NYU FRE 7773 - Week 3

Machine Learning in Financial Engineering

Ethan Rosenthal

Feature Engineering & Model Selection

Machine Learning in Financial Engineering

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Feature Engineering

The ML Recipe

1. Think up some model
2. Feed **data** into the model and make predictions.
3. Calculate the loss between predictions and true values.
4. Determine the model parameters that produce the minimum loss.

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1. Think up some model
2. Feed **data** into the model and make predictions.
    a. We decide what data to include.
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Feature Engineering:

Turning *data* into *features*

Nonlinear Features for Linear Models

- We can do whatever we want to the features **X**.

$$y_i = \sum_{j=0}^{p} \beta_j X_{ij}$$

- We can square a feature, we can multiple features by each other, we can apply a sine, etc...

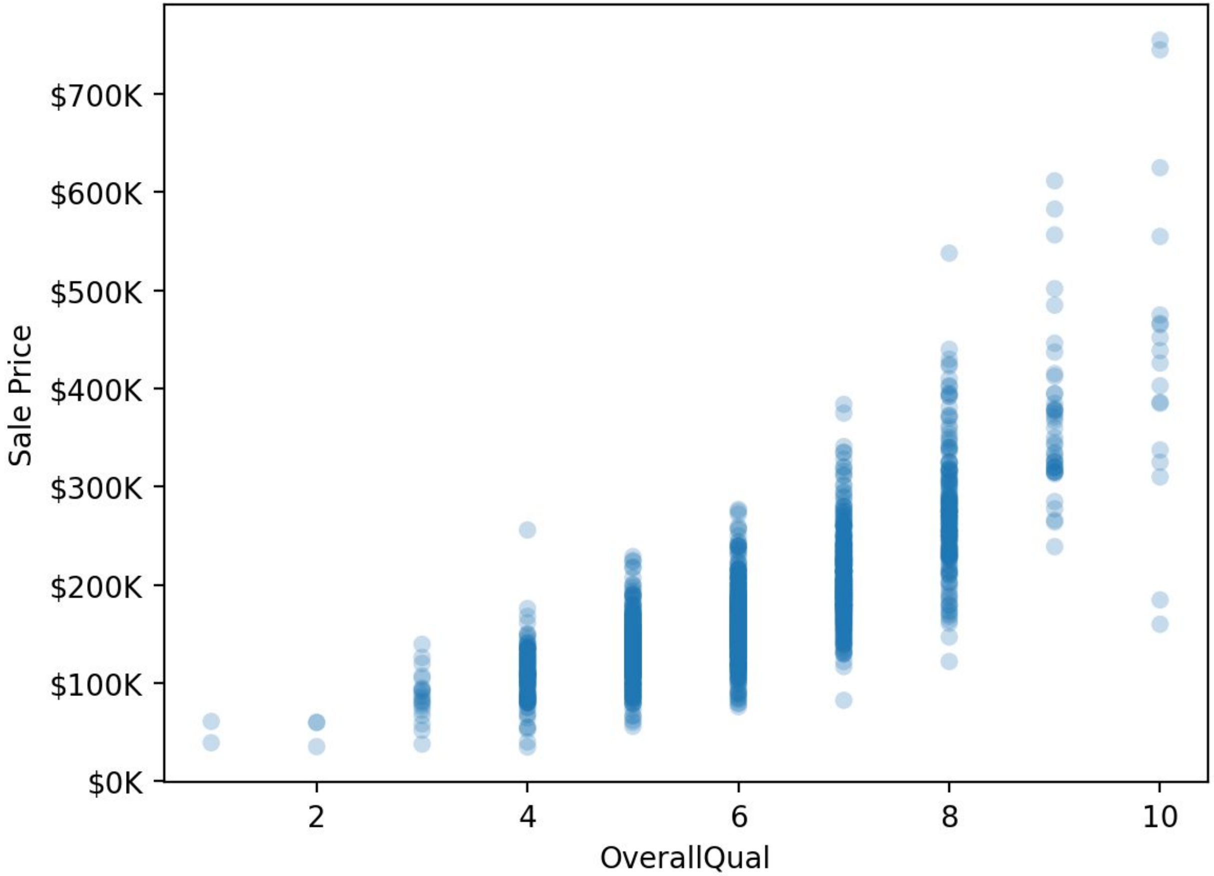
$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i1}^2 + \beta_3 X_{i1} X_{i2} + \beta_4 sin\left(X_{i3}\right)$$

- While these features are nonlinear, the model is linear in the parameters β.

Why Engineer Features?

We know a better

data <> target relationship



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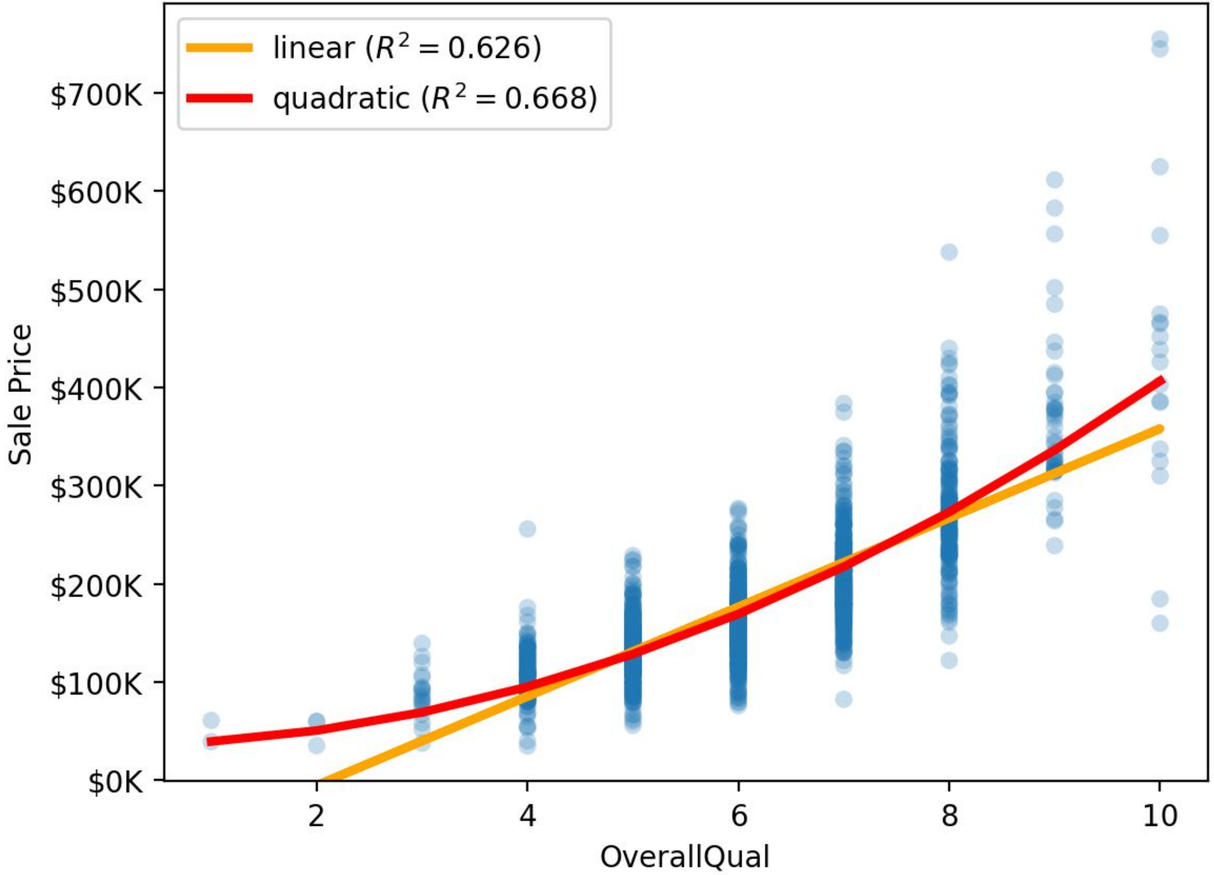
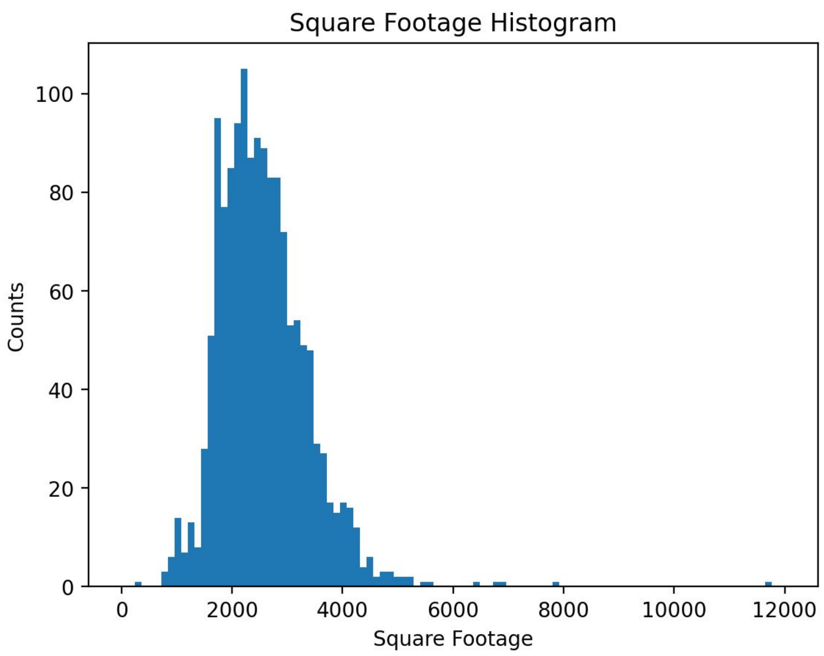
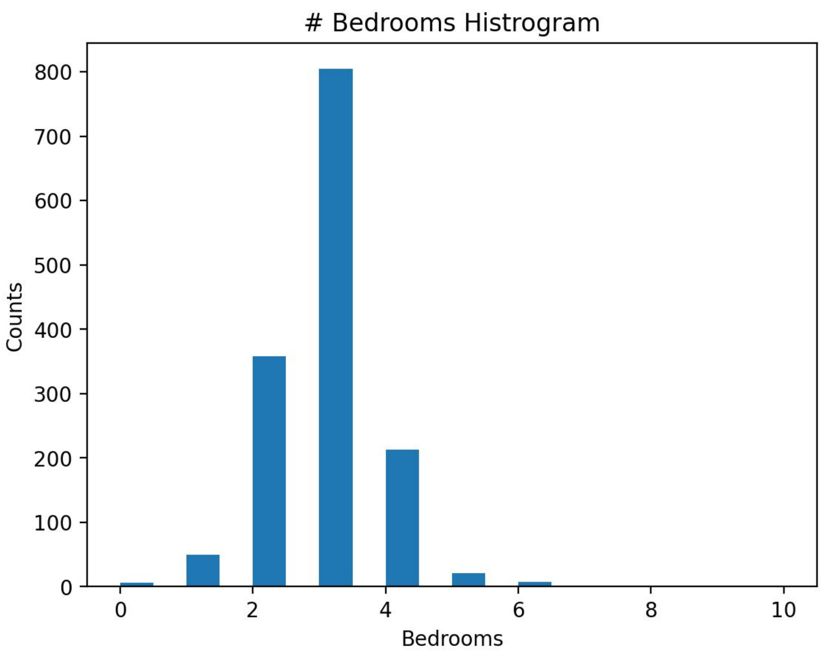


Why Engineer Features?

