HARP DAAL Update

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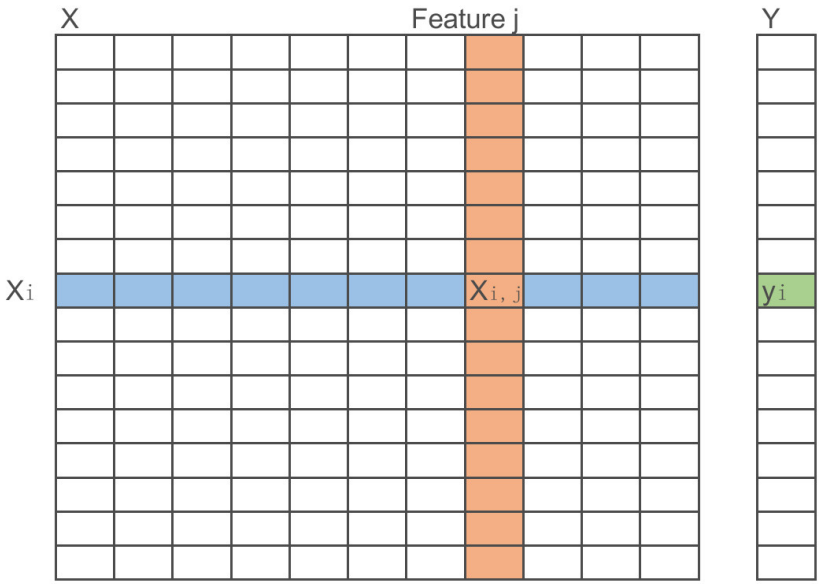
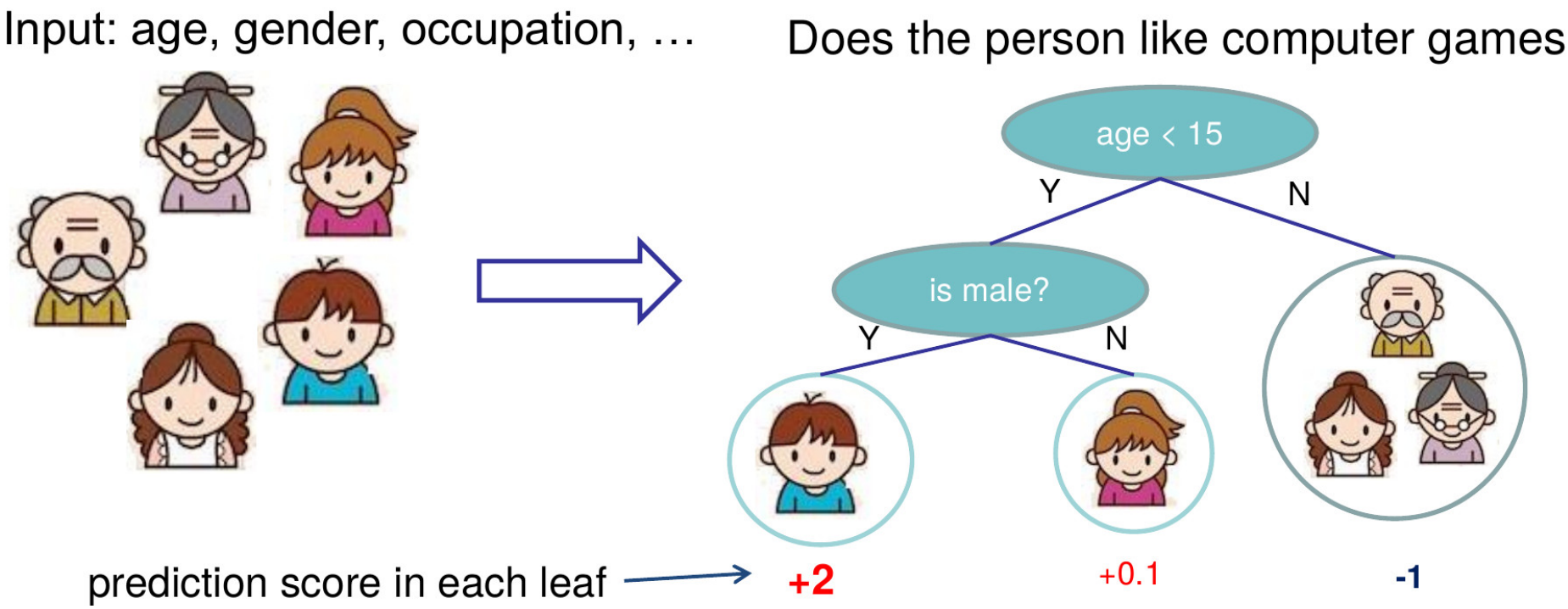
Outline

