Data Mining

Practical Machine Learning Tools and Techniques

Slides for Chapter 6 of *Data Mining* by I. H. Witten and E. Frank

Decision trees

- Extending previous approach:
  - to permit numeric attributes: *straightforward*
  - to deal sensibly with missing values: *trickier*
  - stability for noisy data: *requires pruning mechanism*
  - to handle regression
- End result: C4.5
  - Best-known and (probably) most widely-used learning algorithm
  - Commercial successor: C5.0

Review of Basic Strategy

- Strategy: top down
  Recursive *divide-and-conquer* fashion
  - First: select attribute for root node
    Create branches depending on the values of attribute at the root.
  - Then: split instances into subsets
    One for each branch extending from the node
  - Finally: repeat recursively for each branch, using only instances that reach the branch
- Stop if all instances have the same class

Review: Splitting Attribute

- Entropy function:

$$\text{entropy}(p_1, p_2, \ldots, p_n) = -p_1 \log p_1 - p_2 \log p_2 \ldots - p_n \log p_n$$

- Example of information calculation:

$$\text{info}([2,3]) = \text{entropy}(2/5, 3/5) = -2/5 \log(2/5) - 3/5 \log(3/5)$$

- information gain = info[v]-info[children of v]

Numeric attributes

- Standard method: binary splits
  - E.g. temp < 45
- Unlike nominal attributes, every attribute has many possible split points
- Solution is straightforward extension:
  - Evaluate info gain for every possible split point of attribute
  - Choose "best" split point
  - Info gain for best split point is info gain for attribute
- Computationally more demanding

Weather data (again!)

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
...	...	...	...	...

```
If outlook = sunny and humidity = high then play = no
If outlook = rainy and windy = true then play = no
If outlook = overcast then play = yes
If humidity = normal then play = yes
If none of the above then play = yes
```


Weather data (again!)

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny				
Overcast				
Rainy				
Rainy				
Rainy				
...				

Outlook	Temperature	Humidity	Windy	Play
Sunny	85	85	False	No
Sunny	80	90	True	No
Overcast	83	86	False	Yes
Rainy	70	96	False	Yes
Rainy	68	80	False	Yes
Rainy	65	70	True	No
...	...	...	...	...

```
If outlook = sunny and humidity = high then play = no
If outlook = rainy and windy = true then play = no
If outlook = overcast then play = yes
If humidity = normal then play = yes
If none of the
```

```
If outlook = sunny and humidity > 83 then play = no
If outlook = rainy and windy = true then play = no
If outlook = overcast then play = yes
If humidity < 85 then play = no
If none of the above then play = yes
```


Example

- Split on temperature attribute:

64	65	68	69	70	71	72	72	75	75	80	81	83	85
Yes	**No**	**Yes**	**Yes**	**Yes**	**No**	**No**	**Yes**	**Yes**	**Yes**	**No**	**Yes**	**Yes**	**No**

  - E.g. temperature < 71.5: yes/4, no/2
    temperature ≥ 71.5: yes/5, no/3
  - Info([4,2],[5,3])
    = 6/14 info([4,2]) + 8/14 info([5,3])
    = 0.939 bits
- Place split points halfway between values
- Can evaluate all split points in one pass!

Can avoid repeated sorting

- Sort instances by the values of the numeric attribute
- Does this have to be repeated at each node of the tree?
- No! Sort order for children can be derived from sort order for parent
  - Drawback: need to create and store an array of sorted indices for each numeric attribute

Binary *vs* multiway splits

- Splitting (multi-way) on a nominal attribute exhausts all information in that attribute
  - Nominal attribute is tested (at most) once on any path in the tree
- Not so for binary splits on numeric attributes!
  - Numeric attribute may be tested several times along a path in the tree
- Disadvantage: tree is hard to read
- Remedy:
  - pre-discretize numeric attributes, *or*
  - use multi-way splits instead of binary ones

Missing values

- Simplest strategy: send instances down the popular branch.
- More sophisticated: Split instances with missing values into pieces
  - A piece going down a branch receives a weight proportional to the popularity of the branch
  - weights sum to 1
  - During classification, split the instance into pieces in the same way

