Learning Intermediate Concepts
(Extended Abstract)

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Abstract. In most concept learning problems considered so far by the learning theory community, the instances are labeled by a single unknown target. However, in some situations, although the target concept may be quite complex when expressed as a function of the attribute values of the instance, it may have a simple relationship with some intermediate (yet to be learned) concepts. In such cases, it may be advantageous to learn both these intermediate concepts and the target concept in parallel, and use the intermediate concepts to enhance our approximation of the target concept.

In this paper, we consider the problem of learning multiple interrelated concepts simultaneously. To avoid stability problem, we assume that the dependency relations among the concepts are not cyclical and hence can be expressed using a directed acyclic graph (not known to the learner). We investigate this learning problem in various popular theoretical models: mistake bound model, exact learning model and probably approximately correct (PAC) model.

Keywords: multiple concepts, mistake bound algorithm, exact learning, PAC learning, membership queries

1 Motivation

In a typical concept learning problem, an instance \( x = \langle x_1, ..., x_n \rangle \) is classified according to a single unknown target concept \( f \). The learner’s task is to find a good hypothesis \( h \) that approximates \( f \). In some practical situations, the target concept may be very complex when expressed as a function of only the attribute values of the instance. However, it may be expressible in a simpler form using some intermediate concepts in addition to the attributes of the instance.

As a pedagogical example, suppose you want to predict tomorrow’s perceived temperature, which can be different from the air temperature depending on tomorrow’s humidity, wind and other factors. However, you can only measure the current weather indicators. It may be difficult to predict the perceived temperature directly from these indicators as they may bear a complex relationship with
the future perceived temperature. However, the prediction task may be made easier if we were to learn to predict tomorrow’s humidity, wind pattern and other factors (which may have a simpler relationship with the current weather indicators), and then use them to predict tomorrow’s perceived temperature. In such scenario, it may be advantages to also learn the intermediate concepts (various weather indicators) and use these intermediate predictions to enhance our approximation of the target concept (perceived temperature). Similarly, it may be easier to predict humidity level if we can also learn to predict wind speed and direction, air pressure and other indicators.

Another example found in [Car98] is the problem of predicting mortality risk from diseases like pneumonia. The goal here is to identify patients accurately and economically so as to decide whether they need to be hospitalized to receive aggressive treatment. Note that the goal is not to diagnose pneumonia as the diagnosis has already been made. Here, we (or rather the Home Managed Care Organization) are interested in determining how much risk the illness poses to the patient and whether the cost of aggressive treatment is necessary. Unfortunately, the task is made complicated by the fact that many of the useful but expansive tests (like white blood cell count, Hematocrit test, Potassium count, etc) for predicting pneumonia risk are performed only after one is hospitalized. It would be more cost effective if we can separate the low-risk patients from the moderate and high-risk patients through the cheaper measurements (like age, sex, diabetic, asthmatic, chest pain, wheezing, blood pressure, temperature, hear murmur, etc) made prior to admission to hospital. One possible way of enhancing pneumonia mortality rate prediction is to approximate the expansive test results using the initial low-cost measurements, and then learns how mortality rate depends on both test results and initial measurements. Further plausible applications in the medical and image processing domains can also be found in [Car96, CPT97, Car98, DHB95, SK90, SH91].

In this paper, we study how to exploit these intermediately related concepts to enhance prediction accuracy. Although the problem of learning multiple related concepts simultaneously has not been well investigated in the learning theory community, the problem has been extensively studied empirically in the neural network community [Car96, CPT97, Car98, DHB95, SK90, SH91]. Instead of having a neural net with a single output node learning a single concept, these empirical studies showed that better results can be achieved by having a neural net with multiple output nodes each trying to learn a different, but closely related, concept. Subsequently, Baxter [Bax95, Bax97] provided theoretical justifications of this phenomenon. The main theme for this type of research is that by learning multiple closely related concepts simultaneously, the learner is better at constructing useful features (the activation functions of the hidden notes). The difference of our work here is that these earlier results did not assume that there is a dependency relationship among the concepts. Further, in our case, we assume the values of the interrelated concepts are specified in the label.