LOVELY PROFESSIONAL UNIVERSITY

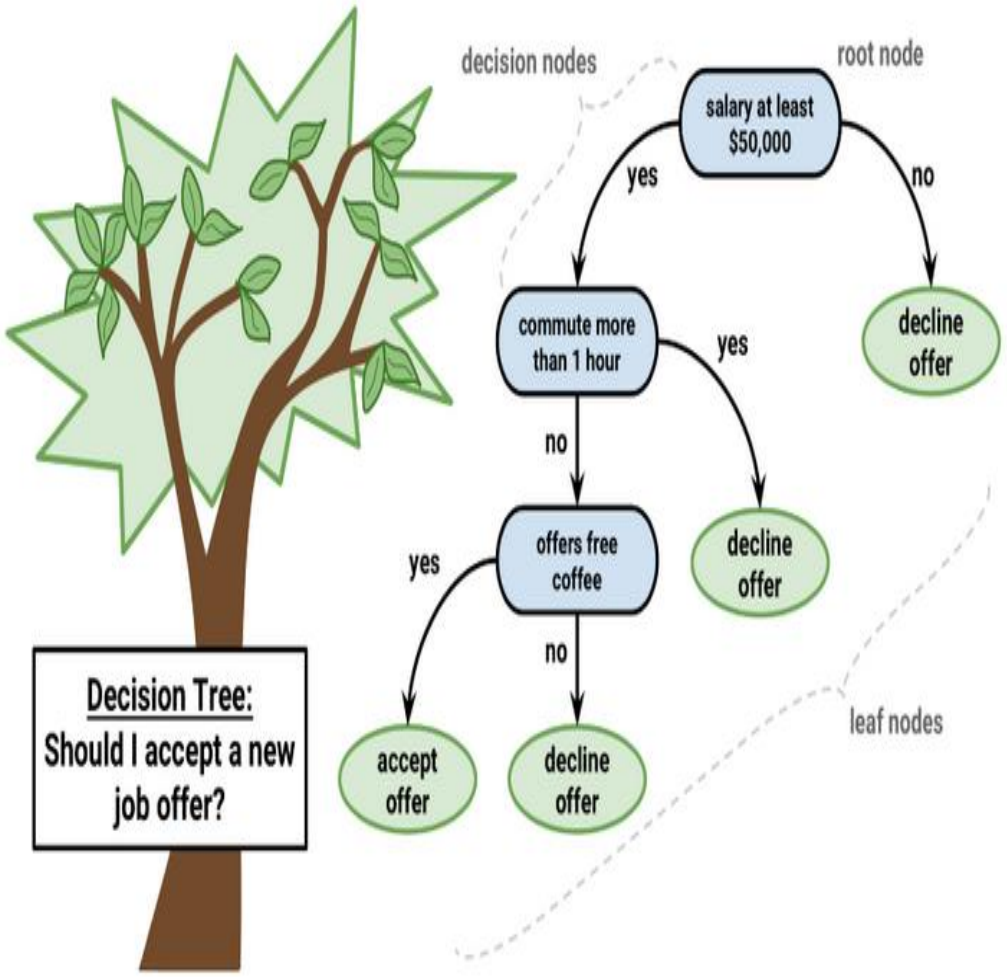
INT247
Machine Learning Foundations

Lecture #3

Decision Trees and Random Forests

Decision Tree Learning

- **Breaking down data by making decisions based on asking a series of questions.**