Put features on the same scale





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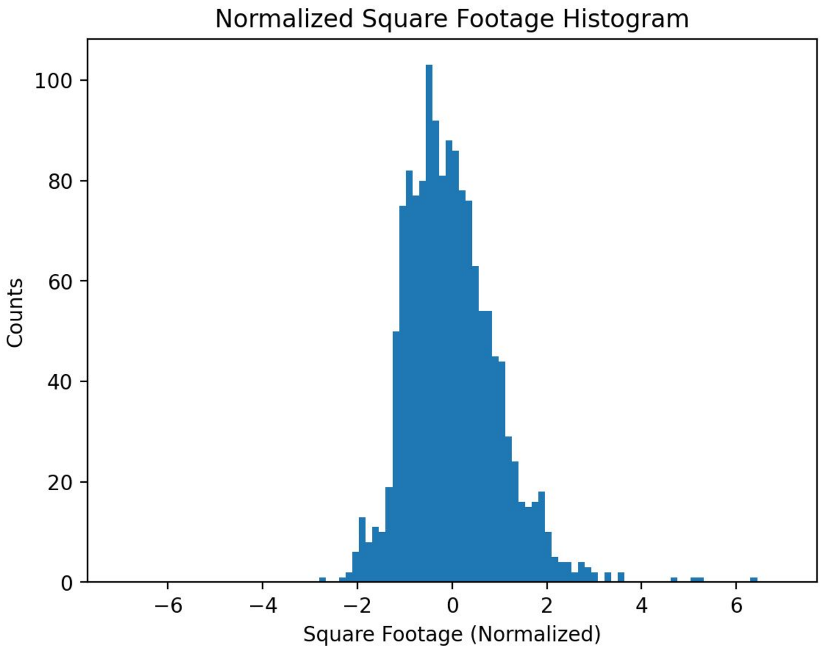

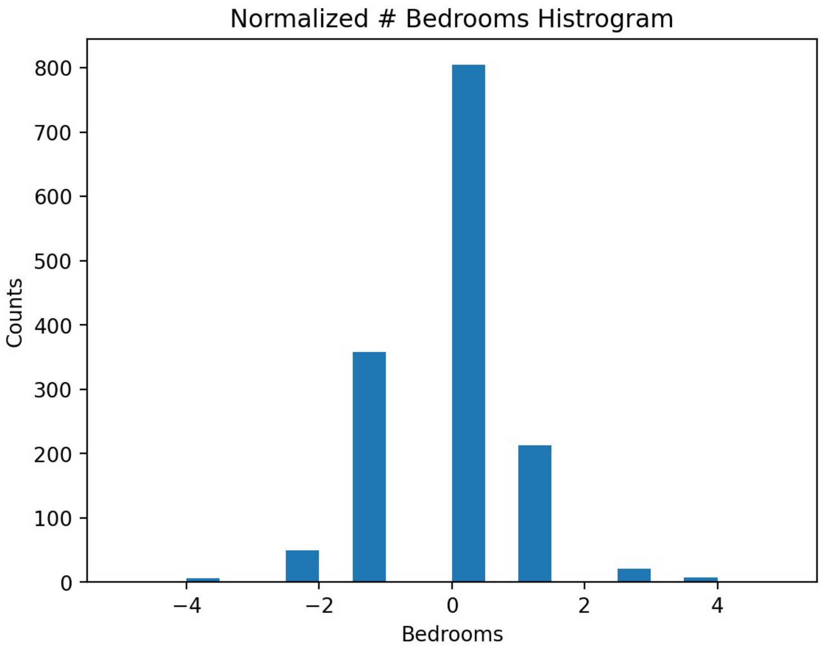

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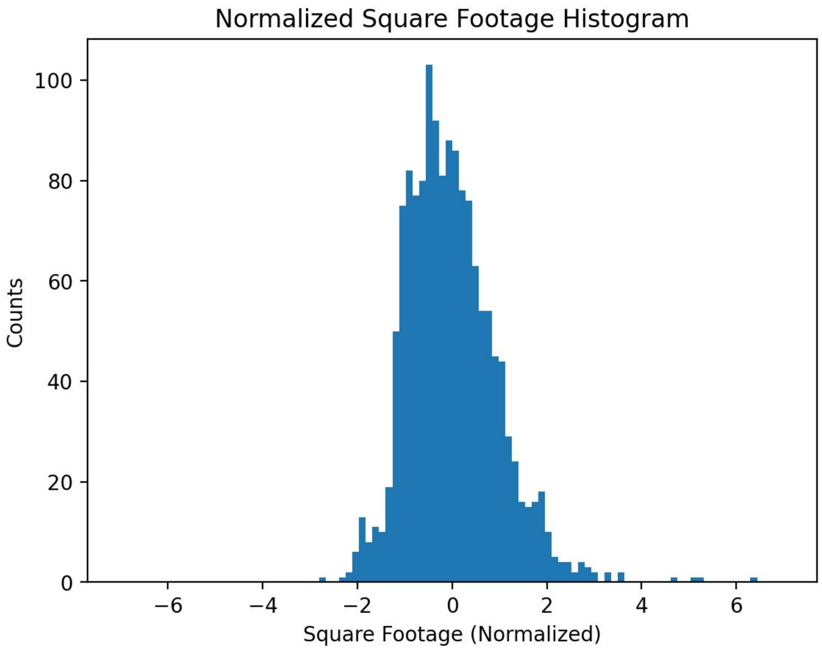


Normalization: $$\vec{\mathbf{X}}_j^* = \frac{\vec{\mathbf{X}}_j - \bar{X}_j}{VAR\left(\vec{\mathbf{X}}_j\right)}$$

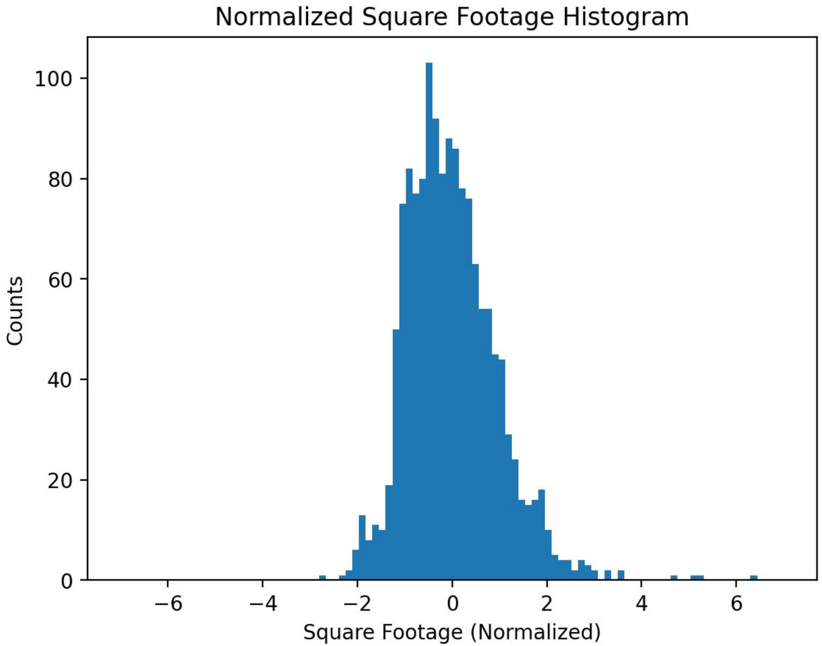
where

$$\bar{X}_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij}$$

$$VAR\left(X_j\right) = \frac{1}{n-1}\sum_{i=1}^{n}\left(X_{ij} - \bar{X}_j\right)^2$$

Why Engineer Features?

Put features on the same scale

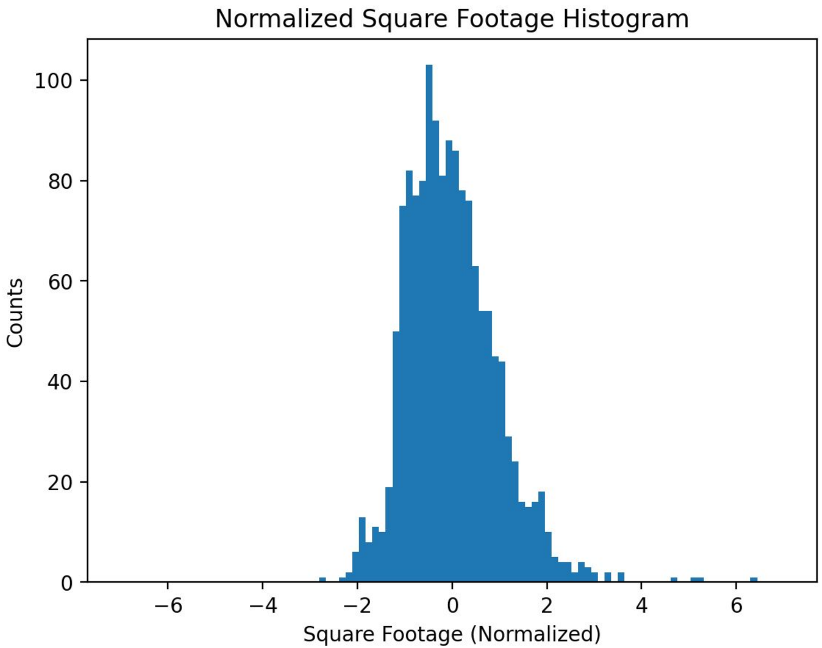


Many other feature scaling techniques:

- Log transform
- Min/Max scaler
- Max Abs Scaler
- Power transform

Why Engineer Features?

Put features on the same scale

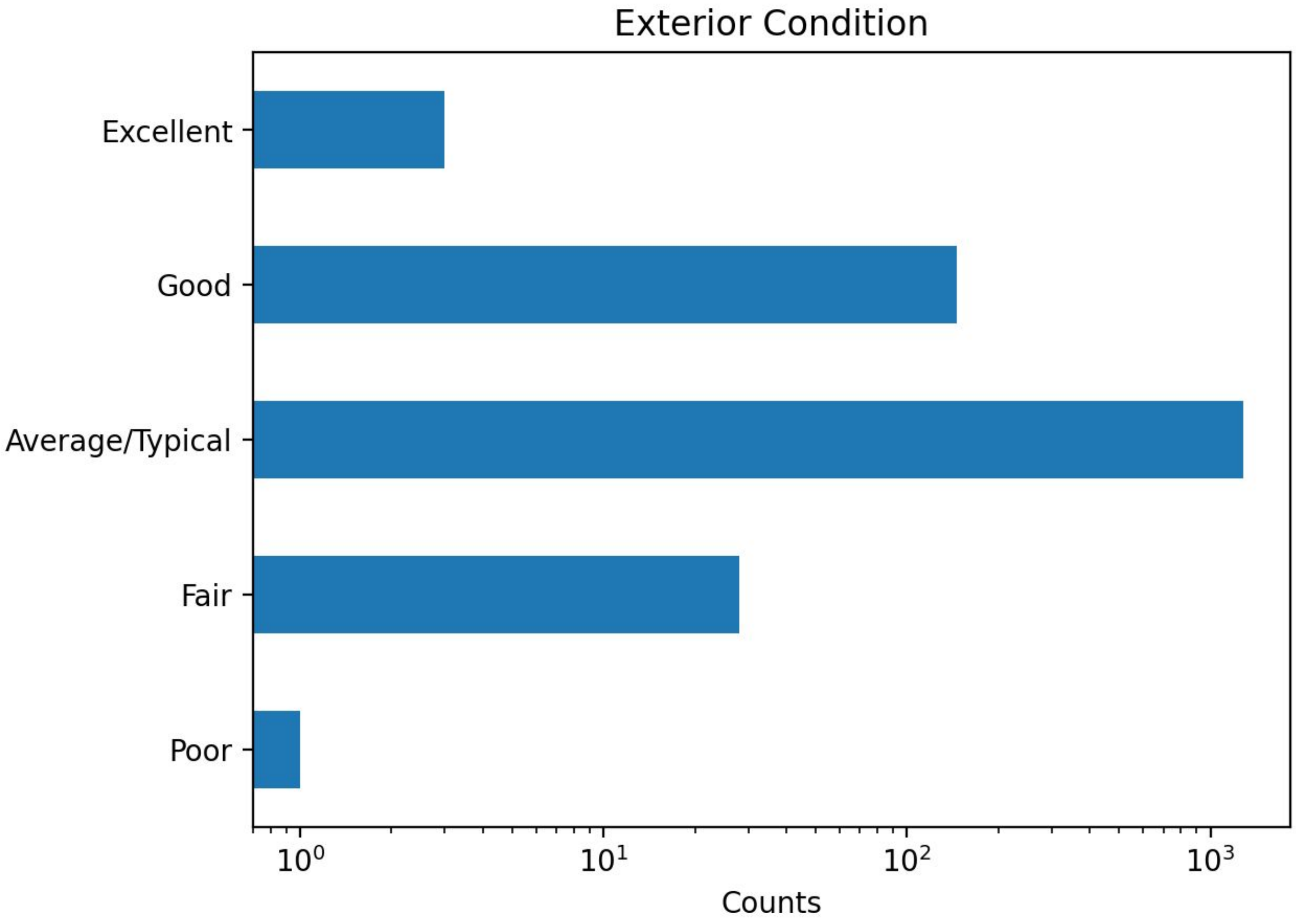


Why put features on the same scale?

- Can draw inferences from linear models.
- Some algorithms converge faster.
- Some algorithms *only* converge if features are scaled.

Why Engineer Features?

