Thinking Strategies Training to Support the Development of Machine Learning Understanding

A study targeting fifth-grade children

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ABSTRACT

Artificial Intelligence applications permeate our lives and are increasingly making the news, surprising society with applications that until a few years ago would have been relegated to the science fiction genre. Thanks to generative artificial intelligence, tools that once could only be used by highly qualified technical personnel are now in the hands of potentially inexperienced users, but unfortunately, the understanding of the layman is very far from the machinery behind the scenes. More than ever, it is necessary to help people develop an awareness that allows them to use these tools in an appropriate way and with the appropriate expectations. We believe this problem should be addressed by exploring ways to train thinking strategies to facilitate understanding of machine learning concepts that can be applied in daily life, not just by developing teaching tools on this or that topic. We describe our current activities with 9-10 years old children attending primary school and the ad hoc unplugged training we have developed to foster an understanding of machine learning mechanisms.

CCS CONCEPTS

• **Artificial Intelligence**; • **Informal Education**; • **K-12 Education**;

KEYWORDS

Thinking strategies, Artificial Intelligence, Machine Learning, Training, Education

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1 INTRODUCTION

In recent years, Artificial Intelligence (AI), and Machine Learning (ML) in particular, have become pervasive in everyday life in every environment, e.g., in homes, offices, cities, etc. The availability of software tools and libraries that make it possible to use ML mechanisms under the no code or the low code paradigm [3] (thus avoiding the burden of programming) opened their use also to untrained people, whose background is often far from an understanding of algorithms, leaving room for far-fetched intuitions. As a result, everyone comes into contact with such technologies, including children and young adults, who are generally very attracted to them. For new generations, ML can be an opportunity, but also a threat if not properly understood and managed [3, 20]. Promoting awareness of the mechanisms, opportunities, and weaknesses of ML is a right of children [19], and it is crucial to equip them so that they can take advantage of ML and not be unconsciously controlled by it.

In this paper, we present the design of a study carried on in collaboration between psychologists and computer scientists. The study is part of a current research project addressing the problem of how to support children's understanding of machine learning concepts through the identification and training of reasoning strategies, rather than through the identification and use of tasks that require knowledge of these concepts. Furthermore, the training we propose is unplugged, that is it does not involve the use of tools and therefore has the broader goal of training not only functional thinking for understanding machine learning concepts but also reasoning and decision making in everyday contexts. As noted in recent works [1, 16], the acquisition of competencies on how to use a tool, does not necessarily correspond to the acquisition of awareness and understanding of how complex mechanisms work. This is particularly true when it comes to ML. For instance, there are tools that help children train and test a model to recognize images [8, 13]. These tools undoubtedly succeed in engaging children. After practicing with them, children are also aware of the powerful abilities that machines can have in classifying images as belonging or not belonging to a category. They may also become aware of the fact that sometimes the machine fails in performing such tasks and gives an unexpected answer. However, the reasons for such success or failure, and therefore the way training should be conducted to perform well, may not be clear to children. Generally, they lack a sense of how the machine works. As a result, they can use the tool and observe how it behaves, but it is more difficult for them to take an active role and control the behavior of the tool (e.g., by giving a sample on which to perform the training that also includes rare or counterexamples), to achieve the expected result. Having the correct understanding of how machine learning works is paramount, considering that the use of ML-based tools is so pervasive that it is unrealistic to assume that children will only use them after proper training. Therefore, it is desirable that training designed to facilitate the understanding of machine learning concepts has general features that effectively promote interaction with tools of different types.

The objective of our work is therefore to set up a training that supports the development of a correct understanding of how machine learning works, generalizing from any specific tool or specific algorithm. The training is specifically aimed at fifth-grade children, corresponding to 9-10 years old children.

This objective leads to two main research questions:

RQ1: How to implement such training?

RQ2: How to evaluate the success of such training?

