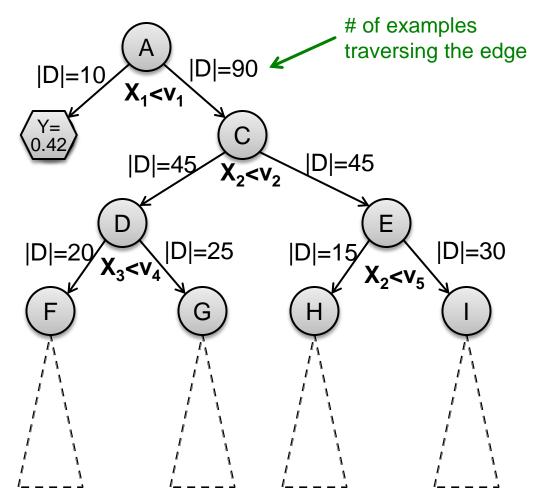
Mining of Massive Datasets Leskovec, Rajaraman, and Ullman Stanford University



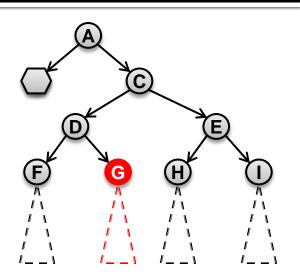
Training dataset D*, |D*|=100 examples



- 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?



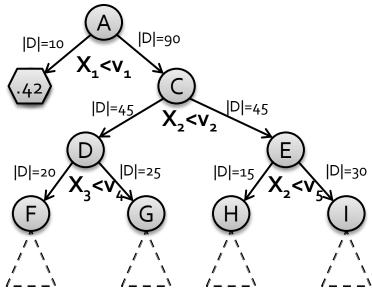
- Continue building the tree recursively
- If not, how do we make a prediction?
 - We need to build a "predictor node"



```
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 StoppingCriteria(D_L) then
                                                                (2)
 3: n \rightarrow \text{left\_prediction} = \text{FindPrediction}(D_L)
                                                                (3)
 4: else
                   BuildSubtree (n \rightarrow \text{left}, D_L)
 5:
 6: if StoppingCriteria(D_R) then
        n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)
 8: else
                   BuildSubtree (n \rightarrow \text{right}, D_R)
 9:
```

Requires at least a single pass over the data!

- (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 | 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?



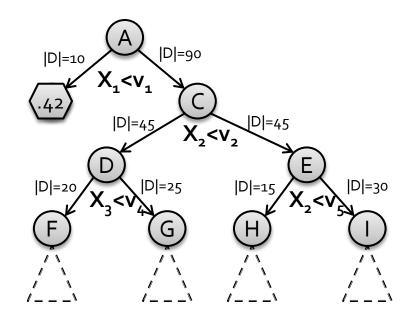
Back to: How to construct a tree?

```
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 StoppingCriteria(D_L) then
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 3: n \rightarrow \text{left\_prediction} = \text{FindPrediction}(D_L)
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                   BuildSubtree (n \rightarrow \text{left}, D_L)
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 6: if StoppingCriteria(D_R) then
        n \rightarrow \text{right\_prediction} = \text{FindPrediction}(D_R)
 8: else
                   BuildSubtree (n \rightarrow \text{right}, D_R)
 9:
```

Requires at least a single pass over the data!

(1): How to split?

- Regression:
 - Find split (X_i, v) that creates D, D_L, D_R: parent, left, right child datasets and maximizes:

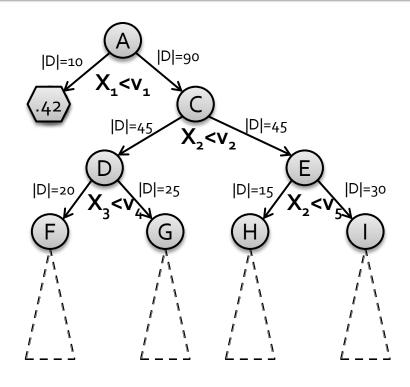


$$|D| \cdot Var(D) - (|D_L| \cdot Var(D_L) + |D_R| \cdot Var(D_R))$$

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

(2) When to stop?

- Many different heuristic options
- Two ideas:
 - (1) When the leaf is "pure"
 - The target variable does not vary too much: $Var(y_i) < \varepsilon$
 - (2) When # of examples in the leaf is too small
 - For example, $|D| \le 10$



(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