Pruning

- Prevent overfitting to noise in the data
- "Prune" the decision tree
- Two strategies:
  - *Postpruning*
    take a fully-grown decision tree and discard unreliable parts
  - *Prepruning*
    stop growing a branch when information becomes unreliable
- Postpruning preferred in practice—prepruning can "stop early"

Prepruning

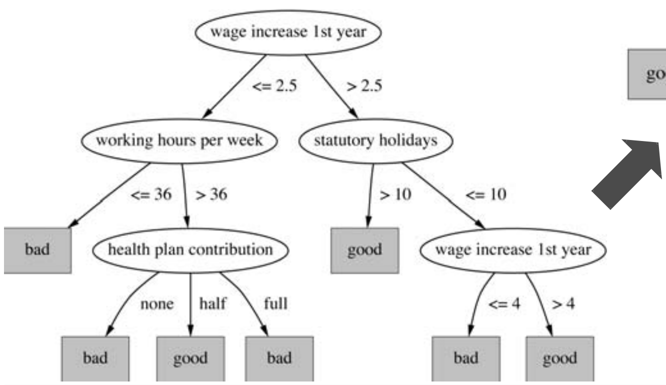
- Based on statistical significance test
  - Stop growing the tree when there is no *statistically significant* association between any attribute and the class at a particular node
- Most popular test: *chi-squared test (ID3)*

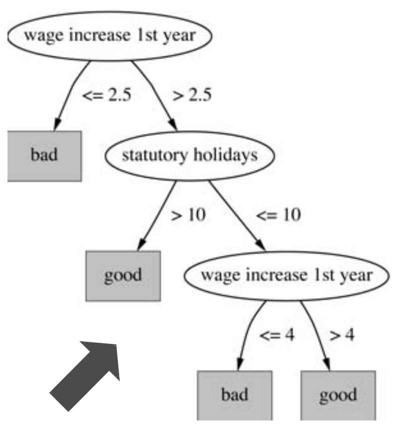
Postpruning

- First, build full tree
- Then, prune it
  - Fully-grown tree shows all attribute interactions
- How? determine whether some subtrees might be due to chance effects
  - Two pruning operations:
    - *Subtree replacement*
    - *Subtree raising*
  - Use error estimation or statistical techniques

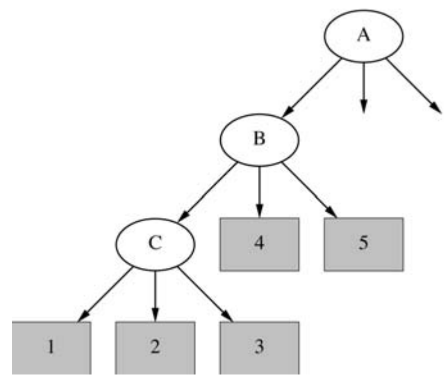
Subtree replacement

- *Bottom-up*
- Consider replacing a tree only after considering all its subtrees

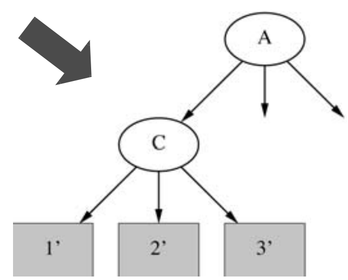




Subtree raising



- Delete node
- Redistribute instances
- Slower than subtree replacement
  (Worthwhile?)



Estimating error rates

- Prune only if it does not increase the estimated error
- Error on the training data is NOT a useful estimator
  (would result in almost no pruning)
- Use hold-out set for pruning
  ("reduced-error pruning")
- C4.5's method
  - Derive confidence interval from training data
  - Use a heuristic limit, derived from this, for pruning
  - Standard Bernoulli-process-based method

Regression trees

- Similar to decision trees but a leaf = average values of instances reaching leaf.
- Differences:
  - Splitting criterion: minimize intra-subset variation – can use standard deviation
  - Termination criterion: std dev becomes small
  - Prediction: Leaf predicts average class values of instances
- More sophisticated version: *model trees – each leaf represents a linear regression function*