1.1 RQ1: Training Thinking Strategies

From a psychological perspective, our theoretical framework is defined by the so-called dual process theories of thinking, according to which there exists intuitive and deliberative thinking (e.g. [6]). *Intuitive thinking* is quick and relies on heuristics and biases that often lead to errors in reasoning. *Deliberative thinking* is slow and cognitively costly, but it pays off because it enables us to reason and hypothesize correctly. Deliberative thinking utilizes working memory, allows us to consider alternative possibilities, and therefore enables us to falsify previously drawn conclusions by considering counter-examples. Relevant to this study, *strategic thinking* is a form of deliberative thinking.

Our approach is to develop engaging activities aimed at training deliberative thinking which, in contrast to intuitive thinking, can lead to a deep understanding of the mechanisms of machine learning. We conjecture that the training will lead to better performance in machine learning understanding. We have designed a study to prove or disprove this conjecture. The value of this research is that our training, if successful, consists of natural activities and one can therefore think about integrating it into school from an early age, without the need for prior knowledge or a specific tool.

- First, we have identified three *thinking strategies* we believe are necessary to improve understanding of ML algorithms. By strategy we mean how a problem is approached; strategy tends to control the person's thinking. The three strategies are:
- *take the necessary time to think* without relying on quick thinking and the first idea that comes to mind;
- *think about the rarest cases*, that exist and are possible; and
- *apply unusual thinking*, i.e., to reason about the correct answer without being distracted by stereotypes, predefined models to which we are accustomed, or using the most salient features that may lead to a wrong conclusion.

To train them, we have developed three unplugged activities that can be carried out in class and which we present in more detail in Section 4.

1.2 RQ2: Evaluate the Success of the Training

An important aspect of our study is the development of a tool to assess the understanding of machine learning and the improvement achieved by training the three thinking strategies outlined above. To this aim, the structure of our study consists of three main phases, detailed in Section 3 and summarized in Figure 2

- a test is performed to determine a child's baseline level;
- the training is administered to the children;
- the test is performed again to assess the improvement.

The difference between our approach and others in the literature, is that most of these latter aim to develop tools or activities to explain concepts to children, the effectiveness of which can be assessed by testing how much the concept has been understood by children. For example, if we consider Google teachable machines [8] (or any other similar tool), we can think of a pre-test in which the task of classification is given, then the children experiment with the tool, and subsequently the same test is performed. If a statistically significant improvement is observed, one can conclude that the tool (or the training in general) is successful in explaining the concept of classification. If no competence is expected before the training, one can perform the post-test to assess the level of competence acquired. This is usually done at school or university, where courses supply knowledge and the exam aims to assess the knowledge acquired by the student on a topic. In these cases, however, the subject of the training and the object of the test are the same, i.e., a specific *ML concept* (or set of concepts) as depicted in Figure 1 (left).

In our approach, instead, the subjects of the training are the *thinking strategies,* while the objective is to increase the *understanding* of machine learning concepts (see Figure 1 – right). To evaluate the effect of the training, we have developed a series of exercises that assess understanding of machine learning and where such understanding requires exploiting the thinking strategies we have identified. The design of the test is presented in Section 5.

2 RELATED WORK

The ubiquity of Machine Learning in everyday life goes hand in hand with a great deal of interest in research into how to introduce children and young adults to the subject. In many countries, schools are also being supported by national and international institutions to include innovative ML activities in their curricula. In this setting,

