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

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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.

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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

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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.

learning relationship between a set of descriptive features and a target feature), ii) Unsupervised ML “concerns the analysis of unclassified examples”, iii) Semi-supervised ML uses unlabeled data with a small amount of labeled data to improve the learning accuracy, and iv) Reinforcement ML employs different scenarios for discovering the greatest rewarded action in a trial-and-error process by collecting feedback from environment.

3. Mutual Learning in the Context of Industry 4.0

Considering the above discussion on human and machine learning, we have identified two groups of learners (human or machine as a learner) and two distinctive but interacting learning concepts. The human and machine interaction and closely collaboration lays the ground for hybridization of the learning concepts, in which “mutual learning” occurs. This is also affected by different potential capacity of human and machine in performing different tasks such as mechanical jobs and decision-making. Quality and performance variation in carrying out a task are the key indicators, which identify and ultimately distinguish the capability of human and machine on performing the assigned task. Table 2 compares quality and performance variation of the learner groups with respect to an assigned task. Similarly, it can be extended to information processing and problem-solving tasks discussed earlier in [20] and [6], respectively.

Table 2: Comparing capability of human and machine (learner groups), based on quality and performance variation (Adopted from [20],[21])

			Human	**Machine**
Capability	**Quality Variation in**	Mechanical Job	• High inter-individual differences and diversities • It can be improved by training and job satisfaction.	• Very low • It can be degraded over lifetime or due to inappropriate maintenance
		Decision-Making	• High inter-individual differences and diversities depending on problem-solving abilities, competences, experiences and qualification level. • Personal, societal and institutional interests may influence on human decision-making. • The complexity and sensitivity (risk) of the decision may affect it.	• Low to high depending on the quality of data (affected by disturbances and noises), preciseness of algorithms, degree of preparation affected by human, and complexity of the problem field. • The quality can be improved after training the system with (relatively large) datasets.
	Performance Variation in	Carrying out a task	• Relatively high (depending on individual capacity, motivation and commitment). • High possibility of work fatigue and job dissatisfaction.	• Very low (depending on the lifetime, associated degradation rate and service quality).

Differences in learners’ capabilities, as exemplified above, reflect the learning potentials for human workers and intelligent machines. The learning process for each group of learners can be independent or dependent. The former refers to distinctive training for each group of learner. The latter considers the co-occurrence of learning through doing a mutual or shared task (set of tasks). For example, Task *A(assembly of a product)* can be segmented into sub-tasks *Ai(mechanical assembly)*, *Aii(data collection)*, *Aiii(quality control)*, which can be either divided between human worker and machine or can be shared. In the literature, the majority of approaches involve ML algorithms for imitating or transferring human skills to robots. For instance, robot learning by observation of human activities are discussed in [22],[23], [24]. In addition, the Google Brain Team recently reported on self-supervised approach to robot learning, which enables robots to grasp objects without involving human supervision (see [25] and [26]). Evidently, there is a lack on exploring co-occurrence of human-machine learning. Hence, we have a strong tendency to differentiate between learning approaches purely subject to human and machine learning, where human and machine specific learning has distinctively examined.

In the context of Industry 4.0, we define **mutual learning as** «*a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration, which results in creating new meaning or concept, enriching the existing ones or improving skills and abilities in association with each group of learners*». Considering smart factory as a learning environment, one may distinguish between three pools of tasks assigned specifically to human or machine and the shared tasks (cf. Figure 1). Performing shared tasks involves exchange, action or influences and results in certain degree of dependency. This hybridization combines elements of human and machine in knowledge acquisition and participating in doing the shared task into a new boundary system in which mutual learning takes place. Figure 1 depicts our conceptual model of mutual learning inspired by the model of hybrid learning proposed by Zitter and Hoeve [27] and the research on applying hybrid learning for vocational education in process technology firms presented by Ritzen et. al. [28].

