Gradient Boosted Decision Trees on Hadoop

jerry ye | jyh-herng chow | jiang chen | zhaohui zheng

Agenda

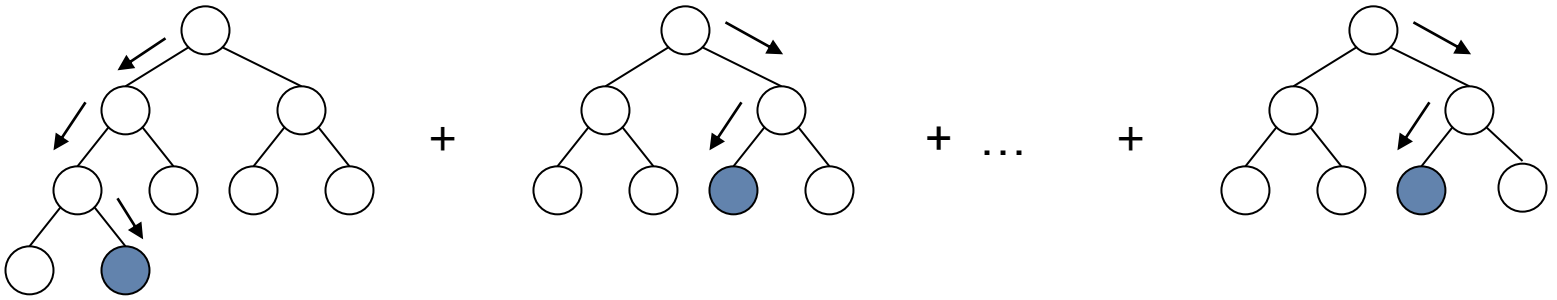
- Overview
  - GBDT
  - Implementations
  - Related Work
- GBDT
  - Learning a tree
  - Boosting
- Method
  - MapReduce Implementations
  - MPI Implementation
- Results
- Conclusion

Introduction

Gradient Boosted Decision Trees (GBDT) is a machine learning algorithm that iteratively constructs an ensemble of weak decision tree learners through boosting.

What is GBDT?

- Gradient Boosted Decision Trees was introduced by Jerome Friedman in 1999
- An additive regression model over an ensemble of trees, fitted to current residuals, gradients of the loss function, in a forward step-wise manner
- Favors many shallow trees (e.g., 6 nodes, 2000 trees)
- Advanced Algorithms: GBRank, SmoothDCG
- Numerous applications within Yahoo!
- Blender in Bellkor's winning Netflix solution



Advantages

- Feature normalization is not required
- Feature selection is inherently performed during the learning process
- Not prone to collinear/identical features
- Models are relatively easy to interpret
- Easy to specify different loss functions

Disadvantages

- Boosting is a sequential process, not parallelizable
- Compute intensive
- Can perform poorly on high dimensional sparse data, e.g. bag of words

Known Implementations

- Salford's TreeNet
- gbm package in R
- PLANET: Massively Parallel Learning of Tree Ensembles with MapReduce, Panda et. al.
- Tong Zhang implemented GBDT while at YRL
- More implementations at this workshop

Algorithm Overview

Algorithm

{y,x}: dataset
Ψ: loss function
γ: node score
M: number of trees
N: training set size
$F_m(x)$: m^{th} tree
y_{im}: residuals
ν: shrinkage

Algorithm:

$$F_0(\mathbf{x}) = \arg\min_\gamma \sum_{i=1}^{N} \Psi(y_i, \gamma)$$

For $m = 1$ to M do:

$$y_{im} = -\left[\frac{\partial \Psi(y_i, F(\mathbf{x}_i))}{\partial \Psi(F(\mathbf{x}_i))}\right]_{F(\mathbf{x})=F_{m-1}(\mathbf{x})}, \; i = 1, N$$

New targets are computed at each iteration

$$\{R_{lm}\}_1^L = \text{growtree}(\{y_{im}, \mathbf{x}_i\}_1^N)$$

Grow L-terminal tree

$$\gamma_{lm} = \arg\min_\gamma \sum_{\mathbf{x}_i \in R_{lm}} \Psi(y_i, F_{m-1}(x_i) + \gamma)$$

Responses for terminal nodes

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \nu \cdot \sum_{l=1}^{L} \gamma_{lm} 1(\mathbf{x} \in R_{lm})$$