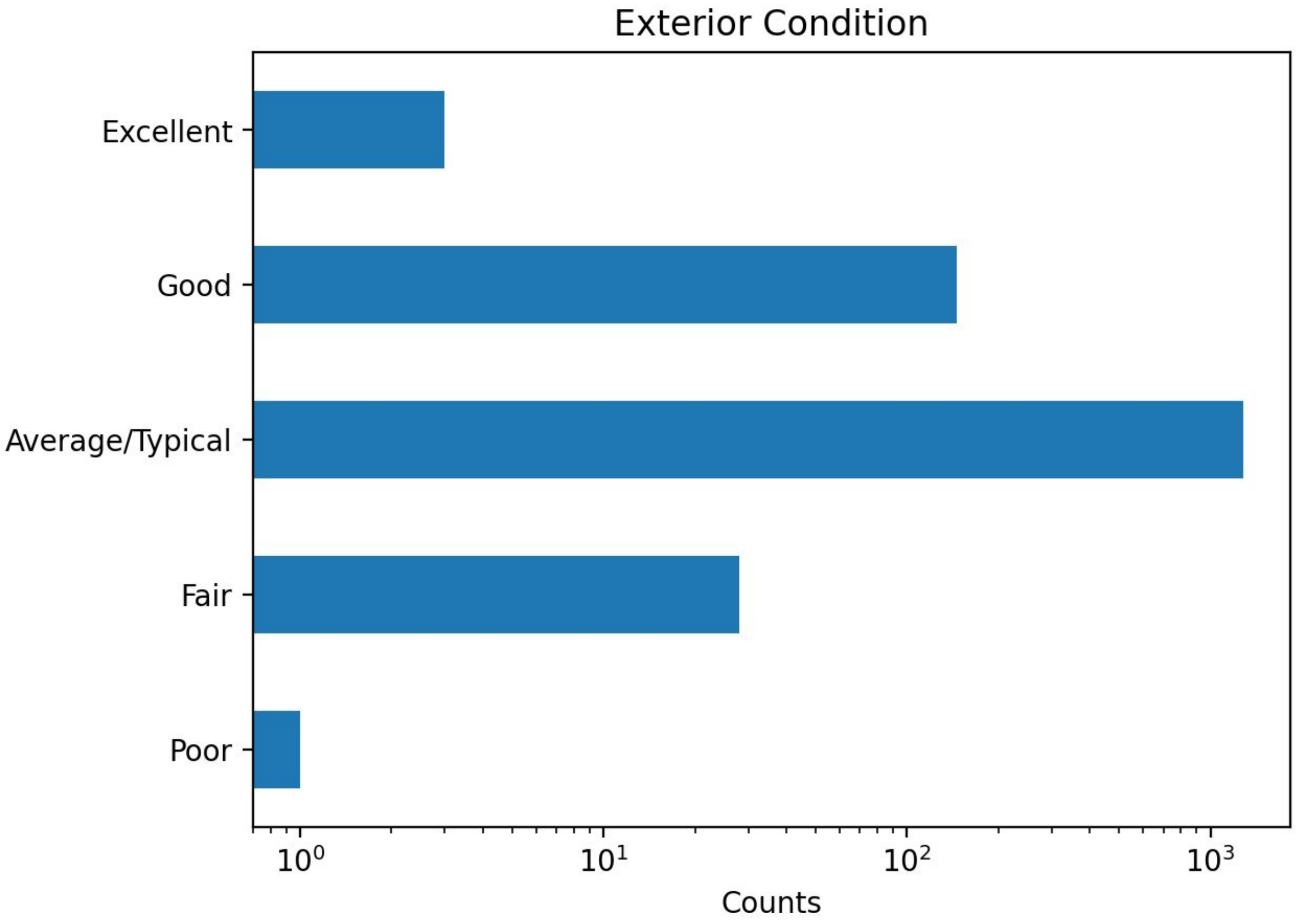
Sometimes we have to:



All Features Must Be Numbers

Why Engineer Features?

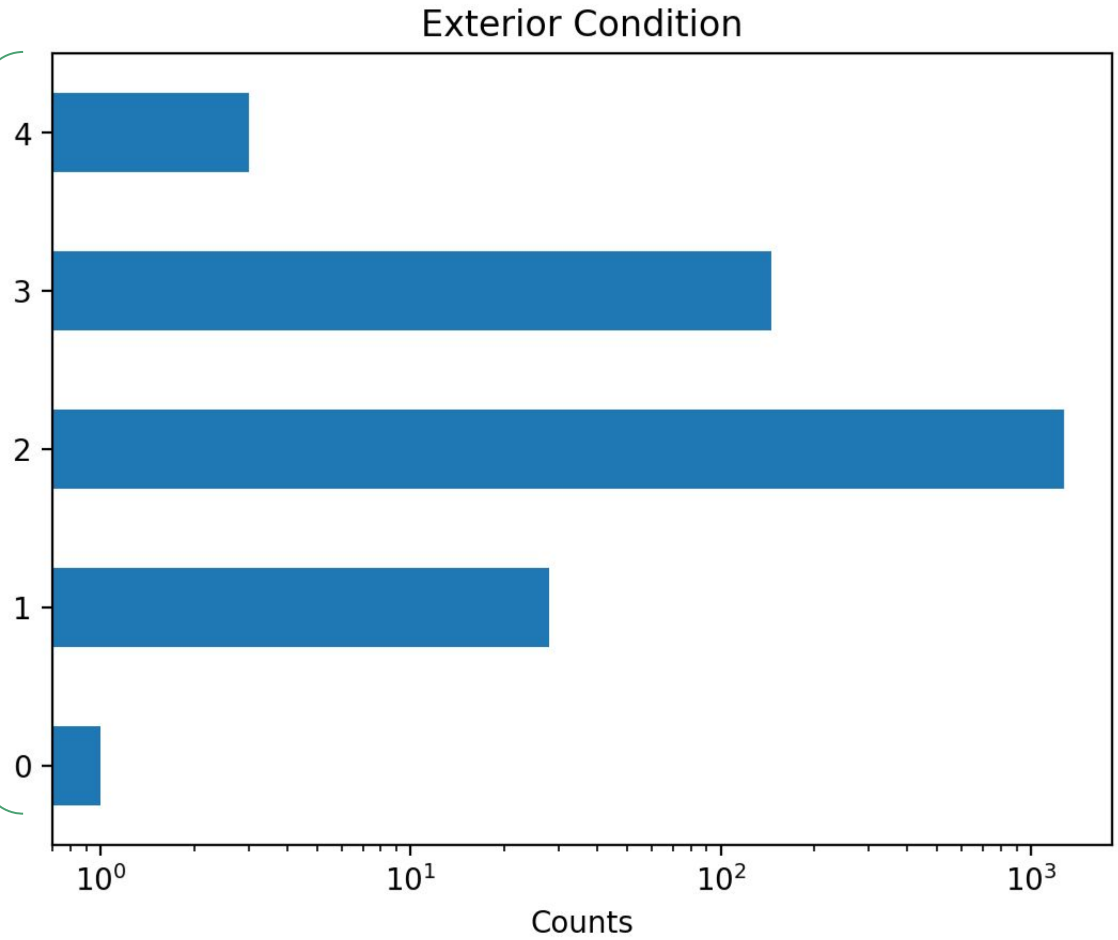
Sometimes we have to:



Why Engineer Features?

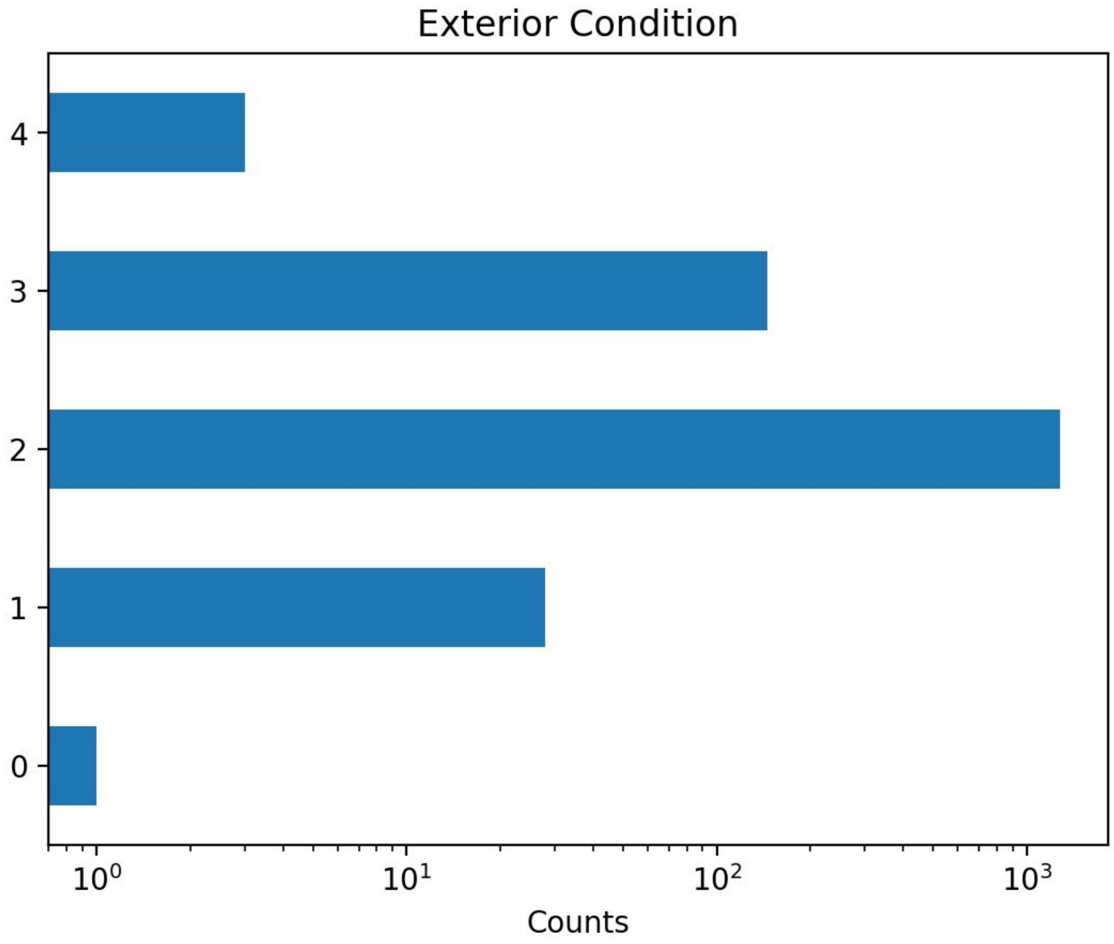
Sometimes we have to:

Numbers!



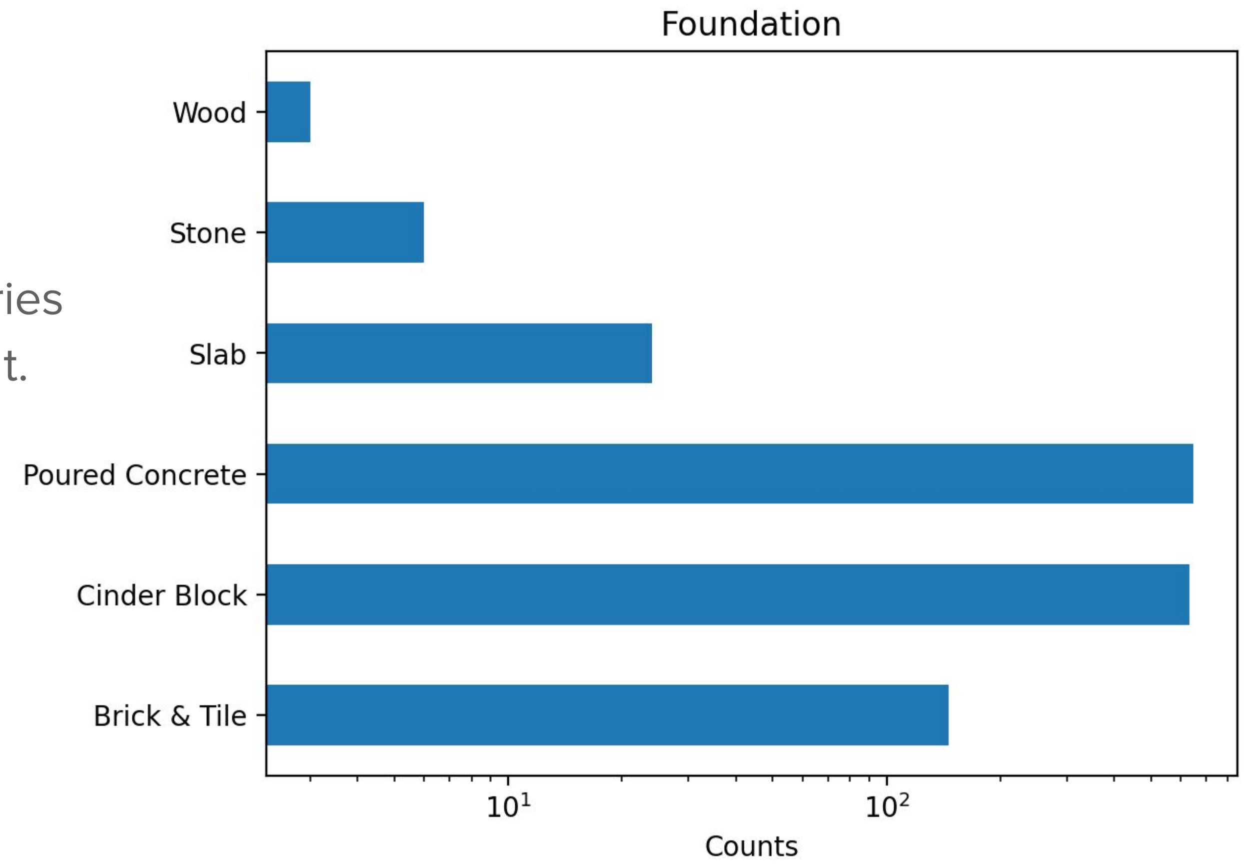
Ordinal Encoding

- If categories have different “distances” from each other, then do ordinal encoding.
- e.g.
  - too small, fits well, too big
  - Strongly disagree, disagree, neurtral, agree, strongly aggree



