TECHNISCHE UNIVERSITÄT DRESDEN

Dresden Database Systems Group

Classification

Programming for Data Science

Warm Up

Dresden Database Systems Group

Answer the following statements! Give reason for your answers.

1. What are the pitfalls of recursion?
2. What is the maximum of any entropy function?
3. What is a good way to partition data in databases by attributes?

https://amcs.website

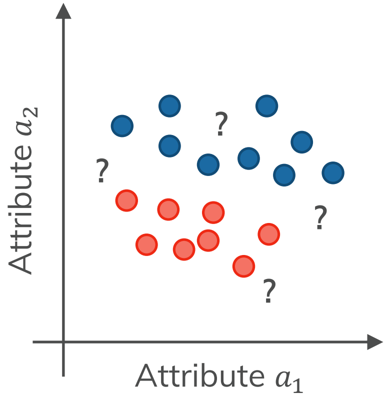
Classification Problem

Given

- A d-dimensional space D with attributes a_i, $(i = 1, \dots, d)$
- A set $C = \{c_1, \dots, c_k\}$ of k different class labels c_j, $(j = 1, \dots, k)$
- A set $X \subseteq D$ of n observations $X = \{x_1, \dots, x_n\}$ with known class labels where $x_l = (a_1, \dots, a_d), (l = 1, \dots, n)$

Goal

- Labeling all observations $D \setminus X$ whose class is unknown
- Better understand the data

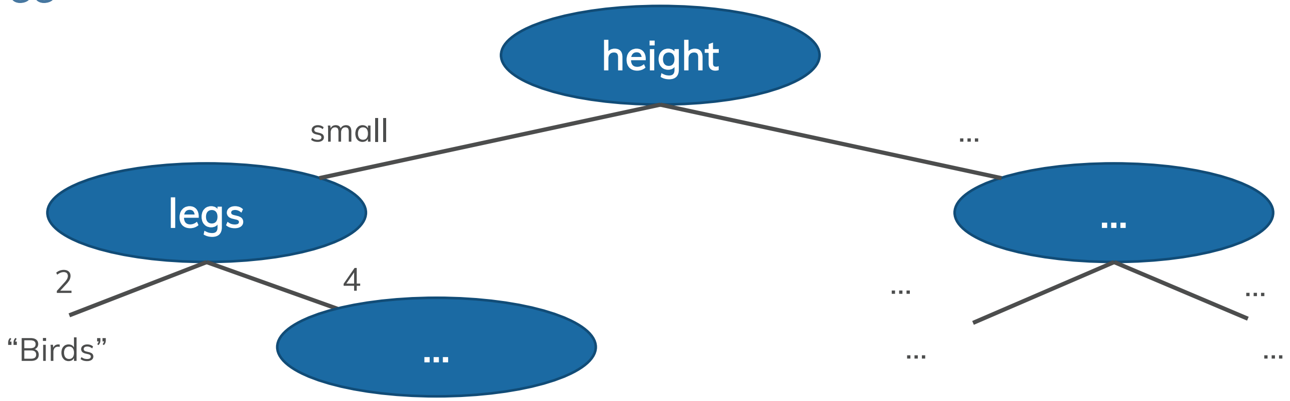


Decision Tree Classifier

Training set

Index	1	2	3	4	...
Height *h*	small	small	tall	small	...
Legs *l*	0	2	2	4	...
Class C	Fish	Bird	Human	Cat	...

