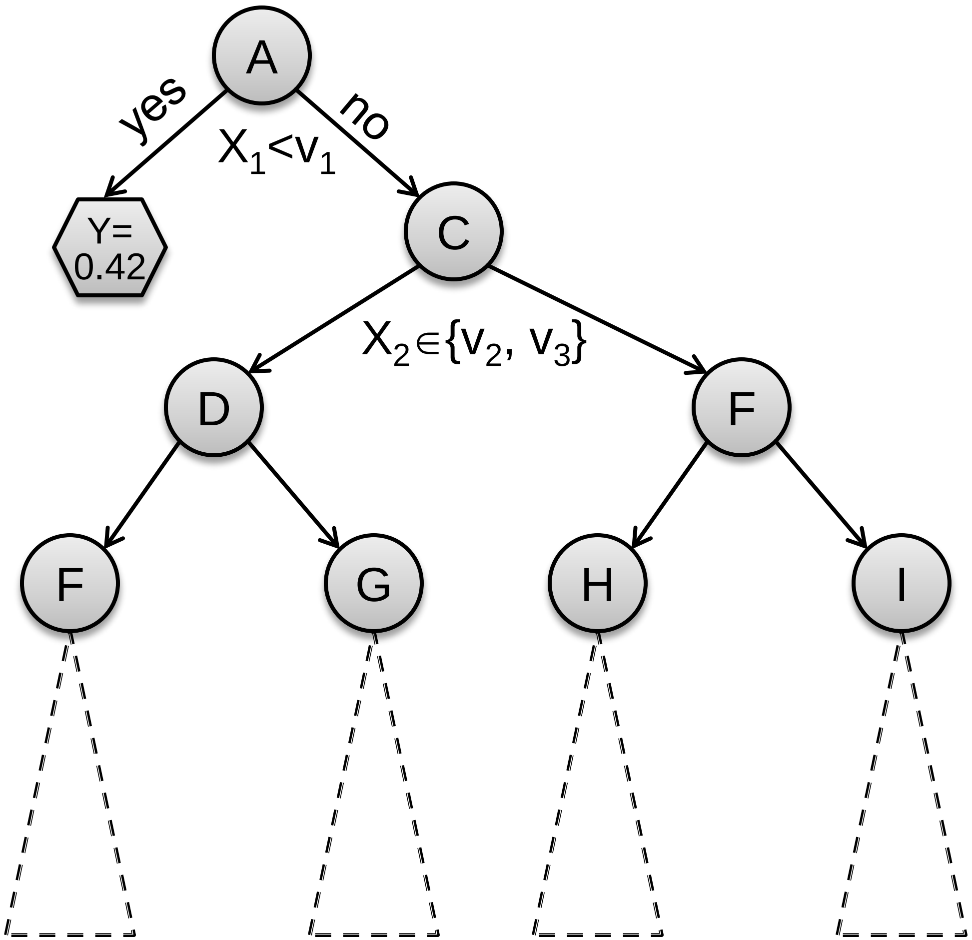
Decision Trees on MapReduce

CS246: Mining Massive Datasets
Jure Leskovec, Stanford University
http://cs246.stanford.edu

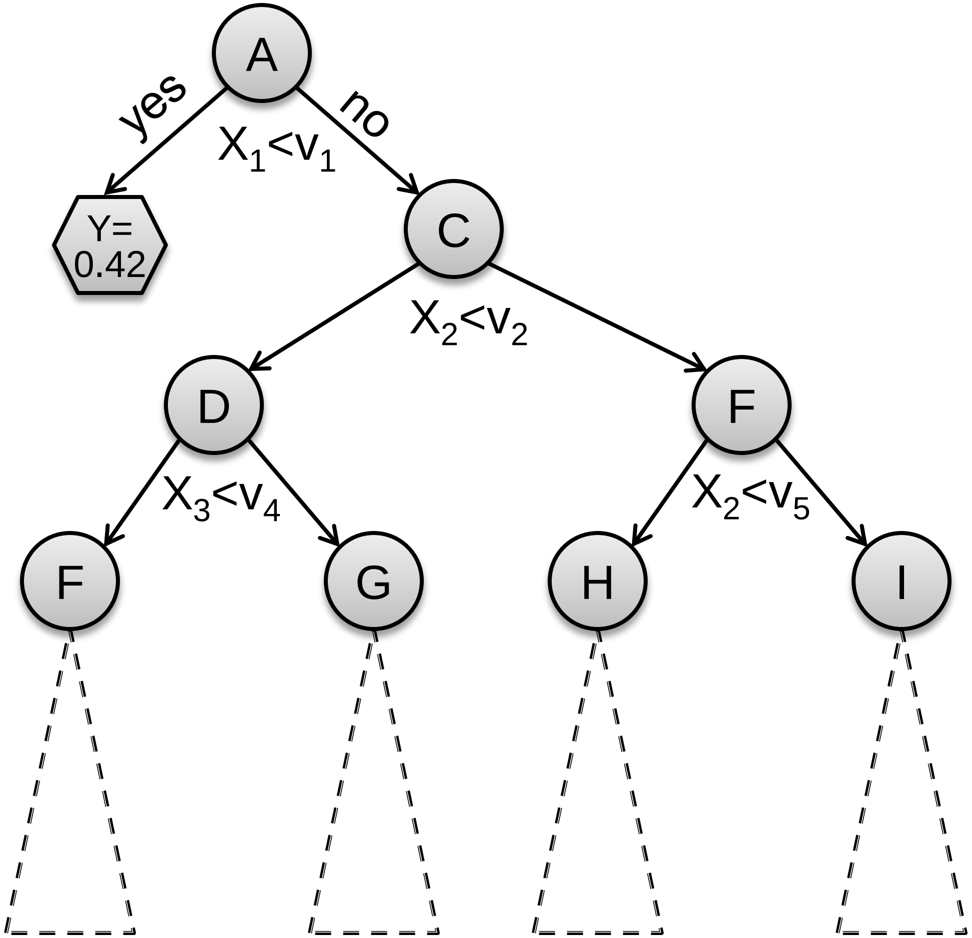
Decision Trees

- **Input features:**
  - N features: $X_1, X_2, \ldots X_N$
  - Each X_j has domain D_j
    - Categorical: D_j = {red, blue}
    - Numerical: $D_j = (0, 10)$
  - Y is output variable with domain D_Y:
    - Categorical: Classification
    - Numerical: Regression
- **Task:**
  - Given input data vector x_i predict y_i



Decision Trees (1)

- **Decision trees:**
  - Split the data at each internal node
  - Each leaf node makes a prediction
- **Lecture today:**
  - Binary splits: $X_j<v$
  - Numerical attrs.
  - Regression

