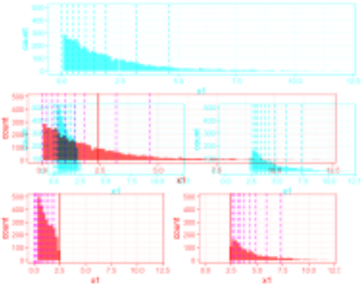
Introduction to Machine Learning

Boosting

Gradient Boosting: Deep Dive XGBoost Optimization



Learning goals

- Understand details of the regularized risk in XGBoost
- Understand approximation of loss used in optimization
- Understand split finding algorithm

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RISK MINIMIZATION / 2

To approximate the loss in iteration m, a second-order Taylor expansion around $f^{[m-1]}(\mathbf{x})$ is computed:

$$
\begin{aligned}
&L(y, f^{[m-1]}(\mathbf{x}) + b^{[m]}(\mathbf{x})) \approx \\
&\qquad L(y, f^{[m-1]}(\mathbf{x})) + g^{[m]}(\mathbf{x}) b^{[m]}(\mathbf{x}) + \frac{1}{2} h^{[m]}(\mathbf{x}) b^{[m]}(\mathbf{x})^2,
\end{aligned}
$$

with gradient

$$
g^{[m]}(\mathbf{x}) = \frac{\partial L(y, f^{[m-1]}(\mathbf{x}))}{\partial f^{[m-1]}(\mathbf{x})}
$$

and Hessian

$$
h^{[m]}(\mathbf{x}) = \frac{\partial^2 L(y, f^{[m-1]}(\mathbf{x}))}{\partial f^{[m-1]}(\mathbf{x})^2}.
$$

Note: $g^{[m]}(\mathbf{x})$ are the negative pseudo-residuals $-\tilde{r}^{[m]}$ we use in standard gradient boosting to determine the direction of the update.

RISK MINIMIZATION / 3

Since $L(y, f^{[m-1]}(\mathbf{x}))$ is constant, the optimization simplifies to

$$
\begin{aligned}
\mathcal{R}_{\text{reg}}^{[m]} &= \sum_{i=1}^{n} g^{[m]}(\mathbf{x}^{(i)}) b^{[m]}(\mathbf{x}^{(i)}) + \frac{1}{2} h^{[m]}(\mathbf{x}^{(i)}) b^{[m]}(\mathbf{x}^{(i)})^2 + J(b^{[m]}) + const \\
&\propto \sum_{t=1}^{T^{[m]}} \sum_{\mathbf{x}^{(i)} \in R_t^{[m]}} g^{[m]}(\mathbf{x}^{(i)}) c_t^{[m]} + \frac{1}{2} h^{[m]}(\mathbf{x}^{(i)}) (c_t^{[m]})^2 + J(b^{[m]}) \\
&= \sum_{t=1}^{T^{[m]}} G_t^{[m]} c_t^{[m]} + \frac{1}{2} H_t^{[m]} (c_t^{[m]})^2 + J(b^{[m]}).
\end{aligned}
$$

Where $G_t^{[m]}$ and $H_t^{[m]}$ are the accumulated gradient and Hessian values in terminal node t.

RISK MINIMIZATION / 4

Expanding $J(b^{[m]})$:

$$
\begin{aligned}
\mathcal{R}_{\text{reg}}^{[m]} &= \sum_{t=1}^{T^{[m]}} \left(G_t^{[m]} c_t^{[m]} + \frac{1}{2} H_t^{[m]} (c_t^{[m]})^2 + \frac{1}{2} \lambda_2 (c_t^{[m]})^2 + \lambda_3 |c_t^{[m]}| \right) + \lambda_1 T^{[m]} \\
&= \sum_{t=1}^{T^{[m]}} \left(G_t^{[m]} c_t^{[m]} + \frac{1}{2} (H_t^{[m]} + \lambda_2)(c_t^{[m]})^2 + \lambda_3 |c_t^{[m]}| \right) + \lambda_1 T^{[m]}.
\end{aligned}
$$

Note: The factor $\frac{1}{2}$ is added to the $L2$ regularization to simplify the notation as shown in the second step. This does not impact estimation since we can just define $\lambda_2 = 2\tilde{\lambda}_2$.

Computing the derivative for a terminal node constant value $c_t^{[m]}$ yields

$$\frac{\partial \mathcal{R}_{\text{reg}}^{[m]}}{\partial c_t^{[m]}} = (G_t^{[m]} + \text{sign}\,(c_t^{m})\lambda_3) + (H_t^{[m]} + \lambda_2)c_t^{m}.$$

The optimal constants $\hat{c}_1^{[m]}, \dots, \hat{c}_{T^{[m]}}^{[m]}$ can then be calculated as

$$\hat{c}_t^{[m]} = -\frac{t_{\lambda_3}\left(G_t^{[m]}\right)}{H_t^{[m]} + \lambda_2}, t = 1, \dots T^{[m]},$$

with

$$t_{\lambda_3}(x) = \begin{cases} x + \lambda_3 & \text{for } x < -\lambda_3 \\ 0 & \text{for } |x| \leq \lambda_3 \\ x - \lambda_3 & \text{for } x > \lambda_3. \end{cases}$$

LOSS MINIMIZATION - SPLIT FINDING / 2

Algorithm (Exact) Algorithm for split finding

Input I: *instance set of current node*
Input p: *dimension of feature space*
$gain \leftarrow 0$
$G \leftarrow \sum_{i \in I} g(\mathbf{x}^{(i)}), H \leftarrow \sum_{i \in I} h(\mathbf{x}^{(i)})$
for $j = 1 \rightarrow p$ **do**
    $G_L \leftarrow 0, H_L \leftarrow 0$
    for i in sorted(I, by x_j) **do**
        $G_L \leftarrow G_L + g(\mathbf{x}^{(i)}), H_L \leftarrow H_L + h(\mathbf{x}^{(i)})$
        $G_R \leftarrow G - G_L, H_R \leftarrow H - H_L$
        compute $\tilde{S}_{LR}$
    end for
end for
Output Split with maximal $\tilde{S}_{LR}$