Announcements:
- Project Milestone feedback
- HW4 is out (due Sat, June 1)

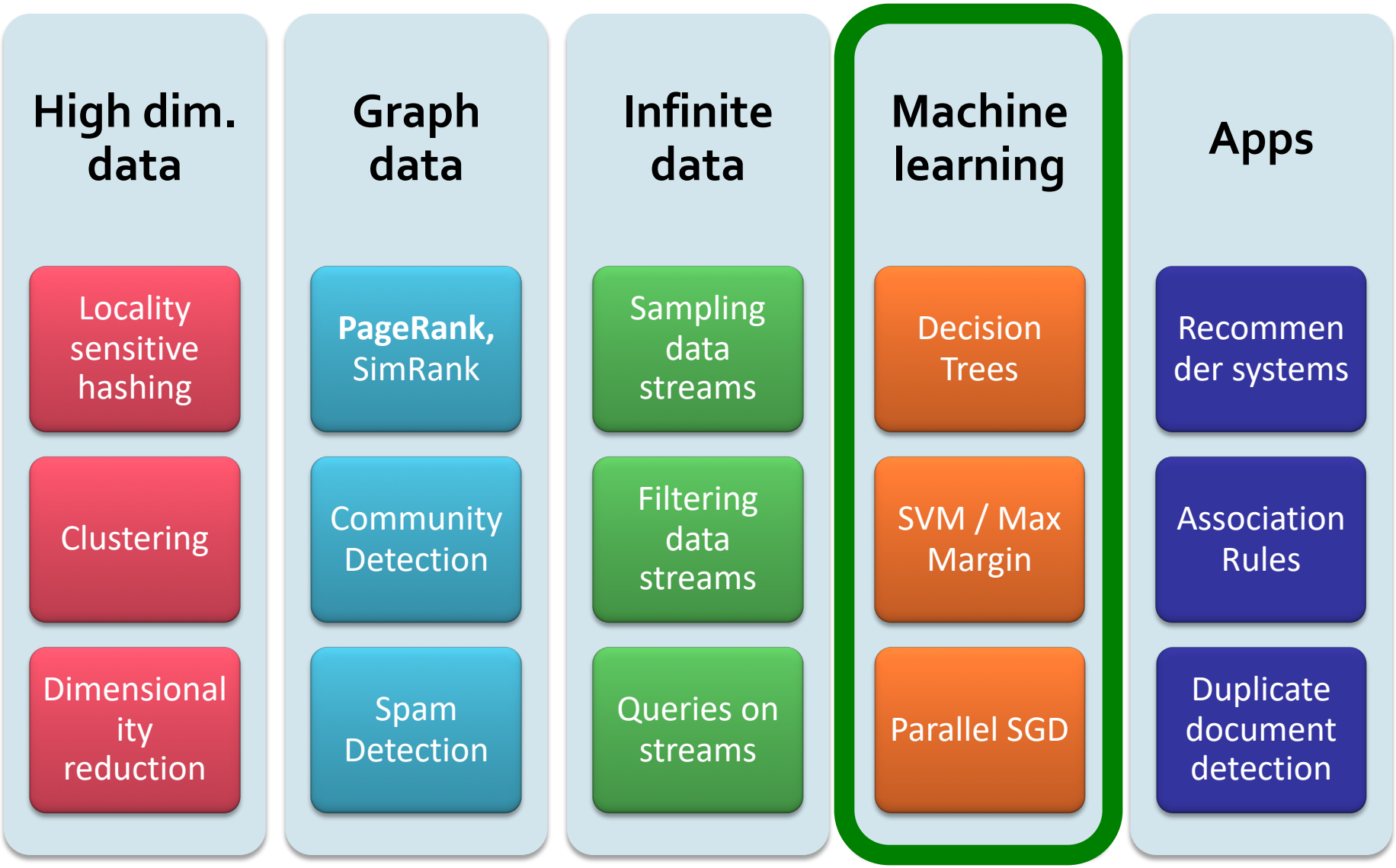
Large-Scale Machine Learning (1)

CS547 Machine Learning for Big Data

Tim Althoff

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

New Topic: ML that scales!



Supervised Learning

Given some data:

- "Learn" a function to map from the **input** to the **output**

- **Given:**

  Training examples $\left(\boldsymbol{x_i}, \boldsymbol{y_i} = \boldsymbol{f}(\boldsymbol{x_i})\right)$ for some unknown function $\boldsymbol{f}$
- **Find:**

  A good approximation to $\boldsymbol{f}$

Many Other ML Paradigms

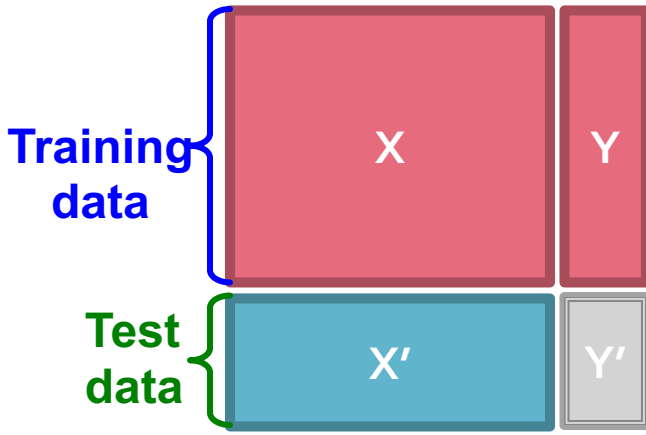
- **Supervised:**
  - Given "labeled data" $\{x, y\}$, learn $f(x) = y$
- **Unsupervised:**
  - Given only "unlabeled data" $\{x\}$, learn $f(x)$
- **Semi-supervised:**
  - Given some labeled $\{x, y\}$ and some unlabeled data $\{x\}$, learn $f(x) = y$
- **Active learning:**
  - When we predict $f(x) = y$, we then receive true y^*
- **Transfer learning:**
  - Learn $f(x)$ so that it works well on new domain $f(z)$

Supervised Learning

- **Would like to do prediction:**
  estimate a function $f(x)$ so that $y = f(x)$
- **Where *y* can be:**
  - **Continuous / Real number:** Regression
  - **Categorical: Classification**
  - **Complex object:**
    - Ranking of items, Parse tree, etc.
- **Data is labeled:**
  - Have many pairs $\{(x, y)\}$
    - **x** … vector of binary, categorical, real valued features
    - **y** … class, or a real number

Supervised Learning

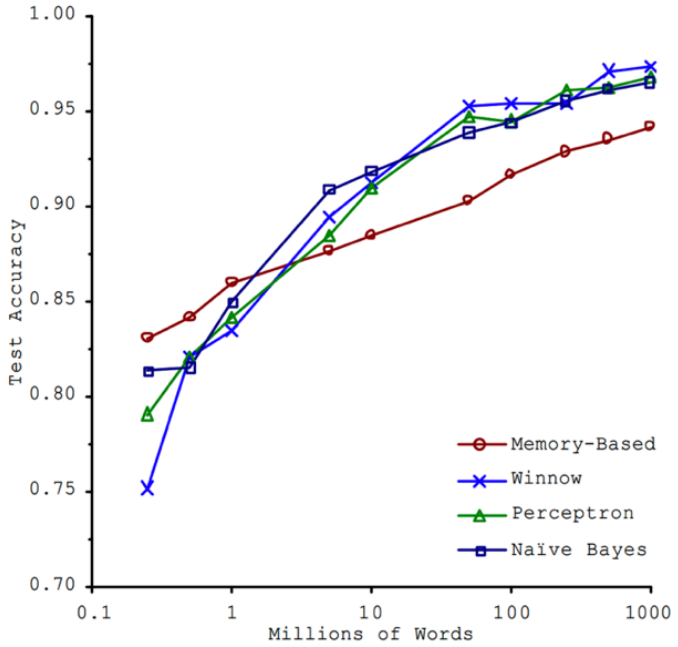
- **Task:** Given data (X, Y) build a model $f()$ to predict Y' based on X'
- **Strategy:** **Estimate $y = f(x)$ on (X, Y)**
  Hope that the same $f(x)$ also works to predict unknown Y'



  - The **"hope"** is called **generalization**
    - **Overfitting:** **If $f(x)$ predicts well Y but is unable to predict Y'**
  - **We want to build a model that generalizes well to unseen data**

Why Large-Scale ML?

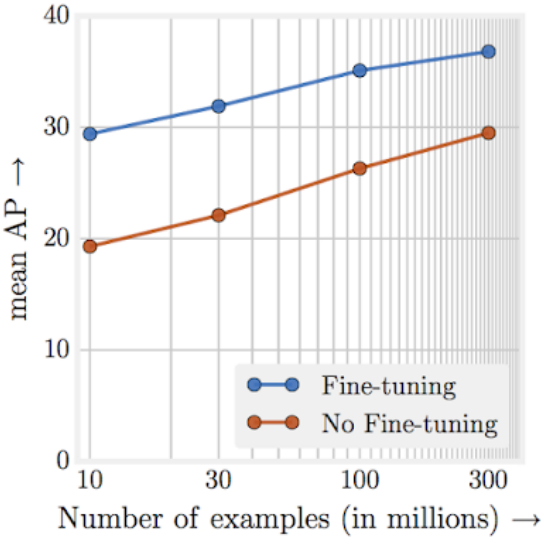
- **Brawn or Brains?**
  - In 2001, Microsoft researchers ran a test to evaluate 4 of different approaches to ML-based language translation
- **Findings:**
  - **Size of the dataset** used to train the model **mattered more** than the model itself
  - As the dataset grew large, performance difference between the models became small



Banko, M. and Brill, E. (2001) , "Scaling to Very Very Large Corpora for Natural Language Disambiguation"

Why Large-Scale ML?