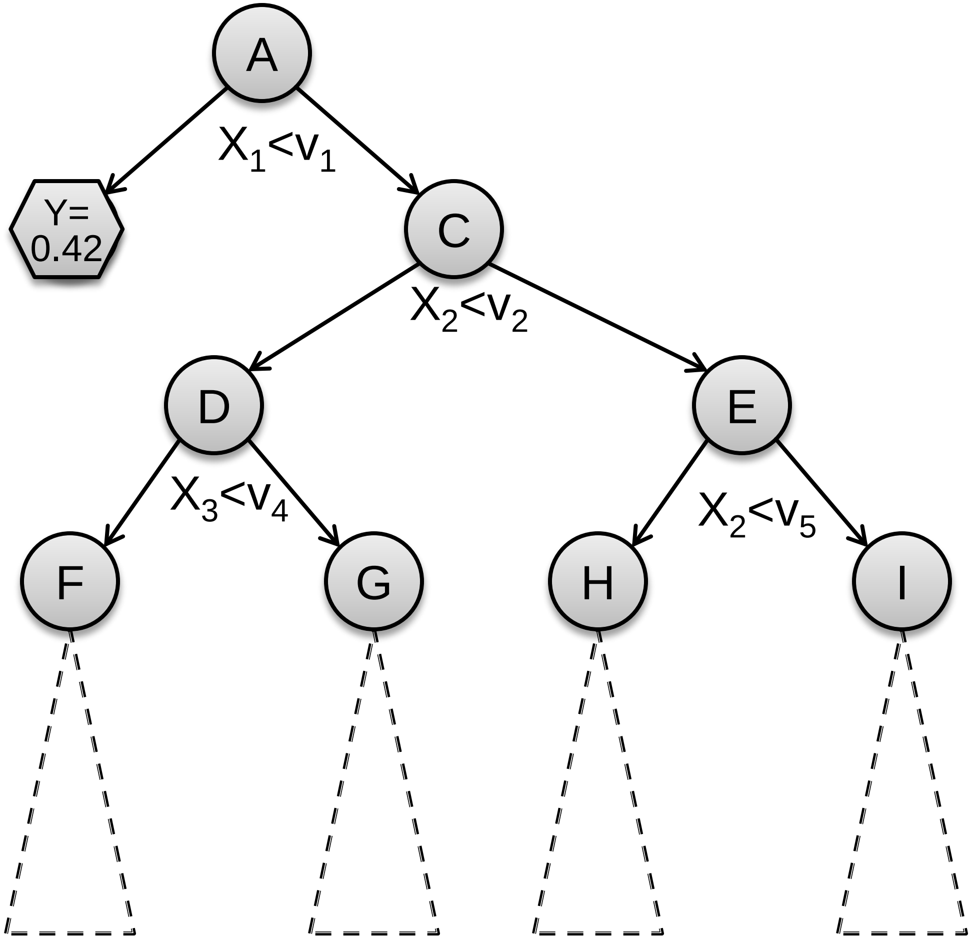


How to make predictions?

- **Input:** Example x_i
- **Output:** Predicted y_i'

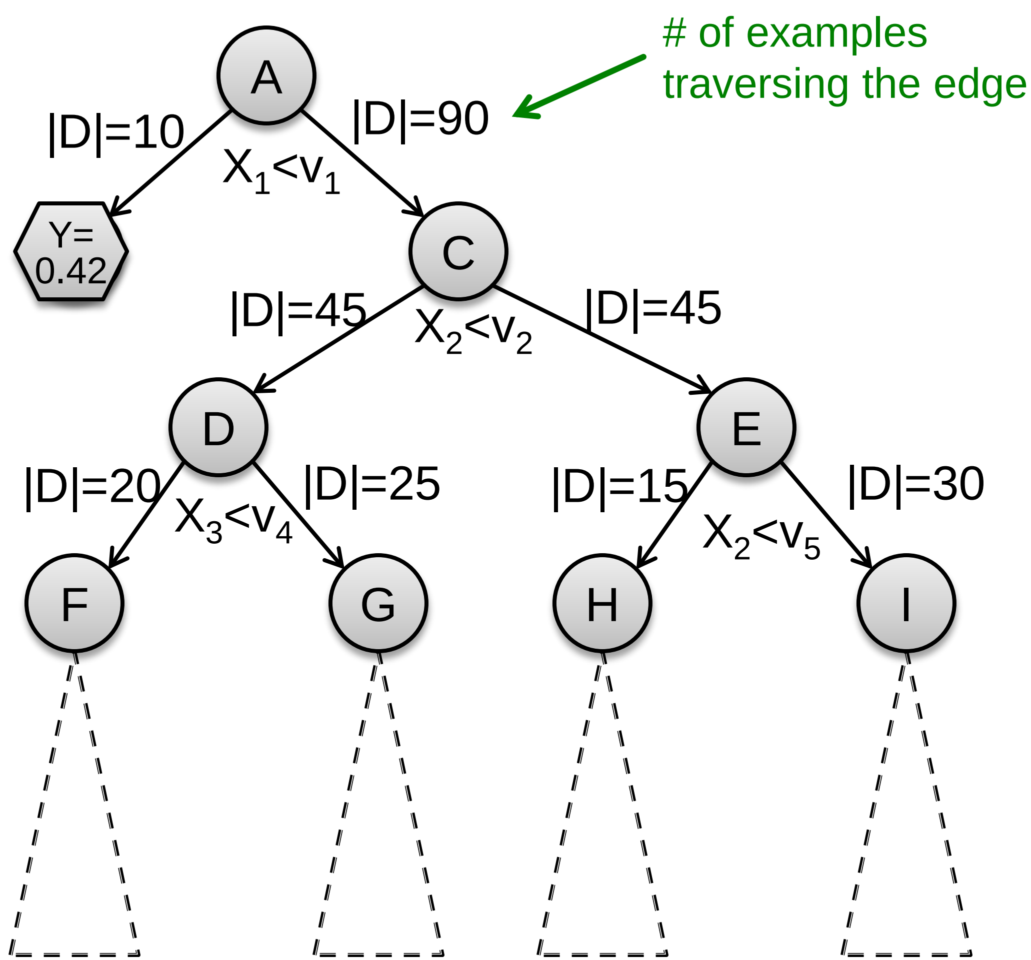
- "Drop" x_i down the tree until it hits a leaf node

- Predict the value stored in the leaf that x_i hits

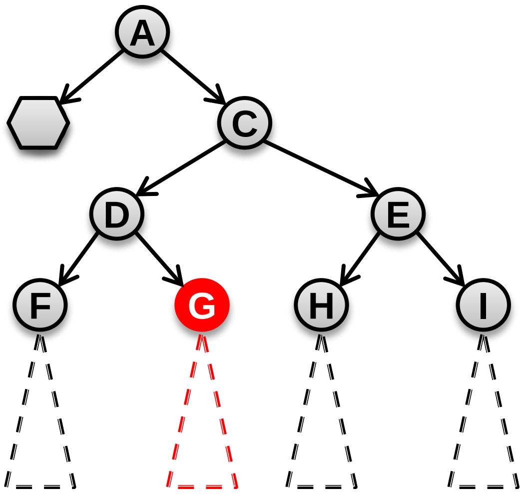


How to construct a tree?