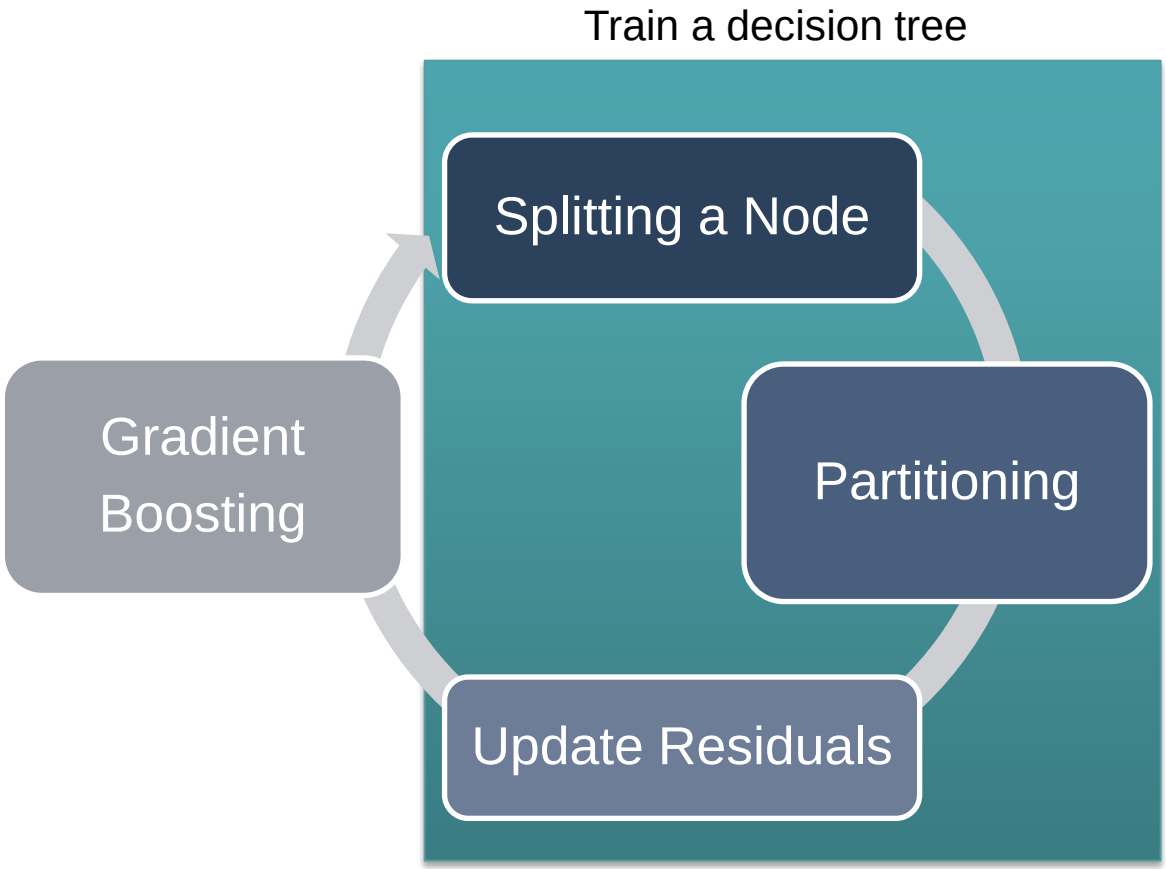
Shrinkage ν controls learning rate

end

Friedman "Stochastic Gradient Boosting", 1999

GBDT Process

- Each tree, partition sample space by growing n nodes
- Compute gradient and repeat



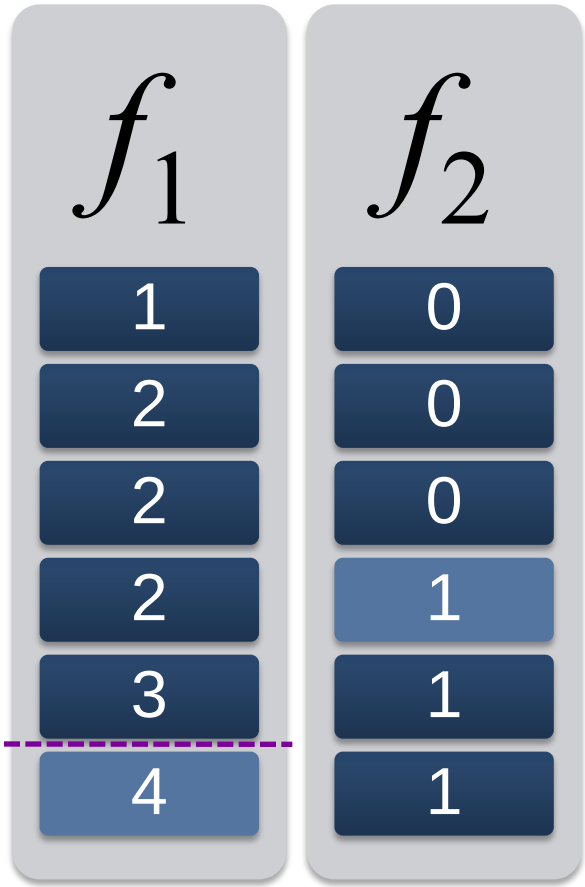
Splitting a node

Find the best split using Information Gain:

- Compute gain for each cut point
- Choose cut with highest gain
- Valid cutpoints:

$f_1 < 1.5$ *gain* = 10
$f_1 < 2.5$ *gain* = 30
$f_1 < 3.5$ *gain* = 57
$f_2 < 0.5$ *gain* = 25

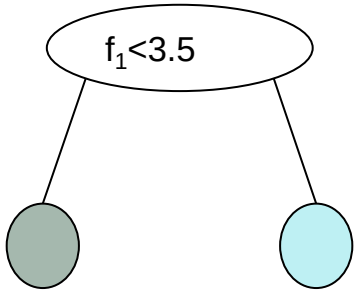
Partitioning



Using best split, partition the data

- samples above the cut goes to left node
- samples below cut goes to right node
- find best cuts for new nodes

$f_1 < 3.5$ *gain = 57*



residual' += mean($target_{node}$)

