HARP DAAL Update

Distributed Gradient Boosting Tree

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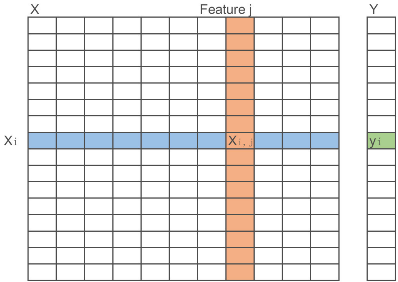
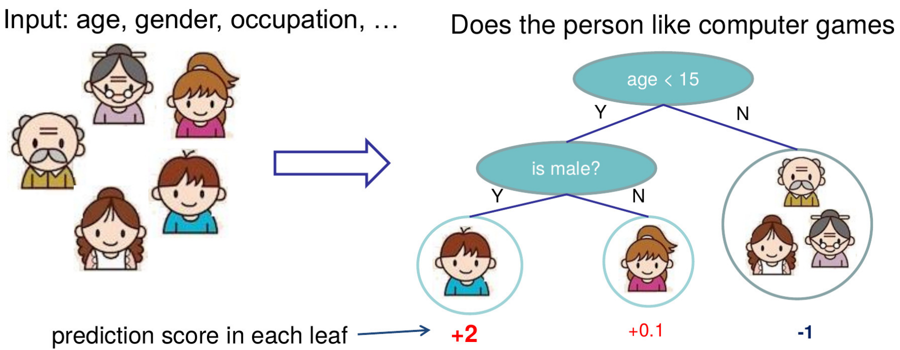
Outline

1. Background
   - GBT Algorithm
2. Parallel and Distributed Implementation
   - I. Shared-Memory
   - II. Distributed
3. Future Work
   - Topics for the Next Step

Regression

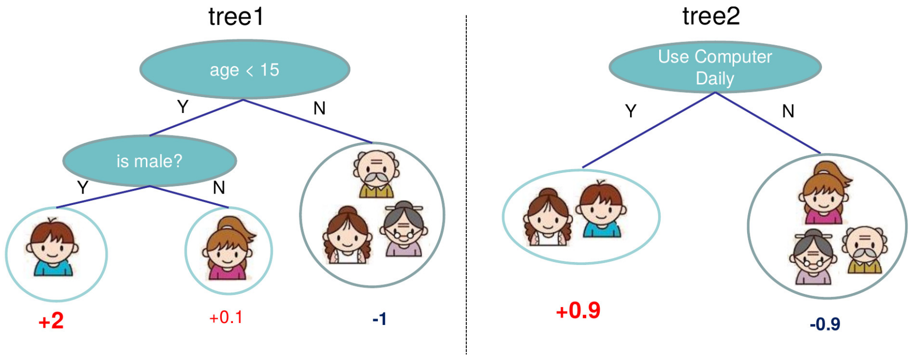


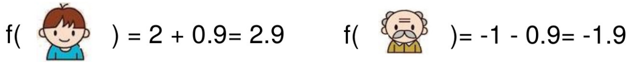
- Problem: find $\widehat{y_i} = \phi(x_i)$ that minimize regularized objective $\mathcal{L}(\phi) = \sum_{i=1}^{n} \ell(\widehat{y_i}, y_i) + \Omega(\phi)$
- Loss function, for example $\ell(\widehat{y_i}, y_i) = (\widehat{y_i} - y_i)^2$
- Data:
  Input: n samples x_i each as a m dimensional vector,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



- Regression Tree: $f(x) = w_{q(x)}$ where $q : \mathbb{R}^m \rightarrow T$
  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





- 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
- How to learn $f_k(x)$?

  stage-wise and train on the previous residual at the next step

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`$(\{(x_i, y_i)\})$
  - $(w, q) = \arg\min_{f_t} \sum_{i=1}^{n} [\ell(\widehat{y}_i^{(t-1)} + \alpha f_t(x_i), y_i)] + \Omega(f_t)$
  - // `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

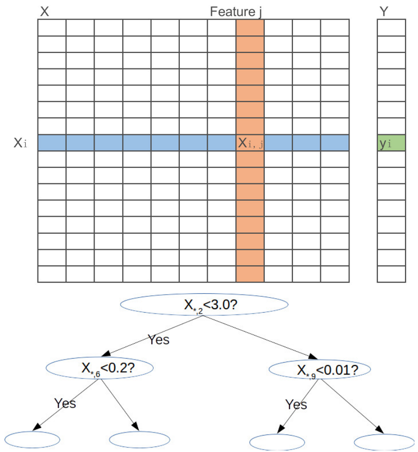
begin
- $score = 0$
- $G = \sum_{i \in I} g_i$
- $H = \sum_{i \in I} h_i$
- **for** $k = 1$ *to* d **do**
  - $G_L = 0; H_L = 0$
  - **for** *j in sorted(I, by* X_{jk}*)* **do**
    - $G_L = G_L + g_j; H_L = H_L + h_j$
    - $G_R = G - G_L; H_R = H - H_L$
    - $score = max(score, \frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda})$

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

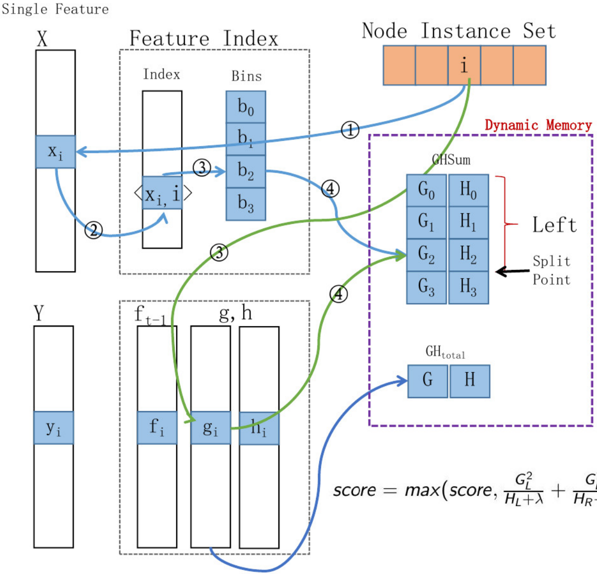
Outline

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

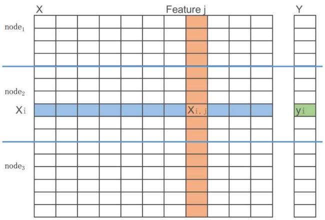


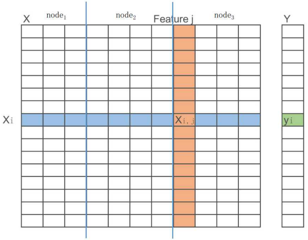
$$score = max(score, \frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda})$$

- 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() → allreduce(GHSum)
- Partition by columns (features)
  - Bins and GHSum are all local, no communication
  - need global communication to select the best feature in findBestSplit() → allreduce(maxscore), also need to broadcast(Split Instance Set)

Issue - Overhead of Synchronization & Communication

- Overhead of communication
  - well designed Bins works as model compression, reducing the data volume of communication
  - pipeline
- Overhead of synchronization
  - load imbalance is the killer of synchronization operation
  - allreduce give chance to model rotation
  - stochastic GBT give chance to timer control

Outline

Topics for the Next Step

- memory access optimization in shared memory system
- load imbalance issue in distributed system
- different Bins design
- dataset with sparsity and high dimensionality

References

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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