- **Training dataset D*, |D*|=100 examples**



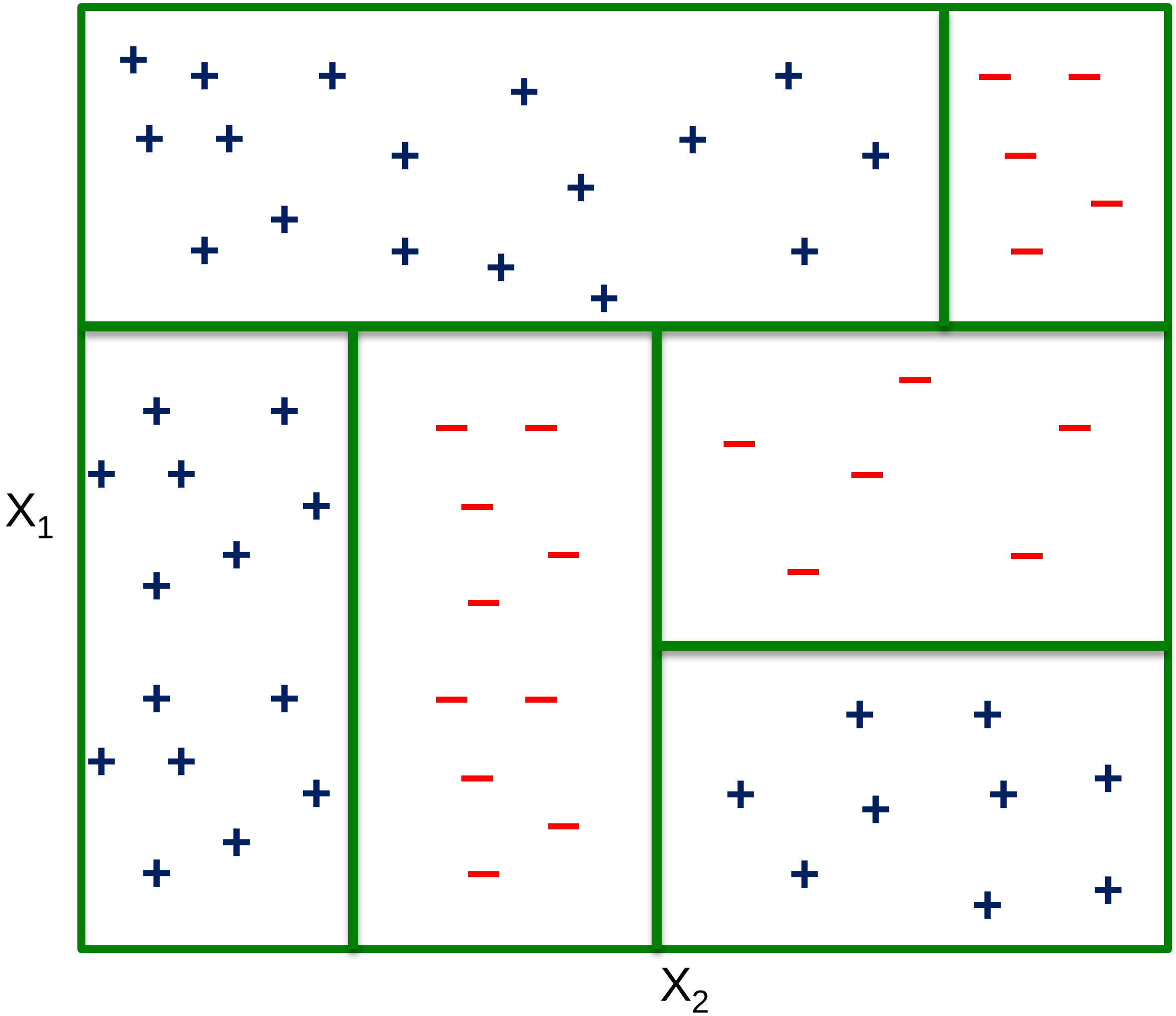
How to construct a tree?



- Imagine we are currently at some node *G*
  - Let D_G be the data reaches *G*
- There is a decision we have to make:
  Do we continue building the tree?
  - If so, which variable and which value do we use for a split?
  - If not, how do we make a prediction?
    - We need to build a "predictor node"

How to construct a tree?

- **Alternative view:**



How to construct a tree?

Algorithm 1 InMemoryBuildNode

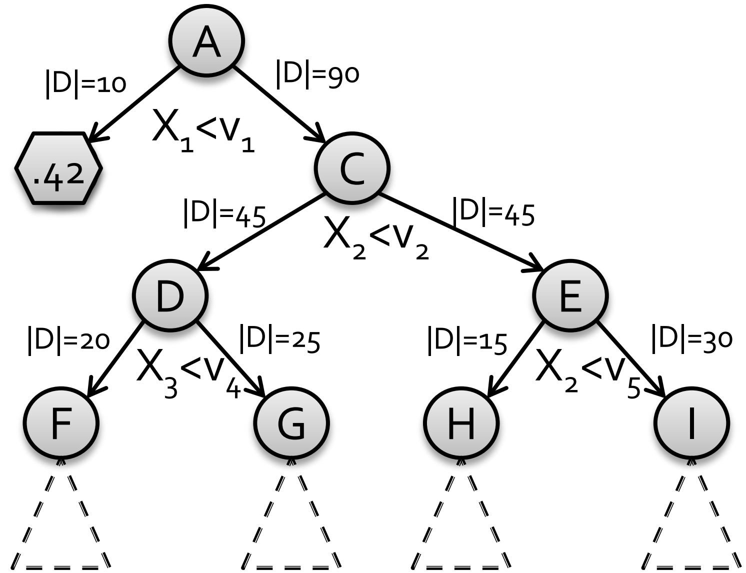
Require: Node n, Data $D \subset D^*$

$(n \rightarrow \text{split}, D_L, D_R) = \boxed{\text{FindBestSplit}(D)}$
if StoppingCriteria(D_L) **then**
    $n \rightarrow \text{left\_prediction} = \boxed{\text{FindPrediction}(D_L)}$
else
    InMemoryBuildNode$(n \rightarrow \text{left}, D_L)$
if $\boxed{\text{StoppingCriteria}(D_R)}$ **then**
    $n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)$
else
    InMemoryBuildNode$(n \rightarrow \text{right}, D_R)$

- **Requires at least a single pass over the data!**

How to construct a tree?

- **How to split?** Pick attribute & value that optimizes some criterion
- **Classification:** Information Gain
  - IG(Y|X) = H(Y) – H(Y|X)
    - Entropy: $H(Z) = -\sum_{j=1}^{m} p_j \log p_j$
    - Conditional entropy: $H(W|Z) = -\sum_{j=1}^{m} P(Z = v_j)\, H(W|Z = v_j)$
      - Suppose Z takes m values (v_1 … v_m)
      - H(W|Z=v) ... Entropy of W among the records in which Z has value v

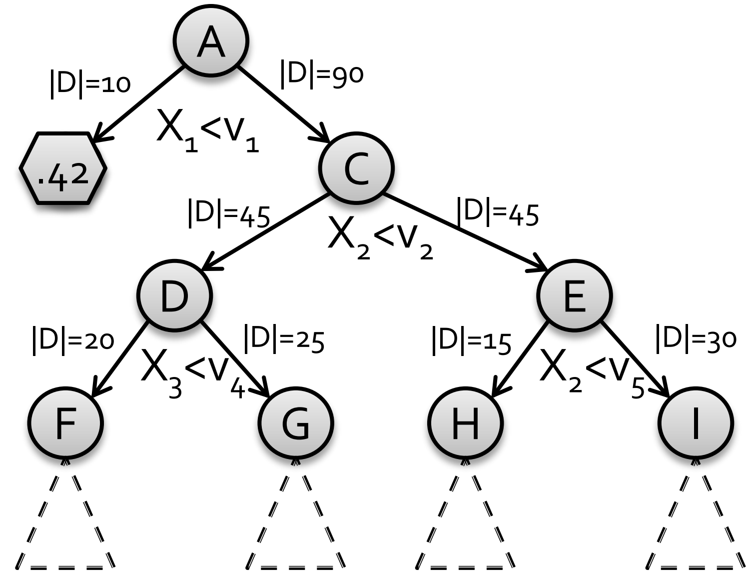


How to construct a tree?