Decision Tree



Decision Tree Classifier (2)

Decision Tree

- Flowchart-like tree structure
- Inner nodes are test attributes
- Leaf nodes represent class label and frequency
- Different paths (different attributes and values) to different class labels

Construction of Decision Tree

- Construction
  - The training set is linked with the root node
  - Partitioning of training set with respect to test attributes
- Pruning
  - Identification and pruning of noise and outliers

Prediction of Decision Tree

- New items are classified by tree traversal
- Class label is determined by leaf node

Decision Tree Classifier (3)

Partition Algorithm (Greedy-like)

- Construction of decision tree: top-down, recursive, divide-and-conquer
- Supports categorical and continuous attributes
- Initially, training set is linked to root node
- Recursive partitioning of training set on each node
  - Passing disjoint subsets of training set to child node
- Selection of test attributes and split points per inner node
  - Usage of heuristics or statistical measures, e. g., information gain

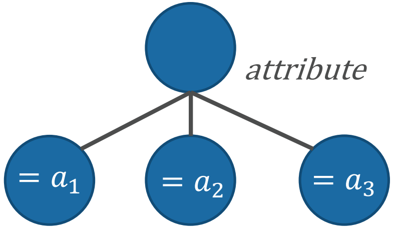
Termination

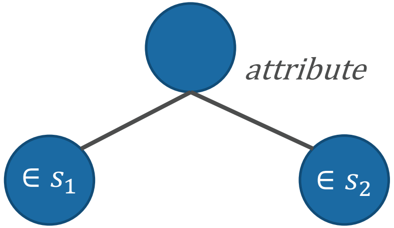
- All observations of training set belong to a class
- There are no attributes that can be used for partitioning (class label is chosen by majority vote)

Decision Tree Classifier (4)

Categorical Attributes

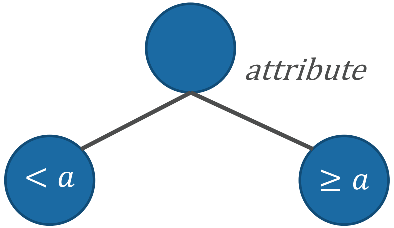
- Split based on equality constraint
  $attribute = value$
- Split based on subset constraint
  $attribute \in set$
- Other alternatives





Continuous Attributes

- Split based on inequality constraint
  $attribute < value$
- Definition of interval with endpoints allows for many decision options
- Other alternatives



Decision Tree Classifier (5)

Dresden Database Systems Group

Accuracy of Splits for Prediction

- Let T be the training set
- Disjoint, complete partitioning of $T = T_1, T_2, \ldots, T_m$
- Relative frequency p_j of class c_j in T_i
- Goal
  - Find a measure that describes the heterogeneity of the test set with respect to their class attributes
  - A split of $T = T_1, T_2, \ldots, T_m$ shall minimize the heterogeneity of each partition T_i

Common Measures

- Information Gain
  - Used for categorical attributes
  - Modifications for continuous attributes exist
- Gini Index (IBM IntelligentMiner)
  - Measure of inequality
  - Used for continuous attributes
  - Modifications for categorical attributes exist

Information Gain

Basics

- *Self-information* represents a unit of information for a given event
- An event with probability p has the self-information I:

$$I(p) = -\log_2 p$$

- The entropy is the expected information of the set T with probability p_i of item i:

$$H(T) = \sum_{i=1}^{k} p_i \cdot I(p_i) = -\sum_{i=1}^{k} p_i \cdot \log_2 p_i$$

Application on Decision Trees

- There are k classes c_i with frequency p_i
- $H(T) = max$ if all classes c_i have the same probability $p_i = 1/k$
- $H(T) = 0$ if one class c_i has $p_i = 1$
- Entropy refers to uncertainty

Information Gain (2)

Dresden Database Systems Group

Definition

- Attribute A realizes partitioning T in $T_1, T_2, \dots, T_m$
- The *information gain* of A with respect to T is

$$\text{informationgain}(T, A) \coloneqq H(T) - \sum_{i=1}^{m} \frac{|T_i|}{|T|} \cdot H(T_i)$$

- The expected value of the information gain is the reduction in the entropy of T by learning from attribute A

Algorithms

- Iterative Dichotomiser 3 (ID3)
- C4.5 as an extension of ID3

Decision Trees (ID3)

Dresden Database Systems Group

Generate the decision tree for the following classification problem.