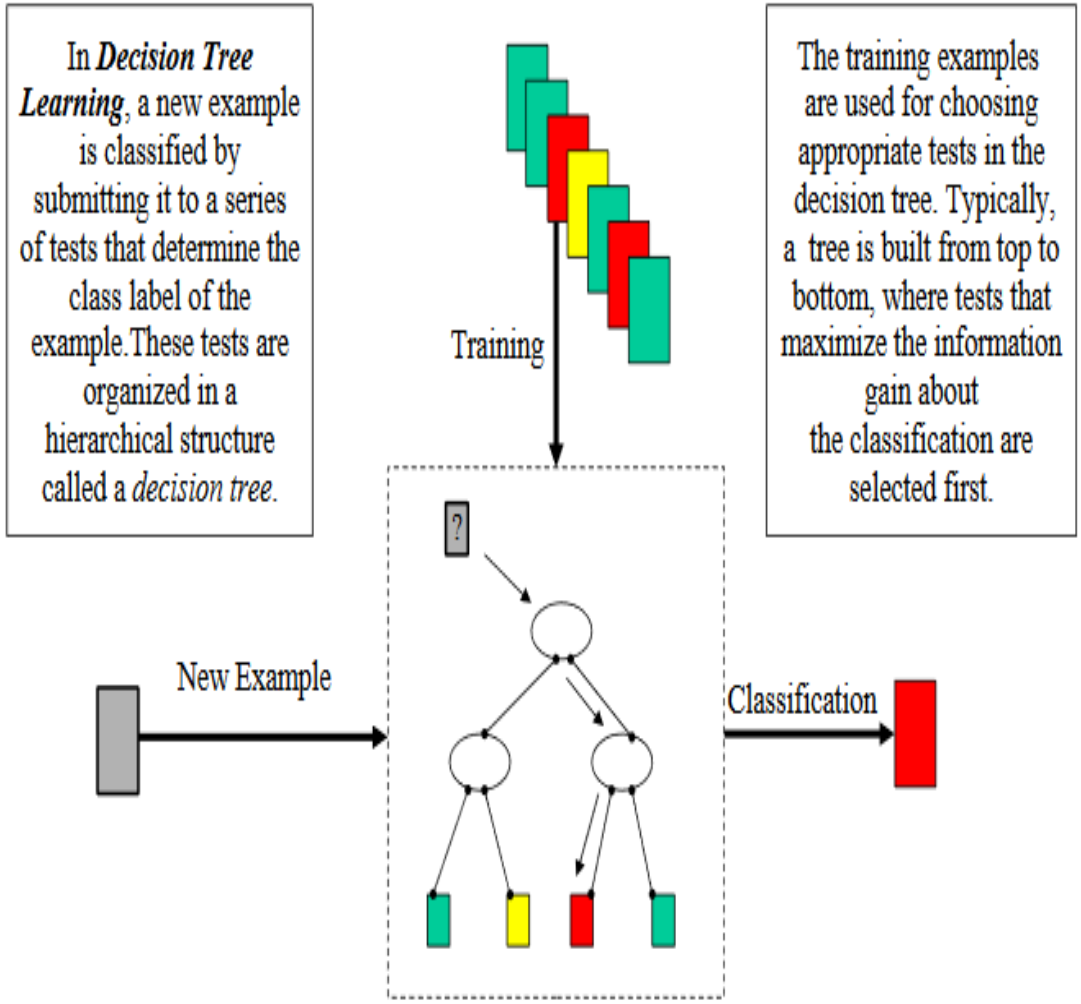


Decision Tree Learning

- A decision tree consists of
  - Nodes
    - Test for the value of a certain attribute.
  - Edges
    - Correspond to the outcome of a test.
    - Connect to the next node or leaf.
  - Leaves
    - Terminal nodes that predict the outcome.

Algorithm

1. Start at the root.
2. Perform the test.
3. Follow the edge corresponding to outcome.
4. Goto step 2 unless leaf.
5. Predict the outcome associated with the leaf.



Design Decision Tree

Day	Temperature	Outlook	Humidity	Windy	Play Golf?
07-05	hot	sunny	high	false	no
07-06	hot	sunny	high	true	no
07-07	hot	overcast	high	false	yes
07-09	cool	rain	normal	false	yes
07-10	cool	overcast	normal	true	yes
07-12	mild	sunny	high	false	no
07-14	cool	sunny	normal	false	yes
07-15	mild	rain	normal	false	yes
07-20	mild	sunny	normal	true	yes
07-21	mild	overcast	high	true	yes
07-22	hot	overcast	normal	false	yes
07-23	mild	rain	high	true	no
07-26	cool	rain	normal	true	no
07-30	mild	rain	high	false	yes

Note: Consider "Outlook" as root node

Exercise

today	cool	sunny	normal	false	?

tomorrow	mild	sunny	normal	false	?