- **How to split?** Pick attribute & value that optimizes some criterion
- **Regression:**
  - Find split (X_i, v) that creates D, D_L, D_R: parent, left, right child datasets and maximizes:

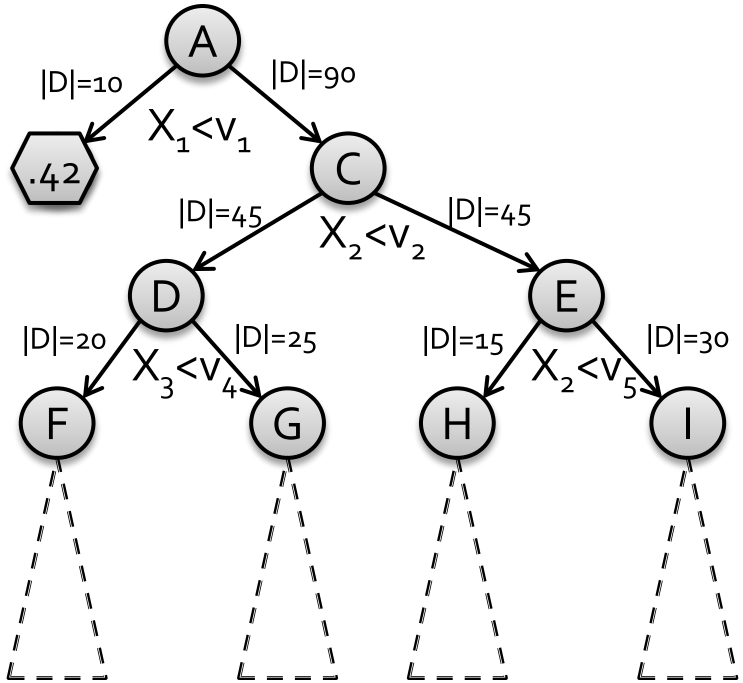
$$|D| \cdot Var(D) - \left(|D_L| \cdot Var(D_L) + |D_R| \cdot Var(D_R)\right)$$

    - For ordered domains sort X_i and consider a split between each pair of adjacent values
    - For categorical X_i find best split based on subsets (Breiman's algorithm)



How to construct a tree?

- **When to stop?**
  - **1) When the leaf is "pure"**
    - E.g., $Var(y_i) < \varepsilon$
  - **2) When # of examples in the leaf is too small**
    - E.g., $|D| \leq 10$
- **How to predict?**
  - **Predictor:**
    - **Regression:** Avg. y_i of the examples in the leaf
    - **Classification:** Most common y_i in the leaf



Building a tree using MapReduce

Problem: Building a tree

- Given a large dataset with hundreds of attributes
- **Build a decision tree!**

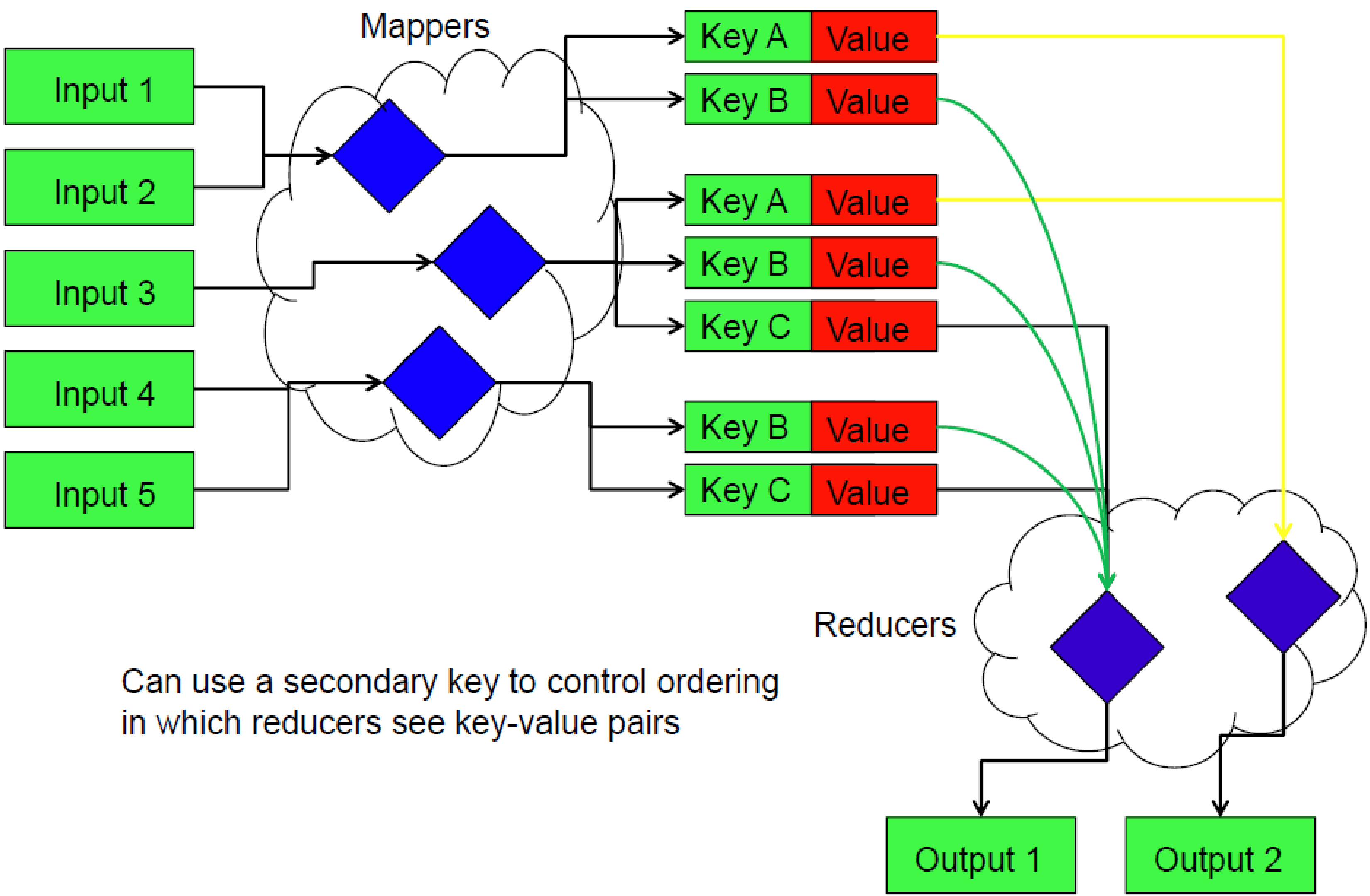
- **General considerations:**
  - Tree is small (can keep it memory):
    - Shallow (~10 levels)
  - Dataset too large to keep in memory
  - Dataset too big to scan over on a single machine
  - **MapReduce to the rescue!**

Algorithm 1 **FindBestSplit**

Require: Node n, Data $D \subseteq D^*$

```
(n →split, D_L, D_R) = FindBestSplit(D)
if StoppingCriteria(D_L) then
    n →left_prediction = FindPrediction(D_L)
else
        FindBestSplit(n →left, D_L)
if StoppingCriteria(D_R) then
    n →right_prediction = FindPrediction(D_R)
else
        FindBestSplit(n →right, D_R)
```

MapReduce



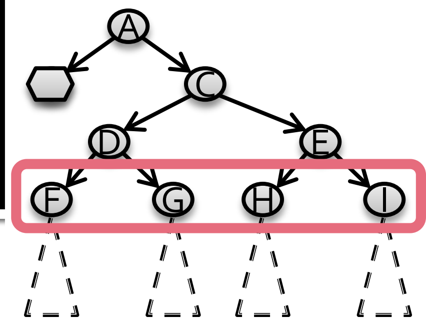
Can use a secondary key to control ordering in which reducers see key-value pairs

