Why is it necessary to introduce so many different statistical learning approaches, rather than just a single best method?

No one method can be same for all possible data sets. On a particular data set, one specific method may work best, but some other method may work better on a similar but different data set.

Hence as a data scientist it is an important to us to decide for any given set of data which method produces the best results.

Selecting the best approach can be one of the most challenging parts of performing statistical learning in practice.

How to measure?

- To evaluate the performance of a statistical learning method on a given data set, we need to look for the predicted response value and how it is close to the true response value for a given observation.

- So, In regression the most commonly-used measure is the mean squared error (MSE) is given by mean squared error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}(x_i))^2,$$

- The MSE will be small if the predicted responses are very close to the true responses

- The MSE is calculated using the training data that was used to fit the model and called as training MSE. But in general, we do not really care how well even works on the training data. We are interested only in the accuracy of the predictions on unseen test data.

- We want to choose the method that gives the lowest test MSE. In other words, if we had a large number of test observations, we can calculate Average of $(Y - \hat{Y})^2$

- We'd like to select the model for which the average of this quantity i.e. test MSE which should be as small as possible.

- **Model selection:** Estimating the performance of different models in order to choose the best one.

- **Model assessment:** Having chosen a final model, estimating its prediction error (generalization error) on new data.