

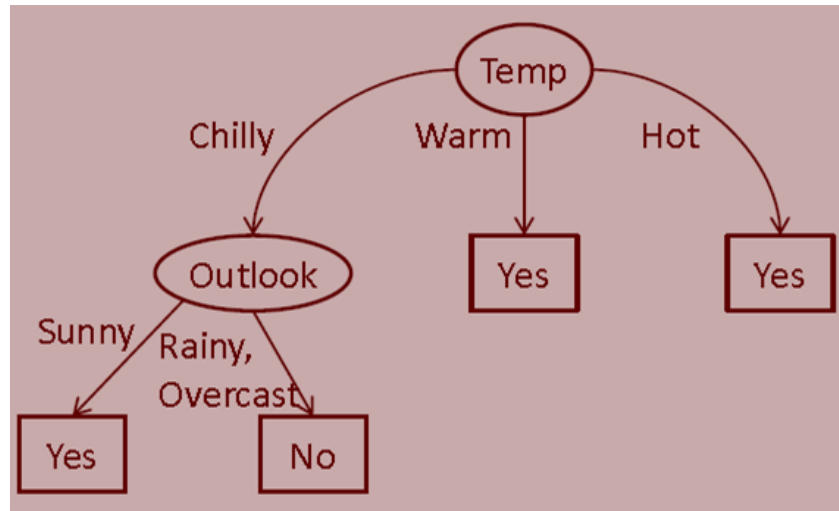
Decision trees. Applications

Lecture 2.5

A decorative graphic consisting of several horizontal lines of varying lengths and colors (brown, white, and grey) extending from the right side of the slide towards the center.

Decision trees for classification

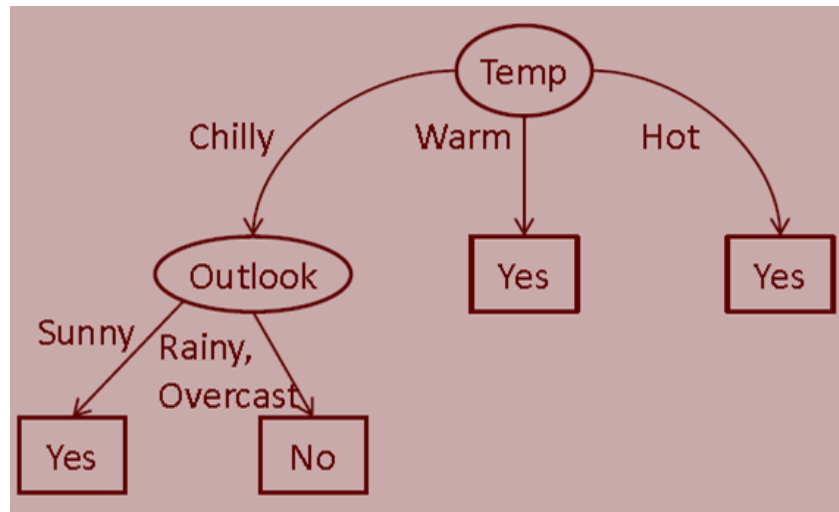
- Classify and make transparent decision
- Each class leaf has its own rule path
- The same result by different reasons



- ID3 algorithm
- Design issues
 - Split criteria
 - Stop criteria
 - Multi-valued attributes
 - Numeric attributes
 - Missing values
 - Overfitting
- ▶ Applications
 - Limitations
 - Real-life examples
 - Extracting rules from trees

Decision trees for data exploration

- The most important attributes are at the top of the tree
- Start each data mining project from exploring the most important attributes with decision trees



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When (not) to use decision trees

Good performance (use decision trees)

- The factors of decision are not less important than the classification accuracy
- The goal is to assign each record to one of a few broad categories (Categorical attributes with low cardinality*)
- **You suspect that there is a set of objective rules underlying the data**

Not that good performance (use something else)