- **The Unreasonable Effectiveness of Big Data**
  - In 2017, Google revisited the same type of experiment with the latest Deep Learning models in computer vision
- **Findings:**
  - Performance increases logarithmically **based on volume of training data**
  - Complexity of modern ML models (i.e., deep neural nets) allows for even **further performance gains**



- **Large datasets + large ML models => amazing results!!**

"Revisiting Unreasonable Effectiveness of Data in Deep Learning Era": https://arxiv.org/abs/1707.02968

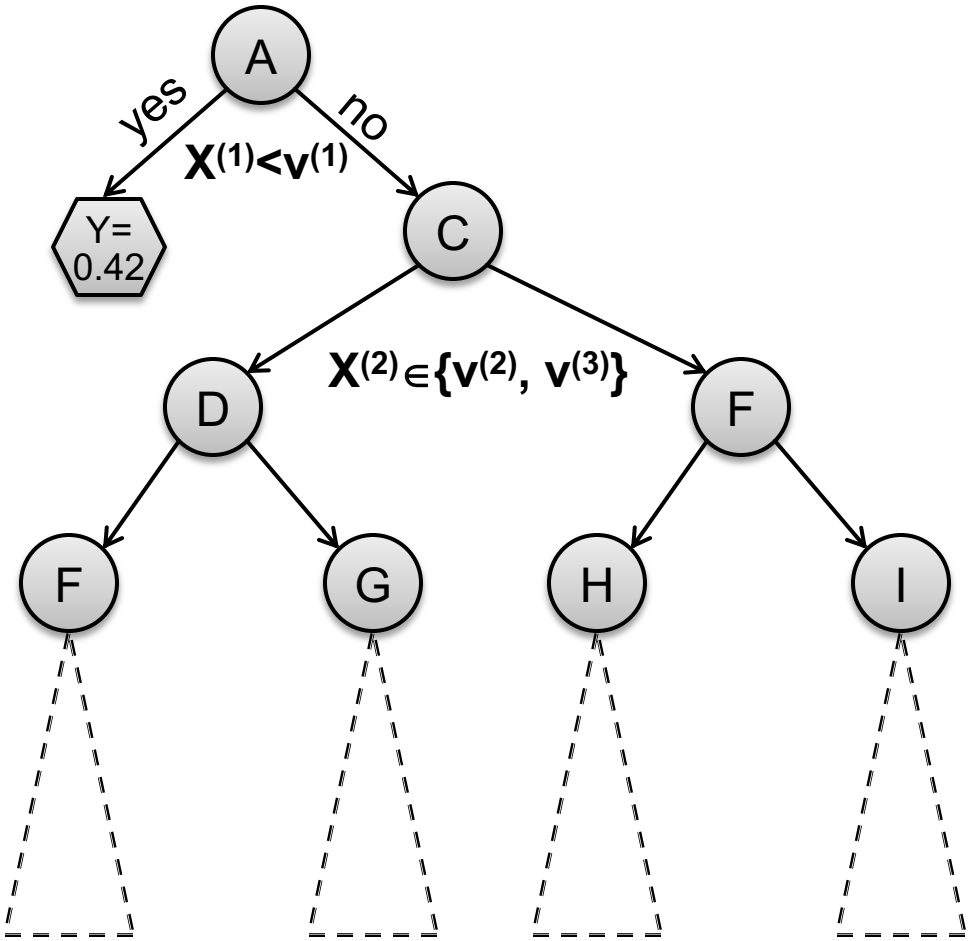
Decision Trees

Decision Tree Learning

- **Given one attribute (e.g., lifespan), try to predict the value of new people's lifespans by means of some of the other available attribute**
- **Input attributes:**
  - **d** features/attributes: $\boldsymbol{x^{(1)}}, \boldsymbol{x^{(2)}}, \ldots\ \boldsymbol{x^{(d)}}$
  - Each $\boldsymbol{x^{(j)}}$ has **domain** $\boldsymbol{O_j}$
    - **Categorical:** $\boldsymbol{O_j} = \{brown, blue, gray\}$
    - **Numerical:** $\boldsymbol{H_j} = (0, 10)$
  - $\boldsymbol{Y}$ is output variable with domain $\boldsymbol{O_Y}$:
    - **Categorical:** Classification, **Numerical:** Regression
- **Data D:**
  - $\boldsymbol{n}$ examples $(\boldsymbol{x_i}, \boldsymbol{y_i})$ where $\boldsymbol{x_i}$ is a $\boldsymbol{d}$-dim feature vector, $\boldsymbol{y_i} \in \boldsymbol{O_Y}$ is output variable
- **Task:**
  - Given an input data vector $\boldsymbol{x}$ predict output label $\boldsymbol{y}$

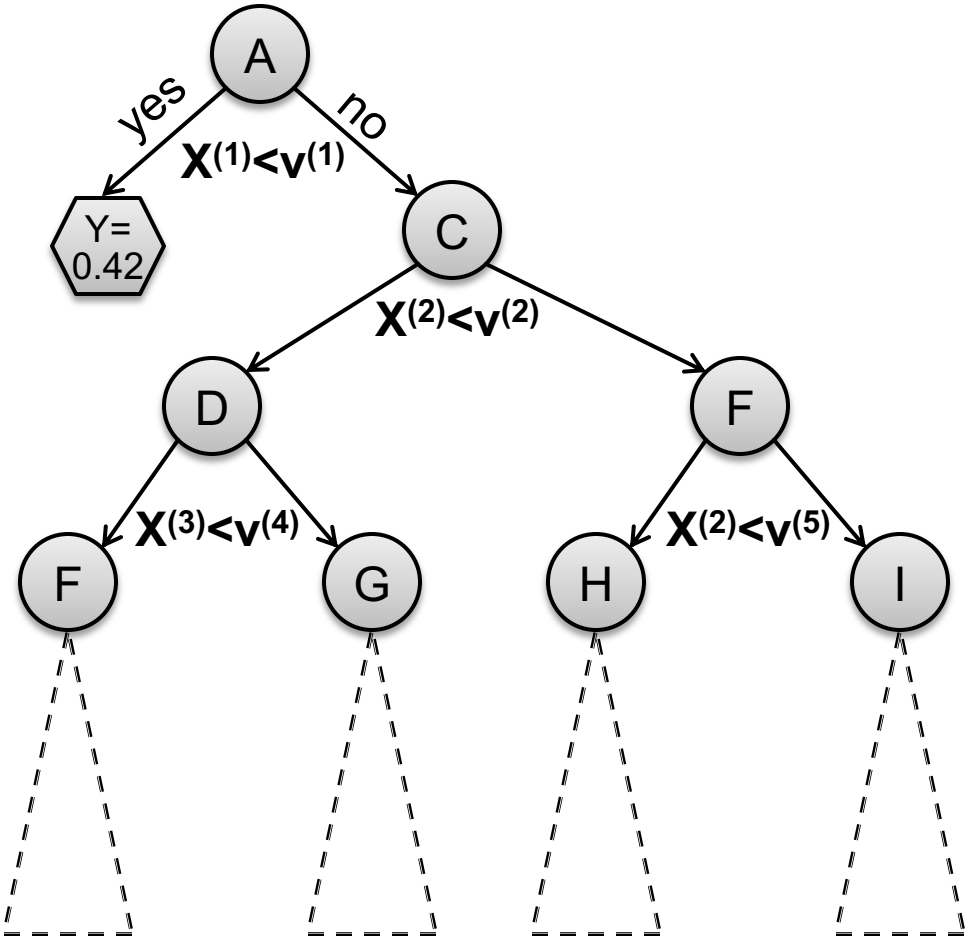
Decision Trees

- A **Decision Tree** is a tree-structured plan of a set of attributes to test in order to predict the output



Decision Trees

- **Decision trees:**
  - Split the data at each internal node
  - Each leaf node makes a prediction
- **Lecture today:**
  - Binary splits: $X^{(j)} < v$
  - Numerical attributes
  - Regression