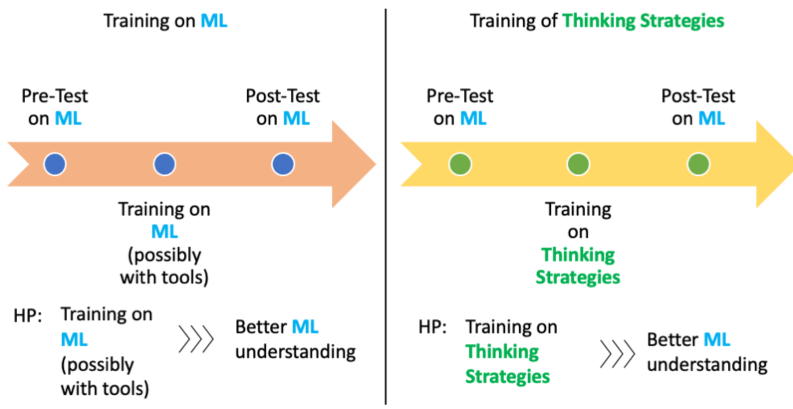

Figure 1: When an ML concept is trained in classical training (possibly with the help of tools), a test of understanding of the ML concept is performed to evaluate the effectiveness of the training. In our proposal, the training is about thinking strategies and the test is about understanding machine learning.

the authors in [15] present a systematic review on research on ML teaching and ML learning in K-12 education. Interestingly, some key findings from this study are echoed in our proposal: (a) creating more ML activities for kindergarten through middle school and education in an informal context; (b) incorporating ML ideas into subject domains other than computer science to promote the integration of ML in schools; (c) developing assessments for ML that can be relevant across grade levels to compare students' ML understanding in different learning environments.

The general pitfall of many approaches to introducing ML is their lack of generalization and explanation [16]: stating that a tool is effective does not explain why it is effective; moreover, there is no guarantee that the tool would give the same result if applied to a different domain scenario or algorithm or regional reality. As highlighted in [16], research in computer science education is still in its infancy when it comes to how people learn to train, test, improve, and deploy ML systems.

There are many solutions for the ML tools, such as [4, 8, 13], allowing children to train a classifier or clustering algorithms. With these tools, children can learn how to define a set of classes, create a training set of labeled examples, and test it. On the one hand, these tools are very appealing and offer the children the opportunity to experience how ML works concretely but, on the other hand, they hardly get any insight into the processes involved and how the mechanism behind the scenes works. For some of these tools, content validity has yet to be demonstrated (see [9] for a review of 16 interactive machine learning tools for K-12). However, there are other approaches that expose the idea of the reasoning model (e.g., Google's TensorFlow Playground).

There are also approaches in the literature that do not rely on the use of tools. For instance, Lindner et al. [11] propose a series of unplugged activities on AI and tested them in German secondary school classes (14 to 16 years old), while Ma et al. [12] presented teaching materials developed to introduce students (12-13 years old) to two important machine learning algorithms: decision trees and k-nearest neighbors.

In general, it is practically impossible to exhaustively cover the proposals in the literature to explain ML concepts, as there is a wide variety of approaches (e.g., with or without the support of tools, practical or theoretical, explanation of how it works or just use of an algorithm, etc.).

The need to introduce general criteria and guidelines has thus become clear, as noticed by [17, 18], who, with the support of the Association for the Advancement of Artificial Intelligence (AAAI) and the Computer Science Teachers Association (CSTA), launched the AI4K12 Initiative (AI4K12.org) and introduced a set of guidelines for teaching AI to K12 students based on the "five big ideas" of AI that every K12 student should know. AI4K12 is now a reference framework for AI teaching.

However, as far as we know, there is no other approach in the literature that proposes to support the understanding of machine learning by training deliberative thinking as opposed to intuitive thinking. However, considering how many ML algorithms work and how datasets are developed, it becomes clear how important it is to consider rare cases or atypical examples. Note that our proposal is not intended as a substitute for teaching Machine Learning concepts. However, the objective of our study is to prove the effectiveness of a training on thinking strategies for understanding ML concepts. An integration of our approach into ML teaching is beyond the scope of this work.

3 STUDY DESIGN

We designed playful unplugged activities for this study, i.e., activities that do not require the use of IT tools. The activities are to be carried out in fifth-grade classes and require individual responses or work in groups.

