PLANET

Massively Parallel Learning of Tree Ensembles with MapReduce

Sugato Basu*
Google Research

*Joint work with Biswanath Panda, Josh Herbach, Roberto J. Bayardo

Outline

Theme:

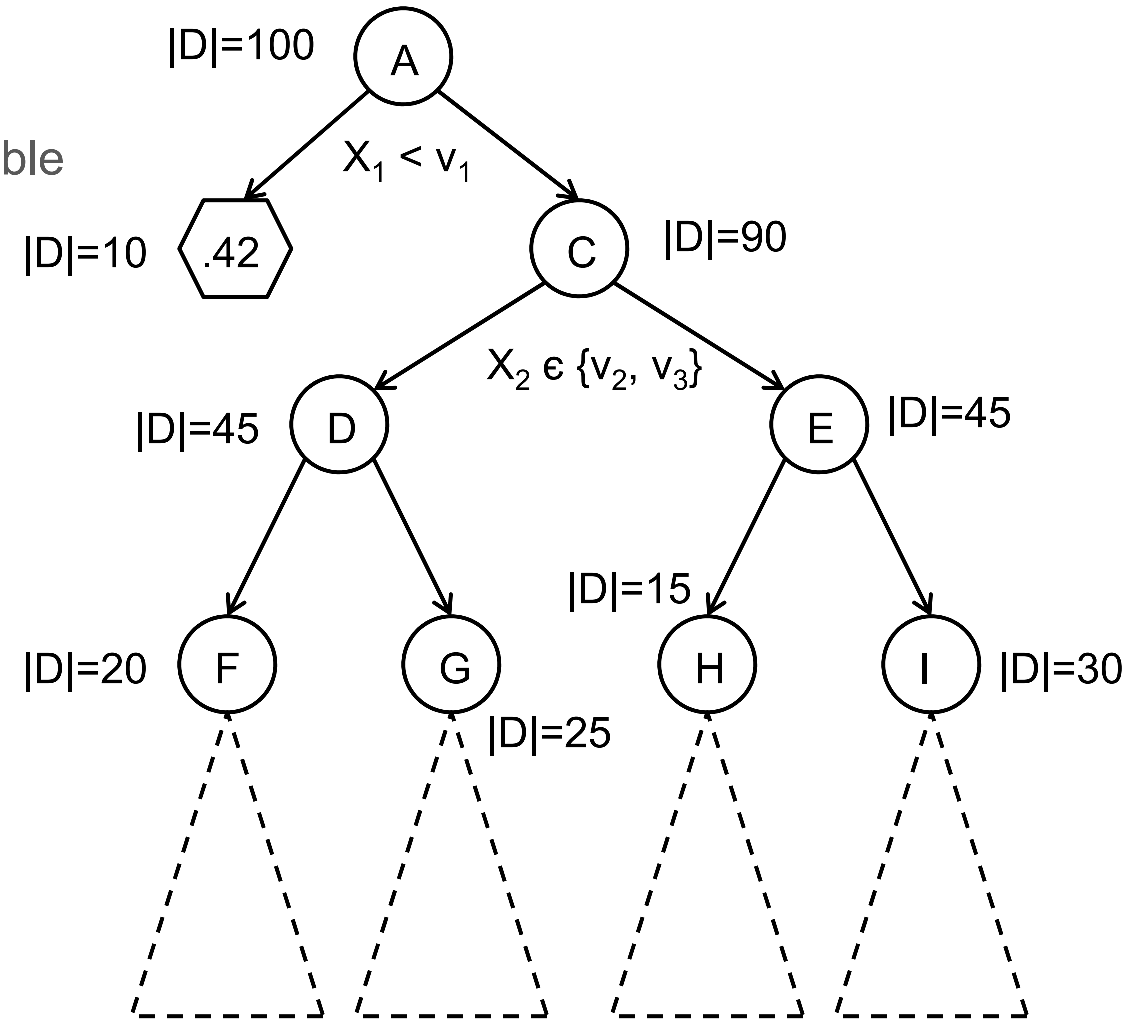
- PLANET – parallel infrastructure for building trees

Highlights:

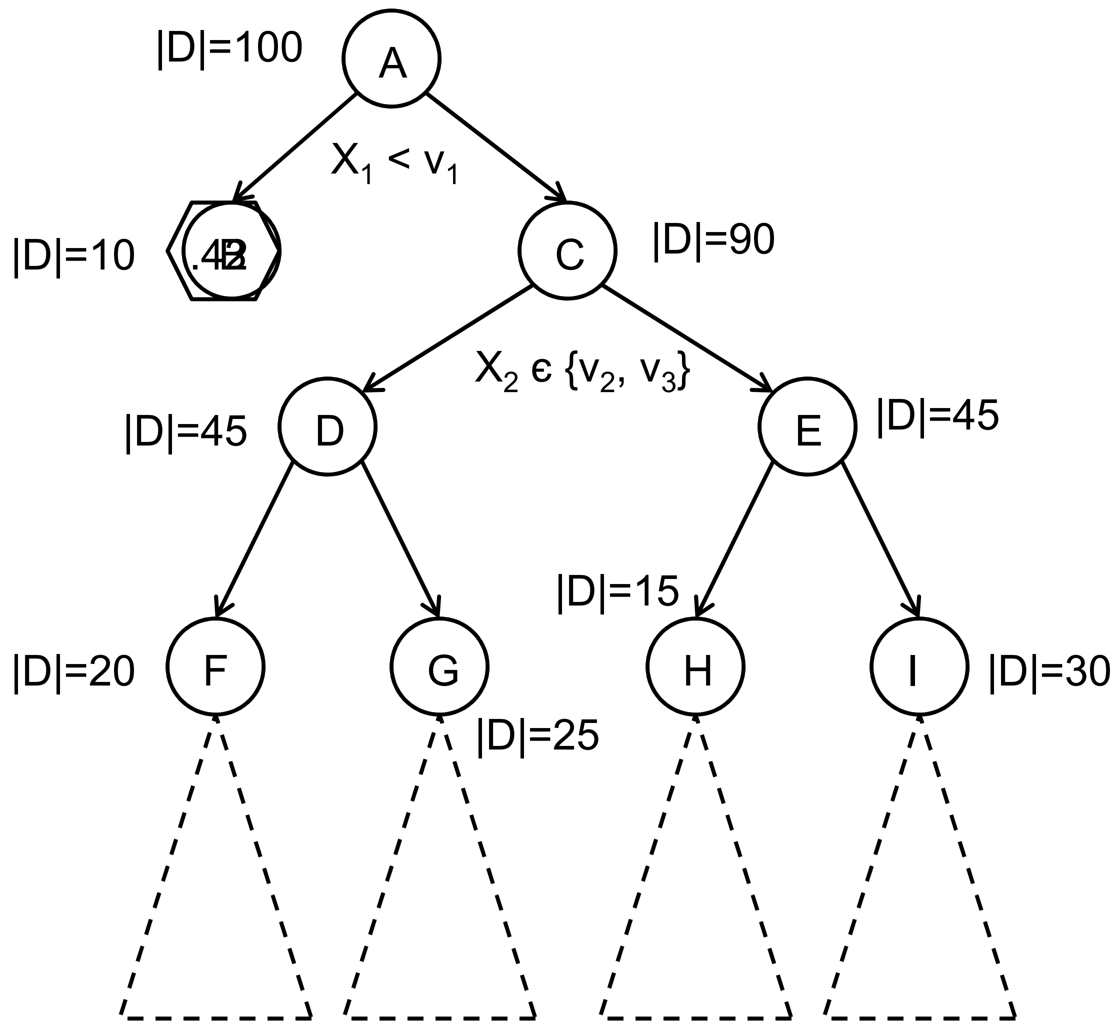
- Decision trees
- Usage of PLANET and motivation
- MapReduce
- PLANET details
- Results
- Future Work