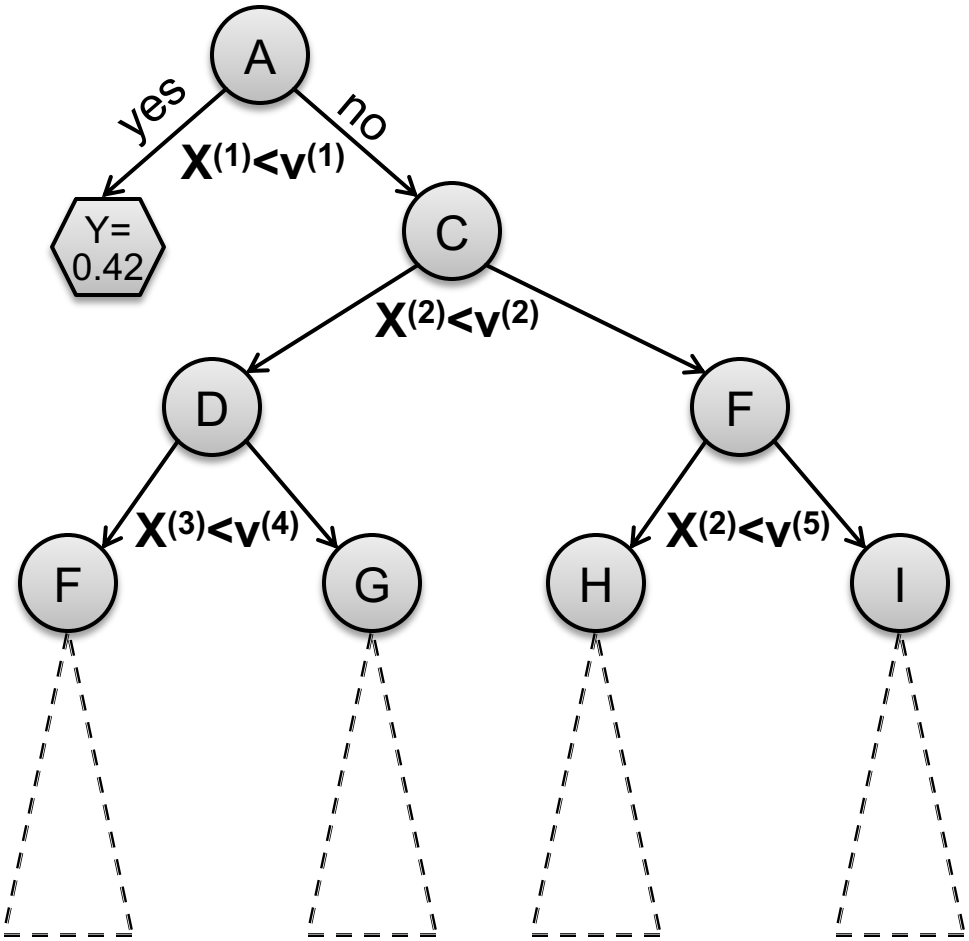


How to make predictions?

- **Input:** Example $\boldsymbol{x_i}$
- **Output:** Predicted $\boldsymbol{\hat{y}_i}$

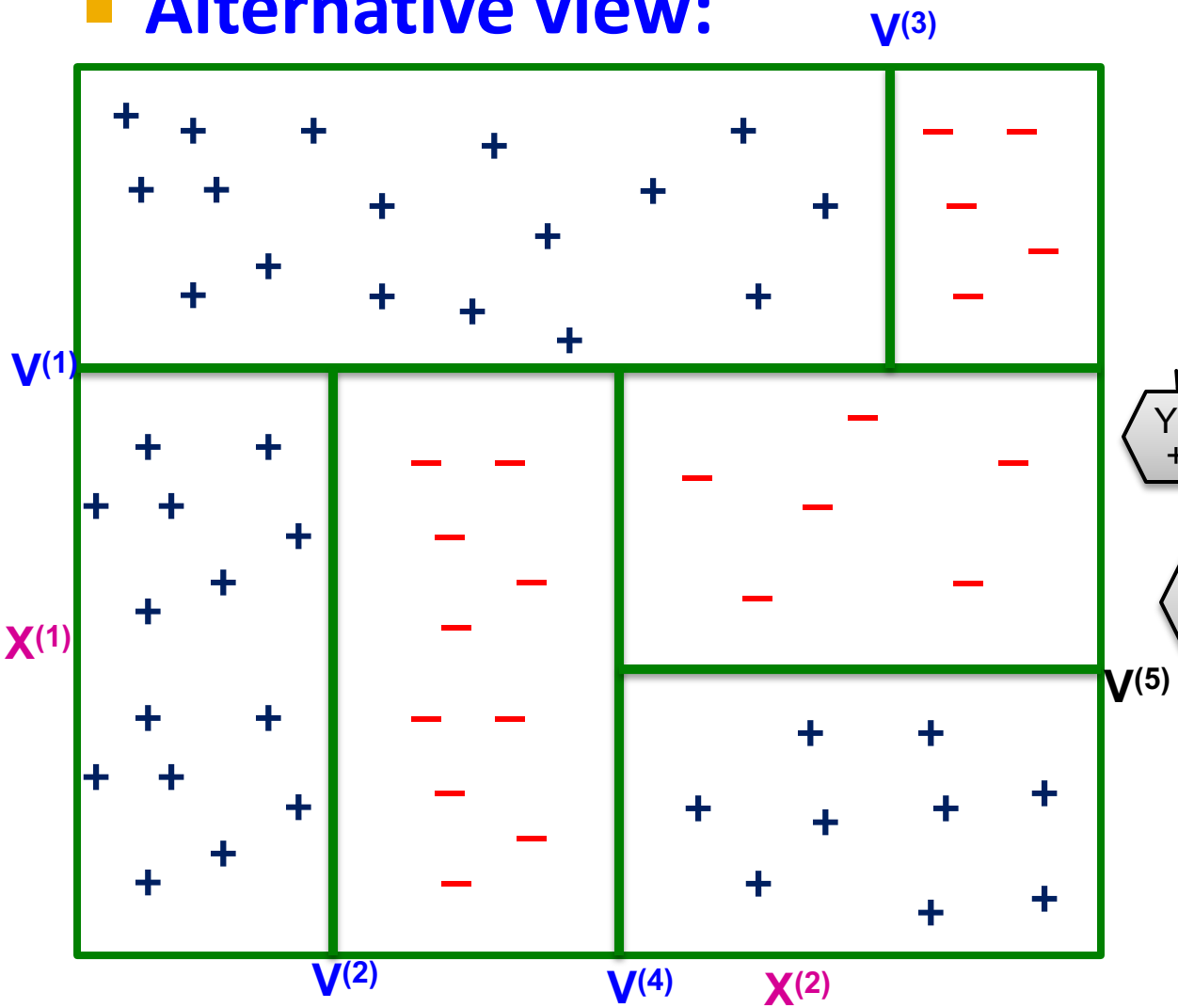
- "Drop" $\boldsymbol{x_i}$ down the tree until it hits a leaf node

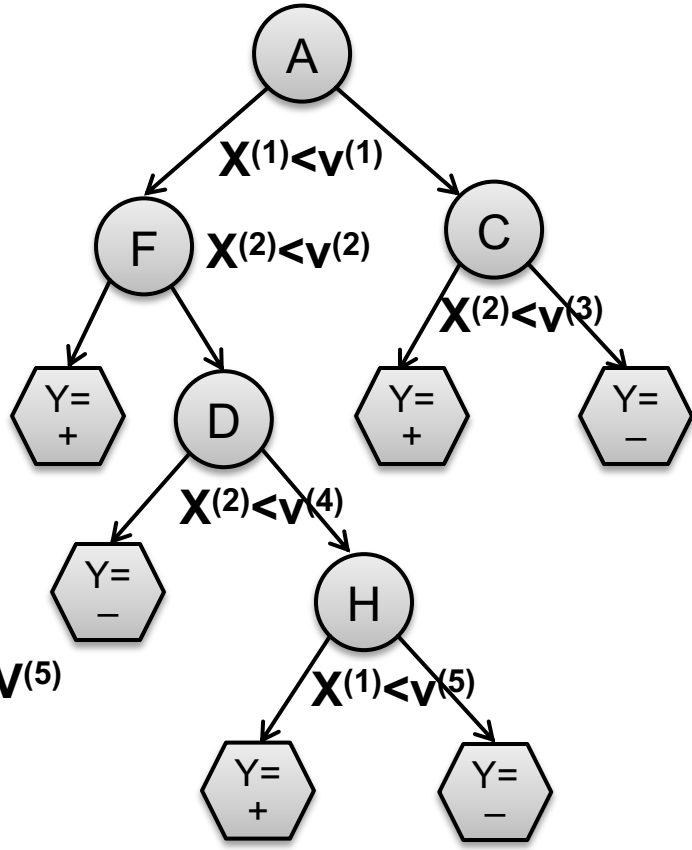
- Predict the value stored in the leaf that $\boldsymbol{x_i}$ hits



