2. The horizontal federated Gradient Boosting Decision Tree optimization method based on a random greedy algorithm according to claim 1, wherein the optimal segmentation point algorithm in the Step 6:

determines a segmentation objective function, including an objective function,

information gain: information gain is the most commonly used index to measure a purity of a sample set; assuming that there are K types of samples in a node sample set D, in which a proportion of a k^{th} type of samples is p_k, an information entropy of D is defined as:

$$\mathrm{Ent}(D) = -\sum_{k=1}^{|K|} p_k \log_2 p_k$$

assuming that the node is segmented into V possible values according to an attribute a, the information gain is defined as:

$$\mathrm{Gain}(D, a) = \mathrm{Ent}(D) - \sum_{v=1}^{V} \frac{|D^v|}{|D|} \mathrm{Ent}(D^v);$$

information gain rate:

$$\mathrm{Gain_ratio}(D, a) = \frac{\mathrm{Gain}(D, a)}{\mathrm{IV}(a)}$$

where

$$\mathrm{IV}(a) = -\sum_{v=1}^{V} \frac{|D^v|}{|D|} \log_2 \frac{|D^v|}{|D|}$$

a Gini coefficient:

$$\mathrm{Gini}(D) = \sum_{k=1}^{|K|} \sum_{k' \neq k} p_k p_{k'}$$

$$\mathrm{Gini_index}(D, a) = \sum_{v=1}^{V} \frac{|D^v|}{|D|} \mathrm{Gini}(D^v)$$

a structural coefficient:

$$\mathrm{Gain} = \frac{1}{2}\left(\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{G^2}{H + \lambda}\right) - \gamma$$

where G_L is a sum of first-order gradients of the data set divided into a left node according to the segmentation point, H_L is a sum of second-order gradients of the data set of the left node, and G_R and H_R are sums of the gradient information of a corresponding right node, γ is a tree model complexity penalty term and λ is a second-order regular term;

determines a candidate list of segmentation values: determining the list of segmentation values according to the data distribution of the current node, wherein the segmentation values