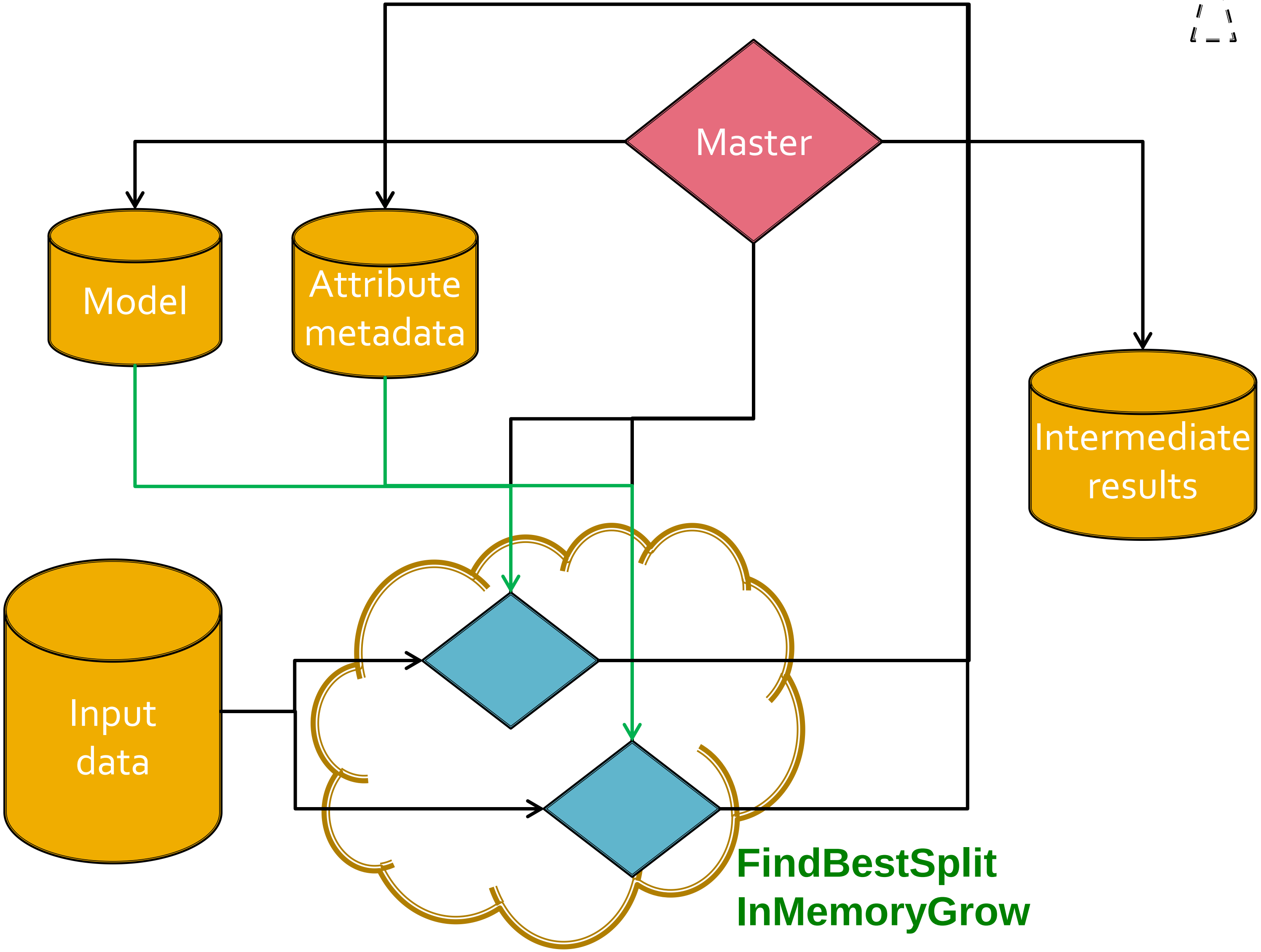
Today's Lecture: PLANET

Parallel **L**earner for **A**ssembling **N**umerous **E**nsemble **T**rees [Panda et al., VLDB '09]

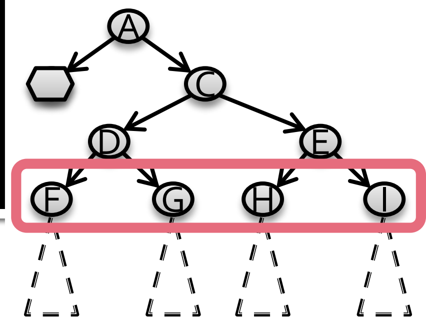
- A sequence of MapReduce jobs that build a decision tree
- **Setting:**
  - Hundreds of numerical (discrete & continuous) attributes
  - Target (class) is numerical: **Regression**
  - Splits are binary: $X_j < v$
  - Decision tree is small enough for each Mapper to keep it in memory
  - Data too large to keep in memory

PLANET Architecture



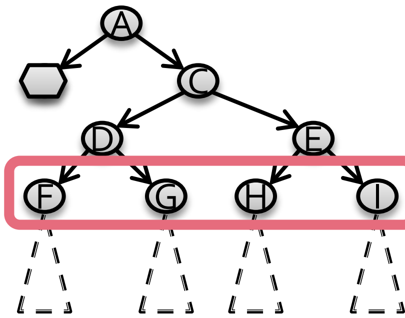


PLANET Overview



- **Mapper** loads the model and info about which attribute splits to consider
- Each mapper sees a subset of the data D*
- Mapper "drops" each datapoint to find the appropriate leaf node *L*
- For each leaf node *L* it keeps statistics about
  - 1) the data reaching *L*
  - 2) the data in left/right subtree under split *S*
- **Reducer** aggregates the statistics (1) and (2) and determines the best split for each node

PLANET: Components



- **Master**
  - Monitors everything (runs multiple MapReduce jobs)
- **MapReduce Initialization**
  - For each attribute identify values to be considered for splits
- **MapReduce FindBestSplit**
  - MapReduce job to find best split when there is too much data to fit in memory
- **MapReduce InMemoryBuild**
  - Similar to FindBestSplit (but for small data)
  - Grows an entire sub-tree once the data fits in memory
- **Model file**
  - A file describing the state of the model

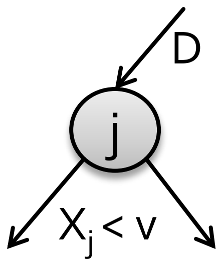
Algorithm 1 **FindBestSplit**

Require: Node n, Data $D \subset D^*$

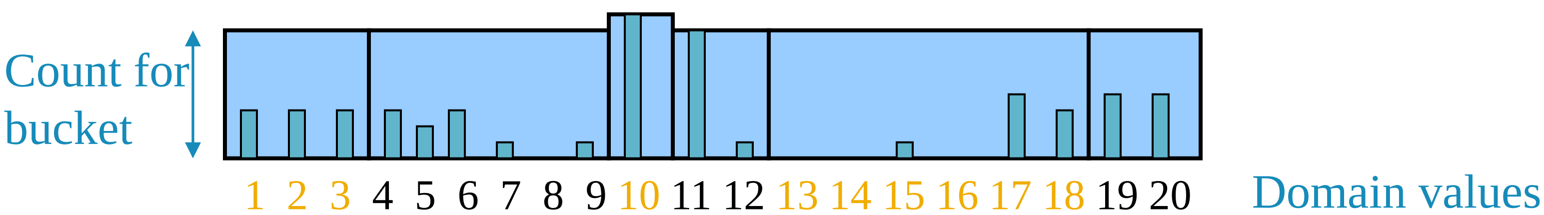
$(n \rightarrow \text{split}, D_L, D_R) =$ $\boxed{\textbf{FindBestSplit}(D)}$
if StoppingCriteria(D_L) then
  $n \rightarrow$ left_prediction=FindPrediction(D_L)
else
  FindBestSplit$(n \rightarrow \text{left}, D_L)$
if StoppingCriteria(D_R) then
  $n \rightarrow$ right_prediction=FindPrediction(D_R)
else
  FindBestSplit$(n \rightarrow \text{right}, D_R)$