Decision Trees: feature space

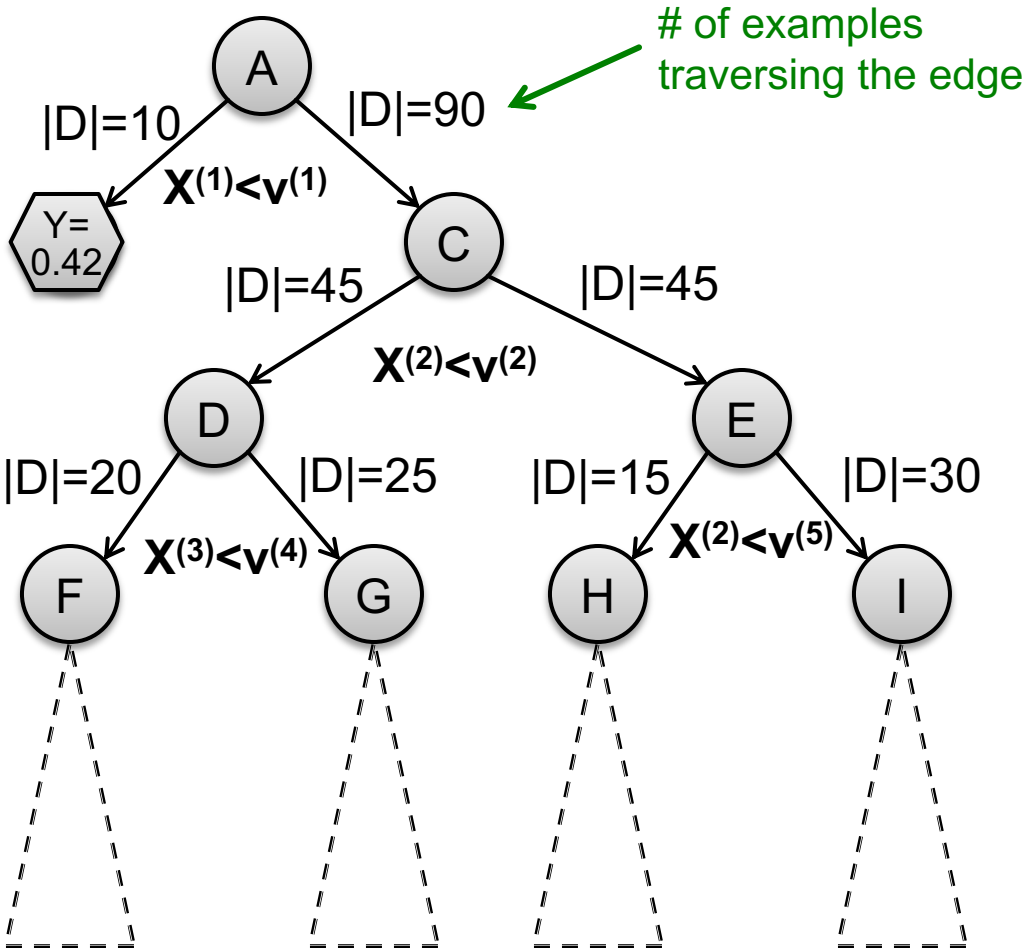
- **Alternative view:**





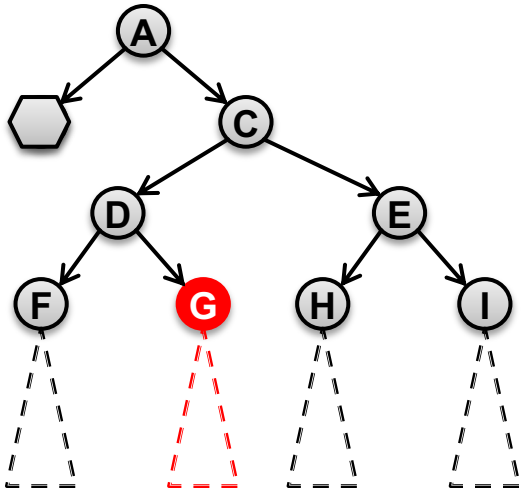
How to construct a tree?

- **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 that reaches ***G***
- **There is a decision we have to make: Do we continue building the tree?**
  - **If yes**, which variable and which value do we use for a **split**?
    - Continue building the tree recursively
  - **If not**, how do we make a prediction?
    - We need to build a **"predictor node"**



3 steps in constructing a tree

Algorithm 1 **BuildSubtree**

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

1: $(n \rightarrow \text{split}, D_L, D_R) = \text{FindBestSplit}(D)$ (1)
2: **if** $\text{StoppingCriteria}(D_L)$ **then** (2)
3: $n \rightarrow \text{left\_prediction} = \text{FindPrediction}(D_L)$ (3)
4: **else**
5: **BuildSubtree** $(n \rightarrow \text{left}, D_L)$
6: **if** $\text{StoppingCriteria}(D_R)$ **then**
7: $n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)$
8: **else**
9: **BuildSubtree** $(n \rightarrow \text{right}, D_R)$

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

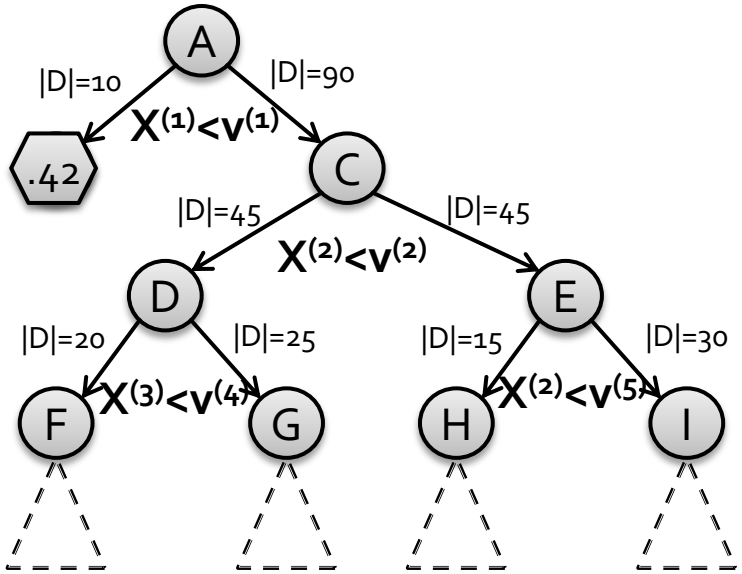
How to construct a tree?

(1) How to split? Pick attribute & value that optimizes some criterion

- **Regression: Purity**
  - **Find split** $(X^{(i)}, v)$ that creates D, D_L, D_R: parent, left, right child datasets and **maximizes**:

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

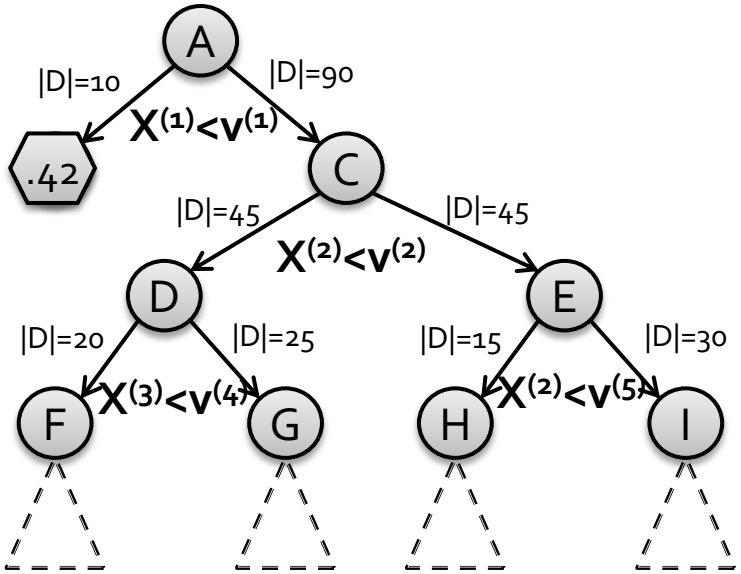
  - $Var(D) = \frac{1}{n}\sum_{i \in D}(y_i - \bar{y})^2$ … variance of y_i in D



How to construct a tree?

(1) How to split? Pick attribute & value that optimizes some criterion

- **Classification:**
  Information Gain
  - **Measures how much a given attribute X tells us about the class Y**
  - $IG(Y \mid X)$: We must transmit Y over a binary link. How many bits on average would it save us if both ends of the line knew X?

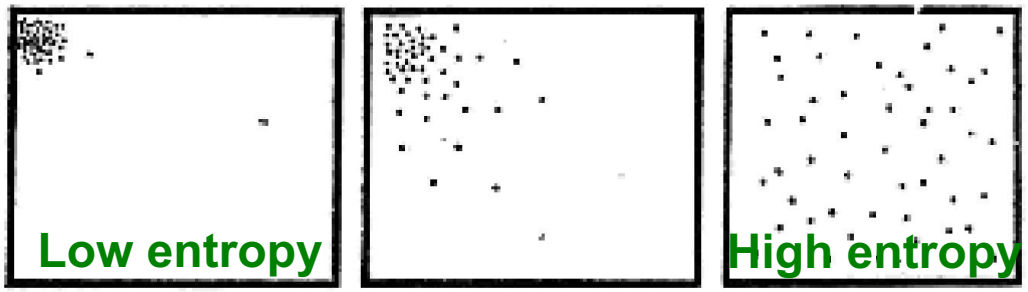


Why Information Gain? Entropy

Entropy: What's the smallest possible number of bits, on average, per symbol, needed to transmit a stream of symbols drawn from X's distribution?

The entropy of X: $H(X) = -\sum_{j=1}^{m} p(X_j) \log p(X_j)$

- **"High Entropy":** X is from a uniform (flat) distribution
  - A histogram of the frequency distribution of values of X is **flat**
- **"Low Entropy":** X is from a varied (peaks/valleys) distrib.
  - A histogram of the frequency distribution of values of X would have many lows and one or two peaks



Why Information Gain? Entropy

- **Suppose I want to predict Y and I have input X**
  - X = College Major
  - Y = Likes Movie "Casablanca"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
Math	Yes
History	No

- **From this data we estimate**
  - $P(Y = Yes) = 0.5$
  - $P(X = Math \,\&\, Y = No) = 0.25$
  - $P(X = Math) = 0.5$
  - $P(Y = Yes \mid X = History) = 0$
- **Note:**
  - $H(Y) = -½\log_2(½) - ½\log_2(½) = \mathbf{1}$
  - $H(X) = 1.5$

Why Information Gain? Entropy

- **Suppose I want to predict Y and I have input X**
  - X = College Major
  - Y = Likes "Casablanca"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
Math	Yes
History	No

- **Def: Specific Conditional Entropy**
  - $H(Y \mid X = v)$ = The entropy of Y among only those records in which X has value v
  - **Example:**
    - $H(Y|X = Math) = 1$
    - $H(Y|X = History) = 0$
    - $H(Y|X = CS) = 0$

Why Information Gain?

