# LEC 7: Decision Trees and Random Forests

Mar 18, 2020

## Quiz

https://forms.gle/pgc1WUBDJJvyRkrK7

### Presentation:

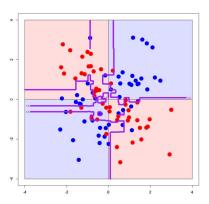
https://docs.google.com/presentation/d/10D1000y0EhAxPLF7iGvdCWzcUrmhzhxDL83zsT3akps/edit#slide=id.q70ef318bc0\_0\_5

## Some models for classification

- 1. Supervised training data with labels provided
  - a. Logistic regression and Maximum Likelihood Estimation
  - b. Support Vector Machines
  - c. Decision Trees and Random Forest
  - d. K-Nearest Neighbors
  - e. Neural Networks
- 2. Unsupervised training data does not require labels
  - a. K-Means
  - b. Expectation Maximization

## Motivation for Decision Trees

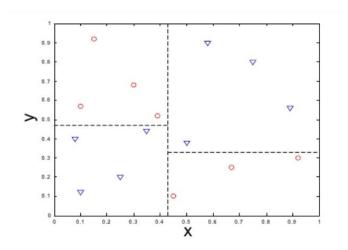
- 1. Model non-linear, complex and non-contiguous boundaries
- 2. Works well with categorical data
- 3. Interpretability: we can see the decisions/splits the algorithm made
- 4. Can return classification probability (SVMs cannot)



## Model: Decision Tree

- Model: Decision Tree
- Target result: Decision flow that outputs 0 when the predicted class is Class 0 and 1 when Class 1
- Minimize: Dissimilarity in true class within a predicted class

# An intuitive example



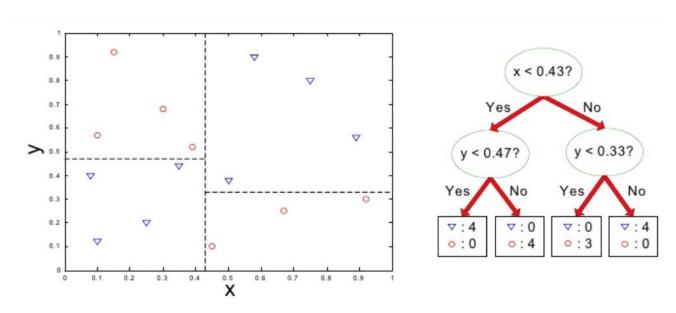
Answer:

How would you define the decision boundaries for classification?

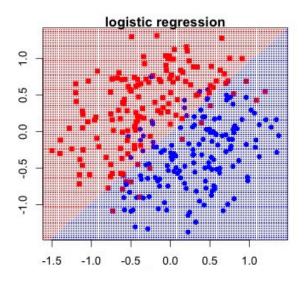
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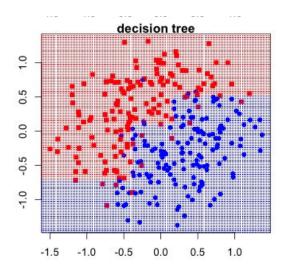
#### Decision trees make linear separations along the axes of the features

Notice the boundaries are vertical/horizontal cuts forming rectangular regions



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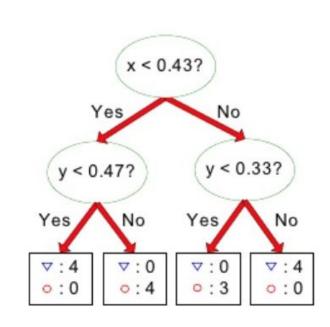




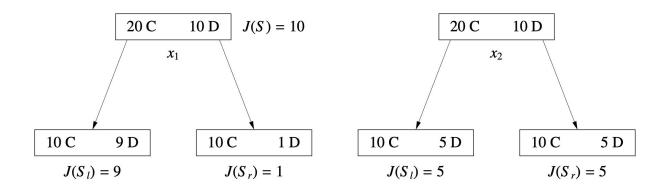
## Trees

#### Vocabulary for decision trees

- Splitting feature (x, y)
- Splitting value (numerical)
- Branches
- Leaves contain the prediction
  For the region demarcated by the leaf
- Parent node
- Child node



# Node splitting

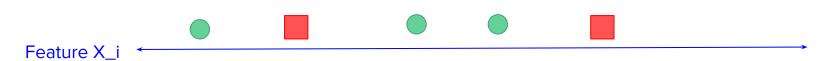


Which is the better split?

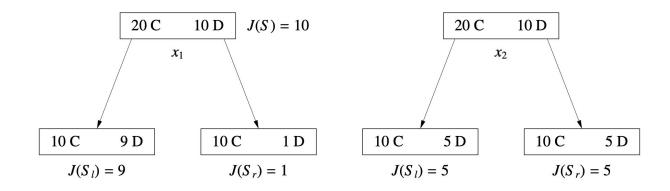
#### How do we determine the split feature and value to choose next?

Greedy heuristic - what does greedy mean?

- Ideally: If the node is **pure** (only contains one class), then return current state
  - Make this the terminating condition to not split the tree any further
- If the node is not **pure**:
  - Go through all the features x\_i in (x, y, ...)
  - For each feature try all the discrete splits into 2 nodes in the range of x\_i
  - Test by doing the split: how much is the "similarity" within child nodes improved?
- Find the best split and continue this on the child nodes



# Measures of "similarity"



Why is cost function Min  $J = J(S_l) + J(S_r)$  not a good cost function?

