Foreword to Machine Didactics: On Peer Learning of Artificial and Human Pupils

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Abstract. Process of human learning has many features in common with the process of machine learning. This allows for creation of human-AI tandems or smaller groups where all members of the tandem or a group learn and develop. Consistenly with Vygotskyan and Piagetian theories of learning and role which peers and intersubjective relations play in such theories, we hypothesize that curricula can be established whereby human and artificial learnings collaboratively learn together, resulting in a win-win situation for both organic and anorganic agents involved.

Keywords: machine didactics · peer learning · machine learning · human-machine parallelism · zone of proximal development

1 Introduction

1.1 Point of departure

We depart from a simple observation: process of learning of humans or other organic beings shares certain features with the process of machine learning (ML) [2]. One observes deeper analogies than those caused by the trivial terminological fact that both such processes are denoted by the participle learning". First and foremost, both human as well as machine learning are able lead to discovery and emergence of practically useful generalizations which allow the agent - no matter whether human or artificial - to arrive to accurate conclusions, execute appropriate decisions and manifest well-adapted behaviors in novel and hitherto unseen present or future environments.

In fact, many among most accurate and efficient machine learning algorithms originated as metaphors transposing insights from neurosciences, behavioral sciences, genetic epistemology or developmental psychology into the *in silico* domain. Neural networks, of course, are the most famous example: triggered by Purkyne's discovery of a neural cell, reinforced by Hebbian associanist rule "cells that fire together wire together" and expressed by progressively evermore complex models of artificial neuron - from perceptron and neocognitron to multi-layered, convolutional network architectures able to provide impressively accurate results in domains as diverse computer vision, speech recognition or time series analysis and prediction.

Asides neurosciences, behavioral psychology has also some words to say: both Thorndike's Law of effect which postulates that a pleasing consequence strenghtens the action which triggered it, as well as Skinner's principles of operant conditioning able to stimulate certain kind of future behaviours by means of a reward or inhibit it by means of a punishment prepared solid empiric ground for what is nowadays known as the 3rd pillar of machine learning, i.e. the reinforcement learning paradigm [9]. Implementation of such algorithms into already existing hardware brings very tangible results: defeat of the human world champion of game of Go by the AlphaGo algorithm or attainment of human level of control in playing of 49 distinct computer games by a one single computational agent [7] gradually prepare us for the world where machines develop their own means how to achieve their objectives [1, 8].

1.2 Human-machine learning parallelism

It is true that one cannot a priori exclude existence of an unsurmountable ontological difference between learning processes realized on an organic, carbon-based substrate of the human central nervous system and learning processes instantiated on universal Turing machines executed on artificial, silicium-based substrate of modern CPUs, GPUs and TPUs.

Still, similarities and characteristics shared between machine learning (ML) and human learning (HL) permit us to postulate that the process of machine learning could lead, mutatis mutandi, to resultsindistinguishable from those issued by and from the process of human learning. In layman terms:

Processes of ML and HL have features in common.

Asides being purely descriptive, the observation that *human-machine learning parallelism exists* yields productive consequences:

Humans and machines can learn together.

In other terms, curricula which combine both ML and HL components can be constructed and, if constructed properly, may have synergic potential to increase efficiency of both ML and HL more, than HL or ML curricula which unfold in isolation. And this brings us to peer learning.

1.3 Peer learning

Discovery of a role of "peers" in processes of socialization and acquisition of knowledge undoubtably belongs to most important moments of modern and post-modern educational sciences. Thus, as surpassed and outdated are nowadays considered those classical and even 19th century educational concepts in which the notion of learning had been reduced to one-directional vertical transfer of information from a socially superordinated "mature" teacher (=adult) to a subordinated "immature" learner (=child). As indicated by both theoretical and empirical observations of Piaget [5] and Vygotsky [6] and confirmed by success of concepts of Freinet, Montessori or Feuerstein, surrounding children can and do significantly influence and modulate cognitive maturation of a child C.

As observed by practically every teacher faithful to his vocation, the field of vivid social forces generated and exerted by "peers" - i.e. siblings, schoolmates, friends or other subjects on a comparable level of intellectual development - impacts formation of pupil's personality and character equally strong - and sometimes even stronger - then force of Teacher's charisma, knowledge, skill and confucian oracle-like authority.

1.4 Human-machine peer learning

The ultimate intention behind this extended abstracit is not constrained to computer-science domain, nor to cognitive-science domain. The ultimate intention is didactical, it is paedagogical: we propose to shift the focus from theoretical algorithmic aspects of machine learning to concrete practical cases of *machine teaching* contextualized in an organized system of a well-thought curriculum.

In order to do so, we hereby introduce the concept of Human-machine peer learning (HMPL) which emerges as a direct logical consequence of conjunction of a human-machine parallelism and human innate affinity to peer and/or collaborative learning scenarios. After combining these two concepts, one states:

Humans and machines can learn from each other.

Main principle of HMPL being thus stated, we now enumerate two major imperatives of HMPL:

1. start small
2. posit zones of proximal development

Primo, the **start small** imperative. This imperative is based on an idea that process of learning of both human as well as artificial learners should depart from quantitatively and stucturally minimal datasets. The strongest empiric evidence for importance of the start small principle in both human as well as machine learning comes from domains of psycholinguistics and computational linguistics. Thus, psycholinguists observe that "*mother's choice of simple constructions facilitated language growth [of a child]*" [4]. In the computational realm, the seminal paper of [3] summarized the reasons of success of a connectionist model of acquisition of English grammar with words: "*... However, when the training data were selected such that simple sentences were presented first, the network succeeded not inly in mastering these, but then going on to master the complex sentences as well.*" [3].

Secundo, the **posit zones of proximal development** (ZPD) imperative. This imperative is based on an observation that didactic process is most efficient there, where structures-to-be-learned are neither too distant - and therefore unreachable - nor too similar - and therefore devoid of interest - from prior knowledge which the learner already has at her/his disposal. Concisely stated, the ZPD-hypothesis provides to any teacher - organic and artificial - a simple but efficient *didactic meta-algorithm* able to positively influence the impact of one's teaching practice. The core of such meta-algorithm is a *didactic loop*:

1. Assess what the learner knows (i.e. prior knowledge).
2. Expose the learner to novel structures which are close to, but not within, the domain of prior knowledge.
3. Once it is obvious that letaner's domain of prior knowledge encompasses the novel structures proceed to step 1.

It is indeed the ability to recognize what the learner already knows (step 1) and what the learner *can* know (step 2) which distinguishes a good teacher from a bad one.

Within HMPL, zones of proximal development are to be assessed for each participant and each competence. If ever it is observed that level-of-mastery for two distinct competences σ and π, as exhibited by two participants X and Y is such that both $X_\sigma >\sim Y_\sigma$ holds in the same time as $X_\pi <\sim Y_\pi$ holds, we say that X and Y are in a state of *a mutual non-equilibrium* in respect to competences σ and π.

In case of such mutual non-equilibria, the main condition that Y can learn from X about σ whilst X will learn from Y something about π, is met.

It is the initial existence of such mutual non-equilibria and their gradual convergence into a state of didactic equilibrium which makes peer learning possible.

Exploration, evaluation and construction of such convergence processes is the main object of study of the research field hereby labeled as machine didactics.

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