Machine Learning Support for Human Articulation of Concepts from Examples – A Learning Framework*

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Abstract. We aim to show that machine learning methods can provide meaningful feedback to help the student articulate concepts from examples, in particular from images. Therefore we present here a framework to support the learning through human visual classifications and machine learning methods.

Keywords: concept learning, machine learning, visual environment, learning framework.

1 Introduction: Research Motivation

In a century where technology is emerged into education, we want to see how can we use machine learning to support the articulation of concepts from examples, and in particular form images. Therefore, our research question is: *How efficient can the feedback of machine learning techniques can be for this human learning process?* That's what we start answering in this paper, by introducing a learning framework based on using machine learning to reason from student classifications. But let us analyze first what is driving our research.

People know from images more then just from using words[1]. Images help people externalize their intuitive knowledge, within a process called articulation, or transfer from tacit to explicit knowledge [2]. We evaluate the learning process though the articulation that a learner can provide to a concept. Articulation means descriptions, and therefore words. Hence, the main focus is on how to support the human learner extract the best words from images? Words, in our case *terms* (or *attributes*, as call them in this paper) need to reflect the topic and to be accepted by the learner and the teacher. Therefore, the teacher can provide an initial descriptive vocabulary, where terms are clues for the definition. In a similar way to a Socratic tutor, a learning system has to guide the human learner in articulating knowledge [3]. But in contrast to Socratic tutors, we want to have all the clues from the beginning and let the student discover the definition. Hence, the human learner will have the set of pieces of a puzzle whose correct arrangement correspond to the articulation of the concept. In addition to this, we know that people learn by classifying objects visually [4,5] and they learn much easier in a visual environment, then using only texts. Thus, one of our goals is learning by classifying in a visual environment to help the student focus.

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Other issues of our research are based on using machine learning to support the human learning of natural concepts [6] and on the use of the limited working memory capacity [7]. Natural concepts are difficult to represent as set of attributes, because they contains borderline cases and are influenced by contextual information. Concepts that people meet in everyday life are like this (such as concepts from *citizenship* or *environment* topics). Natural concepts present also the typicality property: some examples are more likely to belong to a concept, then others [6]. Among machine learning methods, conceptual clustering [8] can deal with typicality, by finding the basic description (applicable to most cases of a concept) and the inference rules (to explain borderline instances). Given the difficulty of describing concepts, we focus on supporting the student to articulate the concept description, by classifying learning objects (images and terms). Classification tasks are using the working memory [7]. Natural concepts affect the organization of memory, in the sense that concepts are organized hierarchically into memory, in a taxonomy [6].

The main research issue concerns the *reasoning via generalizing and specializing*. A previous approach on reasoning from general terms, specializes the terms to remove ambiguities, find relevant images and introduces actions on objects [9]. To learning by specializing, we add in our work the classification task, which is helping the student formulate the general terms (or attributes). More important, we propose to guide and suggest the refinement to the student. Combining generalization and specialization to get a correct concept description is our main research goal. We have to mention here that by generalization we mean building an extended vocabulary with more general terms in order to cover as many examples (images) as possible of the concept to be learned. As we will see, generalization brings conflicts (same general terms cannot distinguish between opposite examples). By specializing we refine the concept description to remove ambiguities (i.e. conflictual situations).

We present next our learning framework, the research hypotheses that will be supported within the framework and the evaluation methodology.

2 Machine Learning Supporting the Human Learn from Examples

In our work we aim to show that machine learning can provide useful feedback in order to help the student articulate the concept description. The problem has several aspects: 1) the learning tasks involving images and terms, 2) the machine learning feedback, 3) the articulation of the concept. Images and terms that we use in our research work are provided by the SILVER project, which focuses on knowledge visualization within e-learning environments [10].

2.1 The HMCD Learning Framework

We propose a learning framework that will use machine learning methods to reason from human visual classification with the purpose of helping the human externalize the intuitive knowledge and articulate the concept description. We call this framework HMCD (Human-Machine Concept Dance), due to the support for the articulation.

<u>Roles.</u> A scenario based on HMCD has three participants with different roles: a teacher, a student and the computer. We analyze first the teacher's role. We agree to the theory

according to which the human learning is situated within a context [11]. Hence, the teacher defines a *topic* to frame the domain. Then, is defining the *target concepts* (i.e. concepts to be learned during the learning session). Afterwards, the teacher selects the learning objects: the initial set of terms and the images. Through terms we understand a vocabulary with specialized keywords utilized in describing the images and the target concepts. Terms are binary attributes, because they represent *what* students can *see* in the image. The teacher gives the specific metadata (links terms to images).

The student is doing two classifications of the learning objects: first, building a hierarchy of terms, through extending the vocabulary with more general terms and second, grouping images in order to correspond to each target concept. The computer reasons from student's classifications and determine the compact metadata (specific terms from the images descriptions are replaced with their most general parents from the hierarchy). At a higher level of generality there are possible conflicts, which we call ambiguities: same metadata corresponds to different classes. For instance, within the topic *environment*, for the target concept *Effect-on-the-environment* [10], the compact metadata introduces conflicts (see table 1).