Good Attribute?

- **Prefers attributes that have a high degree of "order".**
  - **Maximum Order: All examples are of the same class.**
  - **Minimum Order: All classes are equally likely.**

Entropy

Entropy is the measure of

- **Impurity**
- **Disorder**
- **uncertainty**

Entropy for two classes:

$$E(S) = -p_1.log_2 p_1 - p_2.log_2 p_2$$

S is the complete set,
p1 is the proportion of examples in class 1 and
p2=1-p1 is the proportion of examples in class 2.

Exercise

Compute entropy

- **Outlook=sunny**
- **Outlook=overcast**
- **Outlook=rainy**

Entropy for more classes

$$E(S) = -p_1.logp_1 - p_2.logp_2 \ldots - pn.logpn$$

$$= -\sum_{i=1}^{n} p_i.logpi$$

Entropy Disadvantages

- **Only computes the quality of a single subset of examples corresponds to a single value.**

Average Entropy

- **Computes the quality of the entire split corresponds to an entire attribute.**

$$I(S, A) = \sum_i \frac{|s_i|}{|s|} . E(Si)$$

S is the complete set.

A is Attribute that splits S into different subsets.

Properties of Entropy

- **When node is pure, measure should be zero.**
- **When impurity is maximal, measure should be maximal.**

Exercise

- **Compute the average entropy for attribute "Outlook".**

Information Gain

$$Gain(S, A) = E(S) - I(S, A)$$
$$= E(S) - \sum_i \frac{|S_i|}{|S|} . E(Si)$$

Where *S* is complete set and *A* is the attribute that splits the set *S* into subsets S_i.

Note: Maximizing information gain is equivalent to minimizing average entropy, because *E(S)* is constant for all attributes *A*.

Exercise

- **Compute the information gain for**
  - **Gain(S, Humidity)=?**
  - **Gain(S, Wind)=?**
  - **Gain(S, Outlook)=?**
  - **Gain(S, Temperature)=?**

Note:

The attribute with maximum information gain is selected as root node.

Intrinsic Information of an attribute

- **Amount of information need to tell which branch an instance belongs to**

$$Int1(S, A) = -\sum_{i} \frac{|S_i|}{|S|} log(\frac{|S_i|}{|S|})$$

Note:

Attributes with higher intrinsic information are less useful.

Exercise

- **Compute intrinsic information of**
  - **Day**
  - **Temperature**
  - **Humidity**
  - **Windy**
  - **Outlook**

Gain Ratio

- **Modification of the information gain that reduces its bias towards multi-valued attributes.**

$$GR(S, A) = \frac{Gain(S, A)}{Int1(S, A)}$$

Exercise

- **Compute gain ratio of**
  - **Day**
  - **Temperature**
  - **Humidity**
  - **Windy**
  - **outlook**