Boosting

labels

1

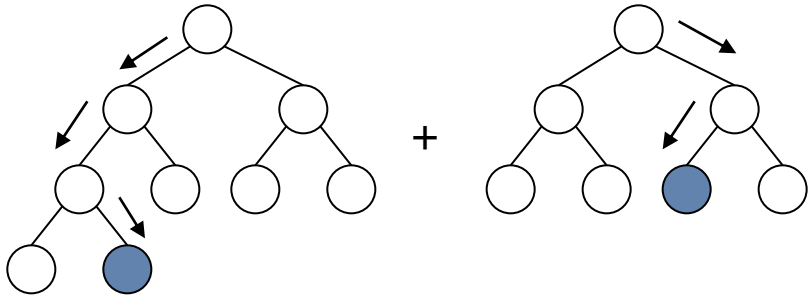
1

1

1

1

2

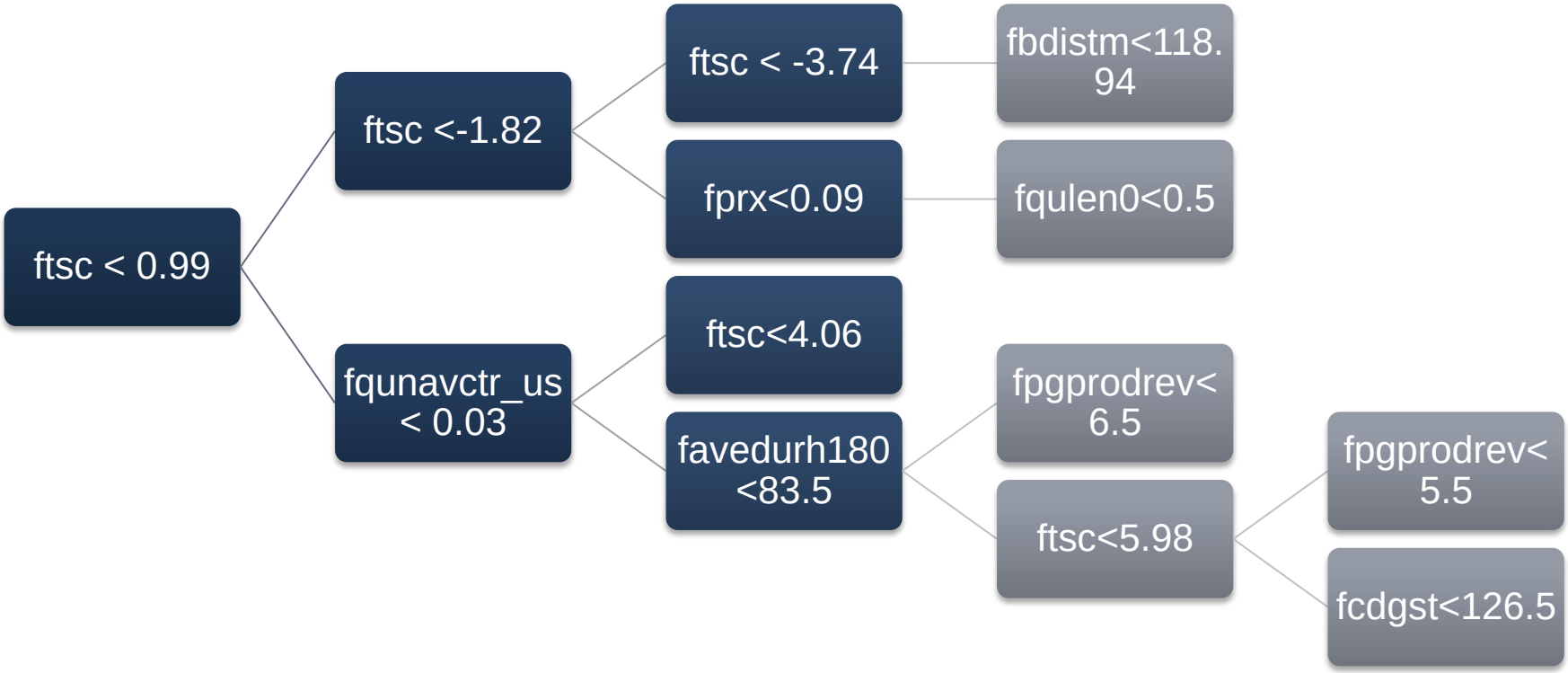


$$F_m(x) = F_{m-1}(x) + \nu \cdot \sum_{l=1}^{L} \gamma_{lm} 1(\mathbf{x} \in R_{lm})$$

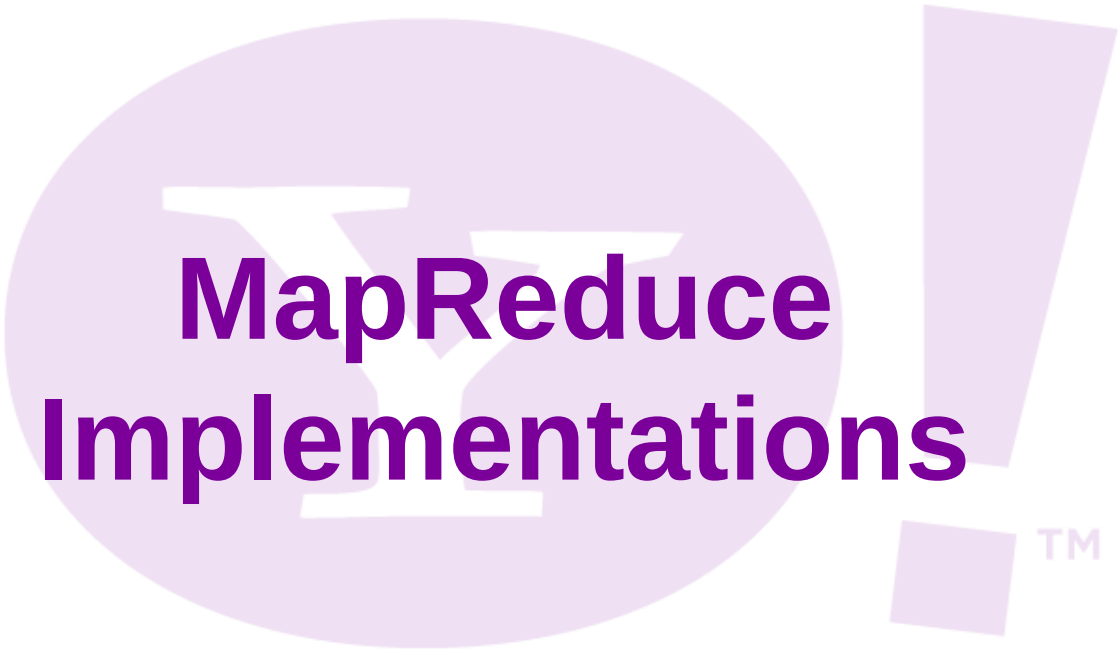
$$gradient_{m+1}(x) = label(x) - F_m(x)$$

- Gradient can vary depending on loss function, least squares shown
- Gradients are targets for next tree
- Stochastic boosting randomly subsamples training data for each tree

