Modeling Data Recap

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Recap

- Programming in python
- 5 V's of Big Data
  - Volume
  - Variety
  - Velocity
  - Veracity (Variability)
  - Value
- Understanding of the Big Data pipeline and basics of handling Big Data
  - Databases/Data Lakes/Data Warehouses/etc.
  - SQL basics
  - Hadoop
  - Spark
- Now: Modeling (Big) Data

Common Uses for Data

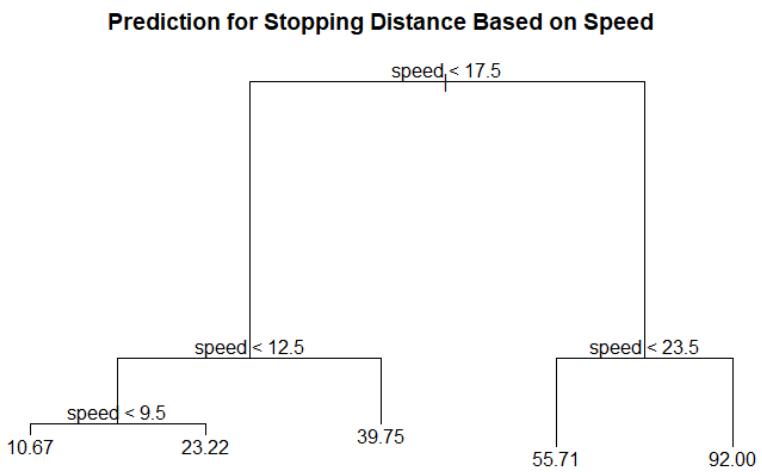
Four major goals with data:

1. Description (EDA)
2. Inference
3. Prediction/Classification
4. Pattern Finding

Statistical Learning

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



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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**
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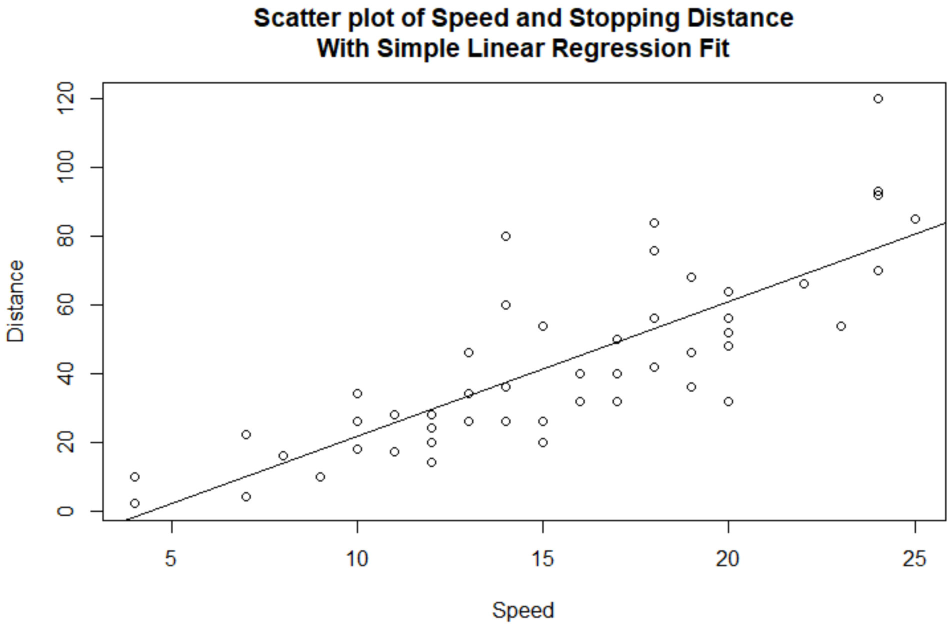
- Common Supervised Learning Models
  - Least Squares Regression
  - Penalized regression
  - Generalized linear models
  - Regression/classification trees
  - Random forests, boosting, bagging

... and many more - tons of models!