Gini Index

- **Measure impurity**

$$Gini(S) = 1 - \sum_i p_i^2$$

- **Average Gini Index**

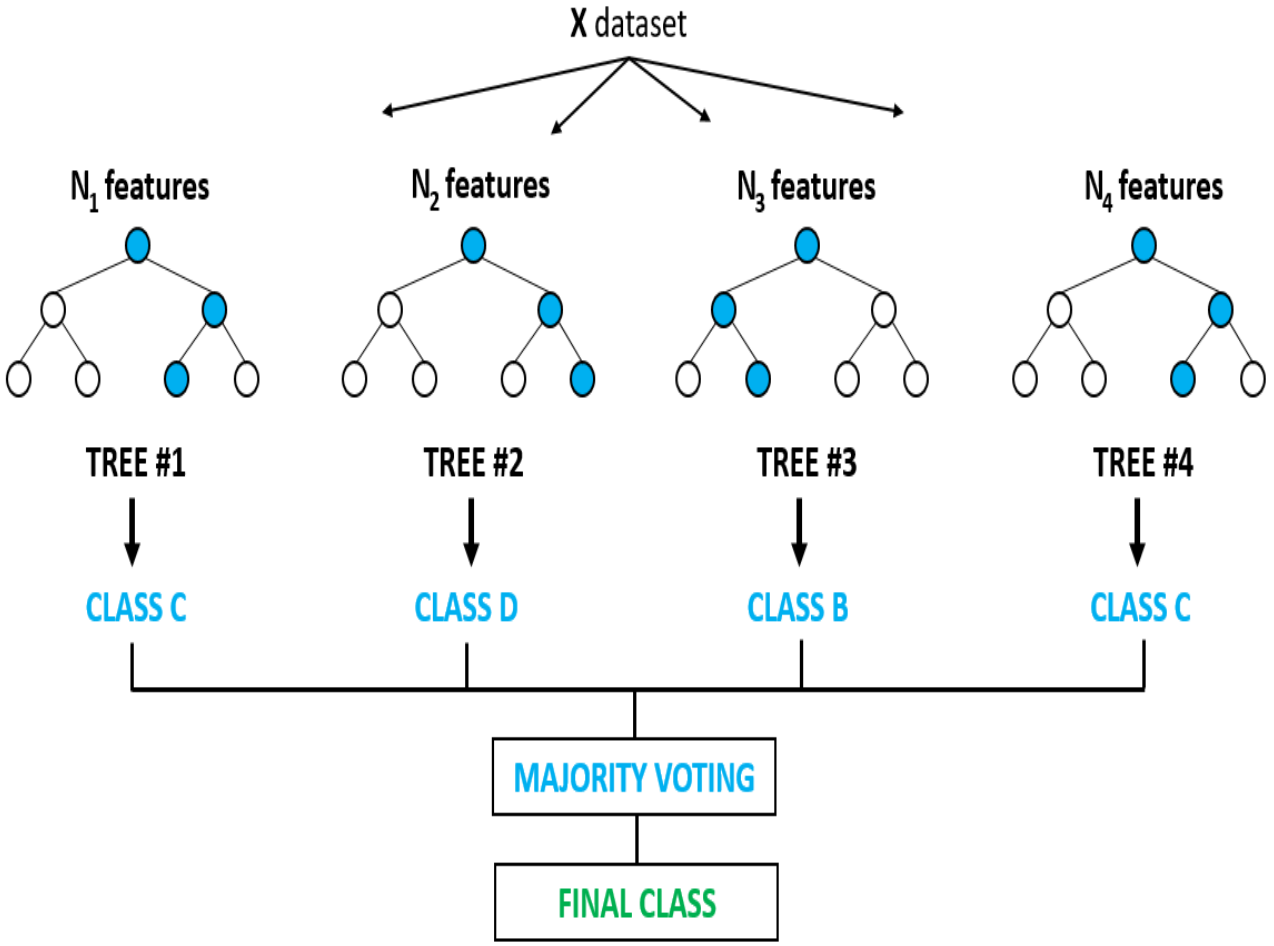
$$Gini(S, A) = \sum_i \frac{|S_i|}{|S|} . Gini(Si)$$

Pruning

- **Pre-pruning:**
  - **Stop growing a branch when information becomes unreliable.**
- **Post-pruning:**
  - **Grow a decision tree that correctly classifies all training data.**
  - **Simplify it later by replacing some nodes with leafs.**

Random Forest

- **Builds multiple decision tree and merges them together to get a more accurate and stable prediction.**



