CS60050 Machine Learning - Weekly Report

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1 Topics covered

- Introduction to Machine Learning
- Concept Learning
- Ordering of Hypothesis
- Find-S Algorithm

2 Summary

2.1 Introduction to Machine Learning

A traditional and knowledge driven computing paradigm is that of computing by algorithms. However, sometime no algorithm may exist and we have to shift to a non-traditional approach of computing by learning where based on several inputs and corresponding outputs which are provided the machine learns to do the task at hand.

Assumptions

1. Existence of a process for generating examples/data from which to learn.
2. Existence of certain patterns in the data.
3. Approximate construction of a model from the examples/data

What does it mean to learn?

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

Types of learning

1. Supervised: Labeled examples, a mapping from input to output. Can be discrete (classification) or continuous (regression).
2. Unsupervised: Unlabeled examples. Find a structure or pattern in the input, for example clustering.
3. Reinforcement: Learn a sequence of actions to reach the goal state.

2.2 Concept Learning

Concept learning is the inference of a boolean-valued function given training examples labelled as members or non-members.

Concept

A concept is a boolean-valued function describing a subset over a larger set. It can be thought of as assigning a labelling of member or non member which decides the membership in the subset.

Notation

Consider the example *EnjoySport*. There are 6 attributes for a given day.

1. X: Set of instances. Each instance is defined by a 6-tuple. For example,

$$\langle Sunny, Warm, Normal, Strong, Warm, Same \rangle$$

2. c: Target concept. In general, c can be any boolean-valued function defined over X; that is, $c : X \to \{0, 1\}$
3. H: Hypothesis space. Can be represented in several ways. We choose a simple representation in which each hypothesis consists of a conjunction of constraints on the instance attributes. The constraints may be ? (any value is acceptable), $\emptyset$ (no value is acceptable), or a specific value.

Task

To find a hypothesis h in H such that $h(x) = c(x)$ for all x in X

2.3 Ordering of Hypothesis

For any concept learning problem a general-to-specific ordering occurs over the hypothesis space. For two hypothesis h_j and h_k, h_j is more general than or equal to h_k if all instances that satisfy h_k also satisfy h_j. $\langle ?, ?, ?, ?, ?, ? \rangle$ is the most general hypothesis and $\langle \emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset \rangle$ is the most specific hypothesis.

2.4 Find-S Algorithm

It leverages the ordering of hypothesis to generate a maximally specific hypothesis consistent with the given training examples. The algorithms is as follows

```
procedure FIND-S
    Initialise h to most specific hypothesis in H
    for each positive training instance x do
        for each attribute constraint a_i in h do
            if the constraint a_i is satisfied by x then do nothing
            else replace a_i in h by the next more general constraint that is satisfied by x
            end if
        end for
    end for
    return h
end procedure
```

3 Challenging concepts

None

4 Interesting concepts

Formalisation of learning and correctness of the Find-S algorithm.

5 Concepts not understood

None

6 Ideas

While the hypothesis we saw in the example was a simple conjunction of constraints, it only captures meaning of the attributes individually. It would be interesting to design a hypothesis representation which could capture meaning between pairs of attributes as well. The hypothesis space would grow and we may get better results.