# Flat-tery Will Get You Nowhere

The effects of dimensional reduction

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- 4. I try to draw lines in a clever way

#### A better answer

I'm going to take you through a classic data science problem and show you how I try to work through it.

#### The Ames Iowa Dataset

Data on houses sold in Ames Iowa

Contains 81 columns that cover an exhaustive list of characteristics

39 columns contain numeric data

#### A few kinds of data

Discrete: counts of something. The data typically consists of whole numbers.

Continuous: Measurements of something. Can be whole numbers or fractions

Ordinal: ranking of things. There's a clear order to 1st, 2nd or 3rd place in a race, but they don't actually measure or count things and you can't do arithmetic operations with them

Categorical: Data that puts things in groups no clear order or arithmetic meaning

### Linear Regression Model

A line that goes through the data and which has the minimum possible distance from each point.

This line can be in an arbitrary number of dimensions.

### My first attempt

The first model I made simply ignored the non-numeric data

Underfit: this model did not have enough data to make good predictions

Actually came out really well: 82% of the variance in the model was accounted for in the features present. It did even better at predicting the test data: 85%

#### My second attempt

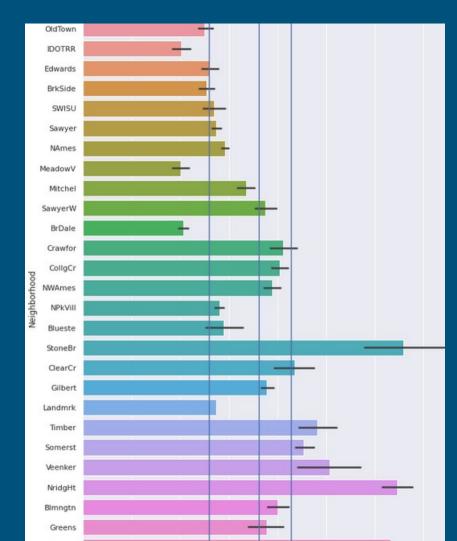
- 1. Take all categorical data and encode it with one hot encoding
- 2. 263 Features
- 3. Overfit..the model did a great job with the training data: 94% but a much worse job with new information 77%



## Feature engineering

Attempt to reduce the total dimensionality of the data while retaining the meaningful data.

- Method 1, desirability score
- I grouped the data into four groups based on the mean sale price
- Turned 25 columns into 4



#### Method 2: Aggregation

The data set included two categorical features pertaining to roof: Roof Style and Roof Mtrl

6 features each for a total of 36 values

I hypothesized that not all possible combinations were present

By grouping them together I was able to cu that t about 15

Results:

I was able to reduce the total dimensionality of the data by over half This did not improve results over the simple dropping non numeric data Why:

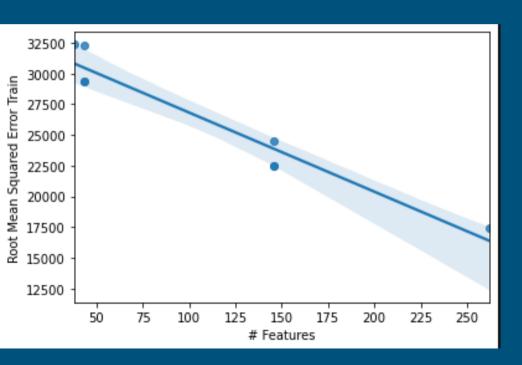
-There was a lot of numeric data

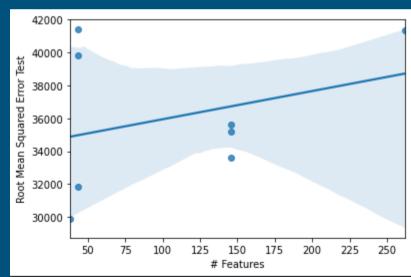
-Some of the data was likely redundant

#### Several of linear models compared:

|   | Model                         | # Features | R2 Training Data   | R2 Test Data       | Mean Squared Error Train | Mean Squared Error Test | Root Mean Squared Error Train | Root Mean Squared Error Test |
|---|-------------------------------|------------|--------------------|--------------------|--------------------------|-------------------------|-------------------------------|------------------------------|
| 0 | Underfit                      | 38         | 0.8274203264852614 | 0.8574404716022525 | 1047828067.7968353       | 894017622.2843026       | 32370.17250180844             | 29900.12746267652            |
| 1 | Overfit                       | 262        | 0.9480446618012022 | 0.7756839765035066 | 302902197.7328259        | 1709187344.2759871      | 17404.085662074463            | 41342.31904811324            |
| 2 | reduced onehot                | 146        | 0.9480446618012022 | 0.7849465219114472 | 504518913.2209439        | 1267222410.866267       | 22461.498463391617            | 35598.06751589567            |
| 3 | reduced numeric               | 43         | 0.9212572911121156 | 0.7894898250668314 | 859289303.1545429        | 1714364272.709657       | 29313.63681214842             | 41404.882232771255           |
| 4 | reduced 1hot ridgeCV (Best)   | 146        | 0.85320553187025   | 0.7653648236174785 | 506663066.0746632        | 1240450578.9059782      | 22509.177374454695            | 35220.03093277998            |
| 5 | reduced 1hot lassoCV (Best)   | 146        | 0.9209226427975585 | 0.8084733158525769 | 602339984.5117174        | 1128588612.4128618      | 24542.61568194632             | 33594.472944412475           |
| 6 | reduced numeric ridgeCV(best) | 43         | 0.853115423925284  | 0.7759227396051694 | 860149118.5720009        | 1586310994.7344778      | 29328.298937579057            | 39828.51986622749            |
| 7 | reduced numeric lassoCV(best) | 43         | 0.8056179127104846 | 0.8583320324631964 | 1043420588.3012797       | 1015110760.7379383      | 32302.021427478492            | 31860.80288909773            |

### Dimensionality and fitness





### Why am I sharing this?

- What I do is hard. It's an iterative process
- I was seeing significant improvements, which I will use to further refine my model
- Specifically, I'm going to see what features are most correlated and filter to hopefully get to approximately 20 features encoding different data
- I'm also going to try to boost the signal with sensible combination of data
- You've already heard about how successful our methods can be. I wanted to show you a little more about how the sausage is made
- I hope you have a better understanding of the work that I do and that this is a WORK. It's a painstaking process, even for experts.
- So you should contract with the best