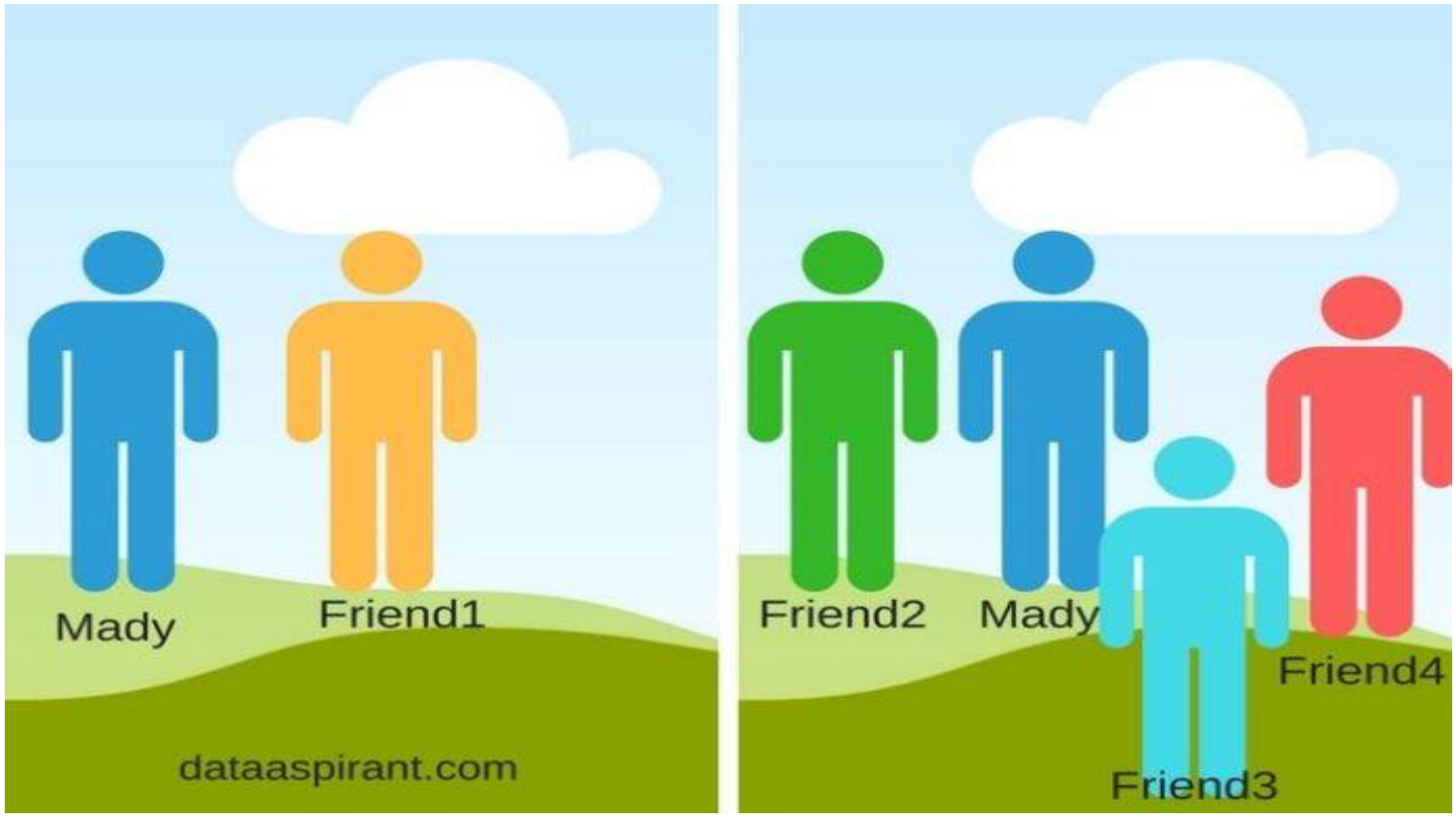
Random Forest Creation Algorithm

1. Randomly select "K" features from total "m" feaures.
   - Where K << m
2. Among the "K" features, calculate the node "d" using the best split point.
3. Split the node into daughter nodes using the best split.
4. Repeat 1 to 3 steps until "l" number of nodes has been reached.
5. Build forest by repeating steps 1 to 4 for "n" number of times to create "n" number of trees.

Random Forest Prediction Algorithm

1. Takes the **test features** and use the rules of each randomly created decision tree to predict the outcome and stores the predicted outcome.
2. Calculate the **vote** for each predicted target.
3. Consider the **high voted predicted target** as the final prediction from the random forest algorithm.