As shown in Figure 2, we have developed three training activities, each lasting two hours. To evaluate the effectiveness of these activities, we conduct a two-hour lesson, in which children have

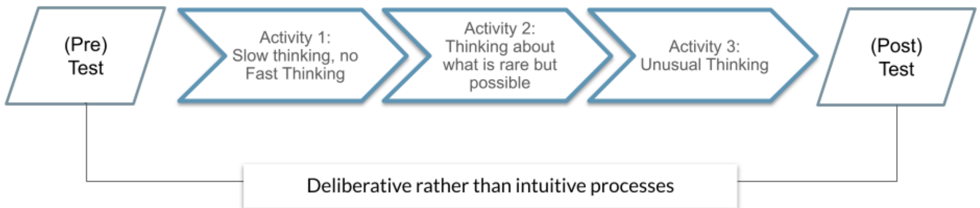

Figure 2: The experimental design performed by the *Experimental* group. The *Control* group performs the Pre- and Post-Test only.

to perform some tasks that represent a *pre-test* for us to evaluate the initial level of each child. After the three activities, the children then take another test with the same level of difficulty (*post-test*). One class meets once a week.

The comparison between the results of the two tests will provide us with a measure of the effect of the training activities. To rule out the possibility that any improvement is due to the regular school activities, we also include a *control group*, i.e., a number of classes that only take the pre-test and the post-test. If the control group does not improve compared to the experimental group, we could ascribe the improvement to the training activities.

In total, we will carry out the activities for around 350 children.

4 TRAINING ACTIVITIES

The three training activities are designed to be performed at the level of class under the guidance of a researcher in psychology. Each activity has a duration of two hours and follows a predefined structure characterized by two main phases: an *experiential phase,* where children carry out practical activities individually, in pairs or in small groups, and a *metacognitive reflection* phase, where, under the guidance of the researcher, children reflect on the cognitive processes involved in carrying out the activity. The activity is introduced to a class by means of a narrative framework where the researcher asks for the help of children to solve a task that has to do with the understanding of how computers model and acquire information, and make decisions. The tasks presented to children vary for each activity since each of them is meant to train a different thinking strategy. In the following, we describe the designed activities. Table 1 summarizes the three activities.

4.1 Activity 1: Slow Thinking, no Fast Thinking

For the experiential phase, each child in the class group receives a booklet with nine questions from the “Cognitive Reflection Test-Developmental Version” [21]. The questions are such that they entail a correct and an immediate answer (e.g., ”If you’re running a race and you pass the person in second place, what place are you in?”. Here the immediate answer would be *first*, while the correct answer is *second*).

In the first phase of the activity, the researcher asks the children to answer the questions in the booklet individually and as quickly as possible in a maximum of one minute using a blue pen. At the end of the activity, the researcher asks the children, without giving any feedback on the task they have just completed, to use a red pen and this time to answer all nine questions again without a time limit and without rushing, to check their answers and change them if necessary. The researcher explains to them that they should take the time they think is necessary to think about the answer before giving it.

During the metacognitive reflection phase, the children will be asked to reflect on *intuitive* (faster and less cognitively demanding) and *deliberate* (slower and more cognitively demanding) thinking and identify the main differences. The researcher will discuss with the class how the use of intuitive thinking can in some cases lead to errors (as might have been the case with answers under time pressure to some questions) and how deliberate thinking, which necessarily requires more time, can instead be effective in finding the correct answer, especially in novel or ambiguous situations (such as those that arose during the activity).

4.2 Activity 2: Thinking About What is Rare But Possible

The first phase of this activity is divided into two parts. In the first part, the class is divided into teams and in each team two groups are identified: the ”give example” and the ”recognize” groups. The ”give example” group is provided with cards representing different objects (e.g., cactus, plant, fish, child, chair, daisy, creek rock) and with a category (e.g., living creature). Among the cards, the ”give example” group selects the adequate examples to show to the ”recognize” group, who has to guess the category. More rounds are performed keeping the same teams and switching ”give example” and the ”recognize” group in the same team. Overall, the winning team is the one where categories were guessed using the fewest number of examples.