Regression



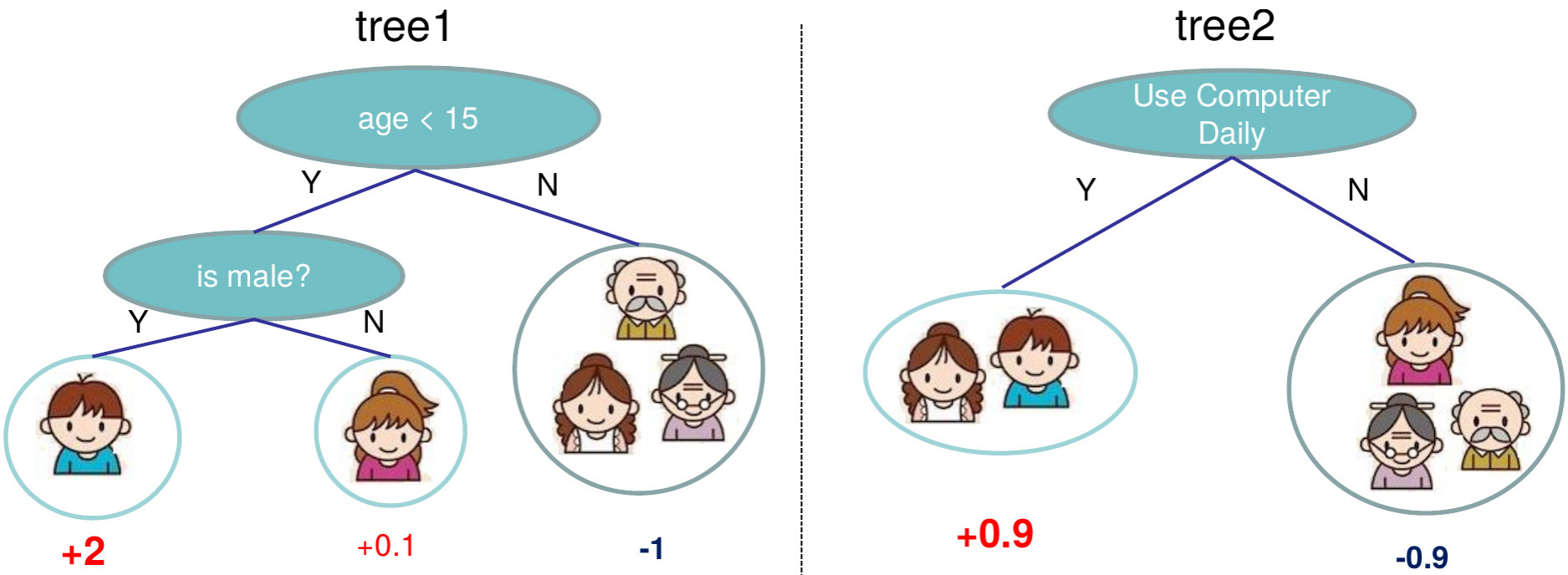
- Problem: find $\widehat{y_i} = \phi(x_i)$ that minimize regularized objective $\mathcal{L}(\phi) = \sum_{i=1}^{n} \ell(\widehat{y_i}, y_i) + \Omega(\phi)$
- Loss function, for example $\ell(\widehat{y_i}, y_i) = (\widehat{y_i} - y_i)^2$
- Data:
  Input: n samples x_i each as a m dimensional vector,
  Response: n responses y_i

Regression Tree



- Regression Tree: $f(x) = w_{q(x)}$ where $q : \mathbb{R}^m \to T$
  q is the tree structure, map x to leaf nodes (T is number of leaves)
  w is leaf weights
- How to learn $f(x)$?
  Greedy algorithm, findBestSplit() according to a score function at each internal node

Boosting



f( ) = 2 + 0.9= 2.9 f( )= -1 - 0.9= -1.9

- Boosting: $\widehat{y_i} = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i)$
- additive model: prediction is the sum score of all the trees