Fitting a Model

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



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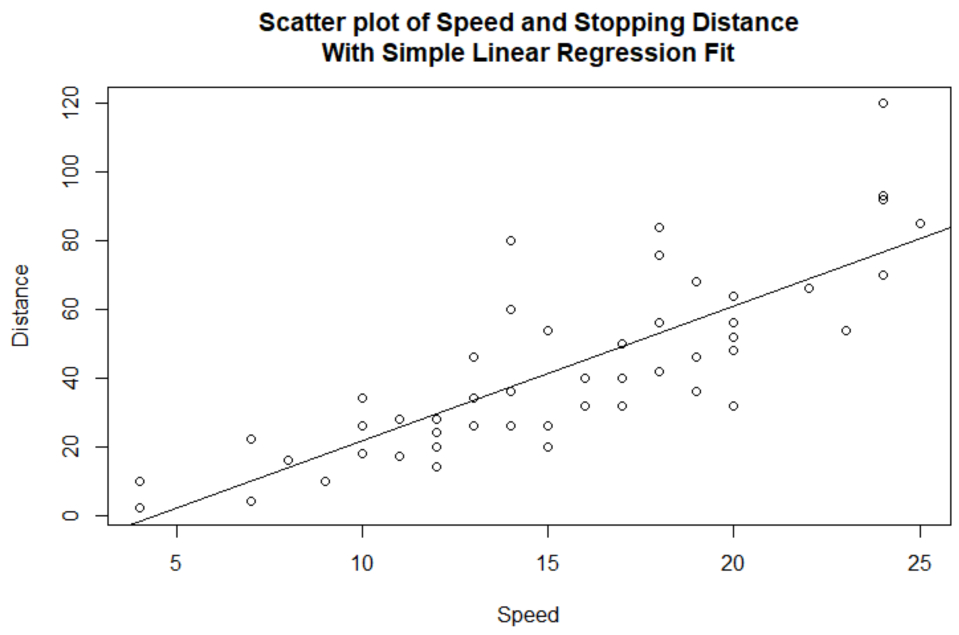

- Models can be used to yield predicted responses for each observation, call these $\hat{y}_i$

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

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

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

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

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), we can look at accuracy
- Accuracy

$$\frac{\text{Sum of correct predictions}}{\text{Total number of predictions}}$$

Training vs Test Sets

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

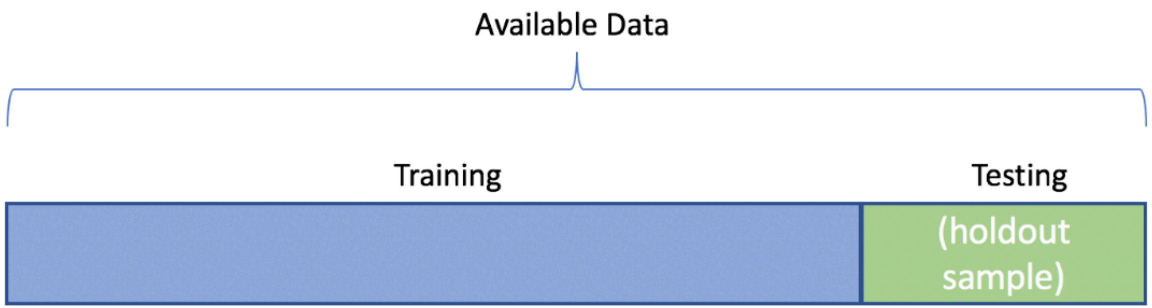
$$\text{Training RMSE} = \sqrt{\frac{1}{\text{\# of obs used to fit model}}\sum_{\text{obs used to fit model}}(y-\hat{y})^2}$$

- 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



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Issues with Trainging 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
- ...

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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
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- 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**
  - Helps determine the 'best' model for a class of models
- With many competing model types, compare best models on test set via our metric

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Plan

- May want to review the videos/notebooks from earlier
- Learn more supervised learning methods
- Implement in `sklearn` and `pyspark`
- Consider nuances of different loss functions and model metrics
- See how to use model **pipelines**