Example Tree



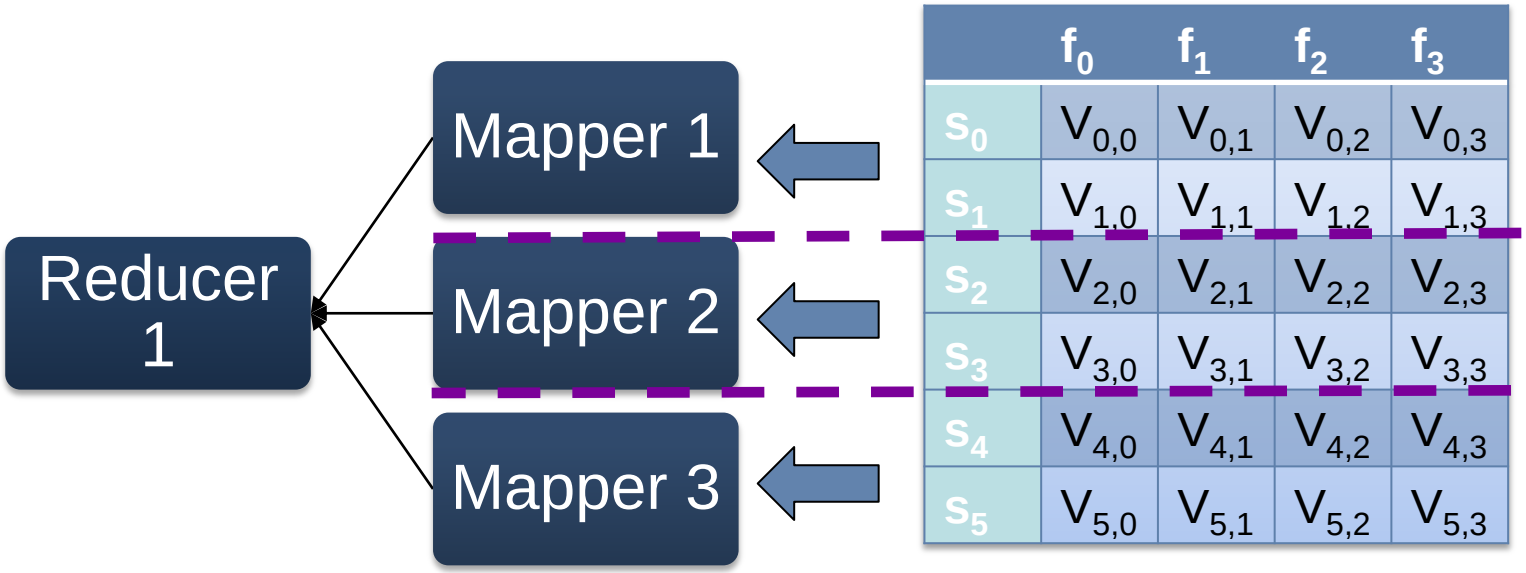
MapReduce Implementations



Horizontal: Finding Cuts

Partition Data:

- Each mapper emits (<feature, value>, <residual, weight>) pairs
- Reducers aggregates pairs and sorts
- Process scales as more nodes are added



Finding Splits

Algorithm 1 Aggregating candidate splits

```
map(key, value):
F ⇐ set of features
sample ⇐ split(value,delim)
for f in F do
    key = (f, sample[f])
    value = (sample[residual], sample[weight])
    emit(key, value)
end for

reduce(key, values):
residual_sum ⇐ 0
weight_sum ⇐ 0
for v in values do
    residual_sum ⇐ residual_sum + v.residual
    weight_sum ⇐ weight_sum + v.weight
end for
emit(key, (residual_sum,weight_sum))
```

- Each mapper emmits: (<feature,value>,<residual,weight>
- Reducer aggregates cuts and sorts
- Output: Sorted list of candidate cutpoints
- Single pass over sorted list to compute best split

Partitioning Data

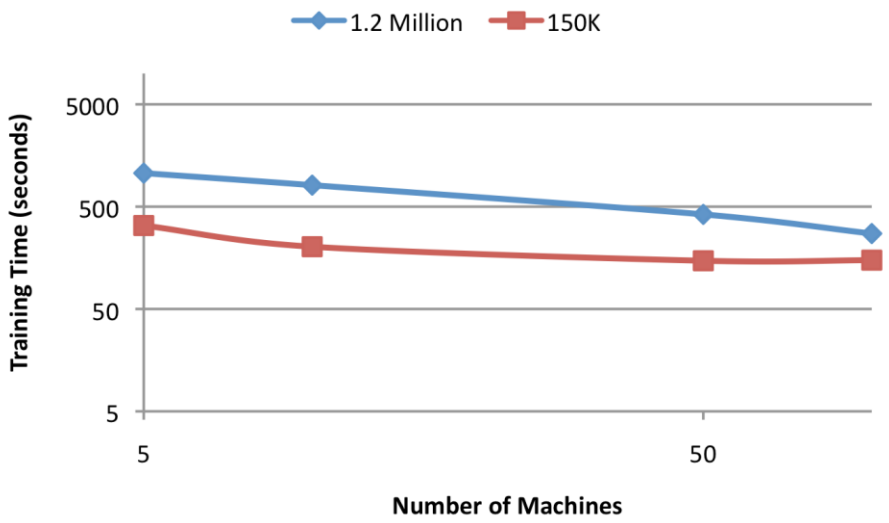
- Split data according to cut
- Output to DFS

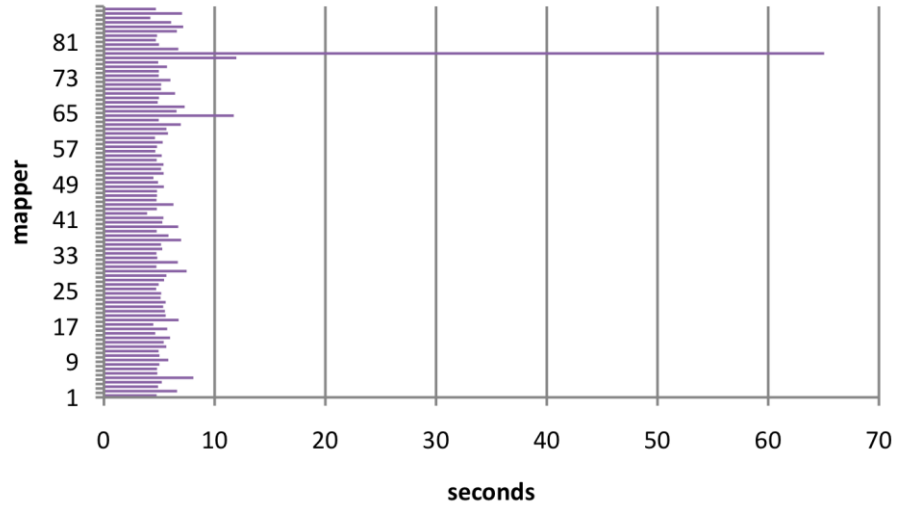
Algorithm 2 Partitioning a Node n

$map(key, value)$:
sample $\Leftarrow$ split(value,delim)
if sample[n.feature] $<$ n.splitpoint **then**
  residual = sample[residual]+ n.left_response
else
  residual = sample[residual]+ n.right_response
end if
emit(key, value)

MapReduce (horizontal)

