Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 23 (2018) 117–122

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

8th Conference on Learning Factories 2018 - Advanced Engineering Education & Training for Manufacturing Innovation

Rethinking Human-Machine Learning in Industry 4.0: How Does the Paradigm Shift Treat the Role of Human Learning?

Fazel Ansari[a,b,*], Selim Erol[a], Wilfried Sihn[a,b]

[a] *Vienna University of Technology (TU Wien), Institute of Management Science, Theresianumgasse 27, 1040 Vienna, Austria*
[b] *Fraunhofer Austria Research GmbH, Theresianumgasse 7, 1040 Vienna, Austria*

Abstract

The paradigm shift in production system known as Industry 4.0 imposes changes on work division between human and machine. A human labor on the one side is assisted by smart devices and machines (human-machine cooperation) and on the other should interact and exchange information with intelligent machines (human-machine collaboration). This paper addresses the challenges of mutual human-machine learning in factories of the future. The ultimate goal is to identify new learning patterns in highly digitalized industrial work scenarios. To this end, we give a definition of mutual human-machine learning in digitalized work scenarios; provide exemplary scenarios in the TU Wien Pilot Factory Industry 4.0, and finally identify future research potentials.

Peer-review under responsibility of the scientific committee of the 8th Conference on Learning Factories 2018 - Advanced Engineering Education & Training for Manufacturing Innovation.

Keywords: Human Learning; Machine Learning, Human-Machine Interaction; Reciprocal Learning; Hybrid Learning; Industry 4.0

1. Introduction

Digital technologies and cognitive computing [1] are shifting the traditional boundaries of manufacturing industries. Through connecting smart devices and machineries, employing self-learning solutions, and enhancing self-direction capabilities, it is envisioned that the communication cost is reduced while flexibility for manufacturing, mass customization capabilities, production speed and quality are increased [2], [3], [4]. These are not only the opportunities

* Corresponding author. Tel.: +43-1-58801-33049.
E-mail address: fazel.ansari@tuwien.ac.at

2351-9789
Peer-review under responsibility of the scientific committee of the 8th Conference on Learning Factories 2018 - Advanced Engineering Education & Training for Manufacturing Innovation.
10.1016/j.promfg.2018.04.003

addressed by the umbrella terms "Industry 4.0" and "Digital Manufacturing" but also reveal several challenges or in a more critical way obstacles to improving productivity at the work place. Among them, work division between human workers and intelligent machines in technology-rich working environment raises question about the concept of human-machine learning in the factories of future. This alters the paradigm shift in work-based and vocational education and related didactical concepts. A recent survey has revealed that only 13% of workers in OECD countries and economies use key information-processing skills, namely literacy, numeracy and problem-solving skills on a daily basis with higher proficiency than computers [5]. Cognitive computing aims at reproducing human skills through building artificial models and computable algorithms deployed for handling human kinds of problems (tasks) and transferring human decision-making processes to intelligent machines [1], [6]. *How does the paradigm shift treat the role of human learning?*

In this paper, we aim at defining and characterizing "mutual human-machine learning" in factories of future. In particular, the key research question is *how to define a mutual learning when there is a learning effect on both human worker and intelligent machine, in different degree of competence and intelligence respectively, through participation in doing a mutual task (task segment)?* To find an answer, we review typical human and machine learning scenarios, and identify human and machine capability in production systems. For this purpose, we distinguish between two types of learning, depending on the target learner, as follows: human learning (i.e. human as a learner) and machine learning (intelligent machine or computer as a learner). Tailoring the practical challenges defined in the context of TU Wien Pilot Factory Industry 4.0 to the theoretical models, we identify research potentials including several directions for applied research and theory development.

2. Human and Machine Learning: Terminologies and Definitions

Human learning has been considered as a subject in the field of education, pedagogy and cognitive psychology in relation to the learning theories (behaviorism, cognitivism, constructivism, and humanism), learning styles, pedagogic models, concept learning and educational psychology [7]. This has led to a wide variation in definition of human learning and thus universal consensus on any single definition is nonexistent [7]. According to Ertmer and Newby [7] the main ideas about learning are incorporated in the "definition by Shuell (as interpreted by Schunk, 1991): Learning is an enduring change in behavior, or in the capacity to behave in a given fashion, which results from practice or other forms of experience"[8],[9],[10]. In particular, Bendar et al. [11] stated that "constructivism is a theory that equates learning with creating meaning from experience"[7]. Constructivist theories such as social constructivism, situated learning, and connectivism [12] have established the "foundation for the majority of teaching methods that have taken hold in recent years (for example, problem-based learning, authentic instruction, computer-supported collaborative learning)"[7]. The five-stage model of adult skill acquisition, in which the experience and skill level of a learner are highly correlated, considers learning with creating concepts and meaning from experience [13]. In the context of learning factories [14], Scenario-Based Learning (SBL) has been considered as an effective approach [15]. It is rooted in constructivist theories in particular situated learning [16] as well as cognitive theories [17]. SBL, as an iterative and interactive process, "uses scenarios, structured descriptions of real-world problems and related instructions, to support active learning" [15].

Table 1: Four Main Families of Machine Learning Algorithms (Adopted from [18])

	Learning Approach	Description	Example of algorithm
Machine Learning	Information-based Learning	Employing concepts from information theory to build models.	Decision Trees
	Similarity-based Learning	Building a model based on comparing features of known and unknown objects, or measuring similarity between past and forthcoming occurrences.	k nearest neighbor (k-NN)
	Probability-based Learning	Building a model based on measuring how likely it is that some event will occur.	Bayesian Network
	Error-based Learning	Building a model based on minimizing the total error through a set of training instances.	Multivariable linear regression

From a cognitive computing perspective, artificial models and computational algorithms resemble the ability of human learning and reproduce human skills. The model building, as the core of this process, is automated using methods of Machine learning (ML). One can classify ML algorithms into four families; namely, information-based, similarity-based, probability-based, and error-based learning (cf. Table 1). Furthermore, main types of ML are distinguished as follows [18], [19]: i) Supervised ML "assumes that training examples are classified (labeled)" (i.e.