

Lecture 8: Handling Numeric Attributes

Madhavan Mukund

<https://www.cmi.ac.in/~madhavan>

Data Mining and Machine Learning
August–December 2020

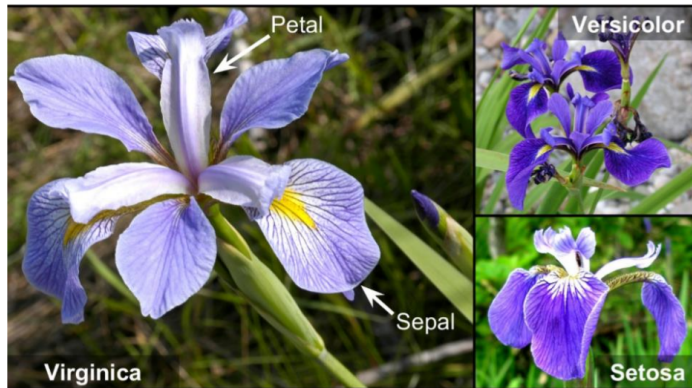
Categorical vs numeric attributes

- So far, all attributes have been categorical
- What age groups make up young, middle, old?
- How are these boundaries defined?
- How do we query numerical attributes?
 - Height, weight, length, income,

ID	Age	Has_job	Own_house	Credit_rating	Class
1	young	false	false	fair	No
2	young	false	false	good	No
3	young	true	false	good	Yes
4	young	true	true	fair	Yes
5	young	false	false	fair	No
6	middle	false	false	fair	No
7	middle	false	false	good	No
8	middle	true	true	good	Yes
9	middle	false	true	excellent	Yes
10	middle	false	true	excellent	Yes
11	old	false	true	excellent	Yes
12	old	false	true	good	Yes
13	old	true	false	good	Yes
14	old	true	false	excellent	Yes
15	old	false	false	fair	No

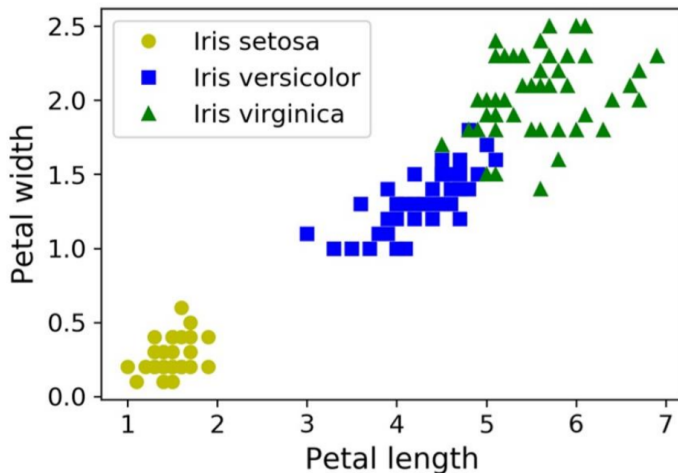
Iris dataset

- Iris is a type of flower
- Three species: *iris setosa*, *iris versicolor*, *iris virginica*
- Dataset has sepal length and width and petal length and width for 150 flowers



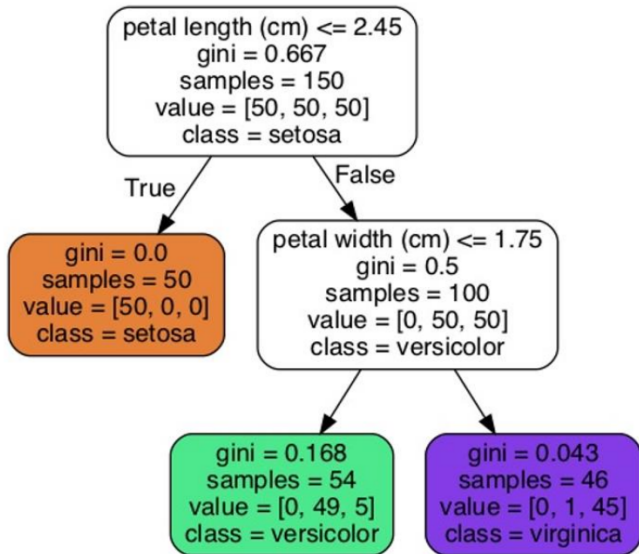
Iris dataset

- Iris is a type of flower
- Three species: *iris setosa*, *iris versicolor*, *iris virginica*
- Dataset has sepal length and width and petal length and width for 150 flowers
- Scatter plot for two attributes, petal length and petal width



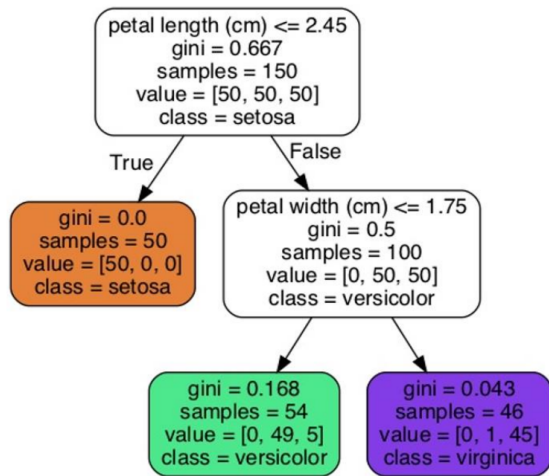
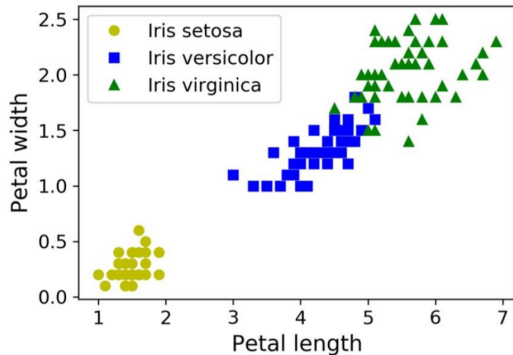
Iris dataset