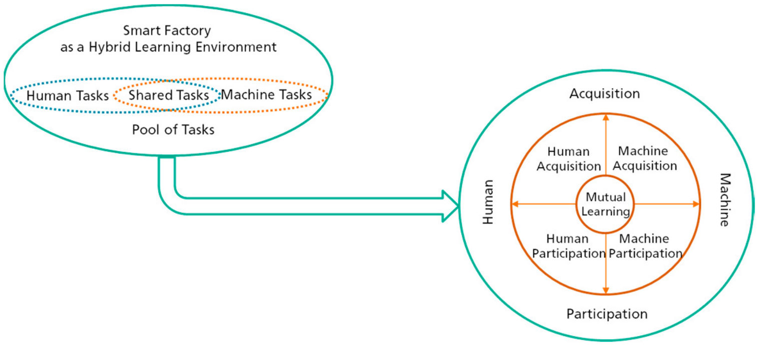

Fig. 1: Mutual learning in relation to human-machine collaboration.

4. Mutual Learning Scenarios in the TU Wien Pilot Factory Industry 4.0

The TU Wien Pilot Factory Industry 4.0 (PFI40) [29] is an endeavor to build an exemplary digitalized and intelligential factory of the future. The PFI40 serves both as a platform for research and showcase to demonstrate solutions for pressing problems in industry. One of these problem areas in industry is division of work between human and machines and subsequent collaboration challenges. In this section, we shortly describe three exemplary collaboration scenarios to discuss potential mutual learning opportunities between humans and machines in the light of a real world factory setting.

4.1. Description of Overall Production Process

In the PFI40, a 3D printer for home use is produced (see Fig. 2). The product consists of 130 unique types of parts (excluding identical items) and 233 parts (including identical items). The main parts of the printer's frame and the printer head are manufactured internally. The printer's control unit and other electrical and electronic parts are purchased from external suppliers as well as all helper materials like screws.

Fig. 2: a) Assembly line in PFI40 with AGV in front (yellow) and handling robot (blue) in the background, b) Autonomous vehicle for materials transport, c) Single arm robot assists human in the mounting tasks.

In the PFI40, we distinguish between manufacturing processes, which transform raw materials into parts and assembly processes. In addition, we have transport processes and handling processes. For parts manufacturing, we have cells for milling, turning and welding. For parts assembly, we have four assembly cells equipped with shooter racks, remote frequency identifiable containers for small parts, touch screens to provide assembly instructions and control, and various mounting tools. Assembly tasks are subdivided into preassembly tasks for parts like the print head and associated parts like the print head, the printer table and the drive units. For material storage, we use simple racks and containers equipped with tags and stock level sensors to be able to track material location and stock at any time in the production process. A flock of three autonomous vehicles accomplishes material transport between the different cells. Both human workers and single arm robots perform handling of materials between different agents in the production process.

4.2. Scenario 1: Human Worker and Single Arm Robot Collaborating in Complex Assembly Tasks

One of the assembly cells is equipped with a stationary single arm robot. The robot is unfenced and works closely with the human (see Fig. 2c). The robot arm has a parallel gripper and is capable to handle (grab, move and release) small work pieces (<5kg). Its gripping force is limited to 20-235 N. The typical advantage of a single arm robot in mechanical tasks is its capability regarding handling of pieces in a spherical three-dimensional space. Its capacity regarding precision, force and endurance makes it advantageous over humans in respective handling tasks. In the current configuration, the robot performs positioning tasks to help the worker during mounting of the print head within the frame. In human-robot collaboration, typical learning takes place when the robot is trained to perform certain movements. Humans can physically program a robot by moving the robots head along a predefined path or can program the robot the traditional way through coding. In our assembly cell, we support positioning tasks by a camera system, which allows detecting exact position of parts. The camera system as part of the robot well is trained by feeding exemplary images of parts to be able to extract geometric information. Both ways are extremely simple forms of instructional learning from human to machine. In scenarios where the robot is equipped with more intelligence, e.g. through additional sensors and a certain kind of memory as well as analytical functions, learning that is more sophisticated can take place. For example, we have equipped human workers with a sensory system that track the movement paths of workers' hands. The data obtained can be used to identify movement patterns which in turn can be fed back to the robot programming interface, e.g. to take over certain material picking tasks. In the end, also complex tasks like screwing can be learned by the robot through a combination of motion tracking, visual pattern recognition and tool data mining methods. Modern screwdrivers have embedded systems that provide data streams on screwing force and angles. The data from data loggers can be linked to screwing tasks, which potentially allows learning screwing sequences from human workers. Machines themselves can evaluate human activities and find better solutions, e.g. a faster sequence of tasks. These improved activities can be fed into an assistive information system, which allows a human to learn these improved activities.