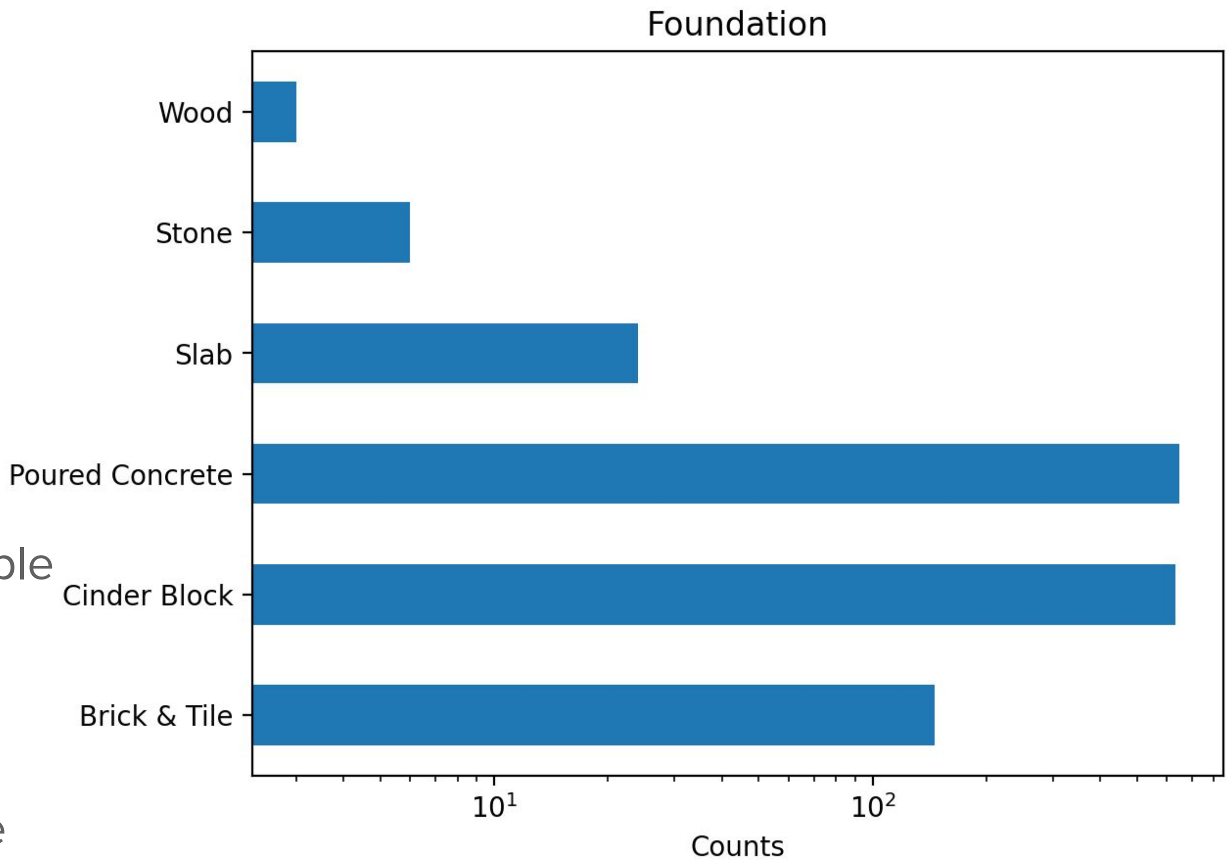
Non-ordinal Categories

- Sometimes the categories are largely independent.



One Hot Encoding

- Imagine C categories.
- Break up into C-1 binary features
- Each feature indicates whether or not the sample belongs to a specific category.
- If all features are False, then this implies sample belongs to Cth category.



One Hot Encoding

	is_wood	is_stone	is_slab	is_poured	is_cinder
“Wood”	1	0	0	0	0
“Slab”	0	0	1	0	0
“Brick & Tile”	0	0	0	0	0

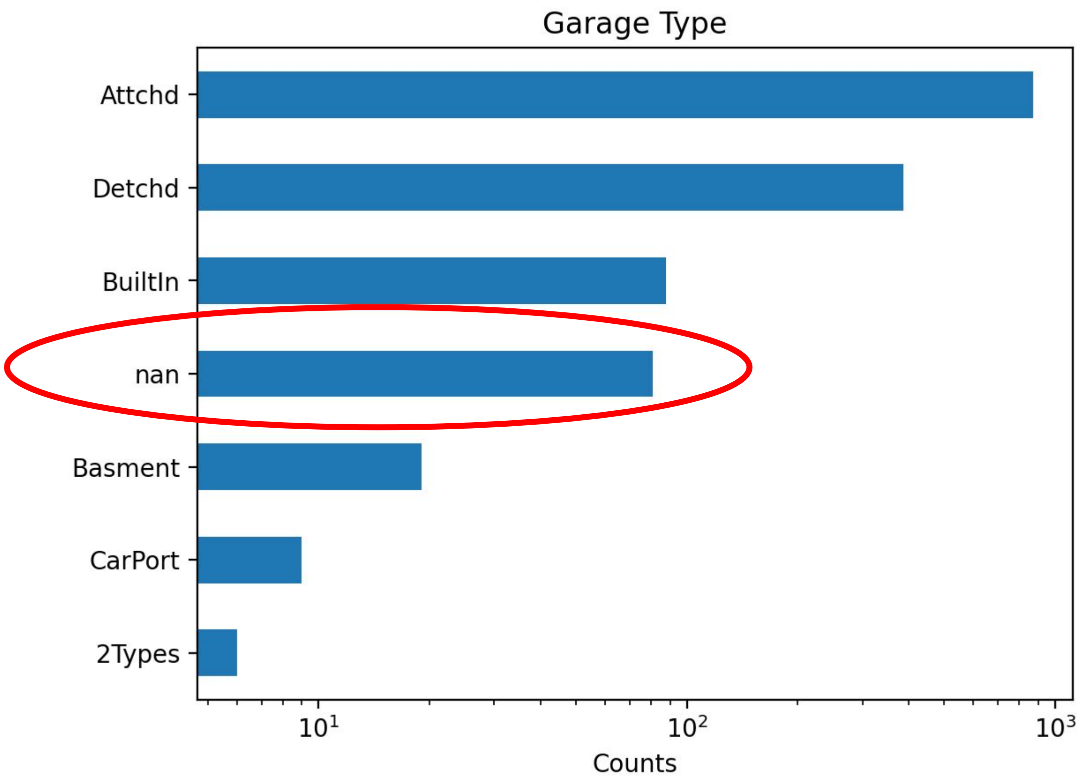
One Hot Encoding Caveats

- Blows up the size of your dataset: n X 1 -> n x C
- Need to combine with more advanced feature engineering for large C.
- Large C examples:
  - Recommender systems: one-hot-encoding every single user and item.
  - Text: one-hot-encoding every unique word or sub-word.
- Large C solutions:
  - Embeddings: embed all categories in a low-dimensional vector space.
    - Each category gets mapped to a O(100)-dimensional vector.
    - Vectors are model parameters. Learn model parameters that embed semantically similar categories near each other in this vector space.
  - Hashing: categories get randomly hashed to binary features.
    - Hash to fewer features than the number of categories.
    - Trade off reduced accuracy (due to hash collisions) for smaller feature space.

Feature Engineering - beyond scaling and encoding

- Streams -> Features
  - “Average order value in the last month”
  - “Standard deviation of the time between keystrokes”
  - “Total minutes watched by this customer for this video category in the last week”
- Images
  - Models -> models
    - Image -> “Pedestrian in front of car” -> “should brake”
  - Deep learning
    - Feed in raw pixels and learn features
- Text
  - Annotation
    - Part of speech tagging
    - Sentiment analysis
    - Named Entity Recognition

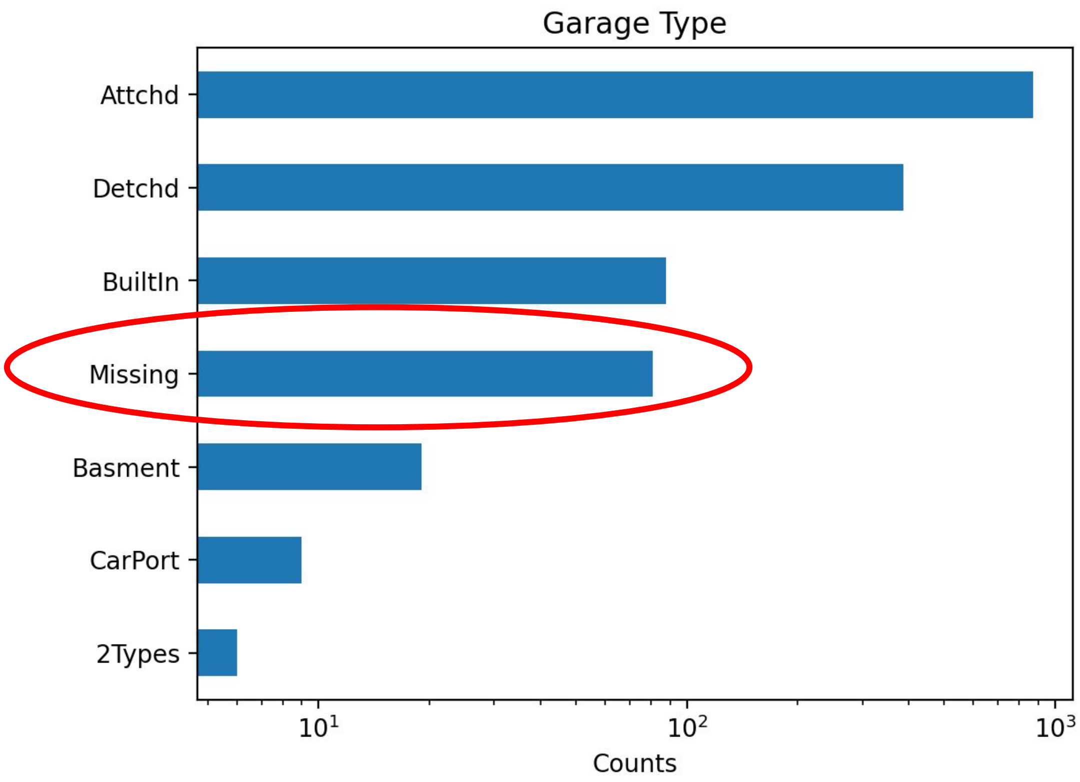
Feature Engineering - Missing Category



Feature Engineering - Missing Category

Simplest solution:

- Create a new "missing" category and then encode.



Feature Engineering - Missing Numerical Data

- Handling missing data is generally called “imputation”.
- Simple solutions:
  - Fill in missing values with the average value
  - Fill in missing values with 0 and create a separate “indicator” binary feature that’s 1/0 when the data is missing/not missing.
- Beware!
  - Data may not be randomly missing.
  - Missing data may be a valuable signal in itself.
  - Do not simply remove missing data from your dataset.