- Iris is a type of flower
- Three species: *iris setosa*, *iris versicolor*, *iris virginica*
- Dataset has sepal length and width and petal length and width for 150 flowers
- Scatter plot for two attributes, petal length and petal width
- Decision tree for this data set



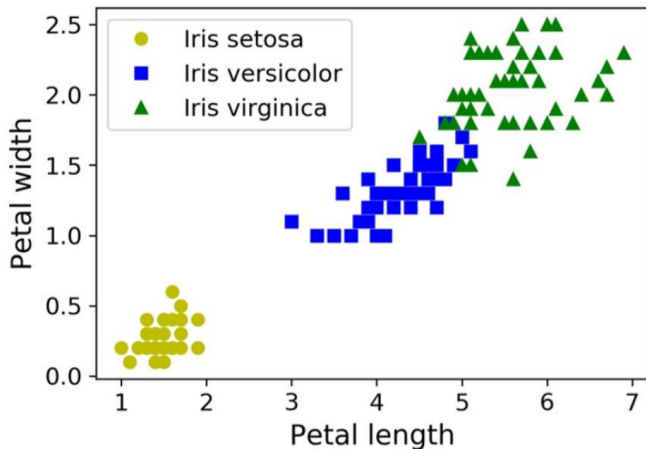
Decision tree for iris dataset

- Queries compare numerical attribute against a value
- How do we find these query values?



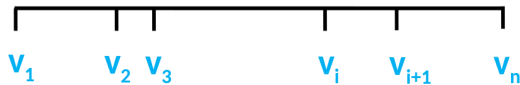
Querying numerical attributes

- Numerical attribute takes values in a range $[L, U]$
 - Petal length : $[1, 7]$
 - Petal width : $[0, 2.5]$
- Pick a value v in the range and check if $A \leq v$
- Infinitely many choices for v
- How do we pick a sensible one?



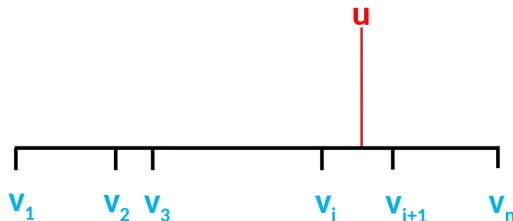
Querying numerical attributes

- Only n values for A in training data
 - Sort as $v_1 < v_2 < \dots < v_n$



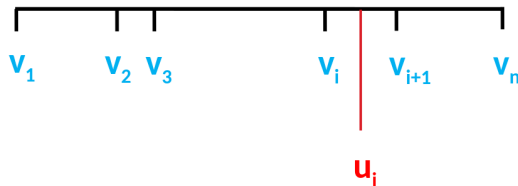
Querying numerical attributes

- Only n values for A in training data
 - Sort as $v_1 < v_2 < \dots < v_n$
- Consider interval $[v_i, v_{i+1}]$
- For each $v_i \leq u < v_{i+1}$, query $A \leq u$ gives the same answer
- Only $n-1$ useful intervals to check



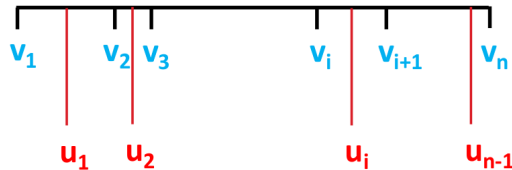
Querying numerical attributes

- Only n values for A in training data
 - Sort as $v_1 < v_2 < \dots < v_n$
- Consider interval $[v_i, v_{i+1}]$
- For each $v_i \leq u < v_{i+1}$, query $A \leq u$ gives the same answer
- Only $n-1$ useful intervals to check
- Pick midpoint $u_i = (v_i + v_{i+1})/2$ as query value for each interval



Querying numerical attributes

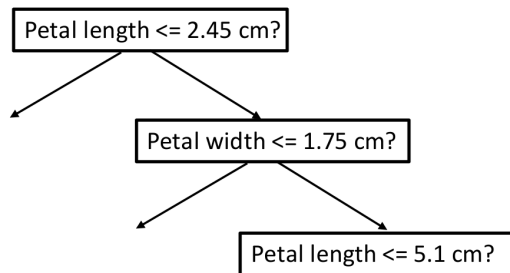
- Pick midpoint $u_i = (v_i + v_{i+1})/2$ as query value for each interval
- Each query $A \leq u_i$ partitions training data
- Choose the query $A \leq u_i$ with maximum information gain
- Assign this as the information gain for this attribute
- Compare across all attributes and choose best one



- Any point within an interval can be used
- May prefer endpoints — midpoints may not be meaningful values

Building a decision tree

- For each numerical attribute, choose query $A \leq v$ with maximum information gain
- Across all categorical and numerical attributes, choose the one with best information gain
- Categorical attributes can be queried only once on a path
- Numerical attributes can be queried repeatedly — interval to query keeps shrinking



Summary

- For numerical attributes, $n-1$ intervals in training data generate $n-1$ comparison queries
- Each query partitions the training data
- Choose the query that maximizes information gain
- The same numerical attribute may be queried repeatedly along a path

