Decision tree learning

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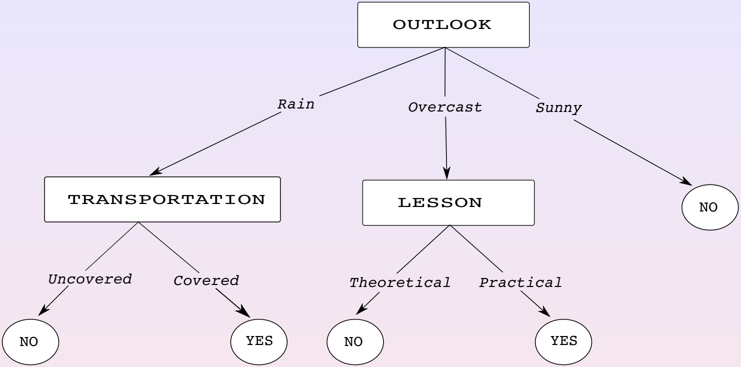
Machine Learning

Learning the concept *Go to lesson*



Decision trees encode logical formulas

- A decision tree represents a disjunction of conjunctions of constraints over attribute values.
- Each path from the root to a leaf is a conjunction of the constraints specified in the nodes along it:

$$\text{OUTLOOK} = \mathit{Overcast} \land \text{LESSON} = \mathit{Theoretical}$$

- The leaf contains the label to be assigned to instances reaching it
- The disjunction of all paths is the logical formula represented by the tree

Appropriate problems for decision trees

- Binary or multiclass classification tasks (extensions to regressions also exist)
- Instances represented as attribute-value pairs
- Different explanations for the concept are possible (disjunction)
- Some instances have missing attributes
- There is need for an interpretable explanation of the output

Learning decision trees

- Greedy top-down strategy (ID3 - Quinlan 1986, C4-5 - Quinlan 1993)
- For each node, starting from the root with full training set:
  1. Choose best attribute to be evaluated
  2. Add a child for each attribute value
  3. Split node training set into children according to value of chosen attribute
  4. Stop splitting a node if it contains examples from a single class, or there are no more attributes to test.
- *Divide et impera* approach

Chosing the best attribute

Entropy

- A measure of the amount of information contained in a collection of instances S which can take a number c of possible values.

$$H(S) = -\sum_{i=1}^{c} p_i log_2 p_i$$

  where p_i is the fraction of S taking value i.
- In our case instances are training examples and values are class labels
- The entropy of a set of labelled examples measures its label inhomogeneity

Chosing the best attribute

Information gain

- Expected reduction in entropy obtained by partitioning a set S according to the value of a certain attribute A

$$IG(S,A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v)$$

  where $Values(A)$ is the set of possible values taken by A and S_v is the subset of S taking value v at attribute A.
- The second term represents the sum of entropies of subsets of examples obtained partitioning over A values, weighted by their respective sizes.
- An attribute with high information gain tends to produce homogeneous groups in terms of labels, thus favouring their classification.

Issues in decision tree learning

Overfitting avoidance

- Requiring that each leaf has only examples of a certain class can lead to very complex trees.
- A complex tree can easily overfit the training set, incorporating random regularities not representative of the full distribution, or noise in the data.
- It is possible to accept impure leaves, assigning them the label of the majority of their training examples
- Two possible strategies to prune a decision tree:

  pre-pruning decide whether to stop splitting a node even if it contains training examples with different labels.

  post-pruning learn a full tree and successively prune it removing subtrees.

Reduced error pruning

- Post-pruning strategy
- Assumes a separate labelled *validation* set for the pruning stage.

The procedure

1. For each node in the tree:
   - Evaluate the performance on the validation set when removing the subtree rooted at it
2. If all node removals worsen performance, STOP.
3. Choose the node whose removal has the best performance improvement
4. Replace the subtree rooted at it with a leaf
5. Assign to the leaf the majority label of all examples in the subtree
6. Return to 1

Issues in decision tree learning

Dealing with continuous-valued attributes

- Continuous valued attributes need to be discretized in order to be used in internal nodes tests
- Discretization threshold can be chosen in order to maximize the attribute quality criterion (e.g. infogain)
- Procedure:
  1. Examples are sorted according to their continuous attribute values
  2. For each pair of successive examples having different labels, a candidate threshold is placed as the average of the two attribute values.
  3. For each candidate threshold, the infogain achieved splitting examples according to it is computed
  4. The threshold producing the higher infogain is used to discretize the attribute

Issues in decision tree learning

Alternative attribute test measures

- The information gain criterion tends to prefer attributes with a large number of possible values
- As an extreme, the unique ID of each example is an attribute perfectly splitting the data into singletons, but it will be of no use on new examples
- A measure of such spread is the entropy of the dataset wrt the attribute value instead of the class value:

$$H_A(S) = -\sum_{v \in Values(A)} \frac{|S_v|}{|S|} log_2 \frac{|S_v|}{|S|}$$

- The *gain ratio* measure downweights the information gain by such attribute value entropy

$$IGR(S, A) = \frac{IG(S, A)}{H_A(S)}$$

Issues in decision tree learning

Handling attributes with missing values

- Assume example x with class $c(x)$ has missing value for attribute A.
- when attribute A is to be tested at node n:

  simple solution: assign to x the most common attribute values among examples in n or (during training) the most common of examples in n with class $c(x)$.

  complex solution: propagate x to each of the children of n, with a fractional value equal to the proportion of examples with the corresponding attribute value

- the complex solution implies that at test time, for each candidate class, all fractions of the test example which reached a leaf with that class are summed, and the example is assigned the class with highest overall value

Random forests

Training

1. Given a training set of N examples, sample N examples *with replacement* (i.e. same example can be selected multiple times)
2. Train a decision tree on the sample, selecting at each node m features at random among which to choose the best one
3. Repeat steps 1 and 2 M times in order to generate a forest of M trees

Testing

1. Test the example with each tree in the forest
2. Return the majority class among the predictions