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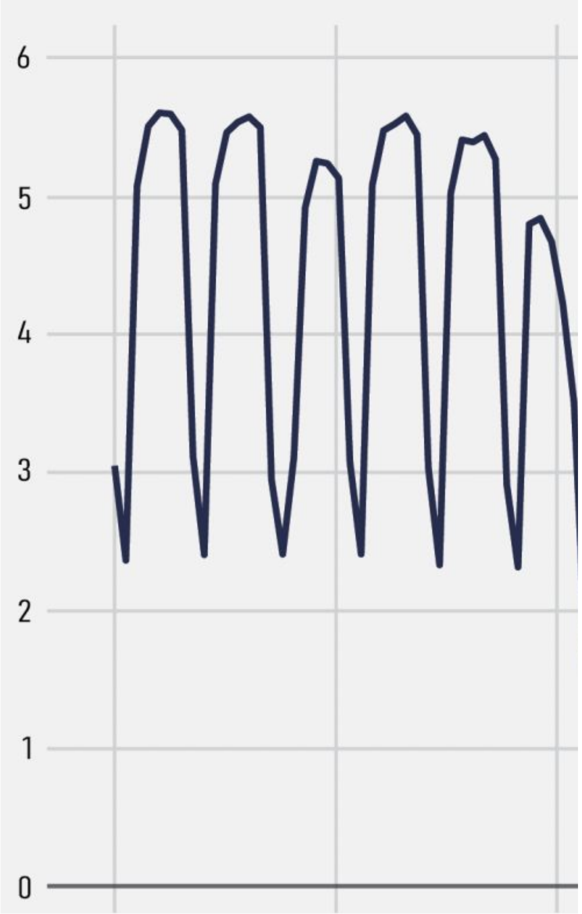
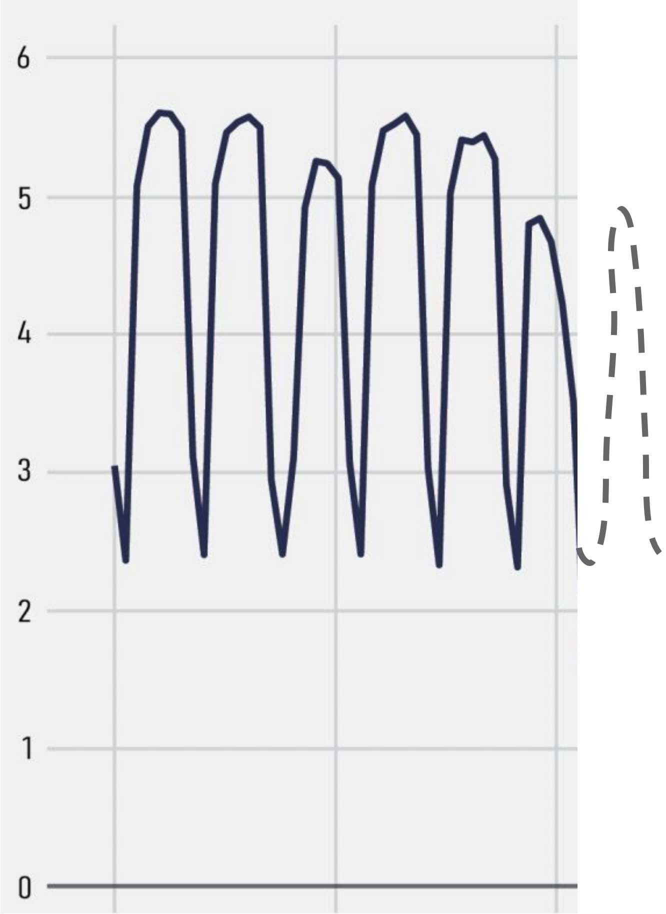
For many use cases, feature engineering is much more important than anything else in this recipe.

Model Selection


6
5
4
3
2
1
0


6
5
4
3
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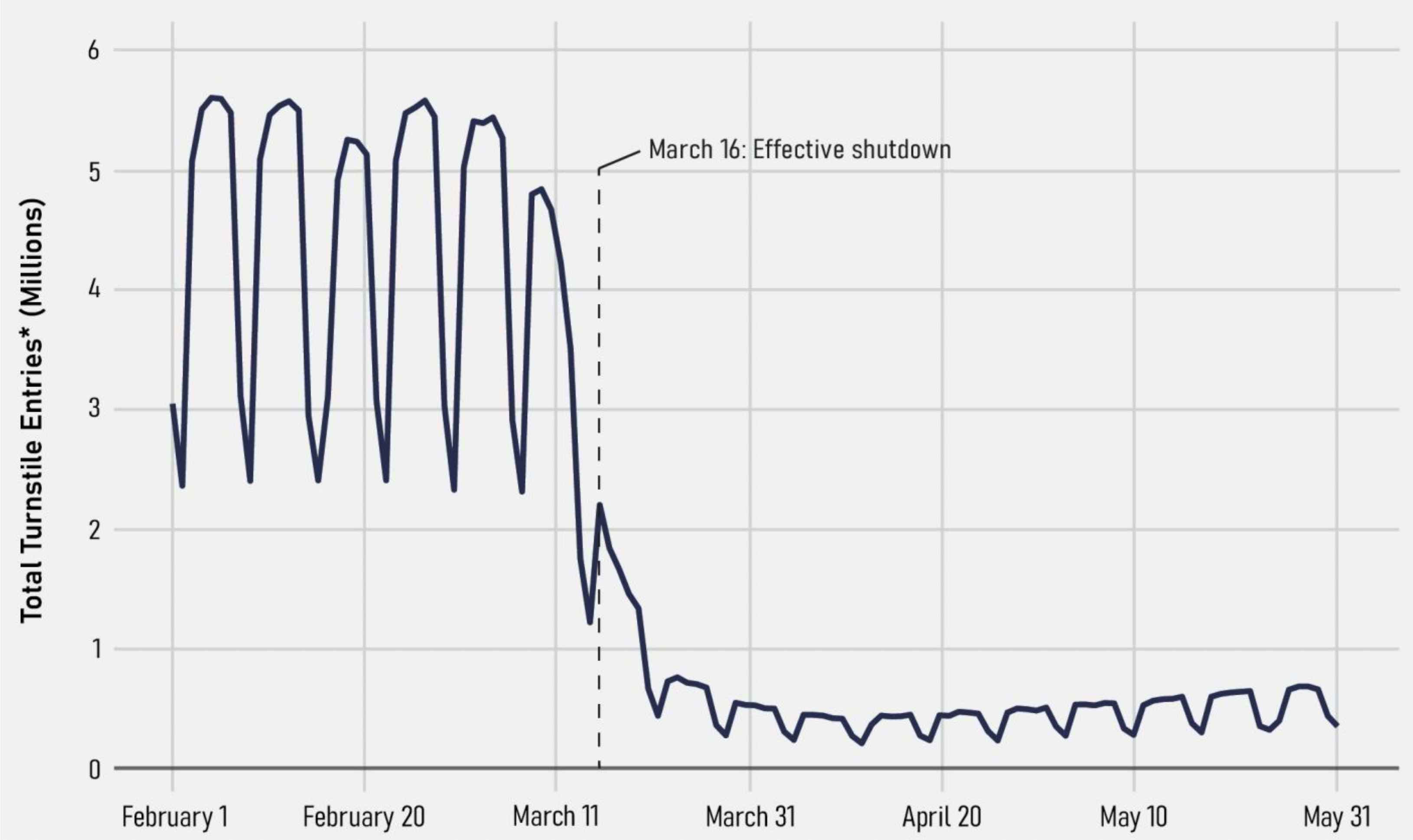
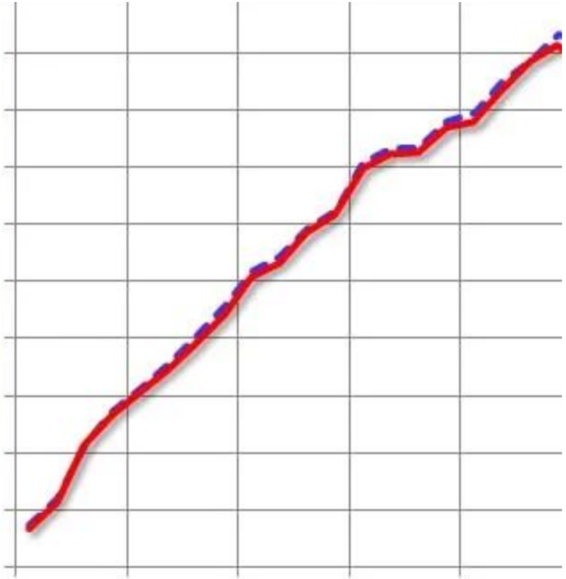
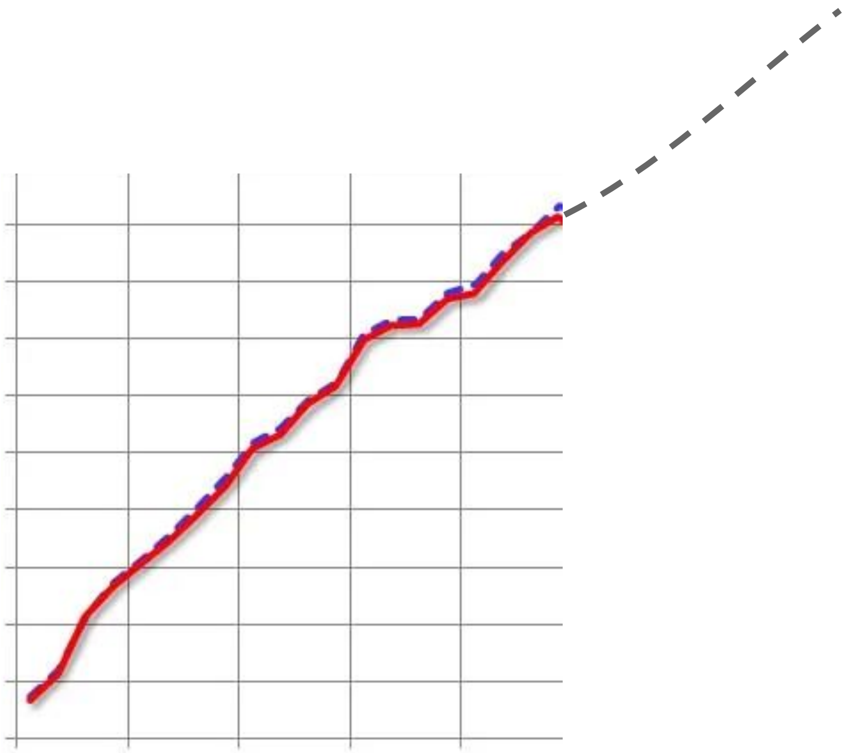
MTA Subway Ridership

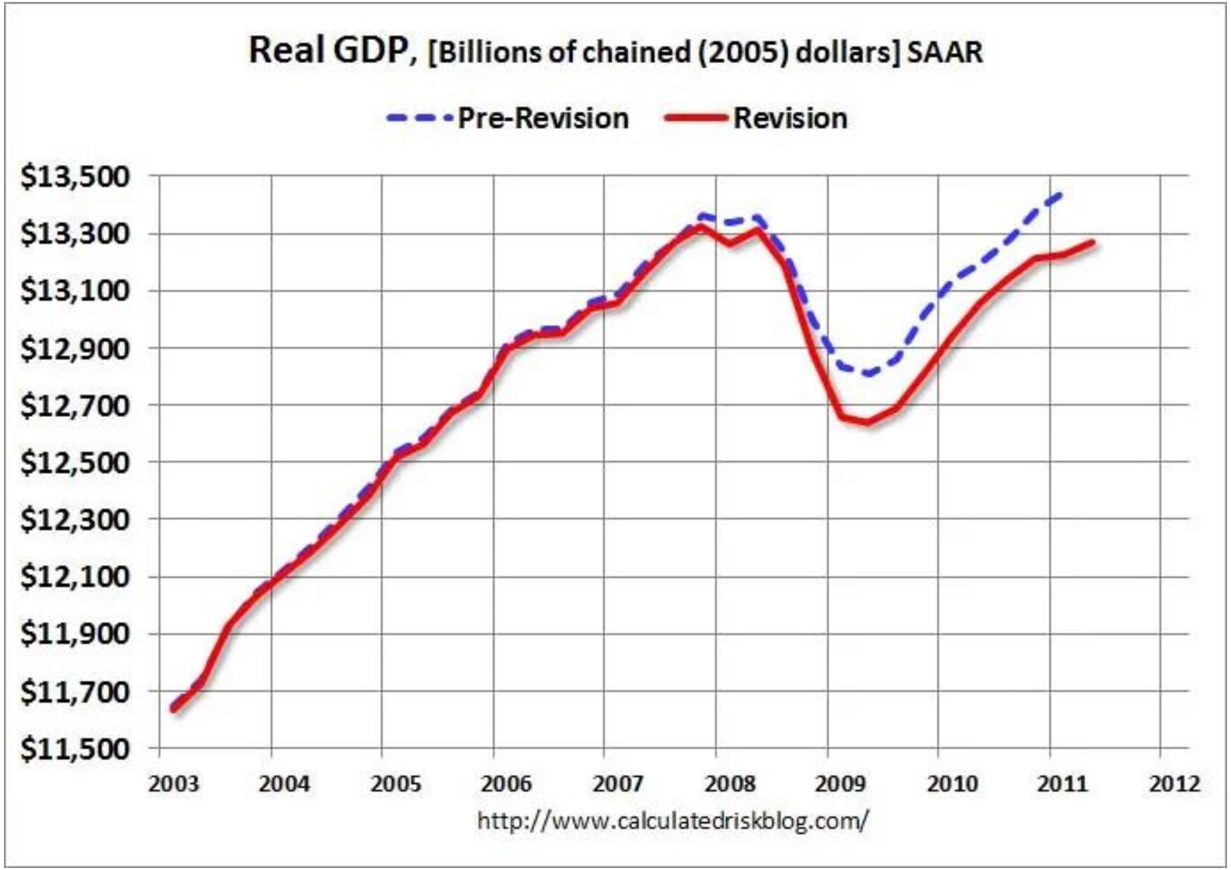


https://wagner.nyu.edu/files/faculty/publications/Full%20Report.pdf





US GDP and the Great Recession



Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

68

By James Vincent | Mar 24, 2016, 6:43am EDT

Via The Guardian | *Source TayandYou (Twitter)*
| 68 comments

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What’s the Theme?