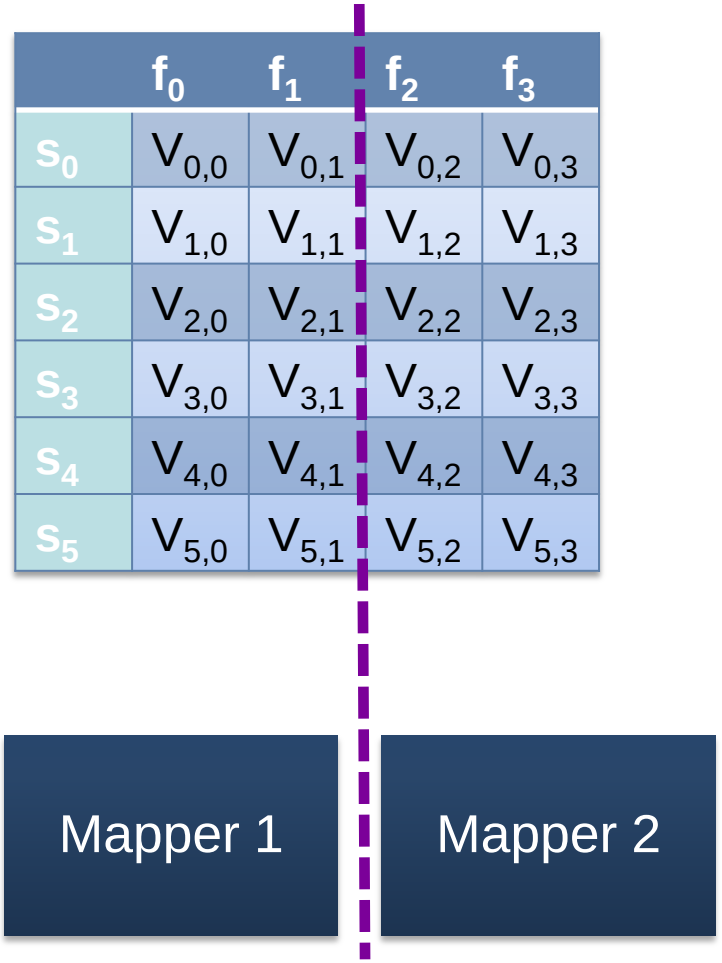
- Scales with more mappers
- Method is slow!
- 5 minutes to train 1 node
- Takes 211 minutes to train a 63 node tree on 1.2M x 500 feature dataset
- Reading from HDFS can take 1-2 minutes. We have 3 MapReduce jobs for a tree node
- Keep information in memory – vertical partitioning



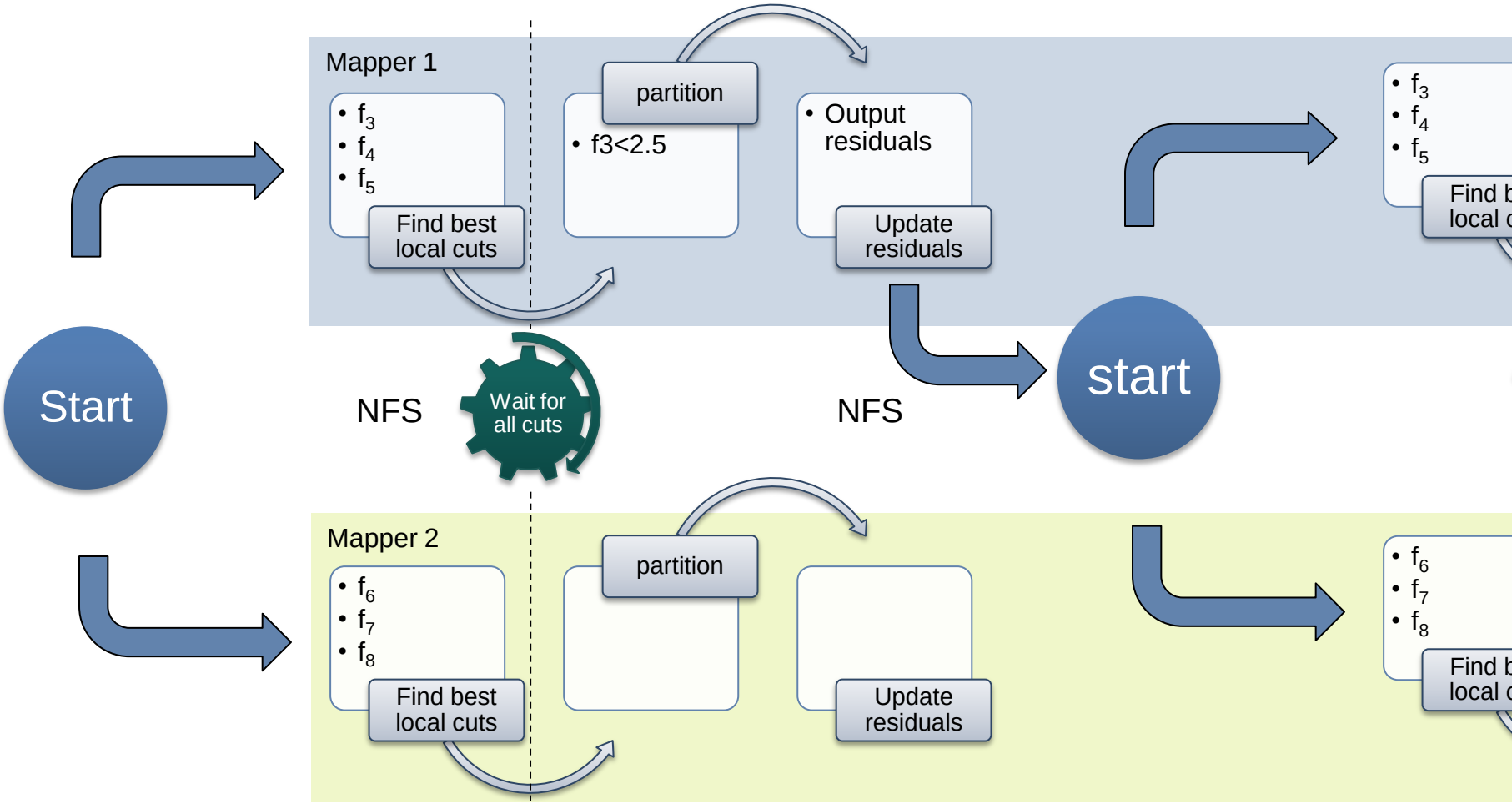


Vertical: Partition Data

- Each mapper gets a subset of features
- Read features into memory
- Mappers are persistent until ensemble is trained



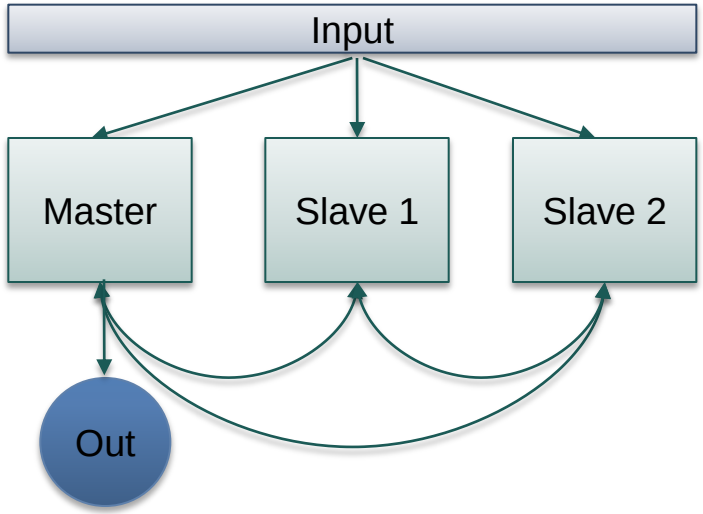
Vertical Mappers



MPI Implementation

Message Passing Interface

- Message Passing Interface (MPI) allows many computers to communicate with each other.
- Dominant model in high performance computing
- Scalable, portable
- Distributed shared memory for high RAM jobs
- OpenMPI is an open source implementation of MPI
- Low level and can be complicated to use
- Modified OpenMPI to run on Hadoop
- Fault tolerance