Table 1. Example of ambiguities introduced by compact metadata

ReconstructionOfVikingHouse (positive effect) PLANT={Grass, Wood} BUILDING_MATERIAL={Wood_shingle} BUSINESS={HighBuildingOccupancyLevel}	TheHeidiWeberPavillion (negative effect) PLANT={Grass, Trees} BUILDING_MATERIAL={Glass, Metal} BUSINESS={PlaceForBusinessOrTourism}

In this particular case (see table 1), specializing the term Business solves the ambiguity and keeps the coherence of describing the rest of the images from the set.

Computer's support is background and the student can choose using the suggested terms for specialization. After the learning session, the computer will verify student's understanding through a test.

Shortly, the computer roles is to detect ambiguities and to explain them to the learner. The computer offers a concept description, as abstract as possible, but discriminative enough. We want an *abstract description* in order to characterize as many example as possible of the concept, and to limit by thus the number of borderline cases of a natural concept [6]. In the same time, abstraction is linked to a limited set of attributes (terms) that can be memorized and understood by the student during a learning task [7].

<u>Components.</u> HMCD has three components (fig. 1): 1) the human visual classifications interface, 2) the ML support (background activity which can be switched on/off by the student) and 3) the articulation of the concept (the computer proposes the terms for specialization and verifies student's knowledge). The ML component explains ambiguities. Ambiguities explanation stimulates the reasoning by understanding close differences and similarities among instances [12].

According to the three components, the steps of the learning process are: a) generalization; b) specialization; c) refinement. Using deductive reasoning, which is a specialization process, and previously defined hypotheses (which in our case are represented by rough descriptions of concepts) determines a quicker learning then using induction (generalization) and accidental hypotheses [13].

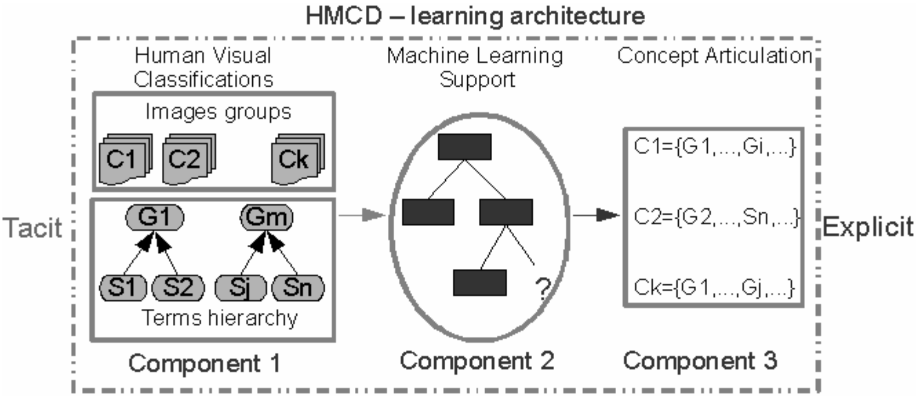

Fig. 1. The learning framework HMCD (Human Machine Concept Dance – using machine learning to support the human articulate the concept description)

2.2 Research Hypotheses

People can generalize, as a natural way of learning [6]. However, generalization brings conflicts (same descriptions for different concepts – as we can see in figure 3). This is caused by the fact that generalized terms hide distinguishing attributes, which can be found by specializing the general terms. We assume there are no conflicts at the most specific level of terms. Our question is *which terms to specialize first and what is the minimal set of terms that have to be specialized in order to remove conflicts but to keep a high level of abstraction*? Given these considerations, we present our research hypotheses:

(H1) People can learn from examples (in particular images) better with machine learning (ML) support than without. Our predictions are that the concept description given by the computer is more accurate and comprehensible due to the use of terms known by the student, but not more faster and not more enjoyable (hence different from the intuitive process of grouping terms and images).

For the second hypotheses, we consider different machine learning techniques, with potential to support learning natural concepts (decision trees - DT, version spaces - VD and conceptual clustering - CC). We know that each of these ML methods has advantages [8, 14]. DT and CC are sound methods (don't introduce errors). VS gives an intuitive understanding of learning as hypotheses searching. CC deals with typicality. From these considerations, it follows the second research hypothesis:

(H2) We can benefit from strength of each ML method mentioned above.

Working with specialized terms alone doesn't develop a general vocabulary. Generalizing only introduces errors in concepts descriptions. From this it results that:

(H3) ML can provide feedback (explanation) so that the human won't overgeneralize, when using machine learning and visual human classifications.

We will validate the hypotheses by evaluating students that will be using HMCD.

2.3 Evaluation Methodology

We consider supporting the hypotheses by evaluating test groups. We will check (H1) by evaluating two test groups: the first group of students works with a learning system based on machine learning feedback, while the second works without it. (H2) can be checked by allowing students to switch between different ML methods. We permit students communicate (they code their answers). Then we measure frequencies of students answers. To check (H3) we give different tasks to students: specialize, generalize, use ML or not. Then evaluate students comments while doing the tasks.

3 Summary and Future Work

In this paper we propose a learning framework based on using machine learning algorithms to support students learn concepts from images. Next we will implement and evaluate the framework. Through our work we highlight how machine learning can guide the human learn concepts from examples in a visual environment.

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