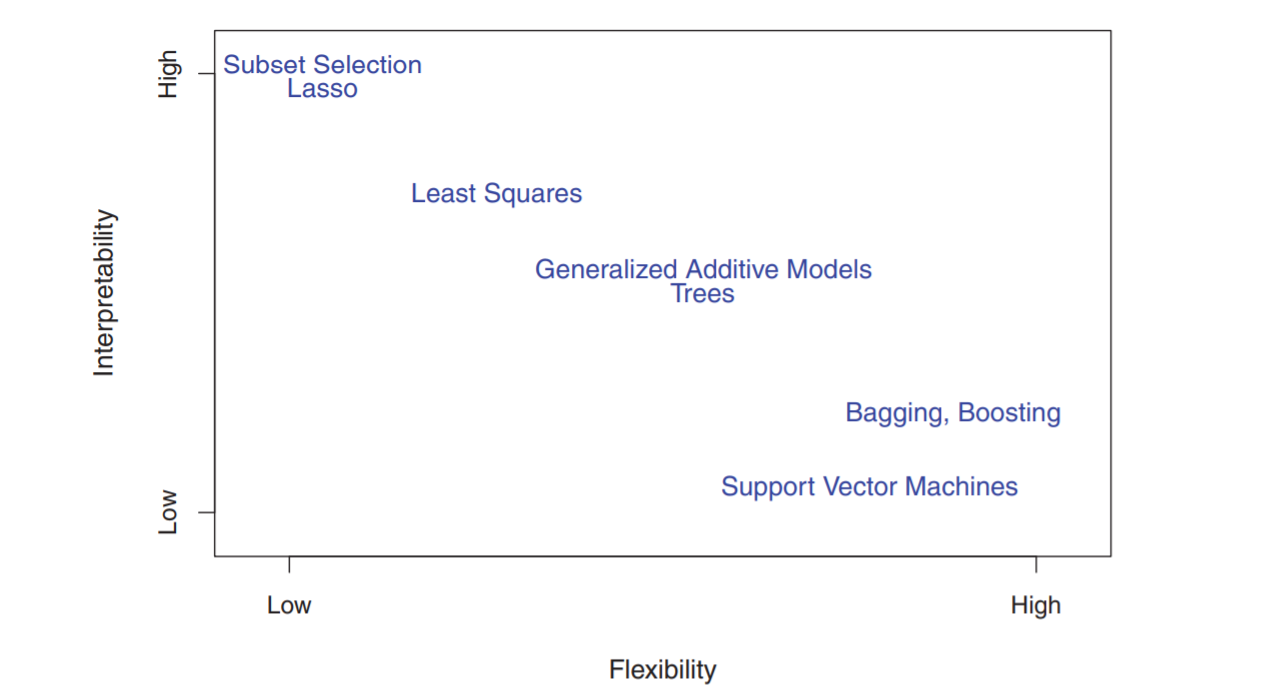
**Notes for Introduction to Statistical Learning**

**Chapter 2**

* We estimate *f* for
  + *prediction (for a given X what is Y)*
  + *inference (how does Y change with respect to X)*
* Accuracy of our model depends on *reducible error*  and *irreducible error(e)*
* **Parametric** Models – reduces the problem of estimating f down to one of estimating a set of parameters (coefficients)
  + First, make an assumption about the functional form ie linear Y = B0 + B1X1 + …+ BnXn
  + After model has been selected fit to training data ie estimate the coefficients B0 … Bn using ordinary least squares
* **Non-parametric** Models – do not make explicit assumptions about the functional form of *f*
  + Main advantage – by avoiding making assumptions have the potential to accurately fit a wider range of possible shapes for *f*
  + Main disadvantage – since we do not reduce problem to estimating parameters, need a large number of observations
  + Example – thin-plate spline
* Tradeoff Prediction Accuracy vs Model Interpetability
  + If we are mainly interested in inference, then restrictive models are muchFo more interpretable
* In unsupervised learning there is labeled training data we only see X vars but no outcome variable – ie cluster analysis like market segmentation
* Quantative Y var = regression, qualitative Y var = classification
* Measuring Model accuratcy
  + For regressions, mean squared error (MSE) = Ave (y – yhat)^2
  + As model flexibility increases training MSE will decrease and test MSE will increase
* Cross validation = method for estimating test MSE using the training data
* Bias-Variance Tradeoff =
  + Expected MSE = variance of *f + (*bais of *f)^2 +* variance of error term *e*
* To minimize expected error need to select a statistical method with low variance and low bias
* **Variance =** the amount by which fhat will change if we estimated using a different training set
  + High variance of a method means small changes in training set will lead to large changes in *f*
  + More flexible methods have high variance
* **Bias =** the error that is introduced by approximating real life problems
  + Ie – linear regressions assume linear relationship b/w dependant & outcome vars – unlikely in real life so linear regression has linear bias
* More flexible models mean high variance and bias will decrease
  + As we increase flexibility = variance increases slower than bais decreases but at certain point bais stops decreasing and variance continues increasing
* Good test set performance of a statistical learning method requires low variance as well as low squared bias

**Classification**

* **Bayes Classifier** – able to minimize the error rate for a classifier by a simple Bayes classifier that assigns each observation to the most likely class given its predictor values
  + Pr(Y = j | X = x0)
* Bayes classifier prediction is determined by the Bayes decision boundary
  + Solve for lowest possible *Bayes error rate*  1 – E(maxPr(Y = y|X) (expectation avarges the probability of over all possible boundaries of X
* K-Nearest Neighbors – KNN identifies the K closest objects and estimates conditional probability based on proportion of x that are a certain class
  + KNN applies Bayes rule and classiﬁes the test observation x0 to the class with the largest probability
  + K = 100 leads to a classifier with low bias but high variance (very flexible)
  + Higher K leads to decreasing training error but U shaped test error

**Summary of Chapter 2:** In both the regression and classiﬁcation settings, choosing the correct level of ﬂexibility is critical to the success of any statistical learning method. The bias-variance tradeoﬀ, and the resulting U-shape in the test error, can make this a diﬃcult task