Splitting a node

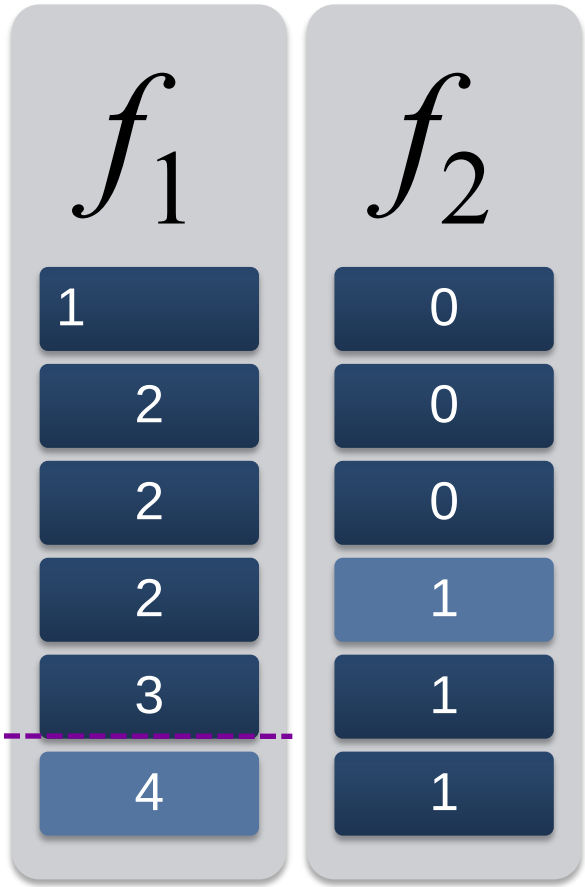
Each machine gets a feature

- Machine 1 finds local best split on f_1
- Machine 2 finds local best split on f_2
- Use MPI to broadcast local splits
- Best global split found

$f_1 < 1.5$	*gain* = 10	Machine 1
$f_1 < 2.5$	*gain* = 30	
$f_1 < 3.5$	*gain* = 57	
$f_2 < 0.5$	*gain* = 25	Machine 2

Global Best: $f_1 < 3.5$

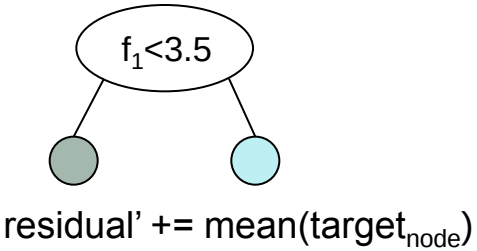
Partitioning



Using best cut, split the data

- Only Machine 1 has f_1 in memory, partition dataset
- Partition is maintained in indices, send updated index to others
- All machines updates residuals

$f_1 < 3.5$ *gain = 57*



Boosting

labels

1

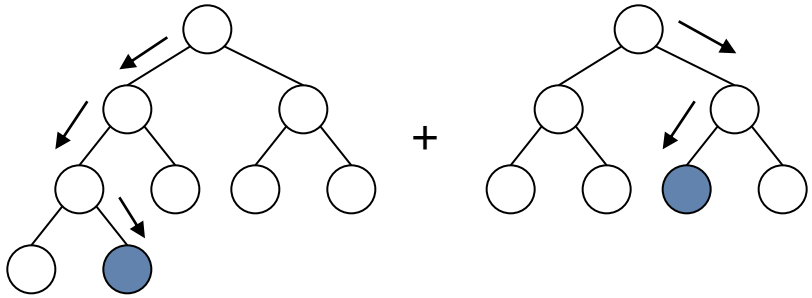
1

1

1

1

2



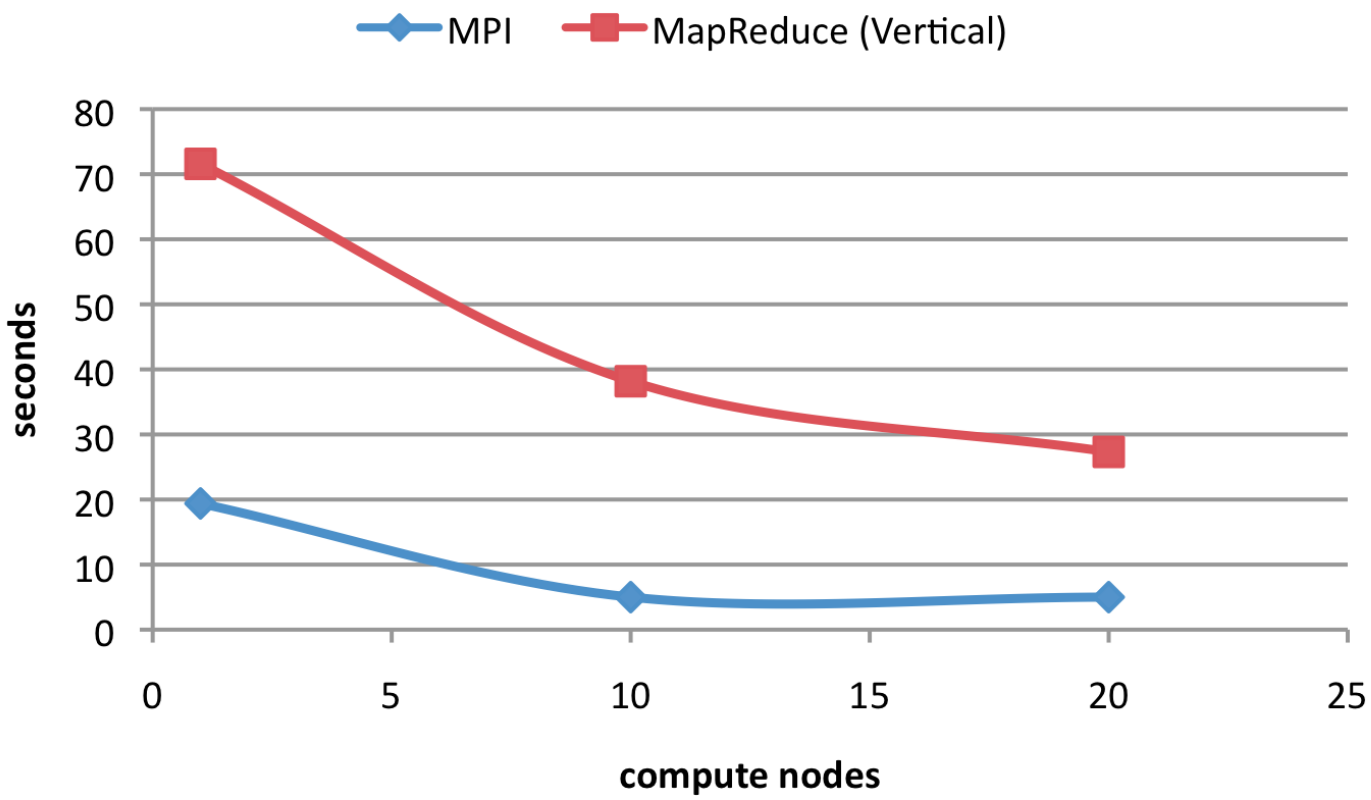
$$F_m(x) = F_{m-1}(x) + \nu \cdot \sum_{l=1}^{L} \gamma_{lm} 1(\mathbf{x} \in R_{lm})$$