GBT:Gradient Boosting Tree

- stage-wise adding new tree:
  $\mathcal{L}^{(t)} = \sum_{i=1}^{n} \ell(\widehat{y}_i^{(t-1)} + f_t(x_i), y_i) + \Omega(f_t)$
- by second order approximation
  $\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} [\ell(\widehat{y}_i^{(t-1)}, y_i) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t)$
  where;
  $g_i = \partial_{\widehat{y}_i^{(t-1)}} \ell(\widehat{y}_i^{(t-1)}, y_i)$
  $h_i = \partial^2_{\widehat{y}_i^{(t-1)}} \ell(\widehat{y}_i^{(t-1)}, y_i)$
- optimal weight w_j^* and value for leaf j should be
  $w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda}$
  $\widetilde{\mathcal{L}}^{(t)} = -\frac{1}{2} \sum_{j=1}^{T} \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T$

GBT Example

- Example
  - square loss: $\ell(\widehat{y}_i, y_i) = (\widehat{y}_i - y_i)^2$
    $g_i = \partial_{\widehat{y}_i^{(t-1)}} \ell(\widehat{y}_i^{(t-1)}, y_i) = 2(\widehat{y}_i^{(t-1)} - y_i)$
    $h_i = 2$
  - intuitively optimal weight w_j^* is just a kind of average residual
    $w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} = \frac{2}{2+\lambda} \frac{(y_i - \widehat{y}_i^{(t-1)})}{|I_j|}$
- Important data structure on leaf j
  - $G_j = \sum_{i \in I_j} g_i$
  - $H_j = \sum_{i \in I_j} h_i$
  - $S(L, R) = \frac{G_{I_L}^2}{H_{I_L} + \lambda} + \frac{G_{I_R}^2}{H_{I_R} + \lambda}$ score function to get best split(impurity,more general the loss reduction)

GBT Algorithm

Algorithm 1: Gradient Boosted Regression Tree

input : dataset $D = (x_i, y_i)_{i=1}^n$, parameter λ, α, m

output: m trees $f(x) = w_q(x)$

begin

- Initialize()
- **for** *t=1 to m* **do**
  - // `BuildTree(`$\{(x_i, y_i)\}$`)`
  - $(w, q) =$ $\arg\min_{f_t} \sum_{i=1}^n [\ell(\hat{y}_i^{(t-1)} + \alpha f_t(x_i), y_i)] + \Omega(f_t)$
  - // `additive update`
  - $f_t(x) = f_{t-1}(x) + \alpha f_t(x)$

Algorithm 2: Greedy Split Finding

input : I, instance set of current node; d, feature dimension

output: split at the position with max score

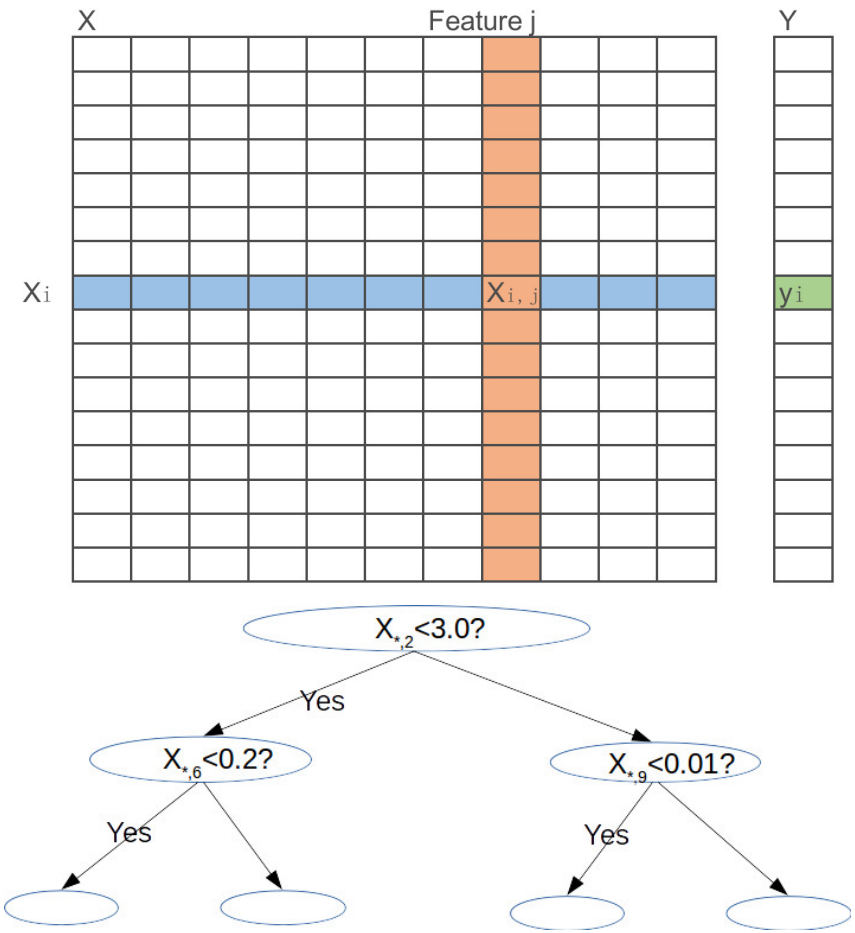
```
1  begin
2      score = 0
3      G = Σ_{i∈I} g_i
4      H = Σ_{i∈I} h_i
5      for k = 1 to d do
6          G_L = 0; H_L = 0
7          for j in sorted(I, by X_jk) do
8              G_L = G_L + g_j; H_L = H_L + h_j
9              G_R = G − G_L; H_R = H − H_L
10             score = max(score, G_L^2/(H_L+λ) + G_R^2/(H_R+λ))
```