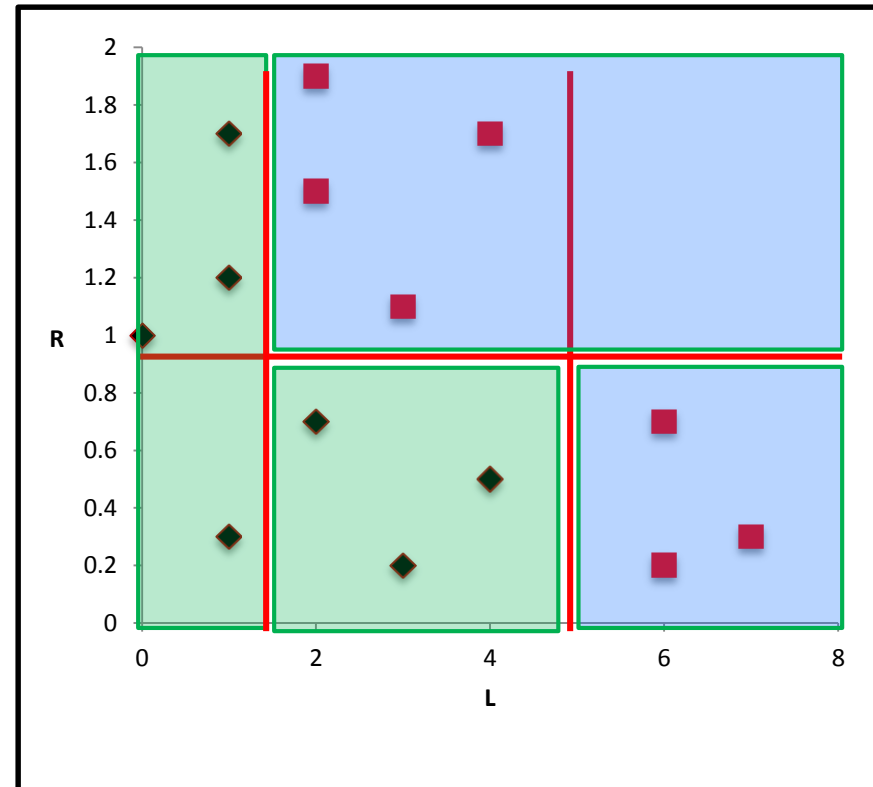
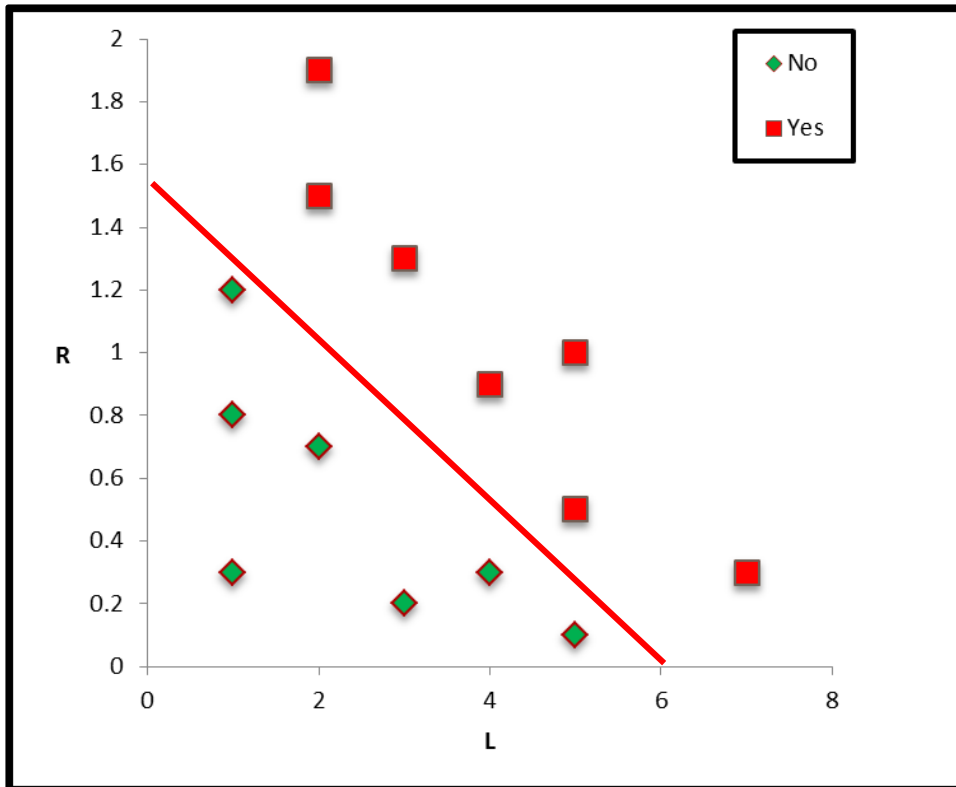
- Continuous numeric attributes, ordinal attributes
- Hierarchical relationships between classes
- High-cardinality attributes
- Numeric value prediction