New data is different than the data the model was trained on

Goal of model selection

- Create a “model” that meets our performance requirements
- Build confidence that our measurement of performance will hold “in the real world”
- We want to approximate how our model will be used in production as best as possible.

Model Selection

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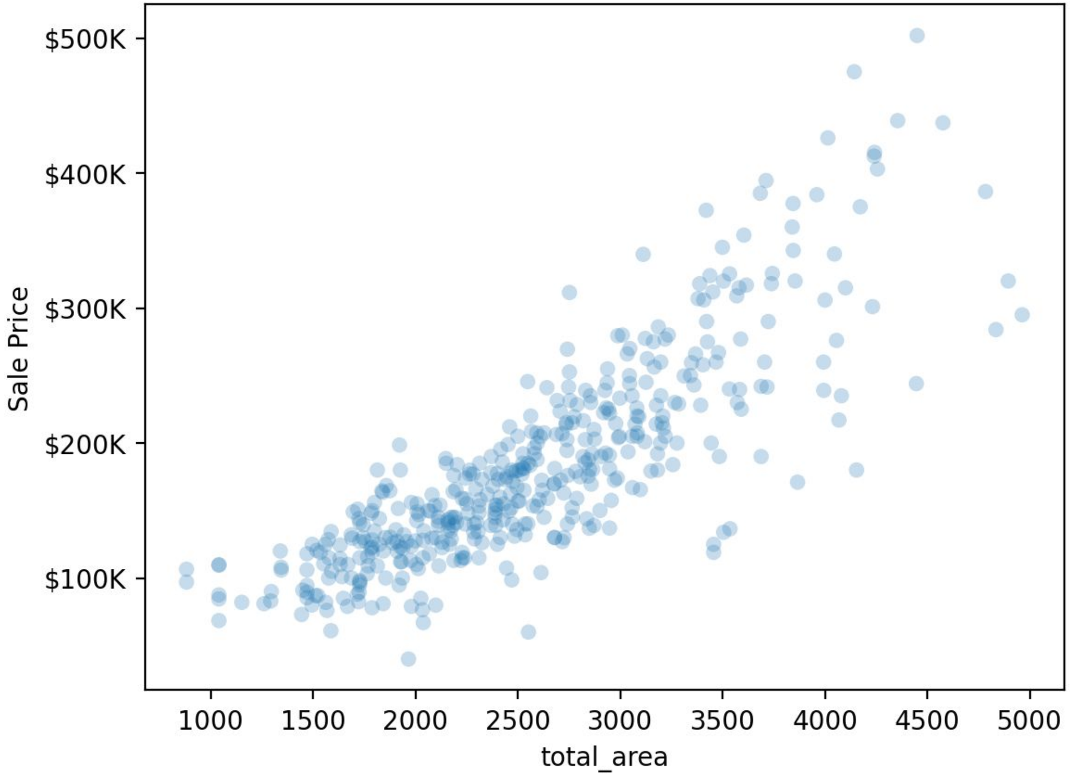
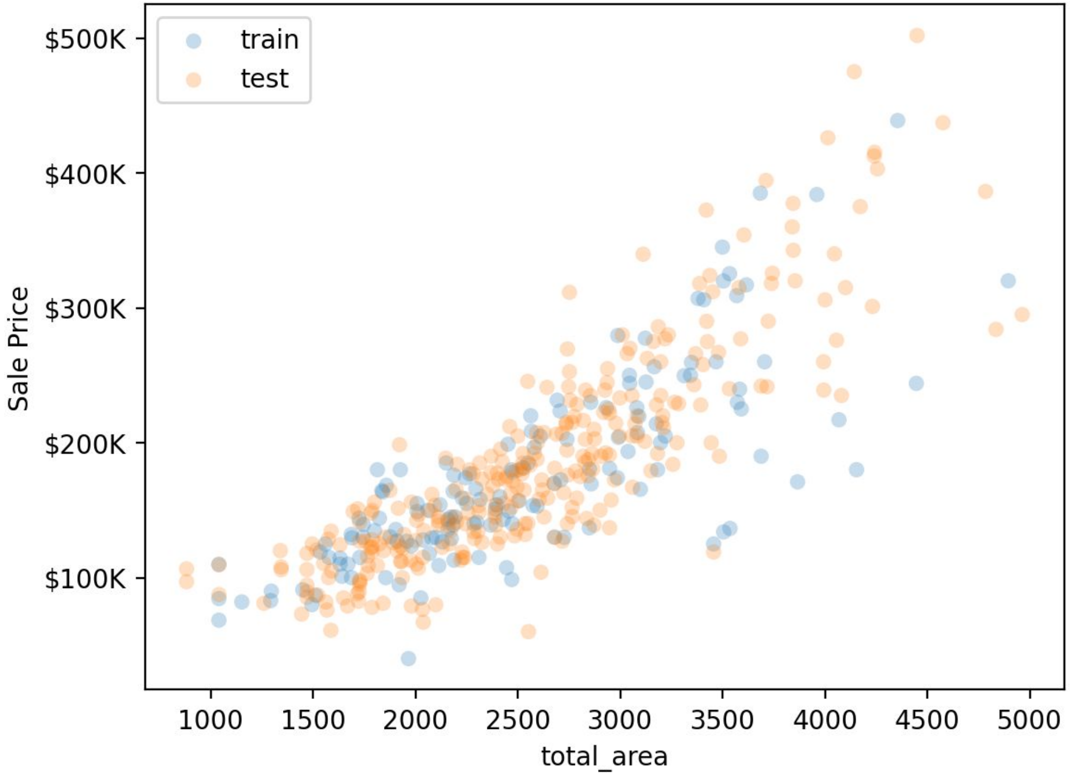
Holdout set aka Train Test Split



Holdout set aka Train Test Split

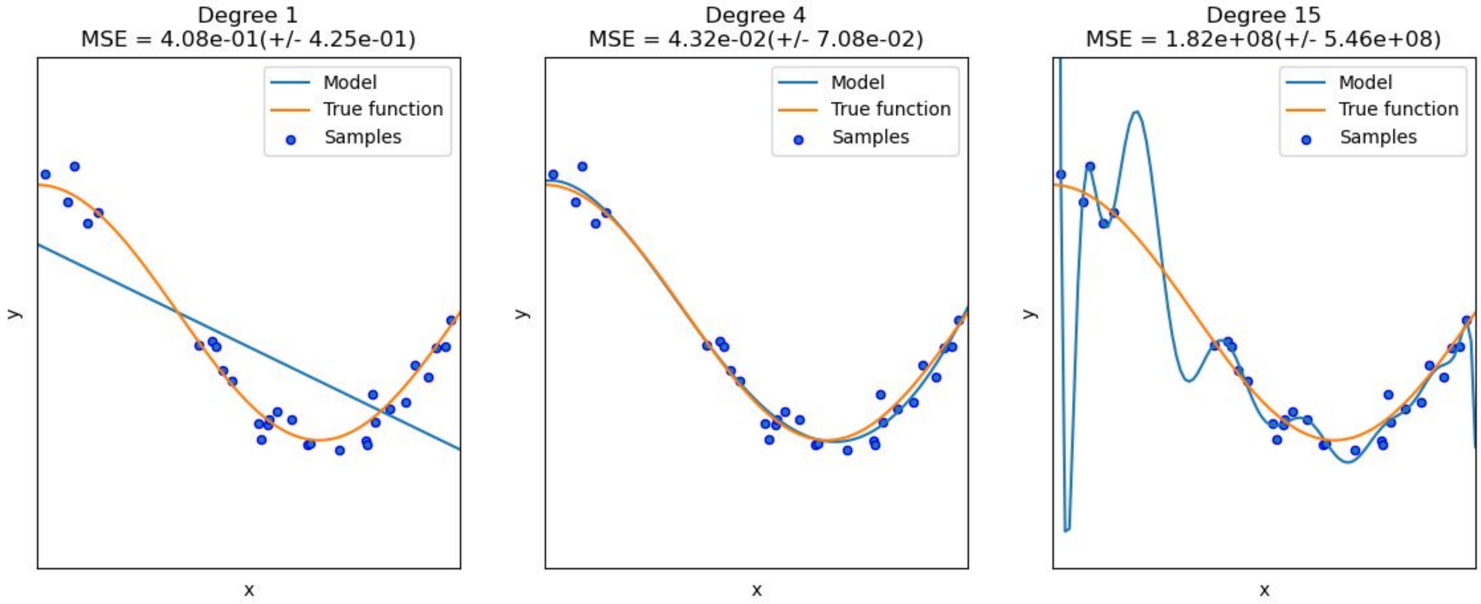
- Randomly separate data into training and test datasets.
- Train model on only the training set.
- Evaluate model using the test set.
- If data is IID, then randomly sampling can give us an unbiased estimate of the model’s “true” performance.



“With four parameters I can fit an elephant, and with five I can make him wiggle his trunk.”

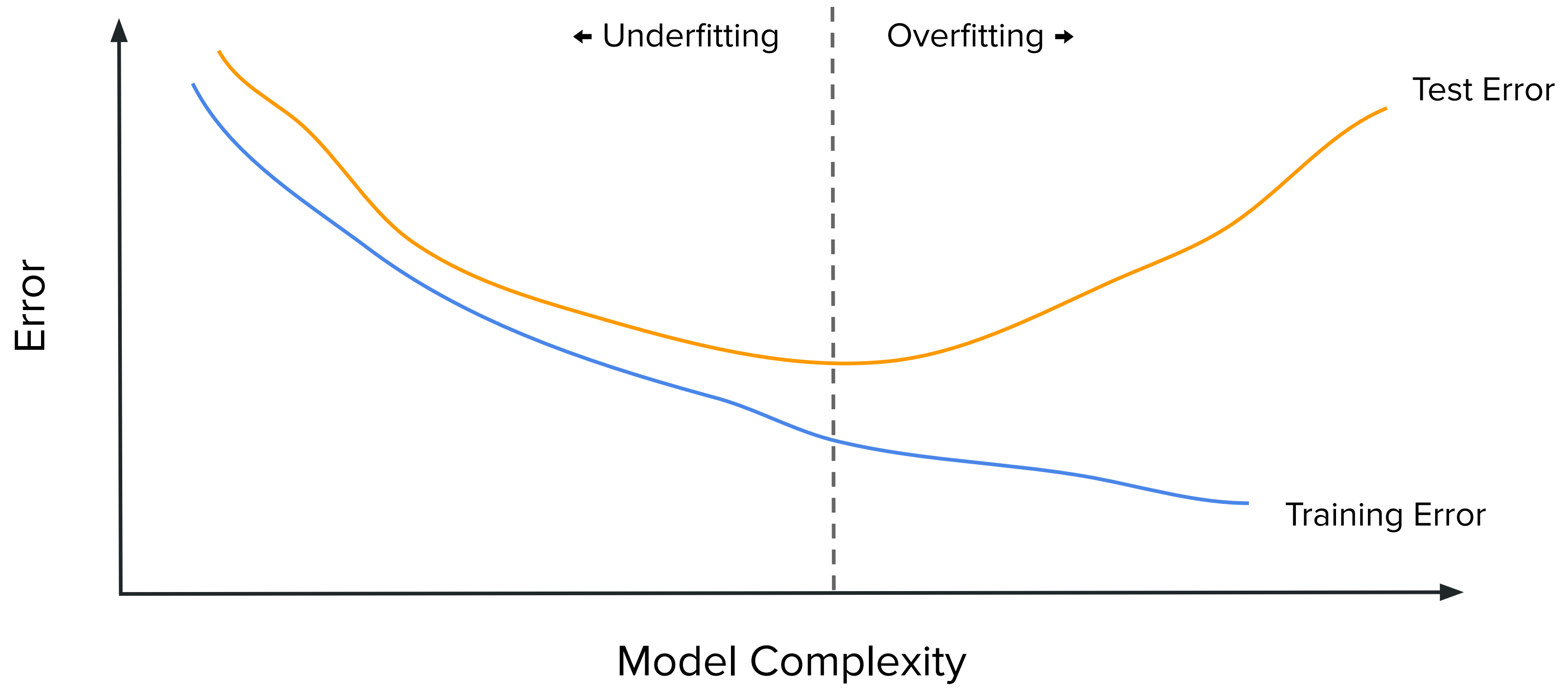
– John Von Neumann

Overfitting and Underfitting



https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html

Overfitting and Underfitting: Change Model Complexity



Overfitting and Underfitting: Regularization

$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2$$

$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \vec{\mathbf{X}}_i \cdot \vec{\beta}\right)^2$$