- **Suppose I want to predict Y and I have input X**
  - X = College Major
  - Y = Likes "Casablanca"

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
Math	Yes
History	No

- **Def: Conditional Entropy**
  - $H(Y \mid X)$ = The average specific conditional entropy of Y
    - = if you choose a record at random what will be the conditional entropy of Y, conditioned on that row's value of X
    - = Expected number of bits to transmit Y if both sides will know the value of X
  - $= \sum_j P(X = v_j) H(Y \mid X = v_j)$

Why Information Gain?

- **Suppose I want to predict Y and I have input X**
  - $H(Y \mid X)$ = The average specific conditional entropy of Y

$$= \sum_j P(X = v_j) H(Y \mid X = v_j)$$

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
Math	Yes
History	No

  - **Example:**

V_j	$P(X=v_j)$	$H(Y\|X=v_j)$
Math	0.5	1
History	0.25	0
CS	0.25	0

  - **So:** H(Y|X)=0.5*1+0.25*0+0.25*0 = **0.5**

Why Information Gain?

- **Suppose I want to predict Y and I have input X**
  - **Def: Information Gain**
    - $IG(Y|X)$ = I must transmit Y. **How many bits on average would it save me if both ends of the line knew X?**

$$IG(Y|X) = H(Y) - H(Y \mid X)$$

X	Y
Math	Yes
History	No
CS	Yes
Math	No
Math	No
CS	Yes
Math	Yes
History	No

  - **Example:**
    - H(Y) = 1
    - H(Y|X) = 0.5
    - Thus **IG(Y|X) = 1 – 0.5 = 0.5**

What is Information Gain used for?

- **Suppose you are trying to predict whether someone is going to live past 80 years**
- From historical data you might find:
  - $IG(LongLife \mid HairColor) = 0.01$
  - $IG(LongLife \mid Smoker) = 0.4$
  - $IG(LongLife \mid Gender) = 0.25$
  - $IG(LongLife \mid LastDigitOfSSN) = 0.00001$
- **IG tells us how much information about Y is contained in X**
  - **So attribute X that has high $IG(Y|X)$ is a good split!**

3 steps in constructing a tree

Algorithm 1 **BuildSubtree**

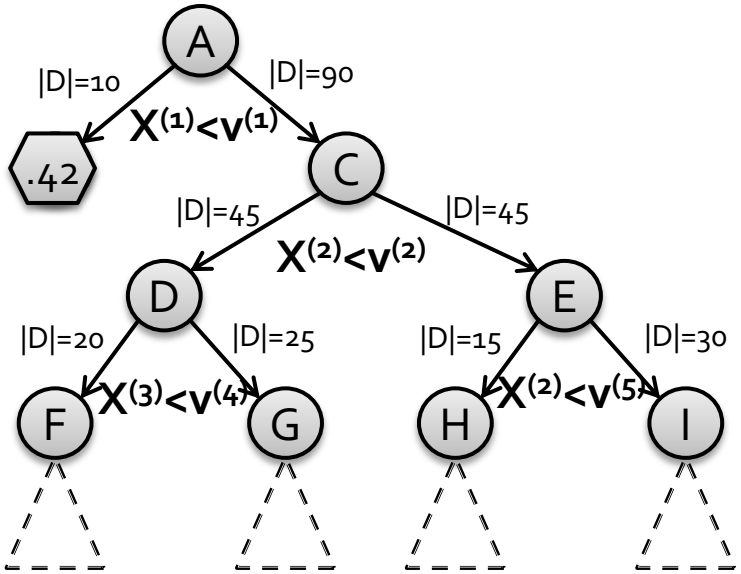
Require: Node n, Data $D \subseteq D^*$

1: $(n \rightarrow \text{split}, D_L, D_R) = \text{FindBestSplit}(D)$ (1)
2: **if** $\text{StoppingCriteria}(D_L)$ **then** (2)
3: $n \rightarrow \text{left\_prediction} = \text{FindPrediction}(D_L)$ (3)
4: **else**
5: **BuildSubtree** $(n \rightarrow \text{left}, D_L)$
6: **if** $\text{StoppingCriteria}(D_R)$ **then**
7: $n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)$
8: **else**
9: **BuildSubtree** $(n \rightarrow \text{right}, D_R)$

When to stop?

(2) When to stop?

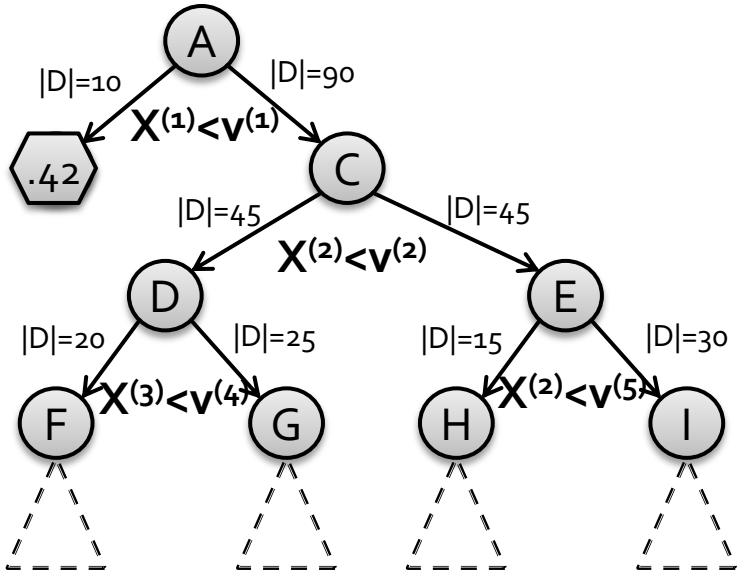
- Many different heuristic options
- **Two ideas:**
  - **(1) When the leaf is "pure"**
    - The target variable does not vary too much: $\boldsymbol{Var(y) < \varepsilon}$
  - **(2) When # of examples in the leaf is too small**
    - For example, $\boldsymbol{|D| \leq 100}$



How to predict?

(3) How to predict?

- **Many options**
  - **Regression:**
    - Predict average y_i of the examples in the leaf
    - Build a linear regression model on the examples in the leaf
  - **Classification:**
    - Predict most common y_i of the examples in the leaf



Building Decision Trees Using MapReduce

Problem: Building a tree

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

Algorithm 1 **BuildSubTree**

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

1: $(n \rightarrow \text{split}, D_L, D_R) = \text{FindBestSplit}(D)$
2: **if** StoppingCriteria(D_L) **then**
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7: $n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)$
8: **else**
9: **BuildSubTree**$(n \rightarrow \text{right}, D_R)$

- **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!**

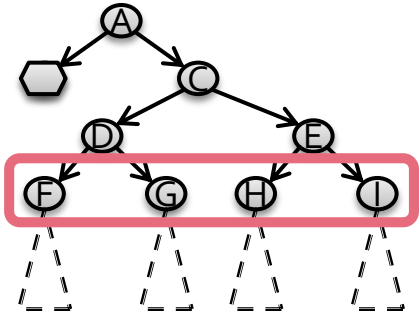
Today's Lecture: PLANET

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

- A **sequence** of MapReduce jobs that builds a decision tree
- Spark MLlib Decision Trees are based on PLANET

- **Setting:**
  - Hundreds of **numerical** (discrete & continuous, but not categorical) attributes
  - Target variable 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