GBTSummary

- basic idea on
  - boosting; function approximation target on the residual (gradient in general)
  - decision tree; weak learner easy to understand and build
- a general framework
  - supporting wide range of loss functions and regularizations
  - the score function to build tree is derived from a wide range of objective functions
- features
  - auto feature selection (kind of)
  - easy to deal with missing values, category values

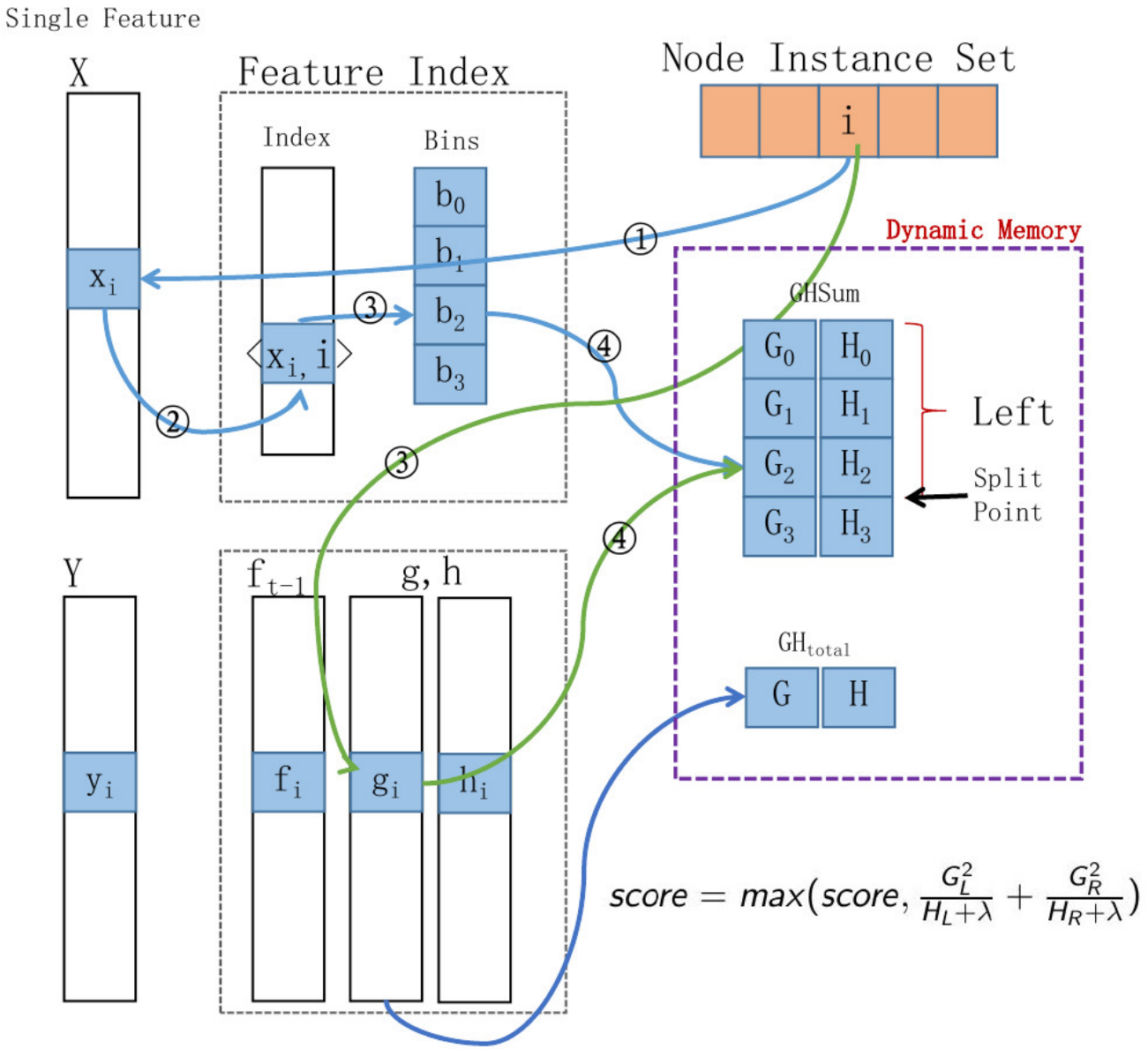
Outline

Parallelism in a Shared-Memory Setting



- Boosting is a sequential process, building trees one by one.(multiclass categorization have multiple boosting processes)
- Parallelism in building one tree
  - parallelFeatures: findBestSplit() works on features independently
  - parallelNodes: same level of nodes in a tree works independently
  - vectorization: lots of $\sum$ operations, G_j, H_j

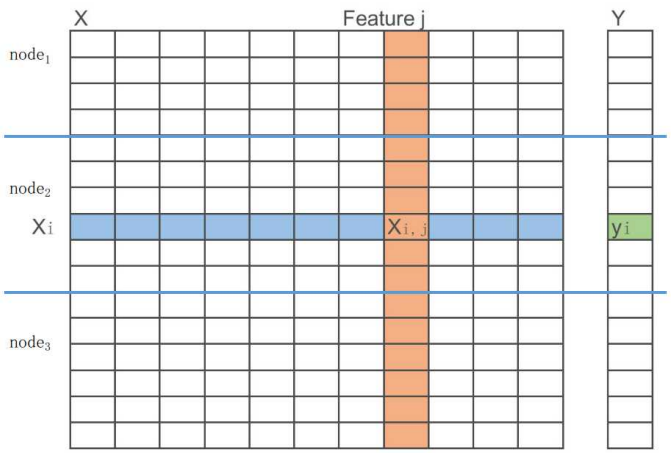
Issues - Non-continous Mem Access

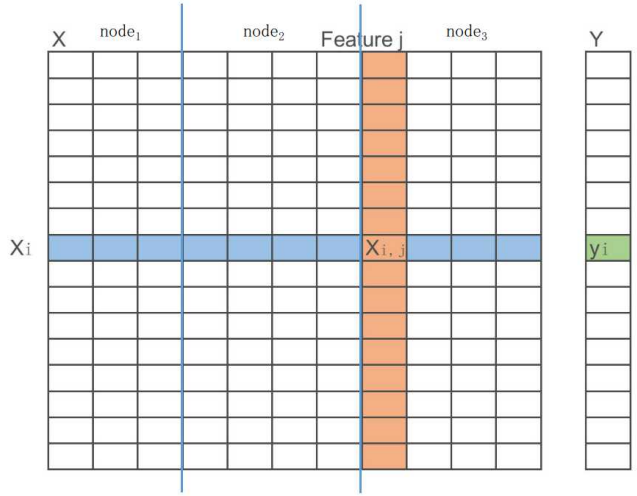


- Bins is a split candidates proposal $B = b_0, b_1, .., b_k$, in general $|B| << n$
- with Bins, the findBestSplit timecomplexity drops from $\mathcal{O}(nlogn)$ to $\mathcal{O}(nlogb)$

Outline

Data Partition





- Partition by rows (samples)
  - need gobal communication to build Bins, once if use global static Bins.
  - need gobal communication to build GHSum for each feature in findBestSplit()
- Partition by columns (features)
  - Bins and GHSum are all local, no communication
  - need global communication to select the best feature in findBestSplit()
  - load imbalance can be a problem

Outline

Topics for the Next Step

- memory access optimization
- different Bins design
- load imbalance issue in distributed setting

References

T. Chen and C. Guestrin, Xgboost: A scalable tree boosting system, in Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, 2016, pp. 785–794..

S. Tyree, K. Q. Weinberger, K. Agrawal, and J. Paykin, Parallel boosted regression trees for web search ranking, in Proceedings of the 20th international conference on World wide web, 2011, pp. 387–396.

The End