# Entropy

For a single data point: Entropy is defined as the surprise of a data point x with label A being in Class A

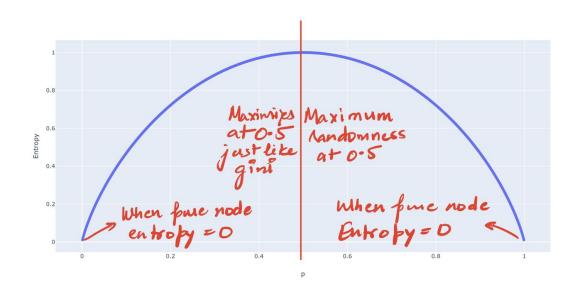
Let p\_c be the proportion of points in set S that are in class C.

$$H(S) = -\sum_{C} p_{C} \log_2 p_{C}$$

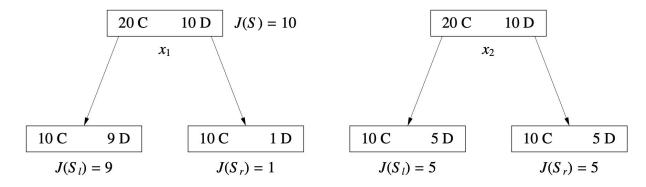
If all points in set S belong to Class A?  $H(S) = 1 \log 2(1) = 0$ 1 is the probability of S bring in class A

Half class A, half class B?  $H(S) = -0.5 \log 2(0.5) - 0.5 \log 2(0.5) = 1$ 

# Why entropy function can be minimized



# Entropy example



Therefore, best split is the split that lowers entropy the most (take weighted avg of the entropies of the nodes)

$$H(S1) = \begin{array}{cc} \frac{19}{30} \left( -\frac{9}{19} \log_2 \left( \frac{9}{19} \right) - \frac{10}{19} \log_2 \left( \frac{10}{19} \right) \right) + \frac{11}{30} \left( -\frac{10}{11} \log_2 \left( \frac{10}{11} \right) - \frac{1}{11} \log_2 \left( \frac{1}{11} \right) \right) \end{array} = 0.79$$

$$H(S2) = ?$$

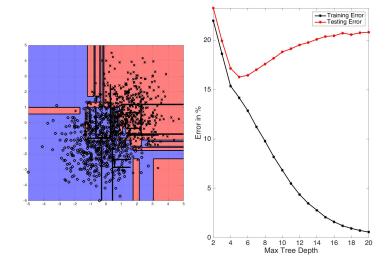
# Overfitting

Decision trees can overfit if they become too deep

For this chart, what is the best tree depth?

#### Solution:

Pruning: try to remove branches from the bottom and see if testing error improves



## **Ensemble methods: Random Forests**

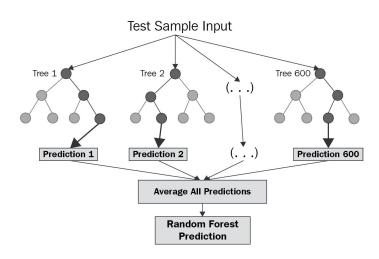
Finds multiple rules - majority wins: effect of drowning out mistakes

**Problem**: The first split in decision trees has an outsize impact on performance

**Solution**: At each split, take random sample of **m** features (out of **d**)

If feature  $x_1$  is a super strong predictor, only a fraction of the trees can choose that predictor as the first split. The split tends to "decorrelate" the trees.

When testing a data point, return the majority vote of the trees

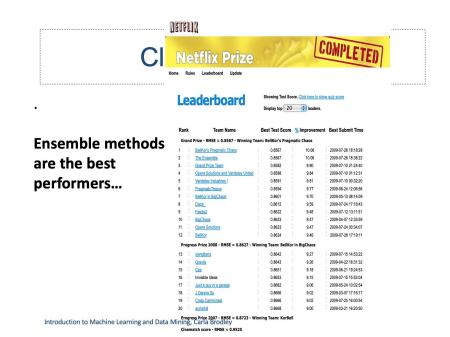


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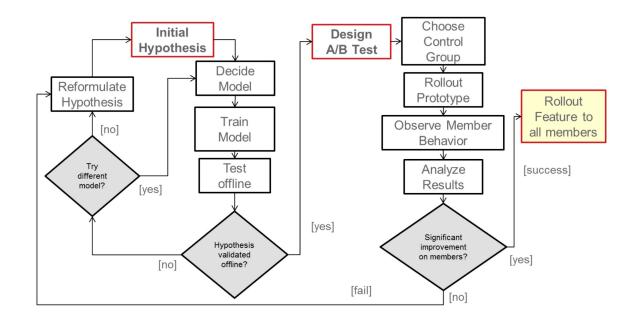
## Business case study: Netflix



- Supervised learning task
  - Training data is a set of users and ratings (1,2,3,4,5 stars) those users have given to movies.
  - Construct a classifier that given a user and an unrated movie, correctly classifies that movie as either 1, 2, 3, 4, or 5 stars
- \$1 million prize for a 10% improvement over Netflix's current movie recommender



Introduction to Machine Learning and Data Mining, Carla Brodley



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## Feedback

https://forms.qle/Uv3YfeGejQqnFXv39

https://tinyurl.com/tw7u8nd