Tree Models

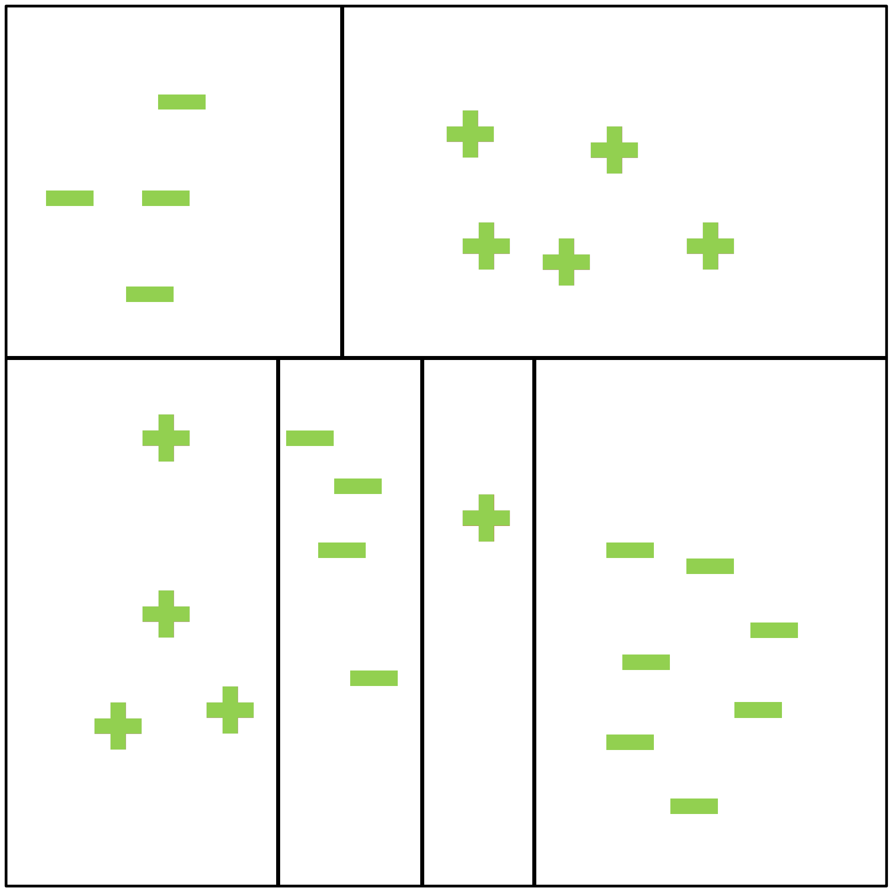
- Classic data mining model
- Interpretable
- Good when built with ensemble techniques like bagging and boosting