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L2 Regularization / Ridge Regression

$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \vec{\mathbf{X}}_i \cdot \vec{\beta}\right)^2 + \lambda_2 \sum_{j=1}^{p} \beta_j^2$$

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L1 Regularization / Lasso

$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \vec{\mathbf{X}}_i \cdot \vec{\beta}\right)^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j|$$

Overfitting and Underfitting: Regularization

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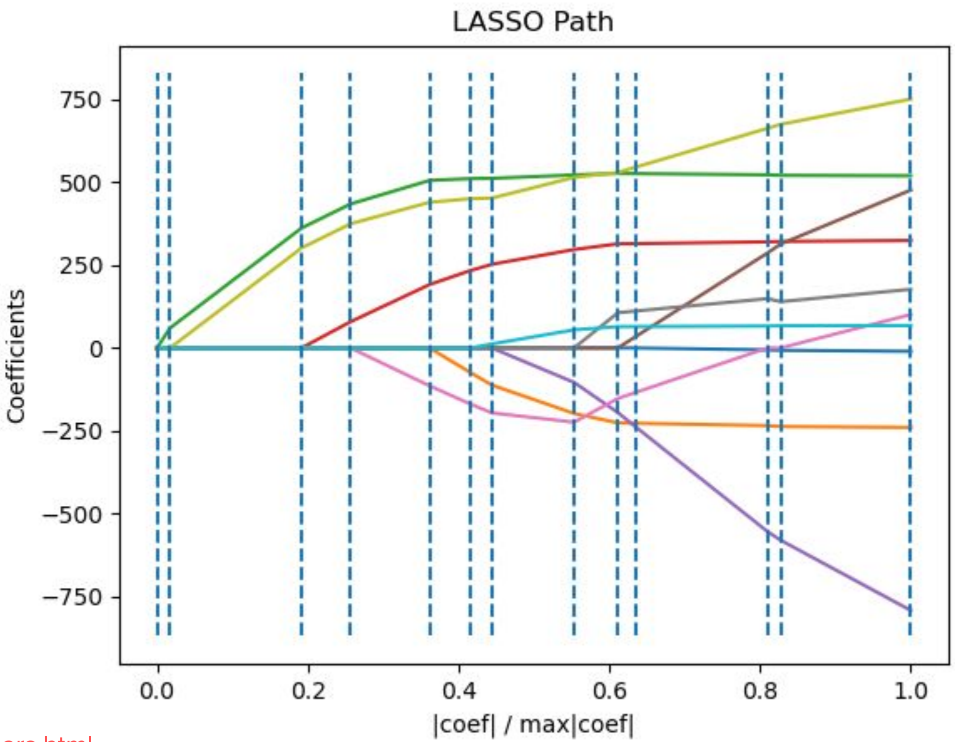
$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \vec{\mathbf{X}}_i \cdot \vec{\beta}\right)^2$$

Elastic Net

$$\mathcal{L} = \sum_{i=1}^{n} \left(y_i - \vec{\mathbf{X}}_i \cdot \vec{\beta}\right)^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| + \lambda_2 \sum_{j=1}^{p} \beta_j^2$$

Overfitting and Underfitting: Regularization

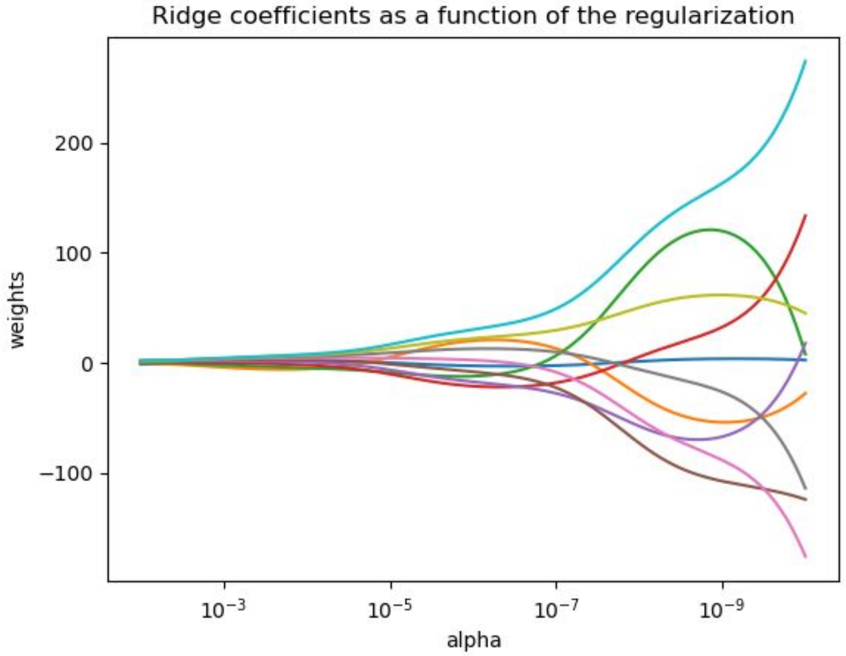
- L1 Regularization can induce "sparsity".
- As you increase the regularization strength, feature coefficients drop to zero.
- Can use this for feature selection.
- If features are correlated, then one may drop to 0 and the other one stays big.



https://scikit-learn.org/stable/auto_examples/linear_model/plot_lasso_lars.html

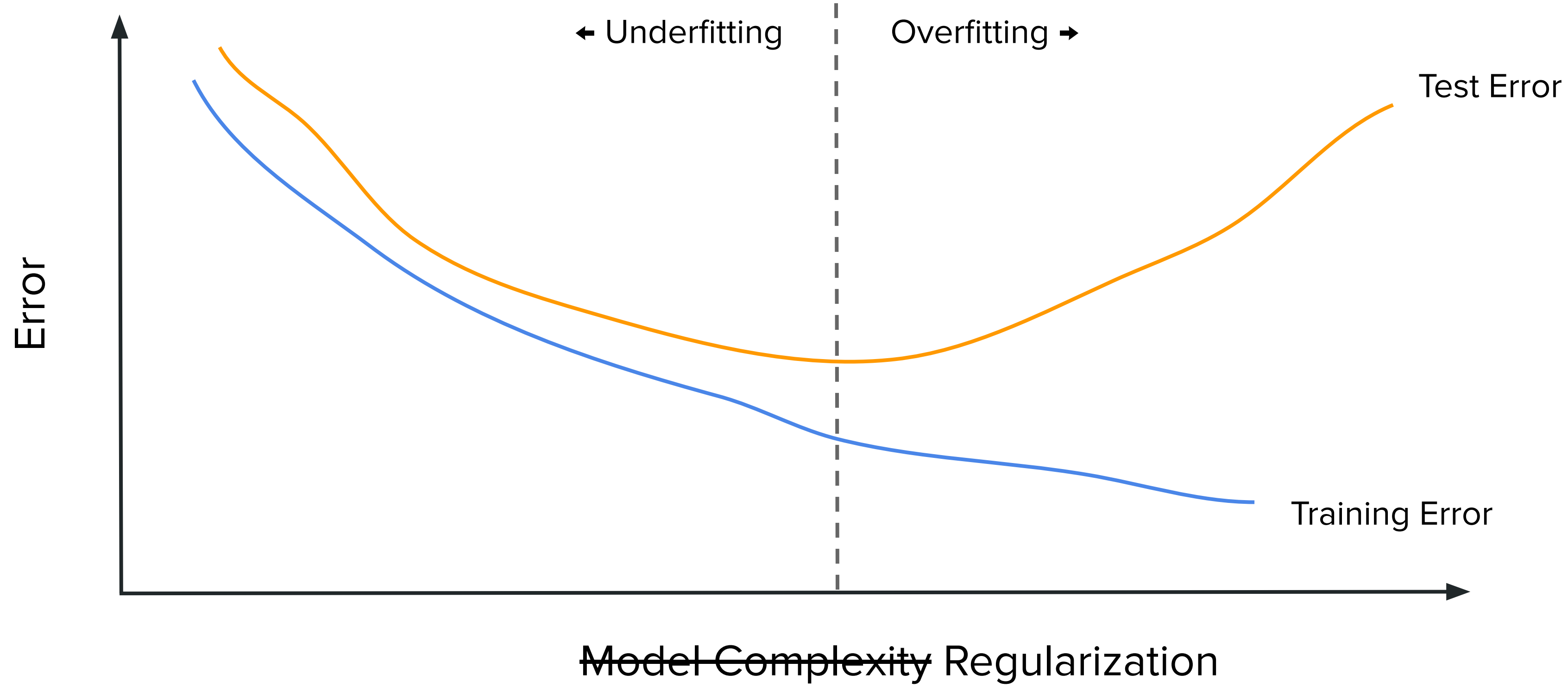
Overfitting and Underfitting: Regularization

- L2 Regularization decreases all coefficients together.
- Correlated features decrease together.
- Does not induce sparsity.
- Regularization is a type of "hyperparameter".
- A hyperparameter is a model parameter that you do not learn as part of the optimization process.



https://scikit-learn.org/stable/auto_examples/linear_model/plot_ridge_path.html

Overfitting and Underfitting: Regularization



Overfitting and Underfitting: Use More Data

Raschka (2018)

Figure 4: Learning curves of softmax classifiers fit to MNIST. https://arxiv.org/abs/1811.12808

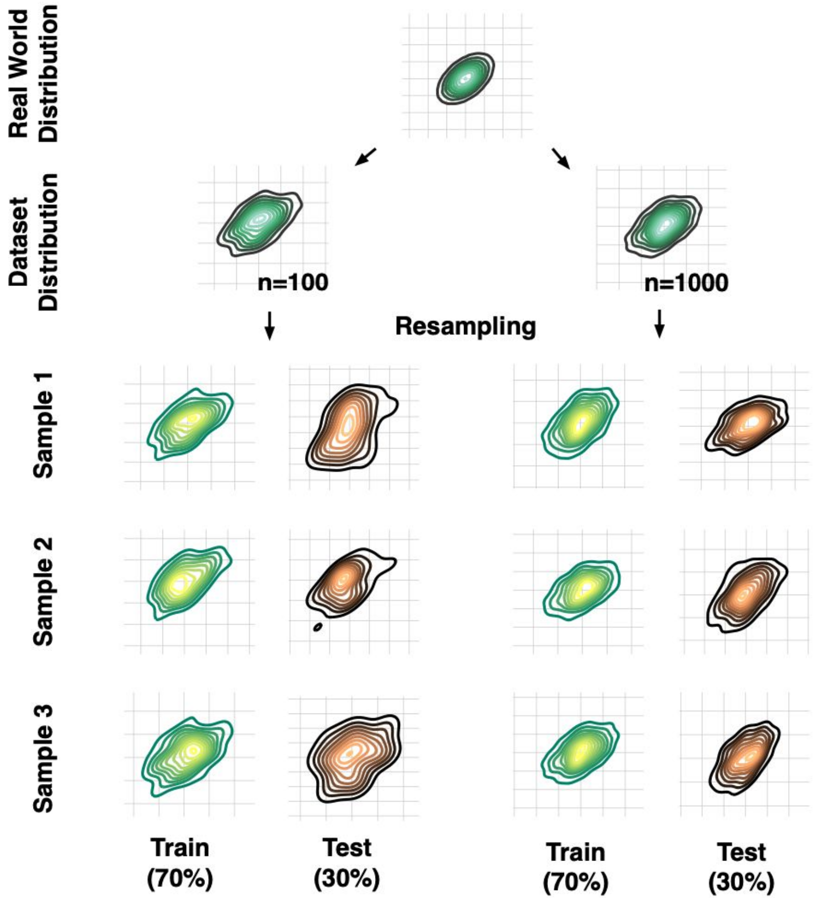


Figure 5: Repeated subsampling from a two-dimensional Gaussian distribution.

Raschka (2018)

https://arxiv.org/abs/1811.12808

- We want a robust estimate of how the model will work "in the wild".
- Small data introduces sampling bias.
- Many other biases can exist in your labelled data.
- Also, time!