Keeps track of the model and decides how to grow the tree

Master

Model

Attribute metadata

Intermediate results

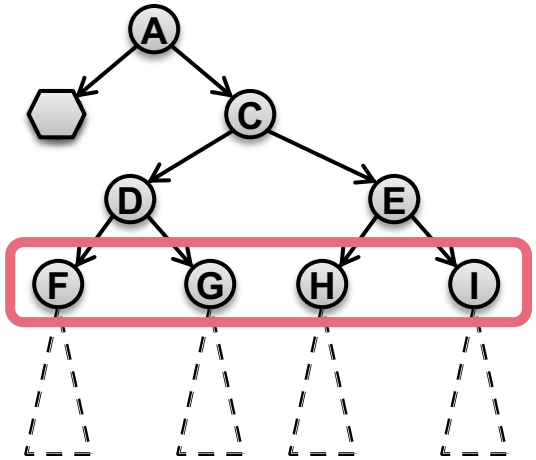
Input data

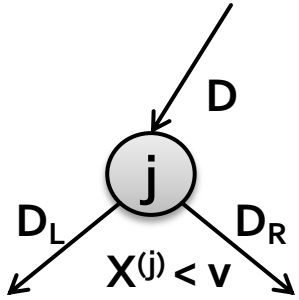
MapReduce

MapReduce: Given a set of split candidates compute their quality

PLANET: Building the Tree

- **The tree will be built in levels**
  - **One level at a time:**

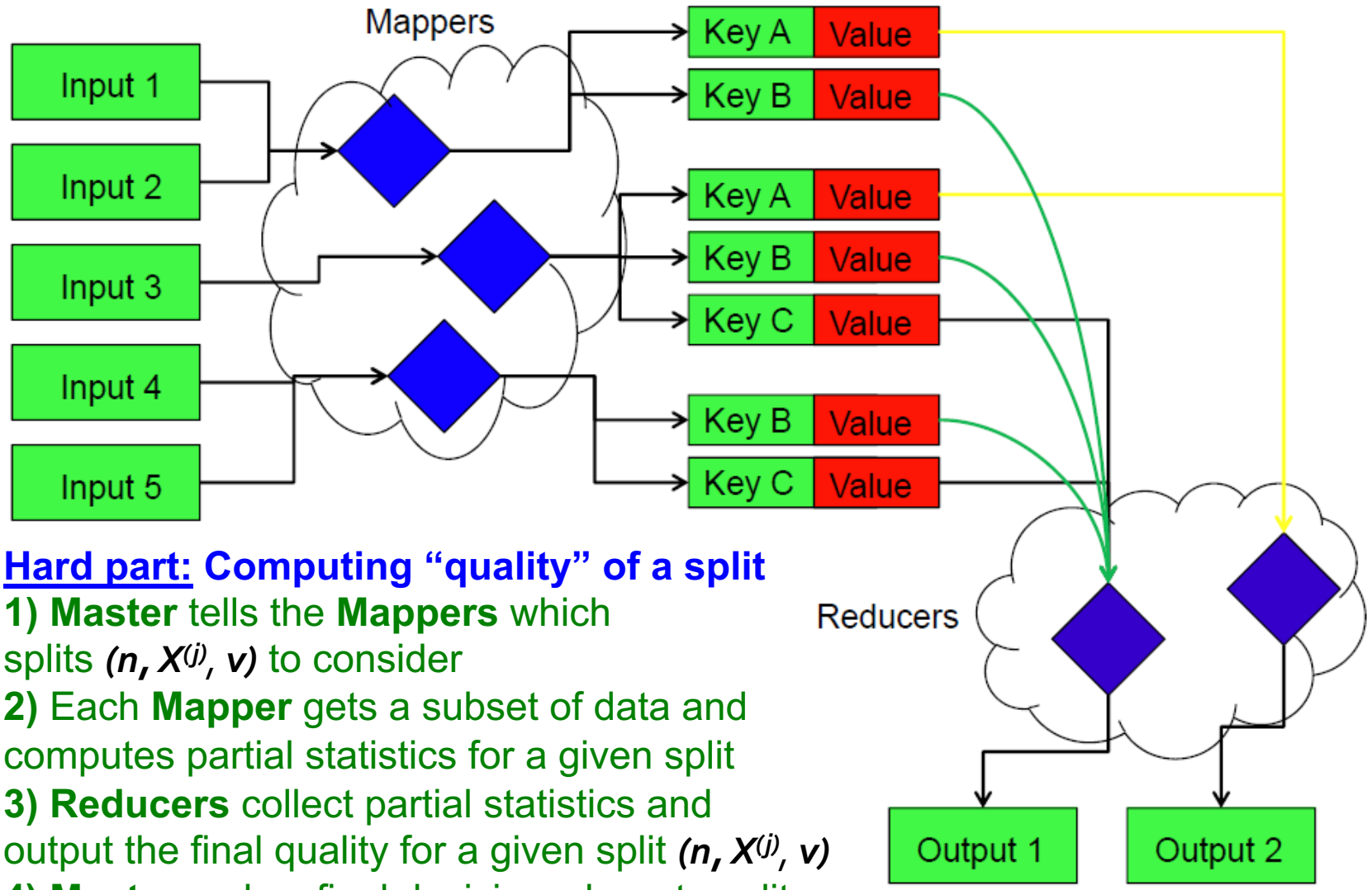




Steps:

- **1) Master decides candidate splits *(n, $X^{(j)}$, v)***
- **2) MapReduce computes quality of those splits**
- **3) Master then grows the tree for a level**
- **4) Goto (1)**

Decision trees on MapReduce



Hard part: Computing "quality" of a split

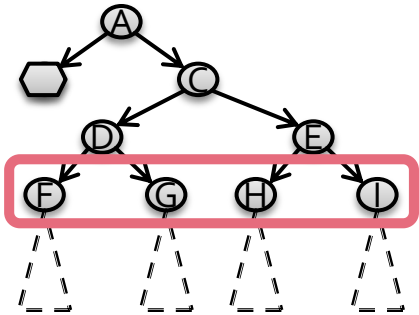
1) Master tells the **Mappers** which splits $(n, X^{(j)}, v)$ to consider

2) Each **Mapper** gets a subset of data and computes partial statistics for a given split

3) Reducers collect partial statistics and output the final quality for a given split $(n, X^{(j)}, v)$

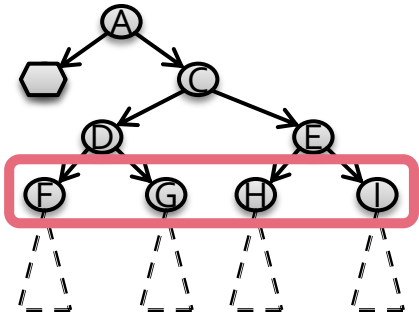
4) Master makes final decision where to split

PLANET Overview



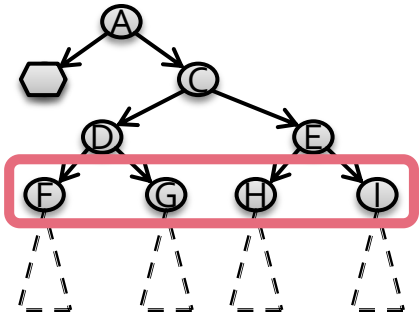
- **We build the tree level by level**
  - One MapReduce step builds **one level of the tree**
- **Mapper**
  - Considers a number of candidate splits **(node, attribute, value)** on its subset of the data
  - For each split it stores **partial statistics**
  - Partial split-statistics is sent to **Reducers**
- **Reducer**
  - Collects all partial statistics and determines best split
- **Master** grows the tree for one level

PLANET Overview



- **Mapper** loads the **DT model** and info about which **attribute splits** (split is a tuple <NodeID, Attribute, Value>) to consider
  - Each mapper sees a subset of the data **D***
  - Mapper "drops"/classifies each datapoint **d** using the tree to find the leaf node ***L*** where **d** lands
  - For each leaf node ***L*** mapper keeps statistics about
    - **(1)** the data reaching ***L***
    - **(2)** the data in left/right subtree under some split ***S***
- **Reducer** aggregates the statistics **(1)**, **(2)** and determines the best split for each tree node

PLANET: Components



- **Master**
  - Monitors everything (runs multiple MapReduce jobs)
- **Three types of MapReduce jobs:**
  - **(1) MapReduce Initialization (run once first)**
    - **For each attribute identify values to be considered for splits**
  - **(2) MapReduce FindBestSplit (run multiple times)**
    - MapReduce job to find best split (when there is too much data to fit in memory)
  - **(3) MapReduce InMemoryBuild (run once last)**
    - Similar to **BuildSubTree** (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

PLANET: Components

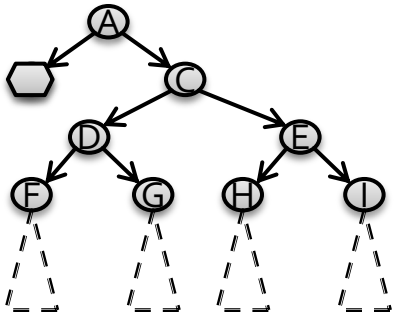
(1) Master Node

(2) MapReduce Initialization (run once first)

(3) MapReduce FindBestSplit (run multiple times)

(4) MapReduce InMemoryBuild (run once last)

PLANET: Master



- **Master controls the entire process**
- **Determines the state of the tree and grows it:**
  - **(1)** Decides if nodes should be split
  - **(2)** If there is little data entering a tree node, Master runs an **InMemoryBuild** MapReduce job to grow the entire subtree below that node
  - **(3)** For larger nodes, Master launches MapReduce **FindBestSplit** to evaluate candidates for best split
    - Master also collects results from **FindBestSplit** and chooses the best split for a node
  - **(4)** Updates the model

PLANET: Components

(1) **Master Node**

(2) **MapReduce Initialization** (run once first)

(3) **MapReduce FindBestSplit** (run multiple times)

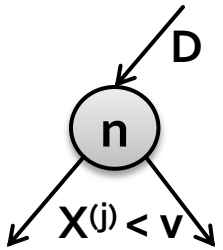
(4) **MapReduce InMemoryBuild** (run once last)

Initialization: Attribute metadata

- **Initialization job: Identifies all the attribute values which need to be considered for splits**
  - Initialization process generates **"attribute metadata"** to be loaded in memory by other tasks

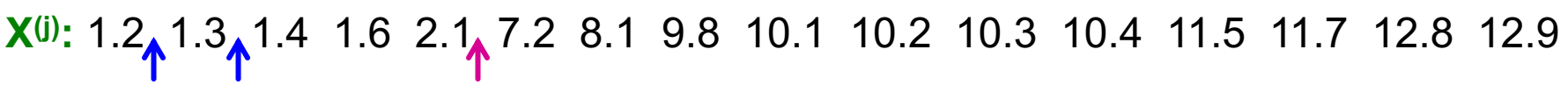
- **Main question:**
  Which splits to even consider?