Construction



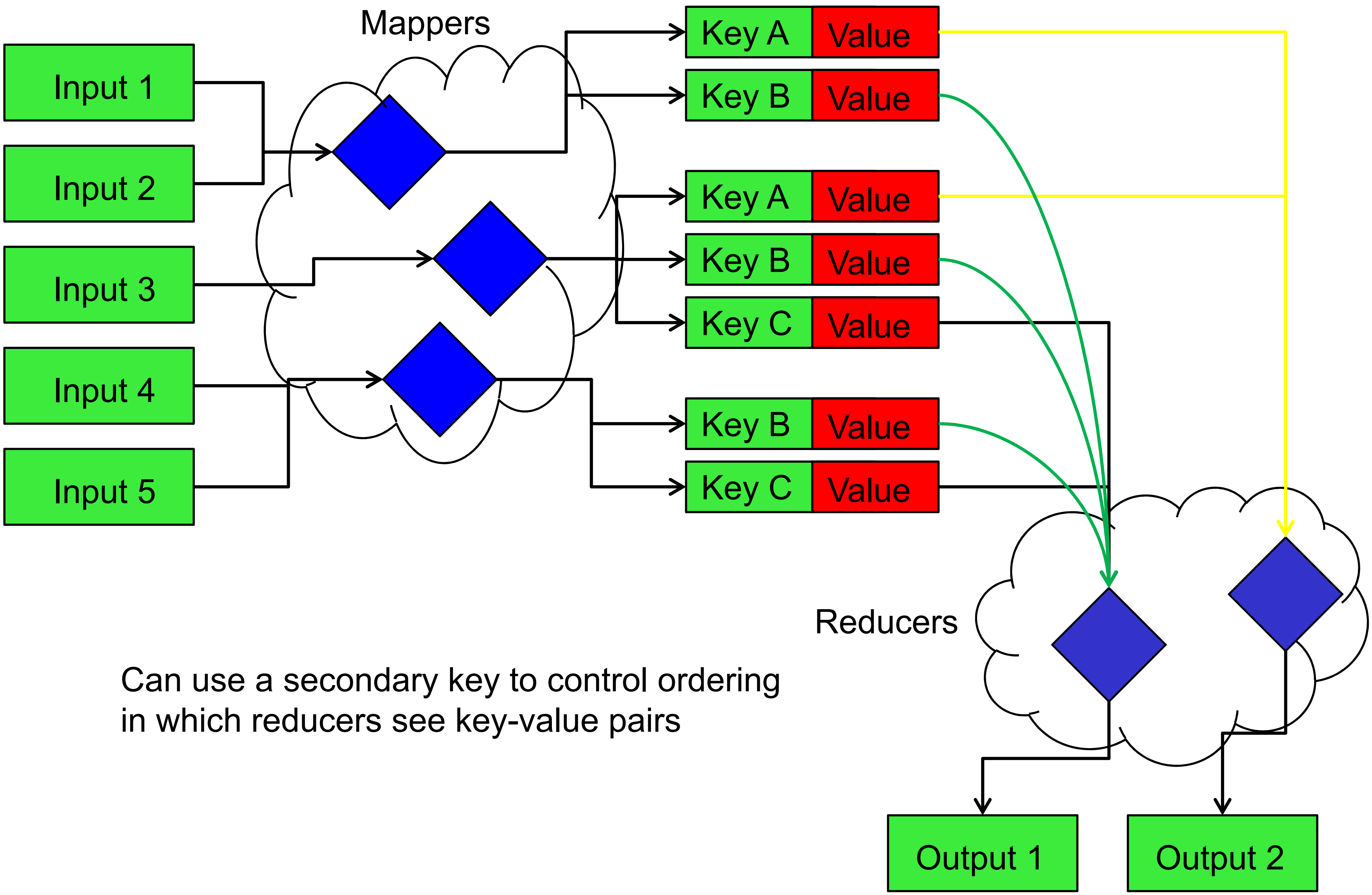
Find Best Split



Trees at Google

- Large Datasets
  - Iterating through a large dataset (10s, 100s, or 1000s of GB) is slow
  - Computing values based on the records in a large dataset is really slow
- Parallelism!
  - Break up dataset across many processing units and then combine results
  - Super computers with specialized parallel hardware to support high throughput are expensive
  - Computers made from commodity hardware are cheap
- Enter MapReduce

MapReduce*



Can use a secondary key to control ordering in which reducers see key-value pairs

*http://labs.google.com/papers/mapreduce.html

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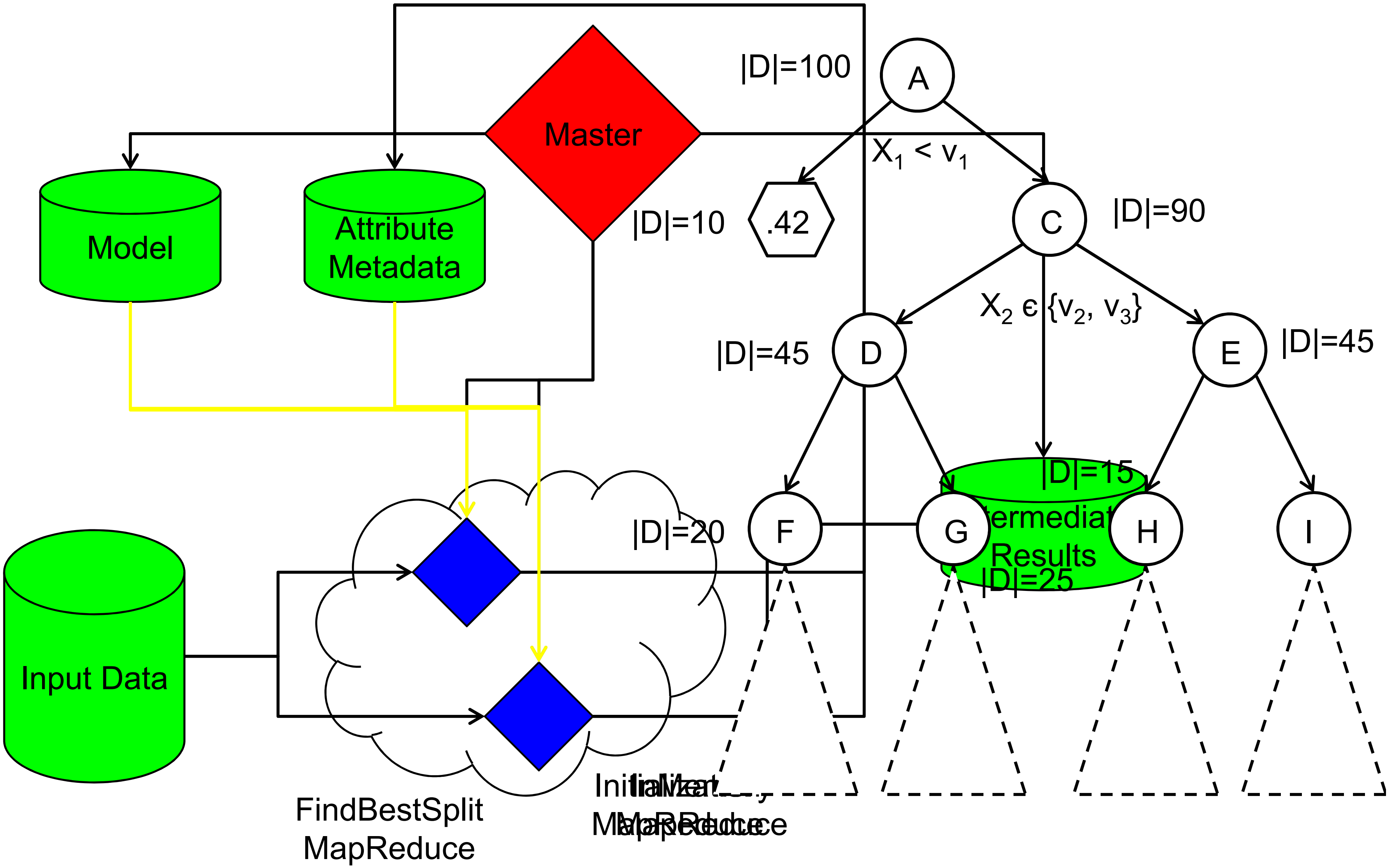
PLANET