Hardest part

Initialization: Attribute metadata

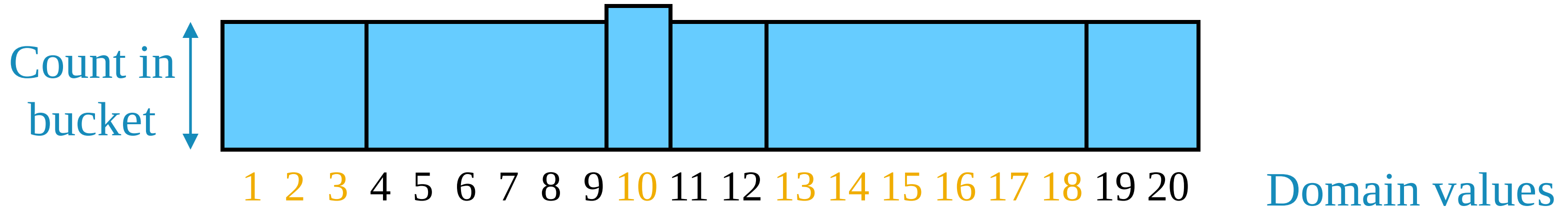


- Identifies all the attribute values which need to be considered for splits
- **Splits for numerical attributes:**
  - Would like to consider very possible value $v \in D$
  - Compute an approximate equi-depth histogram on D^*
    - **Idea:** Select buckets such that counts per bucket are equal



  - **Use boundary points of histogram as potential splits**
- Generates an "attribute metadata" to be loaded in memory by other tasks

Side note: Computing Equi-Depth

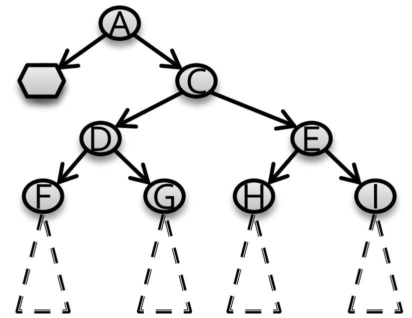


- **Goal:**
  - Equal number of elements per bucket (*B* buckets total)
- Construct by first sorting and then taking B-1 equally-spaced splits

1 2 2 3 4 7 8 9 10 10 10 10 11 11 12 12 14 16 16 18 19 20 20 20

- **Faster construction:** Sample & take equally-spaced splits in the sample
  - Nearly equal buckets

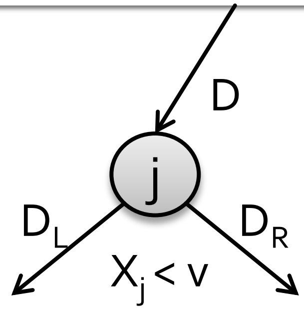
PLANET: Master



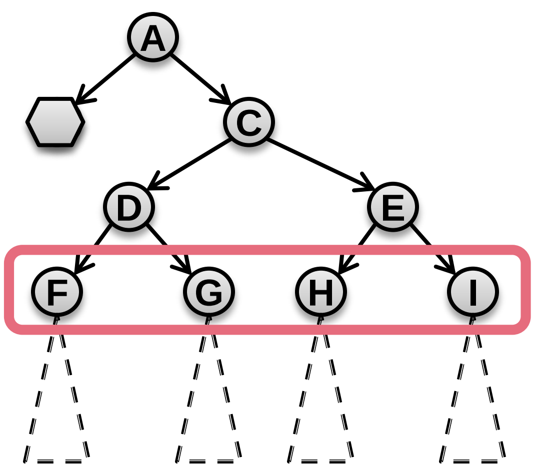
- Controls the entire process
- **Determines the state of the tree and grows it:**
  - Decides if nodes should be split
  - If there is little data entering a node, runs an <u>InMemory-Build</u> MapReduce job to grow the entire subtree
  - For larger nodes, launches MapReduce <u>FindBestSplit</u>
    to find candidates for best split
  - Collects results from MapReduce jobs and chooses the best split for a node
  - Updates model

PLANET: Master

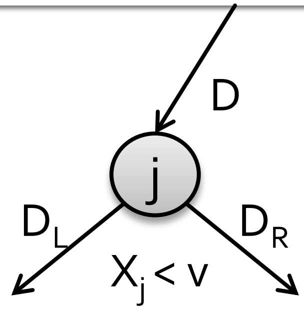
- **Master keeps two node queues:**
  - **MapReduceQueue (MRQ)**
    - Nodes for which *D* is too large to fit in memory
  - **InMemoryQueue (InMemQ)**
    - Nodes for which the data D in the node fits in memory



- **The tree will be built in levels**
  - Epoch by epoch



PLANET: Master



- **Two MapReduce jobs:**
  - **FindBestSplit:** Processes nodes from the MRQ
    - For a given set of nodes *S*, computes a candidate of good split predicate for each node in *S*
  - **InMemoryBuild:** Processes nodes from the InMemQ
    - For a given set of nodes *S*, completes tree induction at nodes in *S* using the InMemoryBuild algorithm
- Start by executing FindBestSplit on full data *D**

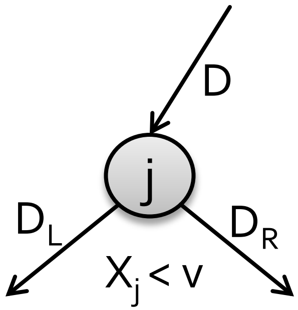
FindBestSplit

- MapReduce job to find best split when there is too much data to fit in memory
- **Goal:** For a particular split node find attribute X_j and value v that maximize:

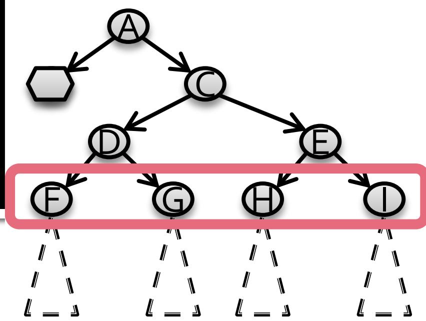
$$|D| \times Var(D) - (|D_L| \times Var(D_L) + |D_R| \times Var(D_R))$$

  - D … training data (x_i, y_i) reaching the node
  - D_L … training data x_i, where $x_{i,j} < v$
  - D_R … training data x_i, where $x_{i,j} \geq v$
  - $Var(D) = 1/(n-1) \ \Sigma_i y_i^2 - (\Sigma_i y_i)^2/n$

  Note: Can be computed from sufficient statistics: Σy_i, Σy_i^2

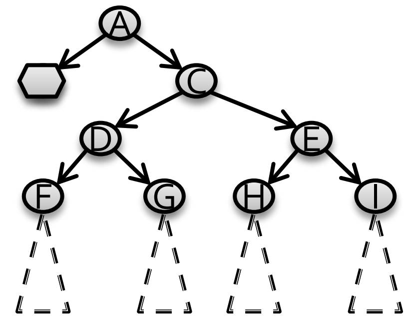


FindBestSplit: Map



- **Mapper:**
  - Initialize by loading from Initialization task
    - Current Model (to find which node each x_i ends up)
    - Attribute metadata (all split points for each attribute)
  - For each record run the Map algorithm
  - For each node store statistics and at the end emit (to all reducers):
    - <Node.Id, $\{ \Sigma y, \Sigma y^2, \Sigma 1 \}$ >
  - For each split store statistics and at the end emit:
    - <Split.Id, $\{ \Sigma y, \Sigma y^2, \Sigma 1 \}$ >
      - Split.Id = (node, feature, split value)