- **A split is defined by a triple:**
  (node n, attribute $X^{(j)}$, value v)



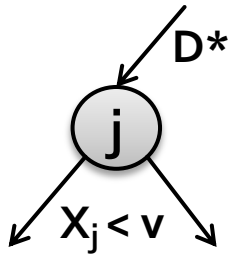
Initialization: Attribute metadata

- **Which splits to even consider?**
  - For small data we can sort the values along a particular feature and consider every possible split
  - **But data values may not be uniformly populated so many splits may not really make a difference**

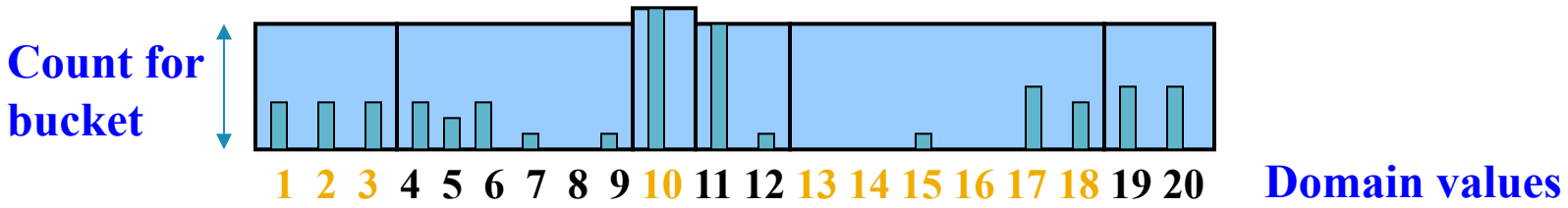


- **Idea: Consider a limited number of splits such that splits "move" about the same amount of data**

Initialization: Attribute metadata

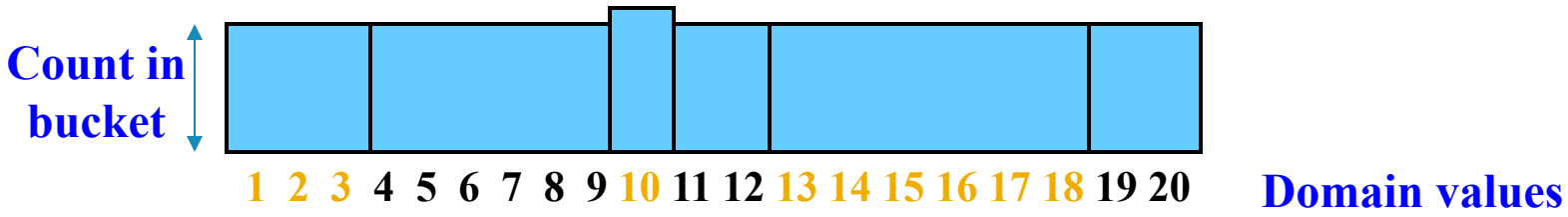


- **Splits for numerical attributes:**
  - **For attribute $X^{(j)}$ we would like to consider every possible value $v \in O_j$**
  - **Compute an approx. equi-depth histogram on *D**
    - **Idea:** Select buckets such that counts per bucket are equal



  - **Use boundary points of histogram as splits**

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: Components

(1) **Master Node**

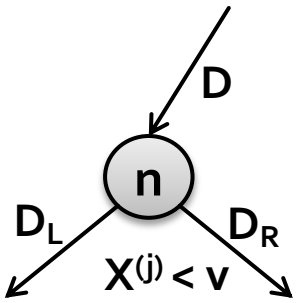
(2) **MapReduce Initialization** (run once first)

(3) **MapReduce FindBestSplit** (run multiple times)

(4) **MapReduce InMemoryBuild** (run once last)

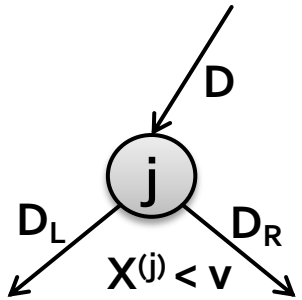
FindBestSplit

- **Goal:** For a particular split node ***n*** find attribute $X^{(j)}$ and value ***v*** that **maximize Purity**:
  - $|D| \cdot Var(D) - \left(|D_L| \cdot Var(D_L) + |D_R| \cdot Var(D_R)\right)$
    - **D** … training data (x_i, y_i) reaching the node **n**
    - D_L … training data x_i, where $x_i^{(j)} < v$
    - D_R … training data x_i, where $x_i^{(j)} \geq v$
    - $Var(D) = \frac{1}{n}\sum_{i \in D} y_i^2 - \left(\frac{1}{n}\sum_{i \in D} y_i\right)^2$



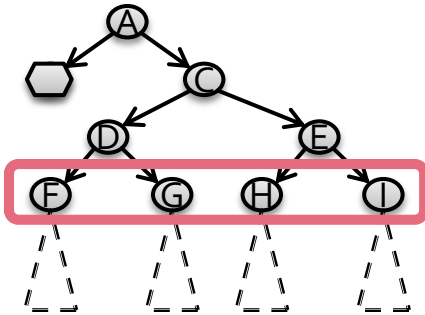
FindBestSplit

- **To compute Purity we need**
  - $Var(D) = \frac{1}{n}\sum_{i \in D} y_i^2 - \left(\frac{1}{n}\sum_{i \in D} y_i\right)^2$



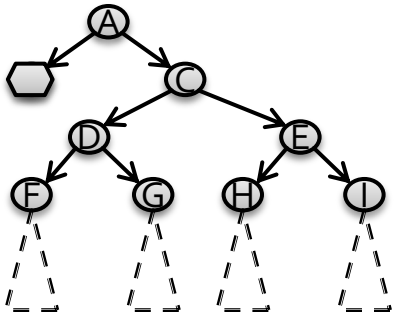
- **Important observation:** Variance can be computed from **sufficient statistics**:
  N, S=Σy_i, Q=Σy_i^2
  - Each **Mapper m** processes subset of data $\mathbf{D_m}$, and computes $\mathbf{N_m}$, $\mathbf{S_m}$, $\mathbf{Q_m}$ for its own $\mathbf{D_m}$
  - **Reducer** combines the statistics and computes global variance and then Purity:
    - $Var(D) = \frac{1}{\sum_m N_m}\sum_m Q_m - \left(\frac{1}{\sum_m N_m}\sum_m S_m\right)^2$

FindBestSplit: Map



- **Mapper:**
  - Initialized by loading results of **Initialization task**
    - **Current model** (to find which node each datapoint $\mathbf{x_i}$ ends up)
    - **Attribute metadata** (all split points for each attribute)
    - Load the set of **candidate splits**: **{(node, attribute, value)}**
  - **For each data record run the Map algorithm:**
    - **For each tree node store statistics of the data entering the node and at the end emit (to all reducers):**
      - **<NodeID, { S=Σy, Q=Σy^2, N=Σ1 } >**
    - **For each split store statistics and at the end emit:**
      - **<SplitID, { S, Q, N } >**
        - **SplitID = (node id, attribute X$^{(j)}$, split value *v*)**

FindBestSplit: Reducer

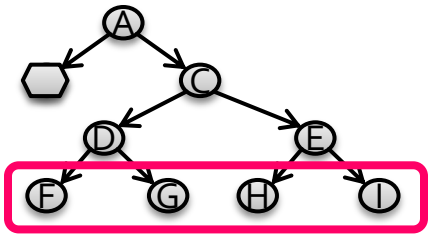


Reducer:

- **(1)** Load all the **<NodeID, List {S_m, Q_m, N_m}>** pairs and **aggregate** the per node statistics
- **(2)** For all the **<SplitID, List {S_m, Q_m, N_m}>** **aggregate** the statistics
  - $$Var(D) = \frac{1}{\sum_m N_m} \sum_m Q_m - \left(\frac{1}{\sum_m N_m} \sum_m S_m \right)^2$$
- **For each NodeID, output the best split found**

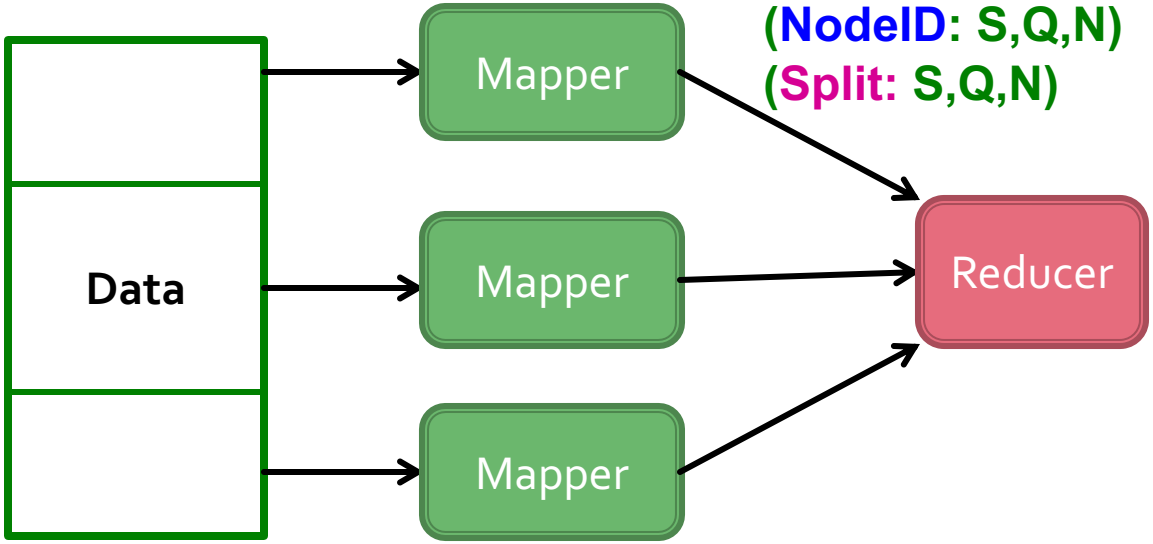
Overall system architecture

- **Master gives the mappers:** **(1) Tree**
  (2) Set of nodes
  (3) Set of candidate splits