- Parallel Learner for Assembling Numerous Ensemble Trees
- PLANET is a learner for training decision trees that is built on MapReduce
  - Regression models (or classification using logistic regression)
  - Supports boosting, bagging and combinations thereof
  - Scales to very large datasets

System Components

- Master
  - Monitors and controls everything
- MapReduce Initialization Task
  - Identifies all the attribute values which need to be considered for splits
- MapReduce FindBestSplit Task
  - MapReduce job to find best split when there is too much data to fit in memory
- MapReduce InMemoryGrow Task
  - Task to grow an entire subtree once the data for it fits in memory
- Model File
  - A file describing the state of the model

Architecture



Master

- Controls the entire process
- Determines the state of the tree and grows it
  - Decides if nodes should be leaves
  - If there is relatively little data entering a node; launch an InMemory MapReduce job to grow the entire subtree
  - For larger nodes, launches a MapReduce job to find candidate best splits
  - Collects results from MapReduce jobs and chooses the best split for a node
  - Updates Model
- Periodically checkpoints system
- Maintains status page for monitoring

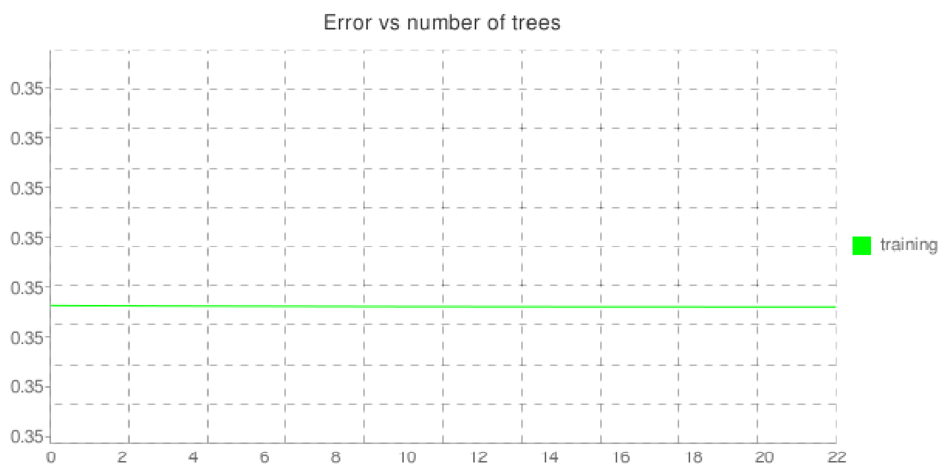
Status page

http://

BoostedTreeTrainer

Status overview:

Initialize Boosting	Done!
Mapreduce	In Progress
Clean Model	Pending
Napping at desk	Skipped



Active Workers:

To write: [redacted]
86 [redacted]/forest_builder-
071113beef7bcca4/building/grow_output_86

tasks: tree_id: 21
node(s): 3, 4

model_file: [redacted]/forest_builder-
071113beef7bcca4/model
nodes_in_model_file: 473
active_trees: 21

Initialization MapReduce

- Identifies all the attribute values which need to be considered for splits
- Continuous attributes
  - Compute an approximate equi-depth histogram*
  - Boundary points of histogram used for potential splits
- Categorical attributes
  - Identify attribute's domain
- Generates an “attribute file” to be loaded in memory by other tasks

*G. S. Manku, S. Rajagopalan, and B. G. Lindsay, SIGMOD, 1999.

