

Chapter 6 Optimization

Siheng Zhang
zhangsiheng@cvte.com

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This part corresponds to **Chapter 1,3,4 of PRML, Chapter of UML**. It mainly introduces some important properties regarding with functions: convexity, smoothness, strong convexity and Lipschitz, which are basis for the next chapters.

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- 1 from decision stump to decision tree
- 2 regression tree

P1

- a) Note that the splitting of bucket M in T_{old} results into the two new buckets M and $M + 1$ in T_{new} , hence, $R_M = \tilde{R}_M \cup \tilde{R}_{M+1}$, i.e., $N_M = \tilde{N}_M + \tilde{N}_{M+1}$, and the former $M - 1$ buckets remain the same,

$$C_{imp}(T_{new}) = \sum_{m=1}^{M-1} N_m Q_m(T_{old}) + \tilde{N}_M \tilde{Q}_M(T_{new}) + \tilde{N}_{M+1} \tilde{Q}_{M+1}(T_{new})$$

So,

$$\begin{aligned} \Delta &= C_{imp}(T_{old}) - C_{imp}(T_{new}) = N_M Q_M(T_{old}) - \tilde{N}_M \tilde{Q}_M(T_{new}) - \tilde{N}_{M+1} \tilde{Q}_{M+1}(T_{new}) \\ &= \sum_{i:x_i \in R_M} \left(y_i - \frac{1}{N_M} \sum_{i:x_i \in R_M} y_i \right)^2 - \sum_{i:x_i \in \tilde{R}_M} \left(y_i - \frac{1}{\tilde{N}_M} \sum_{i:x_i \in \tilde{R}_M} y_i \right)^2 - \sum_{i:x_i \in \tilde{R}_{M+1}} \left(y_i - \frac{1}{\tilde{N}_{M+1}} \sum_{i:x_i \in \tilde{R}_{M+1}} y_i \right)^2 \end{aligned}$$

- b) from a), we know that $R_M = \tilde{R}_M \cup \tilde{R}_{M+1}$, so

$$\begin{aligned} \sum_{i:x_i \in \tilde{R}_M} \left(y_i - \frac{1}{\tilde{N}_{M+1}} \sum_{i:x_i \in \tilde{R}_M} y_i \right)^2 &\leq \sum_{i:x_i \in \tilde{R}_M} \left(y_i - \frac{1}{N_M} \sum_{i:x_i \in R_M} y_i \right)^2 \\ \sum_{i:x_i \in \tilde{R}_{M+1}} \left(y_i - \frac{1}{\tilde{N}_{M+1}} \sum_{i:x_i \in \tilde{R}_{M+1}} y_i \right)^2 &\leq \sum_{i:x_i \in \tilde{R}_{M+1}} \left(y_i - \frac{1}{N_M} \sum_{i:x_i \in R_M} y_i \right)^2 \end{aligned}$$

And the right-side of two inequalities sum up to $\sum_{i:x_i \in R_M} \left(y_i - \frac{1}{N_M} \sum_{i:x_i \in R_M} y_i \right)^2$, which leads to $\Delta \geq 0$.

- c) Note that $|T_{old}| = M$, $|T_{new}| = M + 1$. Since $R^2 = 1 - \frac{C_{imp}(T)}{SST}$, then

$$\begin{aligned} C_\alpha(T_{new}) &\leq C_\alpha(T_{old}) \\ \iff C_{imp}(T_{new}) + \alpha MSST &\leq C_{imp}(T_{old}) + \alpha(M + 1)SST \\ \iff \frac{C_{imp}(T_{new})}{SST} &\leq \frac{C_\alpha(T_{old})}{SST} + \alpha \\ \iff R_{new}^2 - R_{old}^2 &\geq \alpha \end{aligned}$$