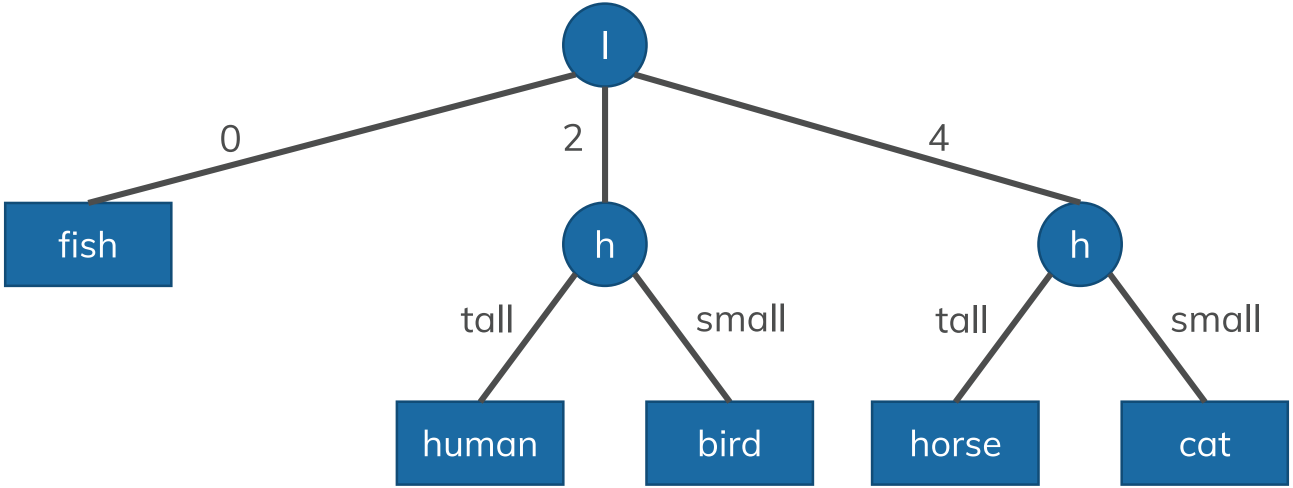
Index	1	2	3	4	5	6	7	8
Height *h*	small	small	tall	small	tall	tall	small	tall
Legs *l*	0	2	2	4	4	2	4	2
Class C	Fish	Bird	Human	Cat	Horse	Human	Cat	Human

- Attributes: $a_1 = h =$ height, $a_2 = l =$ legs
- Classes creatures $C = \{c_{fish}, c_{bird}, c_{human}, c_{cat}, c_{horse}\}$

$$\text{informationgain}(T, A) \coloneqq H(T) - \sum_{i=1}^{m} \frac{|T_i|}{|T|} \cdot H(T_i)$$

$$H(T) = -\sum_{i=1}^{k} p_i \cdot \log_2 p_i$$

Decision Tree (ID3)



Task

Dresden Database Systems Group

Step 0

- You will get a csv file from us. Load it in your language/environment.
- Explore the data in it. Identify the input data X and the labels.

Step 1

- Implement an ID3 decision tree*.

Step 2

- Use your decision tree to classify: rainy forecast, hot temperature, high humidity, strong wind

*use your own implementation

Package suggestions

R

- (data.table)

python3

- numpy
- pandas

Exercise Appointment

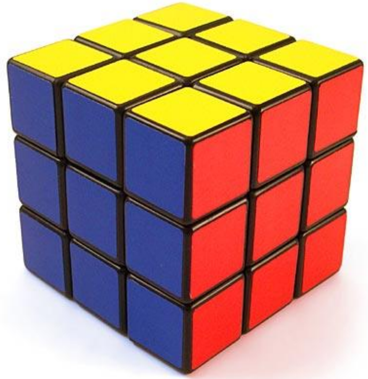
Dresden Database Systems Group

We compare and discuss the results

- Tuesday, 01.12.2020,
- Consultation: Please use the forum in Opal.
- Please prepare your solutions! Send us your code!

If you have questions, please mail us:

claudio.hartmann@tu-dresden.de Orga + Code + R
lucas.woltmann@tu-dresden.de Tasks + Python



Decision Tree (ID3)