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 \(x = (x_1, ..., x_n)\) 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 to-
morrow’s humidity, wind and other factors. However, you can only measure the
current weather indicators. It may be difficult to predict the perceived tempera-
ture 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, heart murmur, etc)
made prior to admission to hospital. One possible way of enhancing pneumonia
mortality rate prediction is to approximate the expensive 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 re-
lated 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 justi-
fications 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.