Raschka (2018)

https://arxiv.org/abs/1811.12808

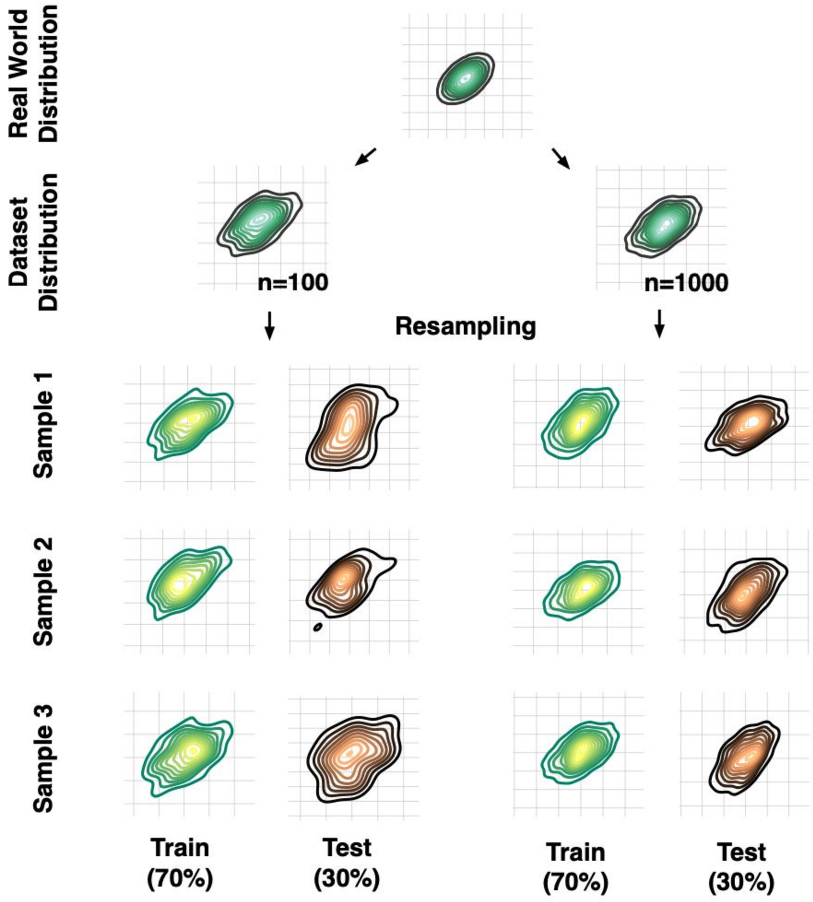
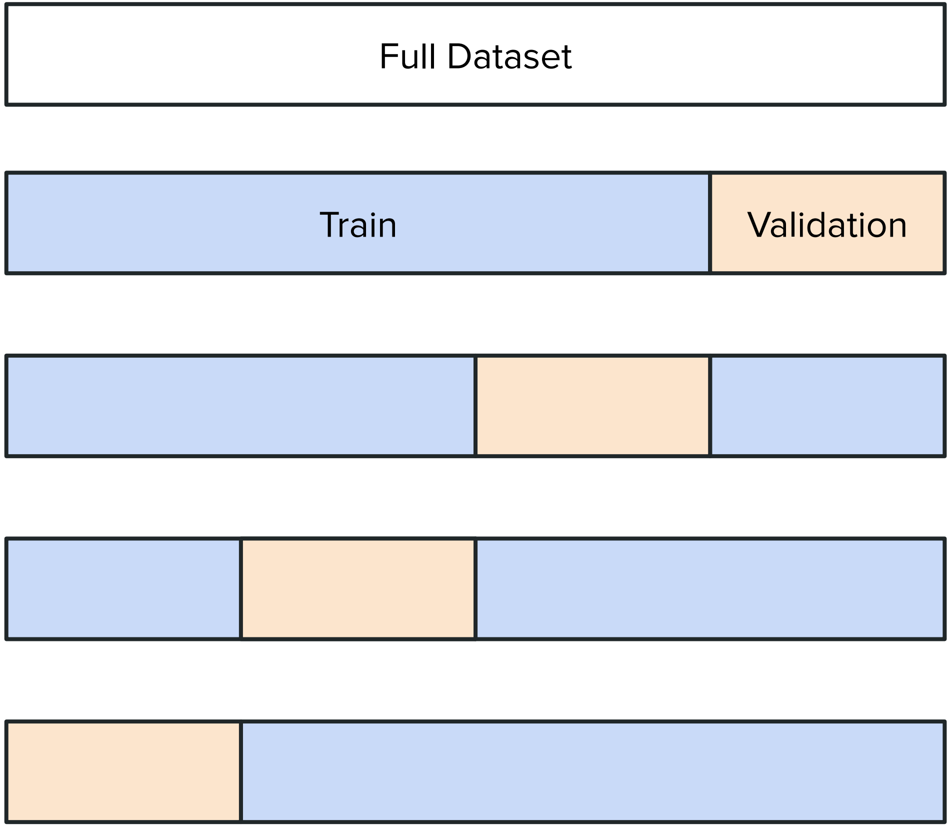


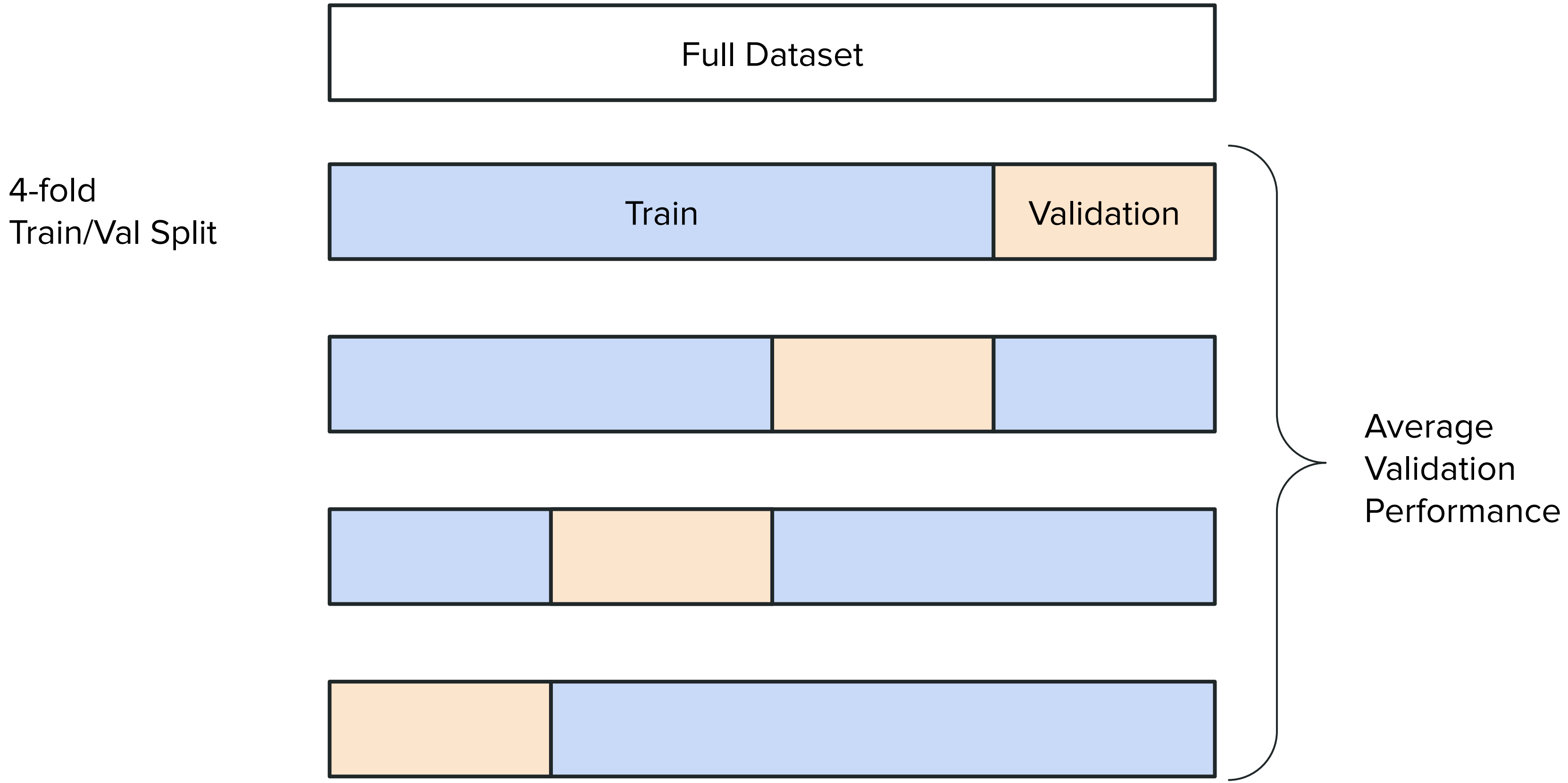
Figure 5: Repeated subsampling from a two-dimensional Gaussian distribution.

K-Fold Cross Validation

4-fold
Train/Val Split



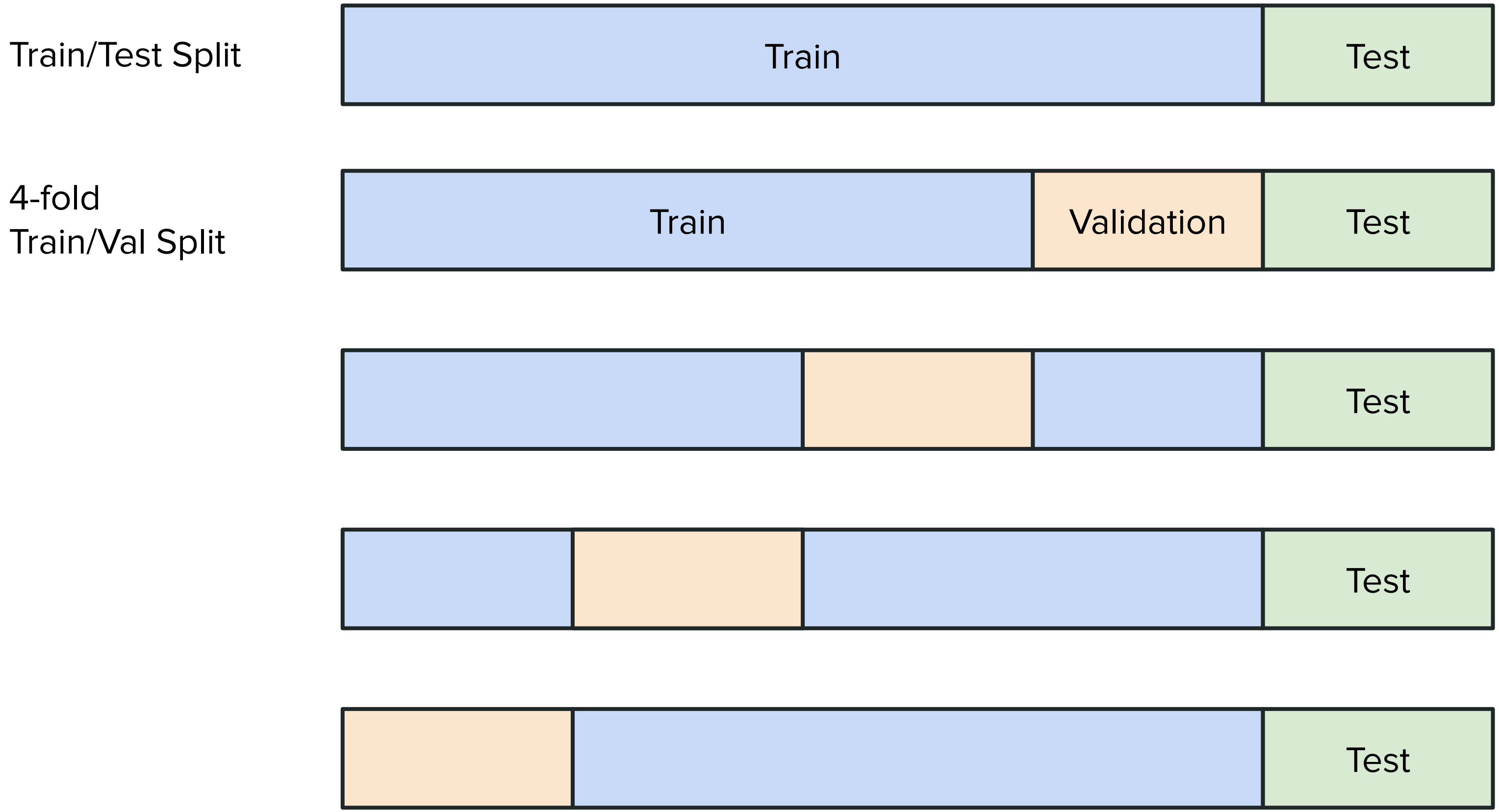
K-Fold Cross Validation



What’s wrong with this?

1. Split my data into training and test sets
2. Do some feature engineering
3. Fit a model on the training set
4. Evaluate model on the test set.
5. Do Steps 2-4 a couple more times, trying out different features.

Model Selection via K-Fold Cross Validation



Model Selection via K-Fold Cross Validation aka Hyperparameter Optimization

1. Separate test set at the beginning.
2. Split train into K disjoint train/validation partitions.
3. For each model configuration (e.g. hyperparameter combo)
   - For each K fold:
     - Fit model on training data.
     - Evaluate model on validation data.
   - Average performance across K folds
4. Determine model configuration with optimal avg performance.
5. Train optimal model on *full* training set.
6. Evaluate model on test set.

Feature Engineering
& Model Selection with scikit-learn