*cardinality - the number of possible distinct values

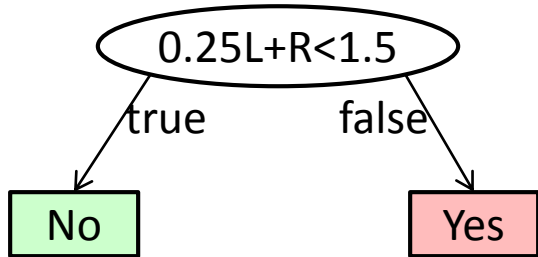
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Limitations. Rectilinear decision boundaries

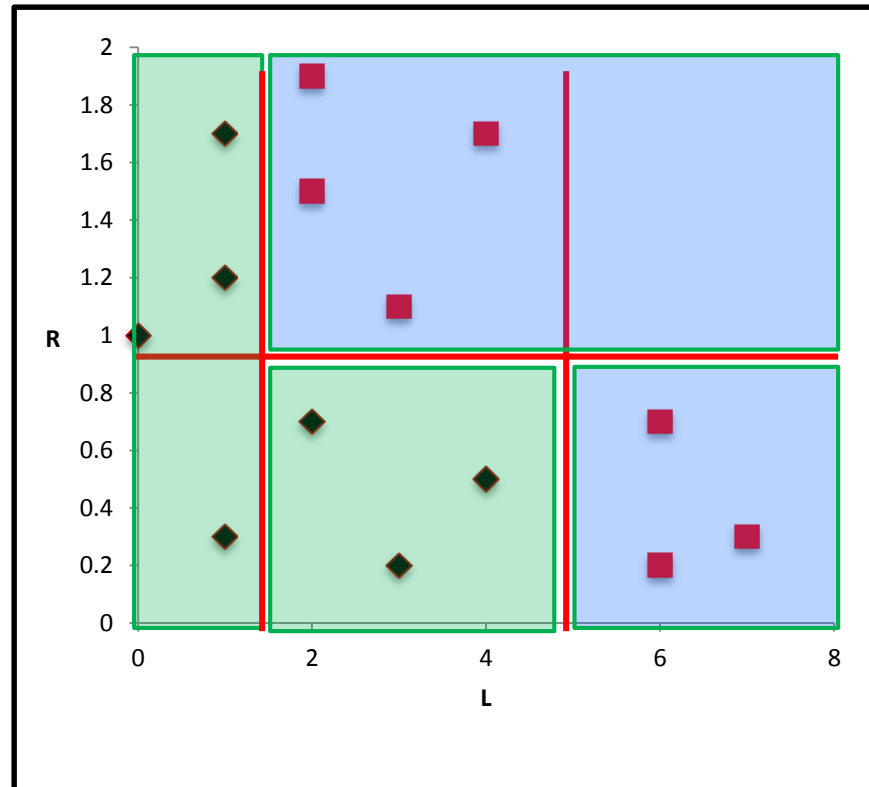
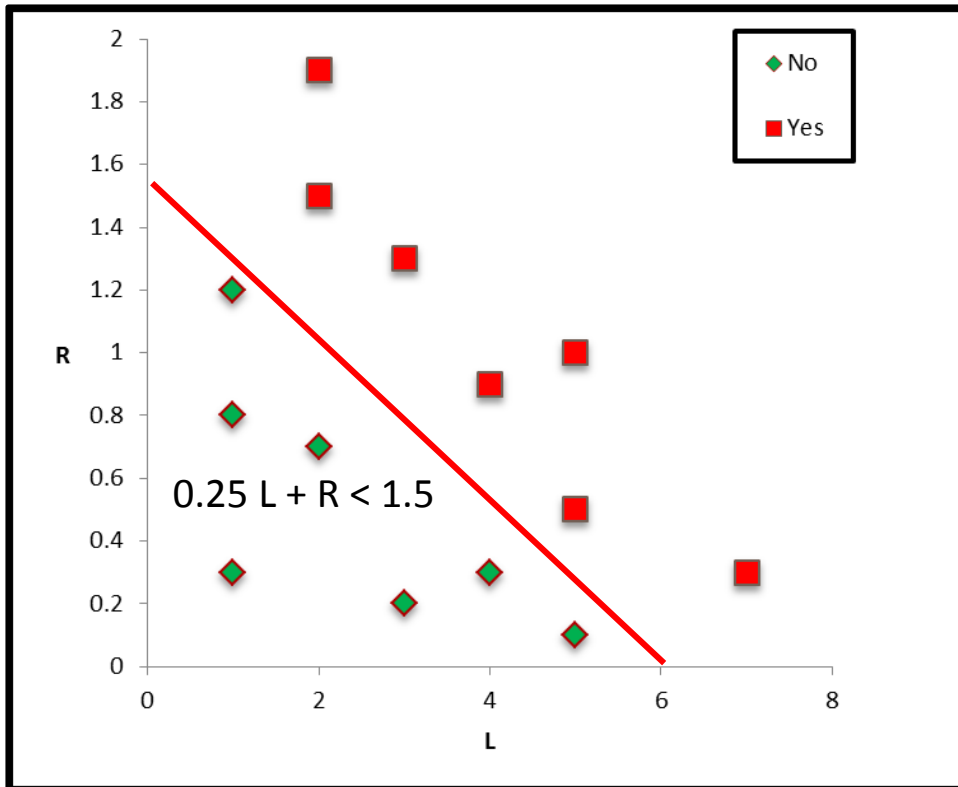
- Boolean split: the instances are divided by the boundaries which are parallel to the axes
- Solution: use all reasonable combinations of attributes.