In a second part of the activity, some terms are presented to the class (e.g., flower, mammal, mobile, etc.). Individually, children are asked to find an example for each of them (e.g., for the mammal the examples could be lion, dog, cat). The examples generated by each child for each term are then collected by the researcher who counts the occurrences of each example on the board (e.g., dog = 2; cat = 3; lion = 1). The researcher then guides children to also think about less common examples. Indeed, it is likely that the children’s suggestions will reflect the most typical examples of the concepts, i.e., the prototypes. The class is thus asked to suggest atypical examples for each term.

After atypical examples have been written on the board, the researcher discusses with the children the features that make them atypical examples. This part of the activity is introductory to the metacognitive reflection phase, where the researcher will ask the

Table 1: Summary of the activities.

Activity	Goal	Task
Slow Thinking, no Fast Thinking	Distinguish intuitive and deliberate thinking and train the latter	Answer tricky questions under time pressure. As a second step of the activity, children have the possibility to carefully think about the questions and revise their answers
Thinking About What is Rare But Possible	Train the ability to think about families of objects both in terms of typical and atypical examples	Guess a family of objects by presenting samples of the family
Unusual Thinking	Train the ability to evaluate the probability of belonging to a certain group based on a detailed analysis of a set of known statements rather than on salient characteristics	Evaluate a set of logical statements to answer some questions. The correct answer involves unintuitive thinking

children to reflect on the fact that, although a category can be identified by many examples, prototypes are not always sufficient to describe the category. In fact, focusing on prototypes can lead to mistakes or to have a limited view of a certain reality. Possible atypical examples are the whale for mammals or the fact that a dog having, for some reason, three legs and no tail remains a dog.

Activity 3: Unusual Thinking

The class will be presented with classic problems from the reasoning literature that elicit the use of heuristics. Two related activities are suggested. In the first activity children are given the following information:

"Marco is 11 years old. He attends fifth grade, enjoys sports, is a fan of his hometown football team, and likes to play video games with his friends."

The task for the children is to order some statements from the most to the least likely considering the above piece of information. Statements are of the kind: *"Marco has the jersey of his favorite soccer player", "Marco has the jersey of his favorite soccer player and is good at school", "Marco is good at school", "Marco does rhythmic gymnastics", "Marco practices rhythmic gymnastics and often goes to the stadium"* and such like.

Once children complete the task, the answers and possible reasons are commented on and discussed at the level of class. In particular, the researcher picks two statements and asks which of the two is more likely:

- a) Marco practices rhythmic gymnastics and often goes to the stadium
- b) Marco practices rhythmic gymnastics

The correct solution (not visible to the participants) is the second one. This introduces the metacognitive reflection phase which consists of reflecting on the probability of events. The researcher's task is to guide the children to reflect on the fact that we tend to evaluate the probability of belonging to a certain group based on some salient characteristics without analyzing them in detail, disregarding even the elementary calculations of probability. The class will reflect on the concept of stereotype and examples will be given of how it often guides our evaluations of reality and represents a model to which we refer in order to give the answer that seems most correct to us. Finally, the researcher will discuss how assessing the probability of an event requires a detailed analysis of the situation that allows us to reach a conclusion without relying on the most salient features of the object of assessment.

As a second part of the activity, the researcher reads two lists of stationery items: the first list consists of elements that are known to be judged as more common by children, while the second of elements known to be considered as less common. Children are then asked which of the two lists is the largest. The expectation is that they will erroneously answer the first one, while the correct answer would be the second.

During the reflection phase, the researcher will guide children to reflect on how we often tend to judge the probability of an event or its frequency by the ease with which exemplary cases, the most famous ones, come to mind.

