Supervised learning *vs* learning with epistemic planning in probabilistic networks

In this paper I will explore the relationship between learning and probabilistic networks and show how learning of different types of concepts can be implemented in dictionary-based networks. I begin by defining a learner in terms of a probabilistic network in which each vertex is a special object called a dictionary and defining the notion of (concept) learnability for dictionary-network learners. I will argue that in dictionary-based networks, learning scientific concepts proceeds very differently from learning concepts related to everyday language.

The distinction which I rely on is similar to that between the manifest and the scientific image of the world described by Wilfrid Sellars [5, 6]. However, for a learner as defined in formal learning theory, scientific concepts can be much easier to learn than those which relate to the "manifest image" of the world. One reason for this is the possibility of reliable supervised learning due to elimination of vagueness. Another is lack of epistemic planning, which makes learning quicker by avoiding model comparison.

Basic concepts. I will define a learner, understood as a learning function [3], in the context of a probabilistic network in which vertices are special objects called dictionaries. First, I will present the notion of a dictionary together with its natural implementation in terms of a mapping object as used in Python programming language.

The fundamental intuition behind dictionary-based networks is that of a *concept*. Let $\mathcal{D}$ be an infinite data stream comprising in a series $\mathcal{D} = \varepsilon_0, \varepsilon_1, \varepsilon_2, \ldots$ where each datum ε_n, $n = 0, 1, \ldots$ has the form `given A, B`. Dictionaries are created based on a data stream $\mathcal{D}$. With each new datum ε_n in $\mathcal{D}$, either a key is added to an existing dictionary, or a new dictionary with a key is created. A set of all dictionaries $\mathfrak{d}_i$, where $i = 0, 1, \ldots$, will be denoted as $\mathfrak{D}$. Each $\mathfrak{d}_i$ can be represented as a set of ordered pairs of the form $\langle k_i, v_i \rangle$, where k_i is a key in dictionary $\mathfrak{d}_i$ and v is a value chosen from the set of available values $\mathcal{V}$, which can take the form $\mathcal{V} = \{0, 1\}$, or the form of an interval $\mathcal{V} = [0, 1]$.

A semantic network is a knowledge base on which a learner will be able to update using predefined rules. Moreover, the fact that the same type of value is used for each key, allows interpreting the numerical values as *links* in the sense of the Semantic Link Network (SLN) scheme [7]. Dictionaries form a semantic network which has a natural respresentation in terms of graphs. In such a graph, two dictionaries are connected by a node if the following condition holds:

Connecting vertices. Two vertices $\mathfrak{d}_1$, $\mathfrak{d}_2$ are connected with a node iff $\mathfrak{d}_1$ occurs as a key in $\mathfrak{d}_2$, or *vice versa.*

I will show how to impose stricter conditions in terms of probabilities for connecting two vertices in order to make use of the values associated with the keys in particular dictionaries. For now, however, it suffices to say that the dictionaries form a network in which non-trivial conditions for connections between vertices is possible, that it, it is not the case that every dictionary is connected to all other dictionaries.

How are concepts learnable? In general terms, a probabilistic network is a graphical model encoding probabilistic relationships between variables of interest. Besides the numerical parameters of the probability distribution, probabilistic networks accommodate qualitative influences between variables, which originate from prior knowledge about the variables or data [4]. By applying our prior knowledge about scientific concents, updating on dictionaries can be relativized to the particular empirical requirements for each concept.

I will demonstrate how this relative update can be implemented relying on algorithmic theory of meaning. That is, the meaning of each concept will be understood as the "algorithm" for computing the object. For dictionary-based probabilistic network, the algorithm will always yield a conditional probability from $\mathcal{V} = [0, 1]$. A concept $\mathbf{c}$ is considered learnable if the learner will converge on the probabilities in $\mathbf{c}$-dictionary which are within a specially defined acceptable limit.

Scientific and ordinary concepts. For natural language concepts, which are vague or the meaning of which changes according to usage, learning requires epistemic planning on the side of the agent [2, 1]. However, learning in the scientific context often relies on well-defined concepts, which can be given to the learner in the process of supervized learning. This means that scientific concepts can be learned much more reliably and quickly than concepts for which the update on the meaning of a concept is required. In my paper I will show examples of concepts, like set membership, which in a scientific context take a well-defined algorithmic form. I will also show how learning them is easier than learning most concepts used in everyday language.

Both methods, that is supervised learning with pre-defined probability distributions and learning with epistemic planning, could in principle be used simultaneously for two types of concepts in a single learner. However, problems arise when the concepts from "the scientific image" and "the manifest image" converge and the Sellarsian "clash" between the two images is reproduced in the procedure of dictionary construction.

References

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