FindBestSplit: Map



- Requires: Split node set S, Model file M, Training record (x_i, y_i)

Node n = TraverseTree(M, x_i)

if $n \in S$:

  Update $T_n \leftarrow y_i$ //stores $\{\Sigma y, \Sigma y_2, \Sigma 1\}$ for each node

  for j = 1 … N: // N… number of features

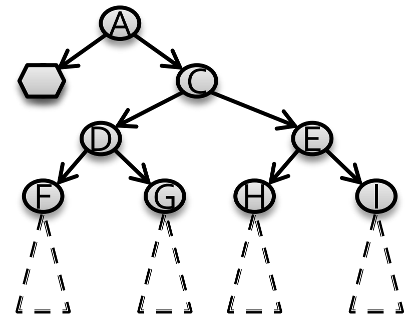
    v = value of feature X_j of example x_i

    for each split point *s* of feature X_j, s.t. s < v:

      Update $T_{n,j}[s] \leftarrow y_i$ //stores $\{\Sigma y, \Sigma_, y_2, \Sigma 1\}$ for each (node, feature, split)

- **MapFinalize: Emit**
  - <Node.Id, $\{ \Sigma y, \Sigma y^2, \Sigma 1 \}$ > // sufficient statistics (so we can later
  - <Split.Id, $\{ \Sigma y, \Sigma y^2, \Sigma 1 \}$ > // compute variance reduction)

FindBestSplit: Reducer

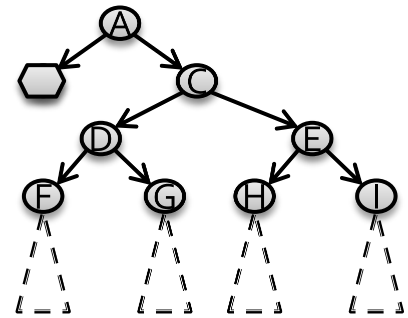


Reducer:

- 1) Load all the <Node_Id, List $\{\Sigma y, \Sigma y^2, \Sigma 1\}$> pairs and **aggregate** the per node statistics
- 2) For all the <Split_Id, List $\{\Sigma y, \Sigma y^2, \Sigma 1\}$> **aggregate** and run the reduce algorithm
- **For each Node_Id, output the best split found:**

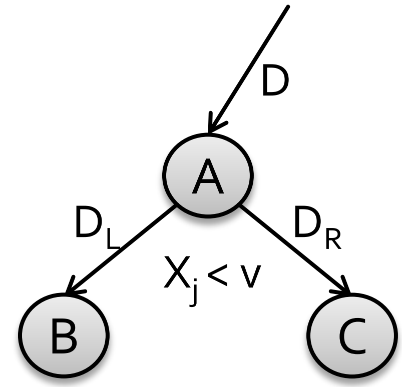
```
Reduce(Split_Id, values):
    split = NewSplit(Split_Id)
    best = BestSplitSoFar(split.node.id)
    for stats in values
        split.stats.AddStats(stats)
    left = GetImpurity(split.stats)
    right = GetImpurity(split.node.stats–split.stats)
    split.impurity = left + right
    if split.impurity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

Back to the Master



- Collects outputs from FindBestSplit reducers

  <Split.Node.Id, feature, value, impurity>
- For each node decides the best split
  - If data in D_L/D_R is small enough put the nodes in the InMemoryQueue
    - to later run InMemoryBuild on the node
  - Else put the nodes into MapReduceQueue

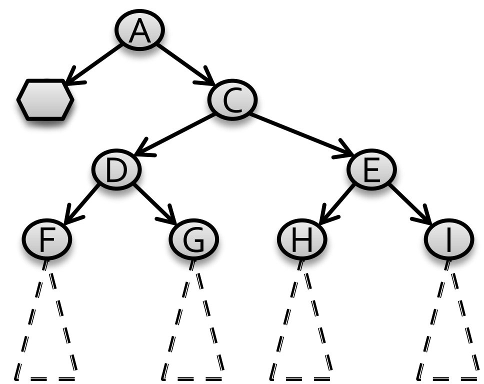


InMemoryBuild: Map and Reduce

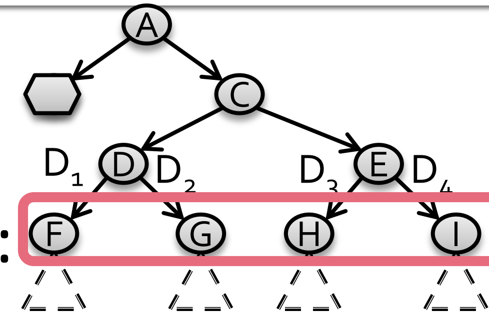
- **Task:** Grow an entire subtree once the data fits in memory
- **Mapper:**
  - Initialize by loading current model file
  - For each record identify the node it falls under and if that node is to be grown, output <Node_Id, Record>
- **Reducer:**
  - Initialize by loading attribute file from Initialization 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

Algorithm 1 InMemoryBuildNode