5 TESTS

With the aim of developing a tool to assess children's machine learning understanding before and after training, we have identified four task categories which form the core of machine learning tasks, and for each of them we have developed a set of exercises that require deliberate thinking rather than intuition (slow thinking vs fast thinking, rare but possible and unusual thinking). In the following, we use some terms that originate from the research field of machine learning [14]. By model we mean the knowledge produced by a learning process that can then be used to perform some tasks, by feature we mean a characteristic that is used to describe an item. An instance or example is an item. A data set is a set of instances, each of which is intended as an ordered tuple of values of certain features. A learning set is a data set that is used for building a model.

The identified categories of tasks are:

- *Model selection*: data can be captured by many models, and not all models are equally good. This category refers to those tasks that involve understanding which model better fits the provided instances and, conversely, which instances are captured by a model.

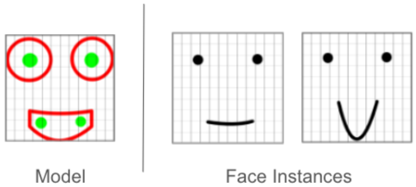

Figure 3: A smile model (left) and two face instances (right) taken from [10].

- *Model construction*: analysis of a learning set to infer some knowledge (typically by generalization), i.e., to build a model;
- *Using a model*: these are classification tasks, i.e., given a non-verbal description of a set of classes and some instances, the goal is to associate each instance to a class.
- *Identification of significant features*: which of the given features best discriminates between instances that belong to different classes?

For each of these categories, we have developed three increasingly challenging exercises. The challenge arises in part from the need to switch from superficial (intuitive) thinking to deep thinking to perform the task correctly. Overall, the test consists of twelve exercises. For each exercise, we have developed a variant with the same level of difficulty, which is presented in the post-test. In this way, we can avoid any learning effect that could occur with identical pre- and post-tests.

5.1 Model Selection

In this series of exercises, inspired by an item from the BEBRAS collection [10] (in Italian), the children are introduced to the problem by explaining that a machine recognizes an image by comparing it to a reference image (the model). The task is to identify the best model from a given set, that is, to select the one that best recognizes smiling faces and distinguishes them from non-smiling ones.

The models given to children are simple, sketched pictures on which some areas are drawn: an area for the mouth and one or two areas for the eyes. When the model is overlaid with an instance of a face, the face is classified as smiling if the mouth and the eyes of the face fall completely within the corresponding areas of the model. Otherwise, it is classified as non-smiling. Figure 3 reports an example of a model (on the left) and of smiling faces (on the right).

The children are given a series of smile models and a series of face instances. The models are devised so that they can be ordered from the model that perfectly recognizes only the desired faces (best performing model) to the least performing model. By comparing such an order with the models provided by the students, scores can be calculated. The models are defined in such a way that the most intuitive answer is not the best one. To give an example, in Figure 3, the model resembles a smiling face, but it fails to recognize one of the faces, namely the one whose smile is more accentuated because the mouth partly falls outside the area. Indeed, the best solution would be one that does not resemble a face and, for this reason, at first glance, it would be discarded as the best solution.

Considering unusual thinking, children must overcome their intuitive model of a smiling face, which immediately comes to mind, and ponder over the most unintuitive instances and models presented to them. As mentioned earlier, the best model will not have the trivially expected shape of a smiling face. The ability to think about what is rare but possible, comes into play by presenting a few examples of slightly smiling and slightly non-smiling faces which need to be classified correctly as well.

5.2 Model Construction

Model construction is the typical task of a machine learning tool: the tool analyzes a set of instances and builds a concise representation (a model) by applying some generalization rule. A typical application is classification. In this case, the instances from the learning set will have associated their intended class, and the model is used to classify new instances. In the exercises belonging to this category, the children become model-builders. Here the difficulty lies in building models that encompass a few unusual instances. For instance, cats have tails, but Manx cats do not. The exercise guides students, making them first build and then revise models, driven by the need to account for unusual instances.

5.3 Using a Model

These exercises concern the classification of fictional characters in a Halloween setting and are inspired by [5]. The focus is on the idea of identifying different kinds of monsters, with increasing levels of difficulty. The children are given a picture of three invented prototypical monsters and a table that describes their features in terms of the following shapes: face, eyes, ears, nose, and mouth. The task is: given some instances (non-prototypical images of monsters), classify them as belonging to one of three given categories. We stress that none of the given images will exactly match any of the given prototypes.