FindBestSplit MapReduce

- MapReduce job to find best split when there is too much data to fit in memory
- Mapper
  - Initialize by loading attribute file from Initialization task and current model file
  - For each record run the Map algorithm
  - For each node output to all reducers
    <Node.Id, <Sum Result, Sum Squared Result, Count>>
  - For each split output <Split.Id, <Sum Result, Sum Squared Result, Count>>

```
Map(data):
    Node = TraverseTree(data, Model)
    if Node to be grown:
        Node.stats.AddData(data)
        for feature in data:
            Split = FindSplitForValue(Node.Id, feature)
            Split.stats.AddData(data)
```

FindBestSplit MapReduce

- MapReduce job to find best split when there is too much data to fit in memory
- Reducer (Continuous Attributes)
  - Load in all the <Node_Id, List<Sum Result, Sum Squared Result, Count>> pairs and aggregate the per_node statistics.
  - For each <Split_Id, List<Sum Result, Sum Squared Result, Count>> run the Reduce algorithm
  - For each Node_Id, output the best split found

```
Reduce(Split_Id, values):
    Split = NewSplit(Split_Id)
    best = FindBestSplitSoFar(Split.Node.Id)
    for stats in values
        split.stats.AddStats(stats)
    left = ComputeImpurity(split.stats)
    right = ComputeImpurity(split.node.stats – split.stats)
    split.impurity = left + right
    if split.impurity < best.impurity:
        UpdateBestSplit(Split.Node.Id, split)
```

FindBestSplit MapReduce

- MapReduce job to find best split when there is too much data to fit in memory
  - Reducer (Categorical Attributes)
    - Modification to reduce algorithm:
      - Compute the aggregate stats for each individual value
      - Sort values by average target value
      - Iterate through list and find optimal subsequence in list*

*L. Breiman, J. H. Friedman, R. Olshen, and C. Stone. *Classification and Regression Trees*. 1984.

InMemoryGrow MapReduce

- Task to grow an entire subtree once the data for it fits in memory
- Mapper
  - Initialize by loading current model file
  - For each record identify the node it falls under and if that node is to be grown, output <Node_Id, Record>
- Reducer
  - Initialize by loading attribute file from Initialization task
  - For each <Node_Id, List<Record>> run the basic tree growing algorithm on the records
  - Output the best splits for each node in the subtree

