## Extending Decision Trees

Alice Gao

Lecture 20
Based on work by K. Leyton-Brown, K. Larson, and P. van Beek

## Outline

## Learning Goals

Non-binary Class Variable

Real-valued features

Noise and over-fitting

Revisiting the Learning goals

## Learning Goals

By the end of the lecture, you should be able to

## Jeeves the valet - training set

| Day | Outlook | Temp | Humidity | Wind | Tennis? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | Sunny | Hot | High | Weak | No |
| 2 | Sunny | Hot | High | Strong | No |
| 3 | Overcast | Hot | High | Weak | Yes |
| 4 | Rain | Mild | High | Weak | Yes |
| 5 | Rain | Cool | Normal | Weak | Yes |
| 6 | Rain | Cool | Normal | Strong | No |
| 7 | Overcast | Cool | Normal | Strong | Yes |
| 8 | Sunny | Mild | High | Weak | No |
| 9 | Sunny | Cool | Normal | Weak | Yes |
| 10 | Rain | Mild | Normal | Weak | Yes |
| 11 | Sunny | Mild | Normal | Strong | Yes |
| 12 | Overcast | Mild | High | Strong | Yes |
| 13 | Overcast | Hot | Normal | Weak | Yes |
| 14 | Rain | Mild | High | Strong | No |

## Jeeves the valet - the test set

| Day | Outlook | Temp | Humidity | Wind | Tennis? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | Sunny | Mild | High | Strong | No |
| 2 | Rain | Hot | Normal | Strong | No |
| 3 | Rain | Cool | High | Strong | No |
| 4 | Overcast | Hot | High | Strong | Yes |
| 5 | Overcast | Cool | Normal | Weak | Yes |
| 6 | Rain | Hot | High | Weak | Yes |
| 7 | Overcast | Mild | Normal | Weak | Yes |
| 8 | Overcast | Cool | High | Weak | Yes |
| 9 | Rain | Cool | High | Weak | Yes |
| 10 | Rain | Mild | Normal | Strong | No |
| 11 | Overcast | Mild | High | Weak | Yes |
| 12 | Sunny | Mild | Normal | Weak | Yes |
| 13 | Sunny | Cool | High | Strong | No |
| 14 | Sunny | Cool | High | Weak | No |

## Extending Decision Trees

1. Non-binary class variable
2. Real-valued features
3. Noise and over-fitting

## The modified ID3 algorithm

Algorithm 1 ID3 Algorithm (Features, Examples)
1: If all examples belong to the same class, return a leaf node with a decision for that class.
2: If no features left, return a leaf node with the majority decision of the examples.
3: If no examples left, return a leaf node with the majority decision of the examples in the parent.
4: else
5: choose feature $f$ with the maximum information gain
6: for each value $v$ of feature $f$ do
7: add arc with label $v$
8: $\quad$ add subtree $I D 3(F-f, s \in S \mid f(s)=v)$
9: end for

## CQ: Calculating the information gain

CQ: Suppose that we are classifying examples into three classes. Before testing feature $X$, there are 3 examples in class $c_{1}, 5$ examples in class $c_{2}$, and 2 examples in class $c_{3}$. Feature $X$ has two values $a$ and $b$. When $X=a$, there are 1 examples in class $c_{1}$, 5 examples in class $c_{2}$, and 0 examples in class $c_{3}$. When $X=b$, there are 2 examples in class $c_{1}, 0$ examples in class $c_{2}$, and 2 examples in class $c_{3}$.
What is the information gain for testing feature $X$ at this node?
(A) $[0,0.2)$
(B) $[0.2,0.4)$
(C) $[0.4,0.6)$
(D) $[0.6,0.8)$
(E) $[0.8,1]$

## Jeeves dataset with real-valued temperatures

| Day | Outlook | Temp | Humidity | Wind | Tennis? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | Sunny | 29.4 | High | Weak | No |
| 2 | Sunny | 26.6 | High | Strong | No |
| 3 | Overcast | 28.3 | High | Weak | Yes |
| 4 | Rain | 21.1 | High | Weak | Yes |
| 5 | Rain | 20.0 | Normal | Weak | Yes |
| 6 | Rain | 18.3 | Normal | Strong | No |
| 7 | Overcast | 17.7 | Normal | Strong | Yes |
| 8 | Sunny | 22.2 | High | Weak | No |
| 9 | Sunny | 20.6 | Normal | Weak | Yes |
| 10 | Rain | 23.9 | Normal | Weak | Yes |
| 11 | Sunny | 23.9 | Normal | Strong | Yes |
| 12 | Overcast | 22.2 | High | Strong | Yes |
| 13 | Overcast | 27.2 | Normal | Weak | Yes |
| 14 | Rain | 21.7 | High | Strong | No |

## Jeeves dataset ordered by temperatures

| Day | Outlook | Temp | Humidity | Wind | Tennis? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 7 | Overcast | 17.7 | Normal | Strong | Yes |
| 6 | Rain | 18.3 | Normal | Strong | No |
| 5 | Rain | 20.0 | Normal | Weak | Yes |
| 9 | Sunny | 20.6 | Normal | Weak | Yes |
| 4 | Rain | 21.1 | High | Weak | Yes |
| 14 | Rain | 21.7 | High | Strong | No |
| 8 | Sunny | 22.2 | High | Weak | No |
| 12 | Overcast | 22.2 | High | Strong | Yes |
| 10 | Rain | 23.9 | Normal | Weak | Yes |
| 11 | Sunny | 23.9 | Normal | Strong | Yes |
| 2 | Sunny | 26.6 | High | Strong | No |
| 13 | Overcast | 27.2 | Normal | Weak | Yes |
| 3 | Overcast | 28.3 | High | Weak | Yes |
| 1 | Sunny | 29.4 | High | Weak | No |

## CQ: Testing a discrete feature

CQ: Suppose that feature $X$ has discrete values (e.g. Temp is Cool, Mild, or Hot.) On any path from the root to a leaf, how many times can we test feature $X$ ?
(A) 0 times
(B) 1 time
(C) $>1$ time
(D) Two of (A), (B), and (C) are correct.
(E) All of (A), (B), and (C) are correct.

## CQ: Testing a continuous feature

CQ: Suppose that feature $X$ has continuous values (e.g. Temp ranges from 17.7 to 29.4.) On any path from the root to a leaf, how many times can we test feature $X$ ?
(A) 0 times
(B) 1 time
(C) $>1$ time
(D) Two of (A), (B), and (C) are correct.
(E) All of (A), (B), and (C) are correct.

## Jeeves training set is corrupted

| Day | Outlook | Temp | Humidity | Wind | Tennis? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | Sunny | Hot | High | Weak | No |
| 2 | Sunny | Hot | High | Strong | No |
| 3 | Overcast | Hot | High | Weak | No |
| 4 | Rain | Mild | High | Weak | Yes |
| 5 | Rain | Cool | Normal | Weak | Yes |
| 6 | Rain | Cool | Normal | Strong | No |
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| 12 | Overcast | Mild | High | Strong | Yes |
| 13 | Overcast | Hot | Normal | Weak | Yes |
| 14 | Rain | Mild | High | Strong | No |

## Revisiting the Learning Goals

By the end of the lecture, you should be able to

