Modeling Recap

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Modeling Ideas

What is a (statistical) model?

- A mathematical representation of some phenomenon on which you've observed data
- Form of the model can vary greatly!

Statistical learning - Inference, prediction/classification, and pattern finding

- Supervised learning a variable (or variables) represents an **output** or **response** of interest
 - May model response and
 - Make **inference** on the model parameters
 - **predict** a value or **classify** an observation

Our Goal: Understand what it means to be a good predictive model (not make inference)

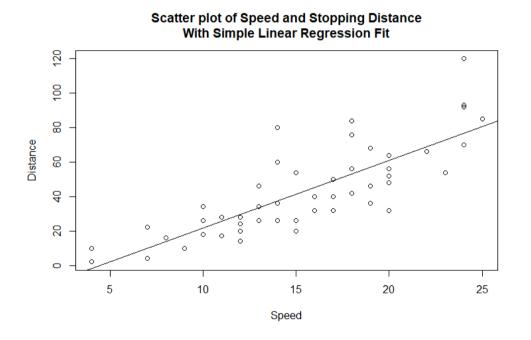
What is a Statistical Model?

- A mathematical representation of some phenomenon on which you've observed data
- Predictive model used to:
 - Predict a numeric response
 - Classify an observation into a category
- Common Supervised Learning Models
 - Least Squares Regression
 - Penalized regression
 - Generalized linear models
 - Regression/classification trees
 - Random forests, boosting, bagging

... and many more - tons of models!

Fitting a Model

Given a model, we **fit** or **train** it using the data



ullet Models can be used to yield predicted responses for each observation, call these \hat{y}_i

Quantifying How Well the Model Predicts

Need a way to quantify how well our prediction is doing (a model metric)

• For a numeric response, we commonly use squared error loss to evaluate a prediction

$$L(y_i, {\hat y}_i) = (y_i - {\hat y}_i)^2$$

• Use Root Mean Square Error as a metric across all observations

$$RMSE = \sqrt{rac{1}{n} \sum_{i=1}^{n} L(y_i, \hat{y}_i)} = \sqrt{rac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Quantifying How Well the Model Predicts

Need a way to quantify how well our prediction is doing (a model metric)

- For classification (binary response here), accuracy and log-loss are common:
 - Accuracy

Sum of correct predictions

Total number of predictions

o Log-loss

$$\sum_{i=1}^n (y_i log(\hat{p}_i) + (1-y_i) log(1-\hat{p}_i))$$

where \hat{p}_i is the model's estimate of the probability of success (\$y = 1\$) for that observation

Training vs Test Sets

Ideally we want our model to predict well for observations it has yet to see

 Predictions over the observations used to fit or train the model are called the training (set) error

Training RMSE =
$$\sqrt{\frac{1}{\# \text{ of obs used to fit model}}} \sum_{\text{obs used to fit model}} (y - \hat{y})^2$$

• If we only consider this, we'll have no idea how the model will fare on data it hasn't seen!

Training vs Test Sets

One method is to split the data into a **training set** and **test set**

- On the training set we can fit (or train) our models
- We can then predict for the test set observations and judge effectiveness with RMSE



Issues with Training vs Test Sets

Why may we not want to just do a basic training/test set?

- If we don't have much data, we aren't using it all when fitting the models
- Data is randomly split into training/test
- Instead, we could consider splitting the data multiple ways and averaging the test error over the results!

Cross-Validation Idea

k fold Cross-Validation (CV)

- Split data into k folds
- Train model on first k-1 folds, find test error on kth fold
- Train model on first k-2 folds and kth fold, find test error on (k-1)st fold
- ...

Find CV error by combining test errors appropriately

- Key = no predictions used in the RMSE were done on data used to train that model!
- Once a best model is chosen, model is refit on entire data set

May Use Both Training/Test & CV

- Recall: LASSO model is similar to an MLR model but shrinks coefficients and may set some to 0
 - Tuning parameter must be chosen (usually by CV)
- Training/Test split gives us a way to validate our model's performance
 - CV can be used on the training set to select tuning parameters
 - o Helps determine the 'best' model for a class of models
- With many competing model types, compare best models on test set via our metric

Plan

- Learn a few more supervised learning methods
- Implement in tidymodels!