4.3. Scenario 2: Autonomous Vehicles and Human Worker Sharing Transport Routes and Tasks

Autonomous vehicles (see Fig.2b) perform material transport between assembly cells. The vehicles are capable of autonomously navigating on flat two-dimensional surfaces. Given a destination location, the vehicle is capable to find its way through fixed and moving obstacles by using an internal map together with a laser scanner to detect and avoid collisions. Its capacity regarding location preciseness is limited to +/-3 cm. Speed range is up to 1.5 m/s, operating time due to battery capacity is limited to 10 hours. Loading capacity is limited to 150 kg. Currently, we train our transport vehicles in their awareness of the physical environment in the factory. In particular, transport vehicles are prepared for their autonomous operation by driving them through the factory in a remote controlled manner. Driving through the factory, vehicles map their environment by a rotating laser array. Thus, a digital map of the factory is created which can be adapted ex-post by a human, e.g. to mark hazardous areas where increased human traffic happens or floor structure is unsuitable for navigation. In the future, we will extend the scenario of learning in terms of route optimization. In particular, data from cameras or sensors can provide information about preferred routes from human movements. Digital layout models created during factory planning can be used to teach vehicles about changes in layout and subsequently allow for altering of programmed paths and internal map. In a different scenario, we plan to use vehicles' laser scanning capabilities to detect unplanned permanent or frequent obstacles.

4.4. Scenario 3: Scheduling of Productions Tasks – Human versus Machine

For controlling the flow of work in our assembly line, we use a software component. Based on a detailed work plan the so-called Sequencer keeps track of the status of all technical systems and task completion progress. Scheduling of tasks is currently performed in a first-in first-out manner. Currently the Sequencer acquires its knowledge on the sequence of tasks from the data maintained in product specific work plans, which is created by a human. Situation specific changes to the order of tasks are not possible for a human worker. For future scenarios bidirectional learning between human planner and the Sequencer might be beneficial. Given a certain intelligence of the scheduler, e.g. by implementing a genetic algorithm to find better task schedules within feasible time, humans can learn from the sequencers suggestions. The other way around, where a human worker overrules the scheduler repeatedly (similar to GPS), can be used to teach the sequencer a human logic of scheduling.

5. Conclusion and Recommendations

Engineering and operation management jobs in the age of Industry 4.0 require more multi- and interdisciplinary skills for handling combined task elements. Collaboration of human and intelligent machines triggers mutual learning. We have defined the term mutual learning and explored certain use-cases in the context of TU Wien Pilot Factory

Industry 4.0. From our point of view, pursuing this line of research beyond the state of the art is tied to theory development and experimental research in the following areas: i) *Redefining job roles*, including clear definition of three tasks pools (human-specific, machine-specific, shared tasks), identifying the shared activities/tasks between human and machine, and defining measures to assess proper fulfillment of the assigned tasks, ii) *Identifying learning areas*, considering human self-learning and machine self-supervised learning capabilities in association with fulfillment of shared tasks, iii) *Examining competence transferability between human and machine*, which impacts on mutual learning, and iv) *Measuring mutual learning outcome*, considering human and machine specific characteristics in relation to key indicators such as human/machine error probability rate, learnability, operation/handling time. Finally yet importantly, the concept of mutual learning in the production and operation management is still vague and requires interdisciplinary research collaboration with educators, data scientists and cognitive psychologists as well.

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