Random Forest Example

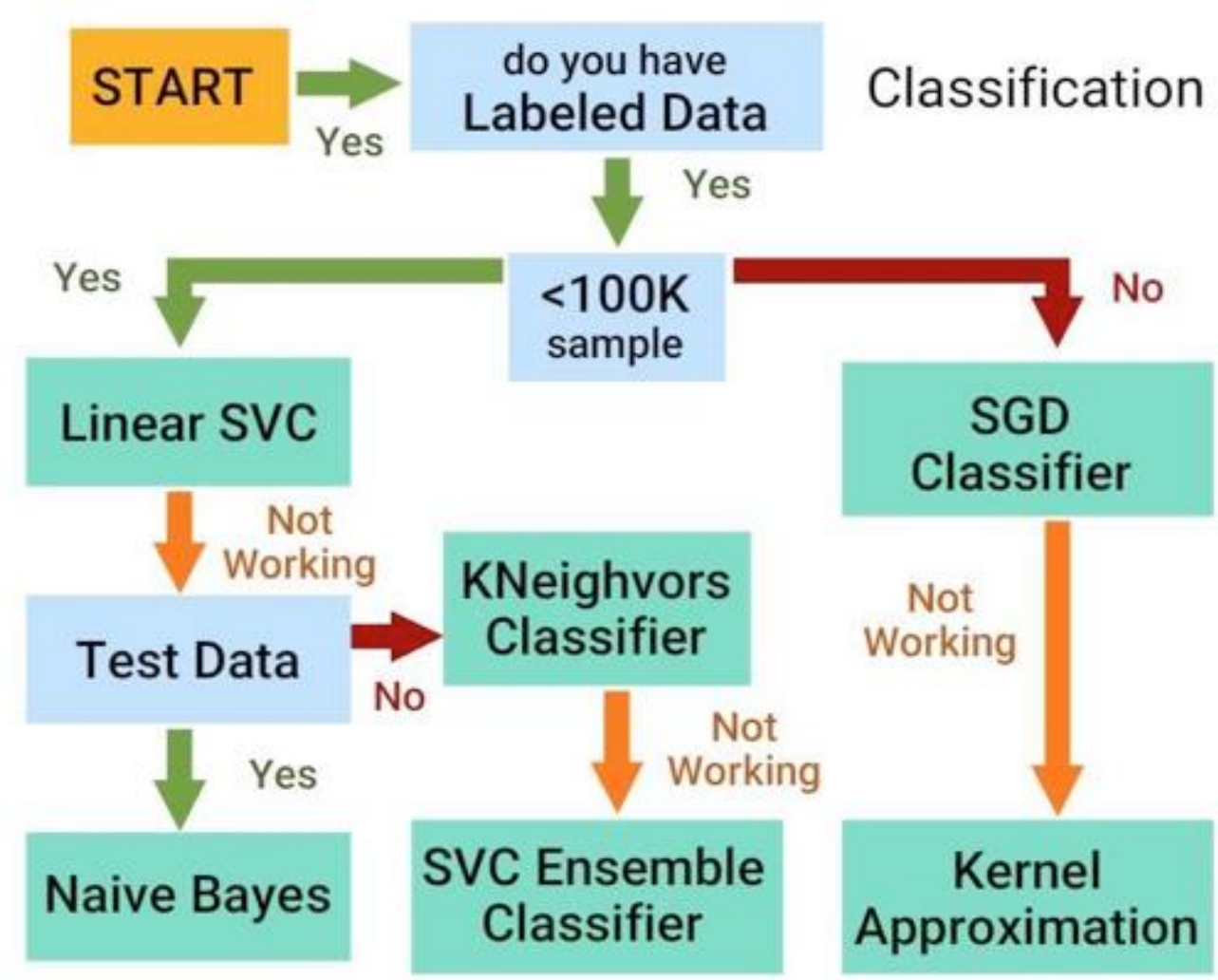


- **Mady takes opinion from friends for some problem.**

Why Random Forest Algorithm?

- **Can be used for both classification and regression.**
- **Handles the missing value.**
- **Not over-fit the model.**

Algorithm Selection




COMING UP