```
Require: Node n, Data D ⊆ D*
(n →split,D_L,D_R)=FindBestSplit(D)
if StoppingCriteria(D_L) then
    n →left_prediction=FindPrediction(D_L)
else
    InMemoryBuildNode(n →left,D_L)
if StoppingCriteria(D_R) then
    n →right_prediction=FindPrediction(D_R)
else
    InMemoryBuildNode(n →right,D_R)
```



Overall system architecture



- Need to split nodes F, G, H, I
- D_1, D_4 small, run InMemoryGrow
- D_2, D_3 too big, run FindBestSplit({G, H}):
  - **FindBestSplit::Map** (each mapper)
    - Load the current model M
    - Drop every example x_i down the tree
    - If it hits *G* or *H*, update in-memory hash tables:
      - For each node: T_n: (node)$\rightarrow\{\Sigma y, \Sigma y^2, \Sigma 1\}$
      - For each split,node: $T_{n,j,s}$: (node, attribute, split_value)$\rightarrow\{\Sigma y, \Sigma y^2, \Sigma 1\}$
    - Map::Finalize: output the key-value pairs from above hashtables
  - **FindBestSplit::Reduce** (each reducer)
    - Collect:
      - T1:<node, List$\{\Sigma y, \Sigma y^2, \Sigma 1\}$ > $\rightarrow$ <node, $\{\Sigma\ \Sigma y, \Sigma\ \Sigma y^2, \Sigma\ \Sigma 1\}$ >
      - T2:<(node, attr. split), List$\{\Sigma y, \Sigma y^2, \Sigma 1\}$> $\rightarrow$ <(node, attr. split), $\{\Sigma\Sigma y, \Sigma\Sigma y^2, \Sigma\Sigma 1\}$>
    - Compute impurity for each node using T1, T2
    - Return best split to Master (that decides on the globally best spit)

Practical considerations

- We need one pass over the data to construct one level of the tree!
- **Set up and tear down**
  - Per-MapReduce overhead is significant
    - Starting/ending MapReduce job costs time
  - 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

Practical considerations

- **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
    - This way each mapper explores a smaller number of splits (needs less memory)

Learning Ensembles

- **Learn multiple trees and combine their predictions**
  - Gives better performance in practice
- **Bagging:**
  - Learns multiple trees over independent samples of the training data
  - Predictions from each tree are averaged to compute the final model prediction

Bagged Decision Trees

- **Model construction for bagging in PLANET**
  - When tree induction begins at the root, nodes of all trees in the bagged model are pushed onto the MRQ queue
  - Controller does tree induction over dataset samples
    - Queues will contain nodes belonging to many different trees instead of a single tree
- **How to create random samples of D*?**
  - Compute a hash of a training record's id and tree id
  - Use records that hash into a particular range to learn a tree
  - This way the same sample is used for all nodes in a tree
  - **Note:** This is sampling D* without replacement (but samples of D* should be created with replacement)

SVM vs. DT

- **SVM**
  - Classification
  - Real valued features (no categorical ones)
  - Tens/hundreds of thousands of features
  - Very sparse features
  - Simple decision boundary
    - No issues with overfitting
- Example applications
  - Text classification
  - Spam detection
  - Computer vision

- **Decision trees**
  - Classification
  - Real valued and categorical features
  - Few (hundreds) of features
  - Usually dense features
  - Complicated decision boundaries
    - Overfitting!
- Example applications
  - User profile classification
  - Landing page bounce prediction

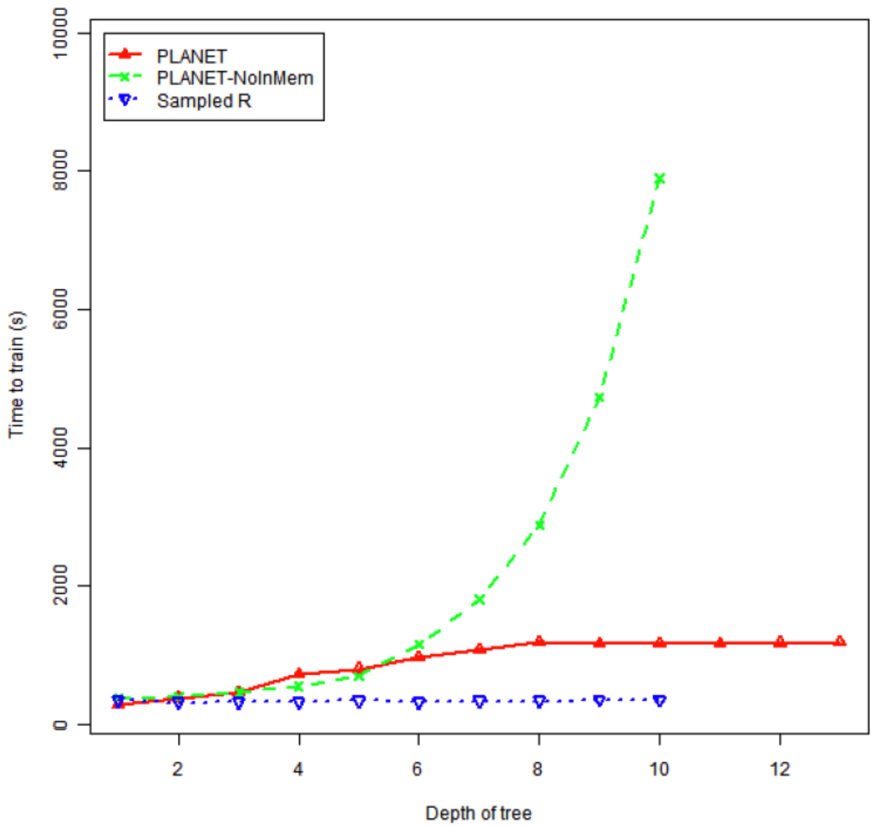
Experiments: Bounce Rate Prediction

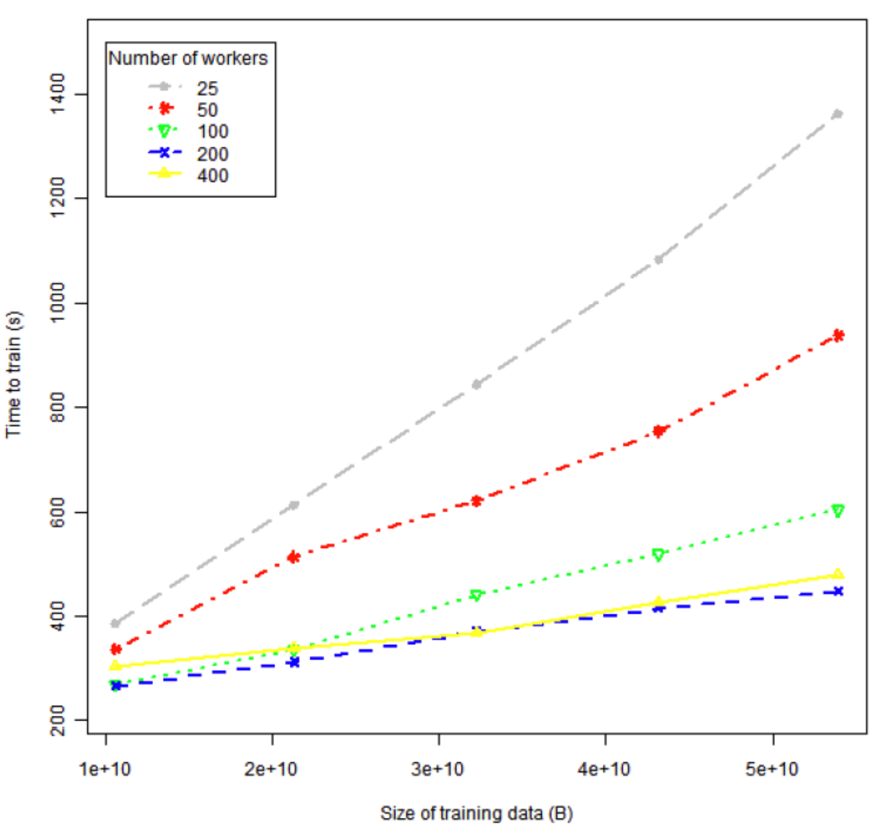
- **Google:** Bounce rate of ad = fraction of users who **bounced from ad landing page**
  - Clicked on ad and quickly moved on to other tasks
  - Bounce rate high --> users not satisfied
- **Prediction goal:**
  - Given an new add and a query
  - Predict bounce rate using query/ad features
- **Feature sources:**
  - Query
  - Ad keyword
  - Ad creative
  - Ad landing page

Experimental Setup

- **MapReduce Cluster**
  - 200 machines
  - 768MB RAM, 1GB Disk per machine
  - 3 MapReduce jobs forward-scheduled
- **Full Dataset:** 314 million records
  - 6 categorical features, cardinality varying from 2-500
  - 4 numeric features
- Compare performance of PLANET on whole data with *R* on sampled data
  - *R* model trains on 10 million records (~ 2GB)
  - Single machine: 8GB, 10 trees, each of depth 1-10
  - Peak RAM utilization: 6GB

Results: Scalability





Results: Prediction accuracy

- Prediction accuracy (RMSE) of PLANET on full data better than *R* on sampled data

Reference

- B. Panda, J. S. Herbach, S. Basu, and R. J. Bayardo. PLANET: Massively parallel learning of tree ensembles with MapReduce. *VLDB* 2009.
- J. Ye, J.-H. Chow, J. Chen, Z. Zheng. Stochastic Gradient Boosted Distributed Decision Trees. CIKM 2009.