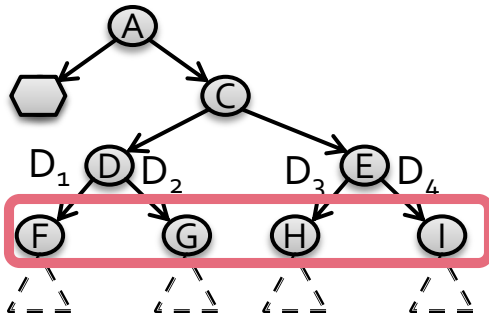
Nodes: F, G, H, I
Split candidates: (G, $X^{(1)}$,$v^{(1)}$), (G, $X^{(1)}$,$v^{(2)}$), (H, $X^{(3)}$,$v^{(3)}$), (H, $X^{(4)}$,$v^{(4)}$)

Mappers output 2 types of key-value pairs:
(NodeID: S,Q,N)
(Split: S,Q,N)



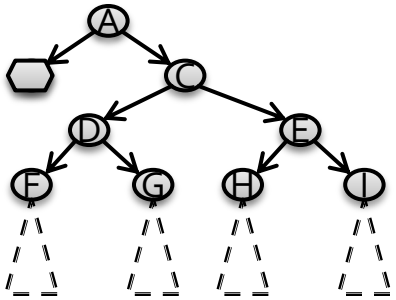
For every (NodeID, Split) Reducer(s) compute the Purity and output the best split

Overall system architecture



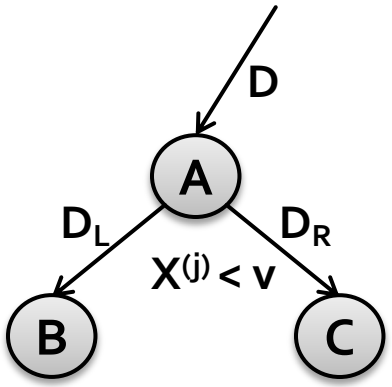
- **Example:** Need to split nodes **F, G, H, I**
- **Map and Reduce:**
  - **FindBestSplit::Map** (each mapper)
    - Load the current model **M**
    - Drop every example $\mathbf{x}_i$ down the tree
    - If it hits ***F/G/H/I***, update in-memory hash tables:
      - For each node: $\mathbf{T_n}$: **(Node)→{S, Q, N}**
      - For each **(Split, Node)**: $\mathbf{T_{n,j,s}}$: **(Node, Attribute, SplitValue)→{S, Q, N}**
    - **Map::Finalize**: output the key-value pairs from above hashtables
  - **FindBestSplit::Reduce** (each reducer)
    - Collect:
      - **T1:**<Node, List{S, Q, N} > → <Node, {Σ S, Σ Q, Σ N} >
      - **T2:**<(Node, Attr., Val), List{S, Q, N}> → <(Node, Attr., Val), {ΣS, ΣQ, ΣN}>
    - Compute Purity for each node using **T1, T2**
    - Return **best split** to Master (which then decides on globally best split)

Back to the Master



- **Collects outputs from FindBestSplit reducers**
  <Split.NodeID, Attribute, Value, Purity>

- **For each node decides the best split**
  - If data in $\mathbf{D_L/D_R}$ is small enough, later run a MapReduce job **InMemoryBuild** on the node
  - Else run MapReduce **FindBestSplit** job for both nodes



Decision Trees: Conclusion

Decision Trees

- **Characteristics**
  - **Classification & Regression**
    - Multiple (~10) classes
  - **Real valued and categorical features**
  - **Few (hundreds) of features**
  - Usually **dense features**
  - **Complicated decision boundaries**
    - Early stopping to avoid overfitting!
- **Example applications**
  - User profile classification
  - Landing page bounce prediction

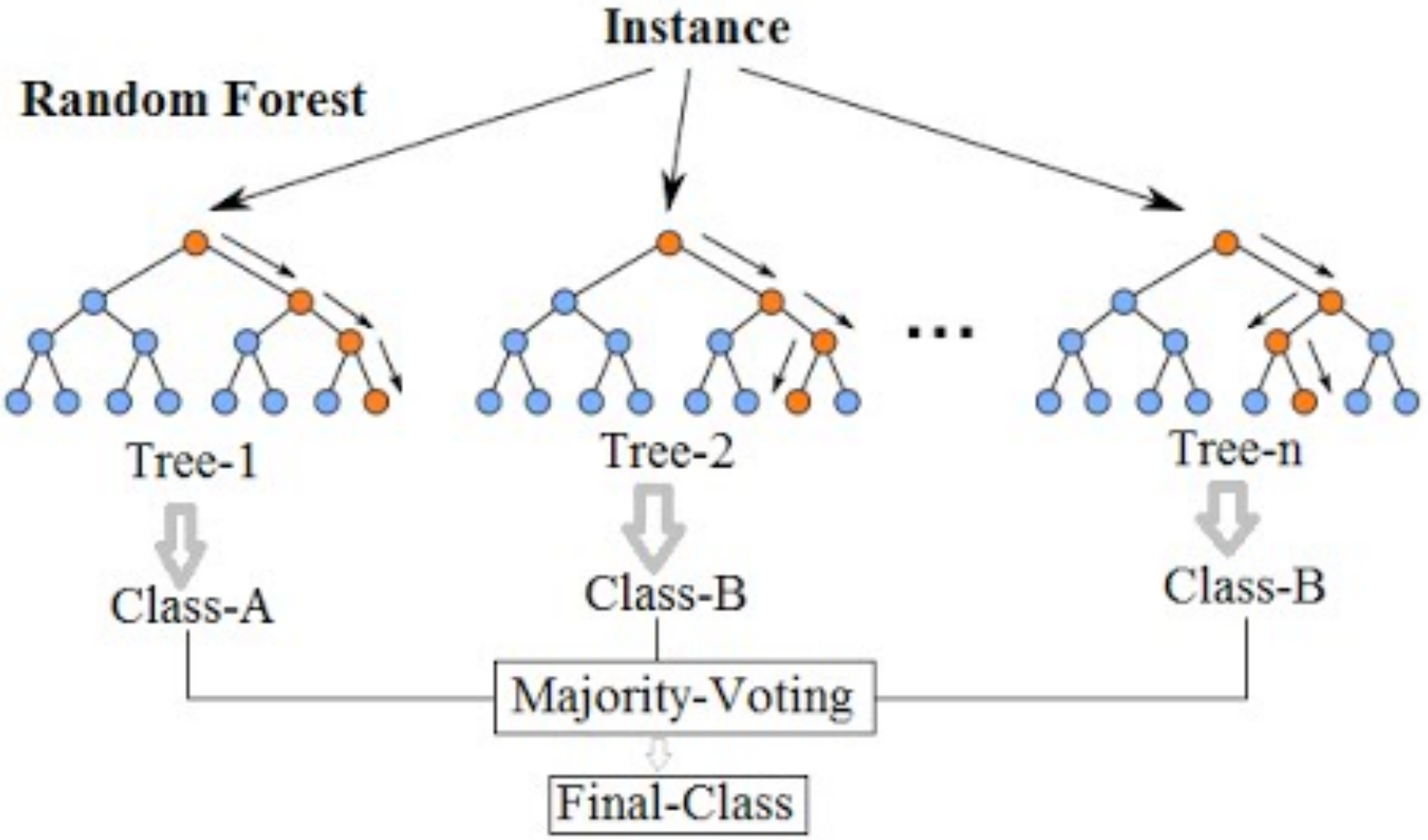
Decision Trees

- **Decision trees are the single most popular data mining tool:**
  - Easy to understand
  - Easy to implement
  - Easy to use
  - Computationally cheap
  - It's possible to mitigate overfitting (i.e., with ensemble methods)
  - **They do classification as well as regression!**

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
    - For a dataset **D** on **n** data points: Create dataset **D'** of **n** points but sample from **D** with replacement
      - Dataset D' will include duplicate data points
  - Predictions from each tree are averaged to compute the final model prediction

Bagging Decision Trees



Improvement: Random Forests

- Train a **Bagged Decision Tree**
- But use a modified tree learning algorithm that selects (at each candidate split) **a random subset of the features**
  - If we have d features, consider $\sqrt{d}$ random features
- **This is called: Feature bagging**
  - **Benefit:** Breaks correlation between trees
    - Otherwise, if one feature is very strong predictor, then every tree will select it, causing trees to be correlated.
- **Random Forests achieve state-of-the-art results in many classification problems!**