$$gradient_{m+1}(x) = label(x) - F_m(x)$$

- Scores are kept for all samples through training of trees
- All machines computes new gradients and updates targets for next tree
- Repeat until finished

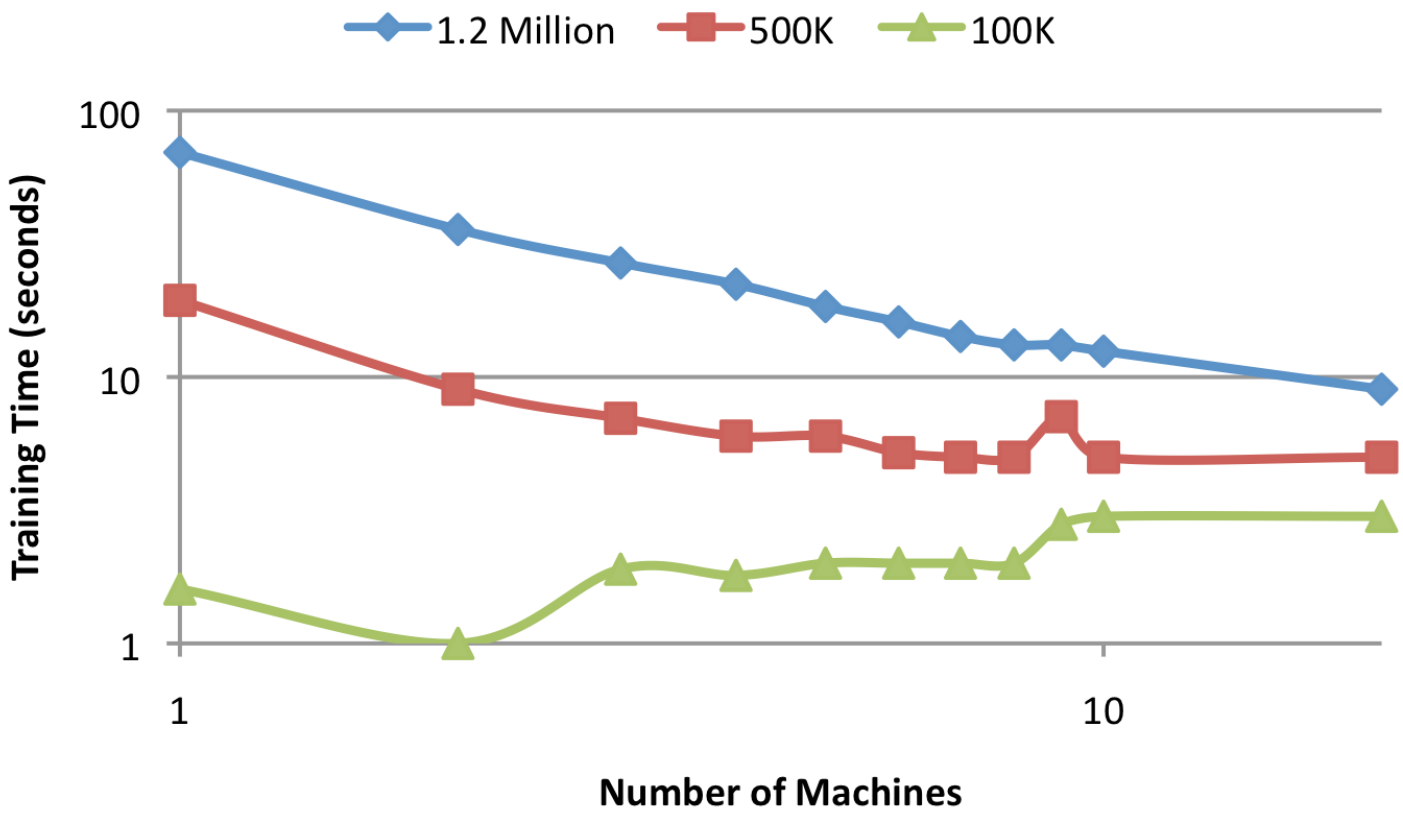
Experiments

Scalability



MPI implementation faster than MapReduce using vertical partitioning

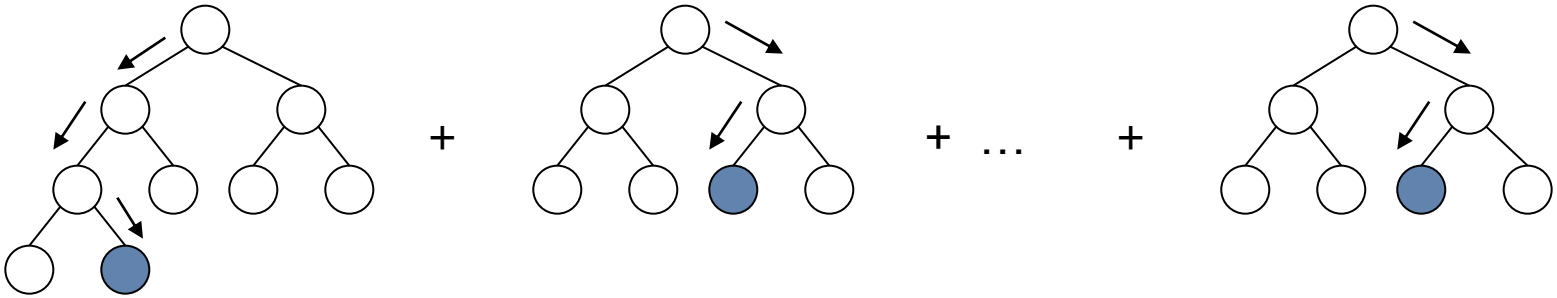
Scalability



Scalability for different dataset sizes

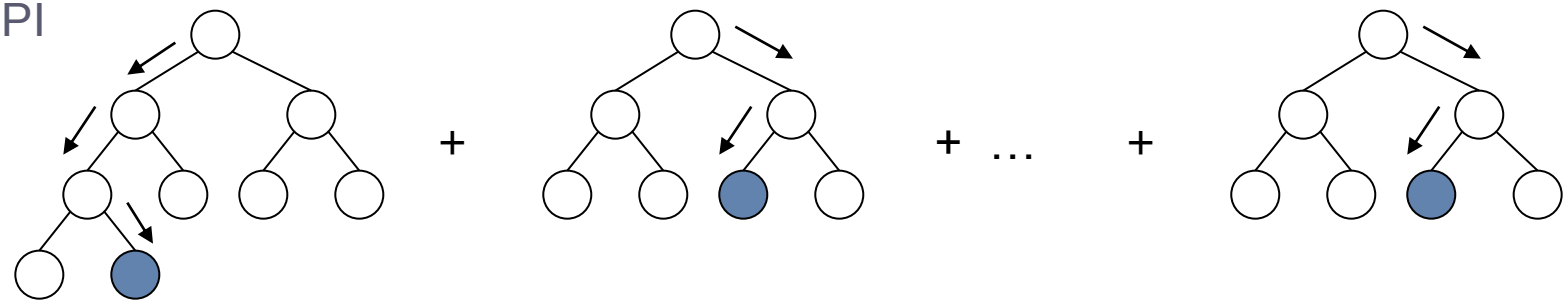
Experiment

MapReduce



Horizontal: 211 minutes x 2500 trees = 366 days x 100 machines
Vertical: 28 seconds x 2500 trees = 19.4 hours x 20 machines

MPI



5 seconds x 2500 trees = 3.4 hours x 10 machines

1800% less node hours!

Application

- Dataset (2M doc, 600 features)
- Tree Parameters: typical
  - Trees(2500), Terminal Nodes(20)
- Running time: (Runtime Memory: 4GB)
  - Single thread, single machine: 7 days
  - Multi-threads (6), single machine: 3.5 days
  - MPI on grid: 9 hours with 20 nodes, 12 hours with 10 nodes
  - More complex loss: 16 days -> 36 hours

Conclusions

- We have implemented a distributed version of GBDT
- Distributed version running faster than sequential version
- Can handle larger datasets that sequential version cannot
- Advanced algorithms based on GBDT can benefit from this framework
- Implementation GBDT uses MPI on Hadoop
- GBDT 6X faster than achievable using MapReduce
- 1800% reduction in node hours

Thanks!

For more info: jerryye@yahoo-inc.com

References

1 AMDAHL, G. Validity of the single processor approach to achieving large-scale computing capabilities. pp. 483–485.

2 CARAGEA, D., SILVESCU, A., AND HONAVAR, V. A framework for learning from distributed data using sufficient statistics and its application to learning decision trees. International Journal of Hybrid Intelligent Systems 1, 2 (2004).

3 CHEN, K., LU, R., WONG, C. K., SUN, G., HECK, L., AND TSENG, B. L. Trada: tree based ranking function adaptation. In CIKM (2008), pp. 1143–1152.

