - A larger “Training” set
  - A smaller “Testing” set
- We build a model w/ the same variables on the Training set
  - New coeffs, New R^2
- Test that model on the “Testing” set and the “Training” set
- Then, compare ‘wrongness’
- If MUCH more wrong on one set than the other? Model doesn’t work!
- If errors are CONSISTENT and evenly distributed? Model does work!



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We did it! We can help Bolson predict housing prices!

What our model looks like:

$$log(Price) = \alpha(Grade) + \beta(Latitude) + \gamma(Waterfront) + \delta(Condition) + \epsilon(Bathrooms) + \zeta(YearBuilt) + Intercept$$

$$log(Price) = \frac{133}{500}\ Grade + \frac{162}{125}\ Latitude + \frac{81}{125}\ Waterfront + \frac{77}{1250}\ Condition + \frac{187}{1000}\ Bathrooms - \frac{1}{250} YearBuilt - 42.651$$