In this case, too, we will bring both superficial and deep thinking and unusual thinking into play by working with dominant and dominated features. In fact, the instances to be classified will show a discordance of features due to the mixing of the characteristics of monsters. The most predominant characteristic (the shape of the face) will belong to one prototype, while all the others will belong to one or more other prototypes. The expectation is that without deep thinking the students will be deceived because the predominant feature will push them to associate the instance to the wrong model, that is to one that does not correspond to the actual classification of the monster (because all the other characteristics belong to another category). The children should use *unusual thinking*, because using the most salient features would lead to wrong conclusions.

5.4 Identify Discriminating Features

In this series of exercises, children are asked to classify a set of instances against two classes. We will not provide a model. Instead, each of the two classes is described by giving nine of its instances. The children will need to induce a model (which features must have which values) in order to correctly classify the new instances.

As a reference environment, inspired by [4], we consider an aquarium whose tanks reproduce the living environment of various

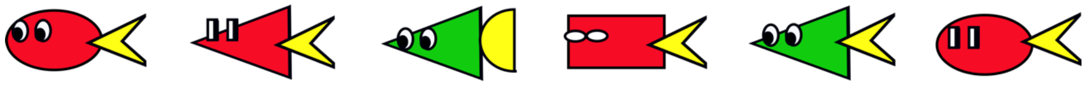

Figure 4: Some of the tropical fishes that are part of the exercises described in Section 5.4.

fish species. We will therefore focus on two tanks: that of Tropical fish and that of the Nordic fish. These will be our classes.

We are currently drawing fictional fishes (see Figure 4) that are characterized by color, body shape, eyes shape and tail shape. The children should find out the rules that characterize the two classes in order to sort a list of newcomers accordingly, so that the Tropical fish swim in warm water and Nordic fish in the cold water. Depending on how the learning set is built, it is possible to devise scenarios in which a predominant characteristic (e.g., color) is deceptive. Unusual thinking comes in handy when the learning instances include cases that do not match the dominant characteristics.

6 DISCUSSION AND FUTURE WORK

Artificial intelligence is having an enormous impact on our society, so much so that even young children have access to digital content and services through interfaces that use machine learning and probabilistic AI approaches. The debate about the use and further development of machine learning systems has become heated because of the possibility of human intelligence being overwhelmed by artificial intelligence. As is so often the case, a lack of knowledge about a particular phenomenon can cause anxiety. It is important to recognize the real risks of these new technologies and distinguish them from those arising from a lack of knowledge [7]. With this in mind, it is extremely important to introduce ML concepts to children and adults so that they can get an accurate picture of its potential and the risks it can bring if it is suffered and not used consciously. We hypothesize that children's understanding of ML concepts can be enhanced by drawing their attention to their mindset and getting them to think consciously rather than intuitively. In particular, we focus on three thinking strategies: taking the necessary time to think without relying on quick thinking and the first idea that comes to mind, thinking about the rarest cases that exist and are possible, and using uncommon thinking. We have argued that these strategies are relevant to four categories of tasks that form the core of machine learning tasks: Model selection, Model construction, Using a model, and Identifying important features. This leads to the prediction that training that focuses on the three thinking strategies should have a positive effect on the ability to solve a machine learning task. We have planned an experiment whose results could be relevant to finding new methods to help children understand ML concepts and get children to think about their thoughts, a practice whose relevance goes beyond teaching ML concepts, and aims to train deep thinking.

We are currently in the process of finalizing the training and test material. The execution of the activities in class and the collection of the data will allow us to confirm or disprove our hypothesis. Based on the results of the study, we will conduct a second round of experiments next school year. In particular, we might consider both improving the current activities and expanding the study to include additional thinking strategies.

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