4 DEAN, J., AND GHEMAWAT, S. Mapreduce: simplified data processing on large clusters. Commun. ACM 51, 1 (2008), 107–113.

5 FOUNDATION, A. Apache hadoop project. lucene.apache.org/hadoop.

6 FRIEDMAN, J. H. Greedy function approximation: A gradient boosting machine. Annals of Statistics 29 (2001), 1189–1232.

7 FRIEDMAN, J. H. Stochastic gradient boosting. Comput. Stat. Data Anal. 38, 4 (February 2002), 367–378.

8 GEHRKE, J., RAMAKRISHNAN, R., AND GANTI, V. Rainforest - a framework for fast decision tree construction of large datasets. In VLDB'98, Proceedings of 24rd International Conference on Very Large Data Bases, August 24-27, 1998, New York City, New York, USA (1998), A. Gupta, O. Shmueli, and J. Widom, Eds., Morgan Kaufmann, pp. 416–427.

9 GRAHAM, R. L., AND GRAHAMT, R. L. Bounds on multiprocessing timing anomalies. SIAM Journal on Applied Mathematics 17 (1969), 416–429.

10 PANDA, B., HERBACH, J. S., BASU, S., AND BAYARDO, R. J. Planet: Massively parallel learning of tree ensembles. In VLDB 2009, Proceedings of the 35th Int'l Conf. on Very Large Data Bases (2009).

11 PROVOST, F., KOLLURI, V., AND FAYYAD, U. A survey of methods for scaling up inductive algorithms. Data Mining and Knowledge Discovery 3 (1999), 131–169.

12 QUINLAN, J. R. Induction of decision trees. In Machine Learning (1986), pp. 81–106.

13 SHAFER, J. C., AGRAWAL, R., AND 0002, M. M. Sprint: A scalable parallel classifier for data mining. In VLDB'96, Proceedings of 22th International Conference on Very Large Data Bases, September 3-6, 1996, Mumbai (Bombay), India (1996), T. M. Vijayaraman, A. P. Buchmann, C. Mohan, and N. L. Sarda, Eds., Morgan Kaufmann, pp. 544–555.

14 STATISTICS, L. B., AND BREIMAN, L. Random forests. In Machine Learning (2001), pp. 5–32.

15 SU, J., AND ZHANG, H. A fast decision tree learning algorithm. In AAAI (2006).

16 ZHENG, Z., CHEN, K., SUN, G., AND ZHA, H. A regression framework for learning ranking functions using relative relevance judgments. Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval (2007), 287–294.