

## Decision Trees – Classification

### Intro

How do decision trees know which features to split from? How are the root node and subsequent nodes chosen?

Decision trees is a greedy algorithm which optimizes how nodes are split through maximization of information gain. This is done through searching for the feature with smallest entropy.

### Definitions

**Entropy:** a measure of randomness – a measure to minimize

$$E(X) = \sum_{i=1}^n -p_i \log_2 p_i$$

where n is the number of classes or labels

**Information Gain:** the reduction in entropy – a measure to maximize

$$IG(Y, X) = E(Y) - E(Y|X)$$

### Example

Supposed we have the following training data:

| Completed Chores | Completed Homework | Played Video Games |
|------------------|--------------------|--------------------|
| Yes              | Yes                | Yes                |
| Partially        | Yes                | Yes                |
| Yes              | No                 | Yes                |
| No               | Yes                | Yes                |
| No               | No                 | No                 |
| Partially        | No                 | No                 |
| Yes              | No                 | Yes                |
| No               | Yes                | Yes                |

### **Contingency Table**

| Completed Chores | Video Games | No Video Games | Total |
|------------------|-------------|----------------|-------|
| Yes              | 3           | 0              | 3     |
| No               | 2           | 1              | 3     |
| Partially        | 1           | 1              | 2     |
| Total            | 6           | 2              | 8     |

$$\text{Entropy (Played Video Games)} = -\frac{6}{8} \log_2 \frac{6}{8} - \frac{2}{8} \log_2 \frac{2}{8} = .81$$

$$\text{Entropy (Played Video Games | Completed Chores = Yes)} = -\frac{3}{3}\log_2\frac{3}{3} - \frac{0}{3}\log_2\frac{0}{3} = 0$$

$$\text{Entropy (Played Video Games | Completed Chores = No)} = -\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3} = .92$$

$$\text{Entropy (Played Video Games | Completed Chores = Partially)} = -\frac{1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2} = 1$$

#### Weighted Average

$$\text{Entropy (Played Video Games | Completed Chores)} = \frac{3}{8} \times 0 + \frac{3}{8} \times .92 + \frac{2}{8} \times 1 = .595$$

#### Information Gain

$$\begin{aligned} &= E(\text{Video Games}) - E(\text{Video Games | Chores}) \\ &= .81 - .595 = .215 \end{aligned}$$

#### Contingency Table

| Completed Homework | Video Games | No Video Games | Total |
|--------------------|-------------|----------------|-------|
| Yes                | 3           | 1              | 4     |
| No                 | 1           | 3              | 4     |
| Total              | 4           | 4              | 8     |

$$\text{Entropy (Played Video Games | Completed Homework = Yes)} = -\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4} = .81$$

$$\text{Entropy (Played Video Games | Completed Homework = No)} = -\frac{1}{4}\log_2\frac{1}{4} - \frac{3}{4}\log_2\frac{3}{4} = .81$$

#### Weighted Average

$$\text{Entropy (Played Video Games | Completed Homework)} = \frac{4}{8} \times .81 + \frac{4}{8} \times .81 = .81$$

#### Information Gain

$$\begin{aligned} &= E(\text{Video Games}) - E(\text{Video Games | Homework}) \\ &= .81 - .81 = 0 \end{aligned}$$

#### Results

Since the information gain for completing chores is larger than the information gain for completing homework (.215 > 0), the feature chosen for the root node will be completing chores.