Non-rectilinear boundaries: attribute combinations



One-level decision tree



Decision trees in real life

- Selecting the most promising eggs for in-vitro fertilization – England, 2000
- Soybean disease classification – 1979, 97% accuracy vs. 72% by human expert
- Classification system for serial criminal patterns (CSSCP) - using three years' worth of data on armed robbery, the system was able to spot 10 times as many patterns as a team of experienced detectives with access to the same data.
- Screening potential terrorists and drug smugglers at border crossings

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Border crossing: gross oversimplification

- Age: 20-25
- Gender: male
- Nationality: Saudi Arabia
- Country of residence: Germany
- Visa status: student
- University: unknown
- # times entering the country in the past year: 3
- Countries visited during the past 3 years: U.K., Pakistan
- Flying lessons: yes

Assessment: possible terrorist (probability 29%)

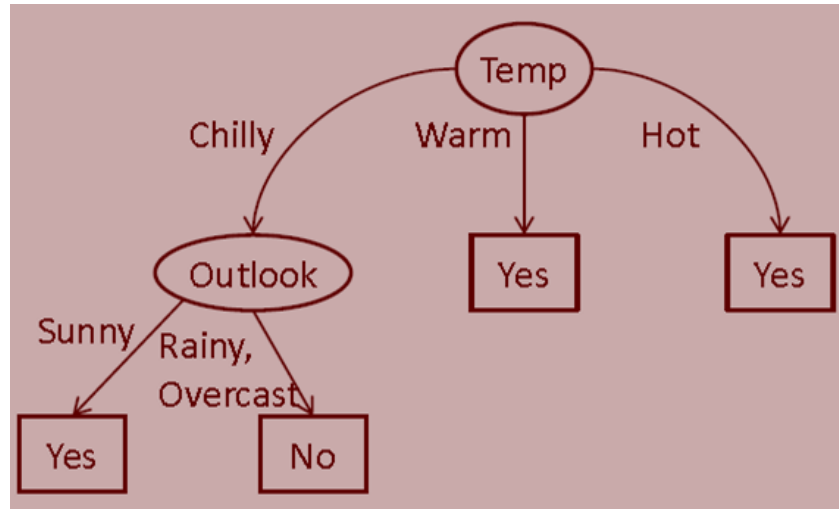
Action: detain and report

Carnival Booth: An Algorithm for Defeating the Computer-Assisted Passenger Screening System

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From trees to rules: how?