Ensembles

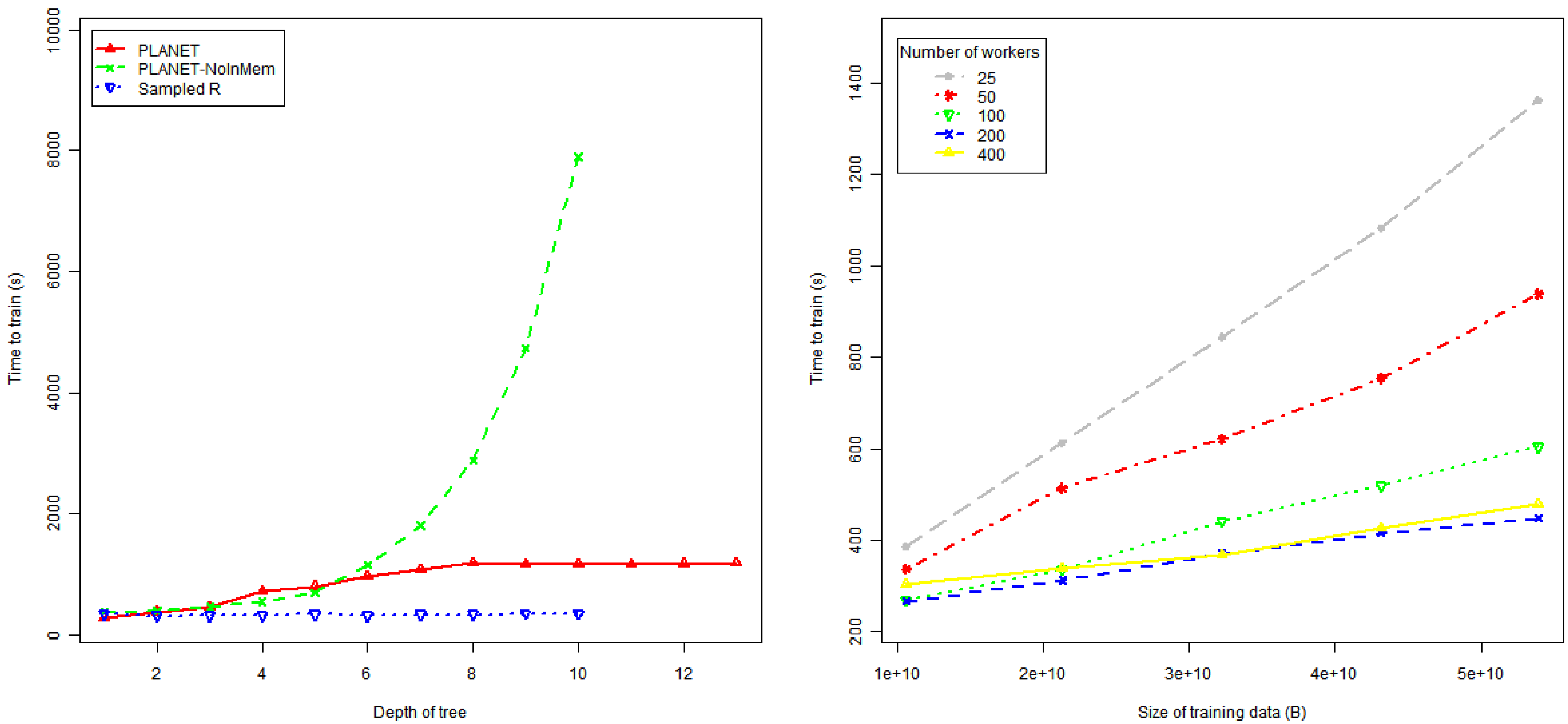
- Bagging
  - Construct multiple trees in parallel, each on a sample of the data
  - Sampling without replacement is easy to implement on the Mapper side for both types of MapReduce tasks
    - Compute a hash of <Tree_Id, Record_Id> and if it's below a threshold then sample it
  - Get results by combining the output of the trees
- Boosting
  - Construct multiple trees in a series, each on a sample of the data*
  - Modify the target of each record to be the residual of the target and the model's prediction for the record
    - For regression, the residual z is the target y minus the model prediction F(x)
    - For classification, $z = y - 1 / (1 + \exp(-F(x)))$
  - Get results by combining output from each tree

*J. H. Friedman. Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 2001.

Performance Issues

- Set up and Tear down
  - Per-MapReduce overhead is significant for large forests or deep trees
  - Reduce tear-down cost by polling for output instead of waiting for a task to return
  - Reduce start-up cost through forward scheduling
    - Maintain a set of live MapReduce jobs and assign them tasks instead of starting new jobs from scratch
- Categorical Attributes
  - Basic implementation stored and tracked these as strings
    - This made traversing the tree expensive
  - Improved latency by instead considering fingerprints of these values
- Very high dimensional data
  - If the number of splits is too large the Mapper might run out of memory
  - Instead of defining split tasks as a set of nodes to grow, define them as a set of nodes to grow and a set of attributes to explore.

Results



10000
8000
6000
4000
2000
0
Time to train (s)
PLANET
PLANET-NoInMem
Sampled R
2
4
6
8
10
12
Depth of tree
1400
1200
1000
800
600
400
200
Time to train (s)
Number of workers
25
50
100
200
400
1e+10
2e+10
3e+10
4e+10
5e+10
Size of training data (B)

Conclusions

- Large-scale learning is increasingly important
- Computing infrastructures like MapReduce can be leveraged for large-scale learning
- PLANET scales efficiently with larger datasets and complex models
- Future work
  - Adding support for sampling with replacement
  - Categorical attributes with large domains
    - Might run out of memory
      - Only support splitting on single values
      - Area for future exploration

- *Algorithm details and References to related work: In our VLDB’09 paper*

Thank You!

Q&A