The Elements of Statistical Learning, Summary

2 Overview of Supervised Learning

$X \in \mathbb{R}^p$: Random vector input
$Y \in \mathbb{R}$: Random variable to predict
$f(X)$: function we seek to predict Y
$L(Y, f(X))$: *Loss function* to penalize error in prediction
$EPE(f) = \mathbb{E}[L(Y, f(X))]$: Expected Prediction Error
Square error loss (or L_2 *lossfunction*): $L(Y, f(X)) = (Y - f(X))^2$
In this case, the sol is $f(x) = \mathbb{E}[Y|X = x]$: *regression function*
Curse of dimension: if $p \uparrow$, local methods fail because density $O(N^{1/p})$
Mean Squared Error of the estimator $\hat{f}$ at x_0: $MSE(\hat{y}_0) := \mathbb{E}_\tau[(y_0 - \hat{y}_0)^2]$
τ (training set) is random, so is $\hat{y}_0 := \hat{f}(x_0)$. True $y_0 := f(x_0)$ is fixed
bias-variance decomposition: $MSE(\hat{y}_0) = Var_\tau(\hat{y}_0) + Bias(\hat{y}_0)^2$
Additive error model : $Y = f(X) + \epsilon$ with $\mathbb{E}[\epsilon] = 0$ and $X \perp \epsilon$
We model f with parameters θ and try to determine f_θ
In *least squares* method, θ chosen to minimize *Residual Sum of Squares*
$RSS(\theta) := \sum_{i=1}^N (y_i - f_\theta(x_i))^2$
Maximum likelihood estimation: maximize $\mathbb{P}$ to have those observations
$\theta = argmax_\theta L(\theta) := \sum_{i=1}^N \log \mathbb{P}_\theta(Y = y_i|X = x_i)$
Least square=Max likelihood if $Y = f_\theta(X) + \epsilon$ with $\epsilon \backsim \mathcal{N}(0, \sigma^2)$
Penalized RSS: $PRSS(f, \lambda) := RSS(f) + \lambda J(f)$, J *roughness penalty*
If output is a categorical variable $G \in \mathcal{G}$, L is a $card(\mathcal{G})$-square matrix
zero-one loss function: $L(G, \hat{G}(X)) = 1_{G=\hat{G}(X)}$: ($f$ noted $\hat{G}$)
In this case, $\hat{G}(x) = argmax_{g \in \mathcal{G}} \mathbb{P}(G = g|X = x)$, called *bayes classifier*

3 Linear Methods for Regression

3.2 Linear Regression and Least Squares

$f(X) = \beta_0 + \sum_{j=1}^p X_j \beta_j$
$RSS(\beta) = \sum_{i=1}^N (y_i - (\beta_0 + \sum_{j=1}^p X_j \beta_j))^2 = (y - X\beta)^T (y - X\beta)$
it's convex, solving $\frac{\partial RSS}{\partial \beta} = 0$, we get $\hat{\beta} = (X^T X)^{-1} X^T y$
X generate a p-dim subspace of $\mathbb{R}^N$, $\hat{y} = X\hat{\beta}$ is the $\perp$-projection of y
If true model is $Y = X\beta + \epsilon$ with $\epsilon \backsim \mathcal{N}(0, \sigma^2)$: $\hat{\beta} \backsim \mathcal{N}(\beta, (X^T X)^{-1}\sigma^2)$
(X considered deterministic, randomness comes from ϵ and Y)

3.3 Subset Selection