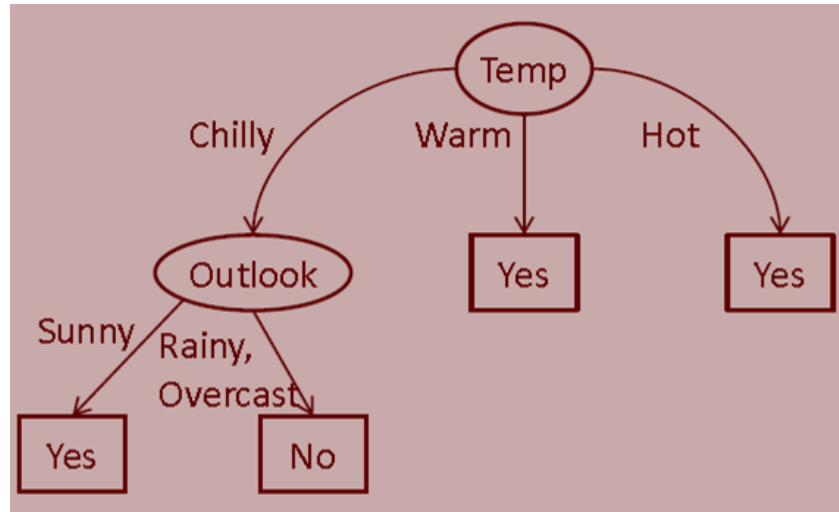
- How can we produce a set of rules from a decision tree?



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From trees to rules – simple

- One rule for each leaf



If Temp = “Warm” **then** play

If Temp = “Hot” **then** play

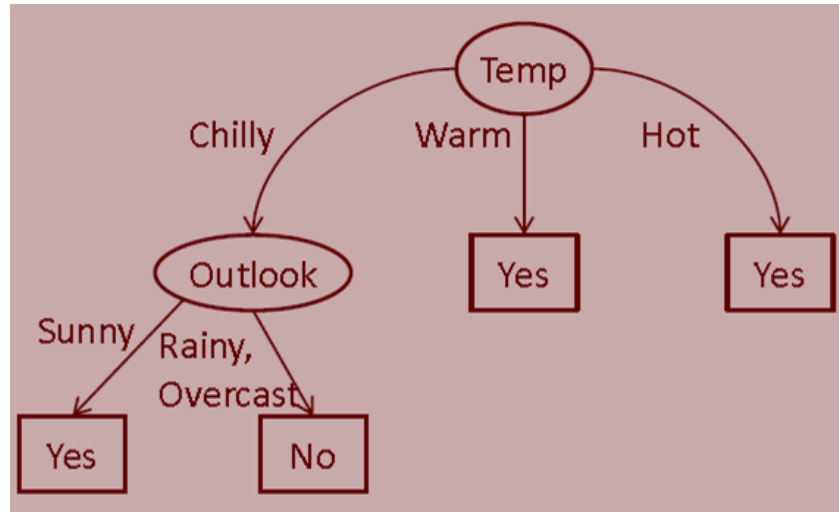
If Temp = “Chilly” and Outlook=“Sunny” **then** play

Default: no play

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From trees to rules – simple

- The set of rules can be minimized



If Temp = “Chilly” and (Outlook=“Sunny” or Outlook = “Overcast”)
then no play
Default: play

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Difference between decision trees and rules

- Rules are more readable than decision trees
- Decision trees describe the **general concept** extracted from the data, while each rule represents **a nugget of knowledge**
- Trees contain predictions for **all class variables**, while each rule predicts only **one class value**

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