2017 IEEE 2nd International Workshops on Foundations and Applications of Self* Systems (FAS*W)

Learning to Learn: Dynamic Runtime Exploitation of Various Knowledge Sources and Machine Learning Paradigms

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***Abstract*—The ability to learn at runtime is a fundamental prerequisite for self-adaptive and self-organising systems that allows for dealing with unanticipated conditions and dynamic environments. Often, this machine learning process has to be highly or fully autonomous. That is, the degree of interaction with humans must be reduced to a minimum. In principle, there exist various learning paradigms for this task such as transductive learning, reinforcement learning, collaborative learning, or – if interaction with humans is allowed but has to be efficient – active learning. These paradigms are based on different knowledge sources such as appropriate sensor measurements, humans, or databases as well as access models considering e.g., availability or reliability. In this article, we propose a novel meta learning approach that aims at dynamically exploiting various possible combinations of knowledge sources and machine learning paradigms at runtime. The approach is learning in the sense that it self-optimises a certain objective function (e.g., it maximises a classification accuracy) at runtime. We present an architectural concept for this learning scheme, discuss some possible use cases to highlight the benefits, and derive a research agenda for future work in this field.**

I. Introduction

Information and communication technology faces a trend towards increasingly complex solutions, e.g. characterised by the laws of Moore [1] and Glass [2]. As a consequence, traditional concepts for design, development, and maintenance have reached their limits. Within the last decade, a paradigm shift in engineering such systems has been postulated that claims to master complexity issues by means of self-adaptation and self-organisation. Concepts and techniques emerged that move traditional design-time decisions to runtime, and from the system engineer to the systems themselves. Examples for research fields focusing on these issues are Organic Computing [3], Autonomic Computing [4], Interwoven Systems [5], or Self-Organising and Adaptive Systems [6].

Technically, realising systems with the ability to react appropriately to unanticipated conditions or to deal with changing system compositions, for example, means to equip these systems with machine learning mechanisms. Learning-based mechanisms may be trained at design-time (e.g, by deriving knowledge from sample data), but they have to extend their knowledge[1] at runtime (e.g., by identifying novel kinds of knowledge and include them in their models or by refining their models based on reinforcement signals). In any case, these systems have to learn at runtime in a partially or even fully autonomous way. That is, humans are either not involved or their knowledge has to be exploited very efficiently (e.g., they can occasionally be asked to provide labels for observations). The research field of Autonomous Learning, for instance, deals with such issues [8].

Typically, online learning is restricted to a specific combination of machine learning paradigm and knowledge source. For example, the possibility to immediately observe the effects of a system's action in its environment can in some cases be exploited with reinforcement learning mechanisms. Or, the availability of humans that give answers to questions offers the chance to utilise Active Learning [9] techniques that ask humans to provide labels for a system's observations. Especially in the context of large-scale systems-of-systems [10] with properties as sketched above, a new challenge arises: How can we effectively and efficiently gather knowledge from a large variety of eventually available knowledge sources by means of various machine learning paradigms? Moreover, how can we learn how to combine these learning paradigms and knowledge sources in a given situation? Examples for knowledge sources include the local physical environment of the system, other systems with similar tasks, humans, or databases. Examples for learning paradigms are reinforcement learning, active learning, collaborative learning, or transductive learning.

As an example for future systems equipped with meta learning capabilities as outlined above consider a mobile robot that explores its environment. It has the task to learn to recognise objects in its environment, e.g., a private household, and to handle them, e.g., to bring the recognised objects to a disabled person. Occasionally, it sees a mug, but it is only able to identify cups. Maybe, an annotated image database available via Internet may help to recognise mugs. Maybe the human owner of the robot could be asked using an active learning mechanism. The robot knows how to grasp and to rise a cup. Maybe this knowledge about cups can be transferred to mugs or the robot could just try to grasp and rise the heavier mug and use a reinforcement learning approach to adapt its knowledge.

In this article, we present a novel concept for a meta learning paradigm: Technical systems are allowed to reflect on the learning paradigms and the knowledge sources they use to

[1]In the context of this paper, we use the term knowledge as representative for any kind of information, data, rules, etc. – and do not refer to the explicit usage as, e.g., in the wisdom pyramid from the data mining domain [7].

978-1-5090-6558-5/17 $31.00 © 2017 IEEE
DOI 10.1109/FAS-W.2017.129

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maintain and improve their behaviour. Therefore, we discuss possible knowledge sources and their particular access cost, as well as the implications for the utilised learning paradigms and derive a research agenda towards a technical realisation.

The remainder of this article is organised as follows: Section II briefly summarises relevant concepts from the state-of-the-art. Afterwards, Section III introduces the concept for autonomous meta learning including an architectural blueprint, a definition of (classes of) knowledge sources, and a discussion of the associated cost functions. Based on this concept, we present a research roadmap towards autonomous meta learning in Section IV. Section V explains the envisioned functionality based on exemplary use cases. Finally, Section VI summarises the article and gives an outlook to future work.

II. State-of-the-art

In this section, we briefly summarise research activities that aim at incorporating different learning paradigms in technical applications. However, we focus at the general concepts and neglect particular instances for the sake of brevity.

Ensemble Learning: From a machine learning point of view, the goal of *ensemble learning* is to combine multiple learning systems in order to obtain an increased performance compared to any of the constituting learning systems. For example, humans tend to consult with different "experts" when they have to make an important decision. Thus, the confidence that the final decision was the right one is increased. A background on ensemble systems, as well as an overview of the ensemble-based algorithms and their applications is given in [11]. Some applications of ensemble systems include, amongst others, feature selection for tweet sentiment analysis [12], wind power forecasting [13], incremental learning [14], or learning in nonstationary environments [15], [16].

Meta learning (algorithm selection): The authors in [17] discuss different views on meta learning based on recent literature. Further summaries are given in [18], [19]. Here, we refer to methods that monitor an autonomous learning process and adapt it according to changes in the environment [20]. This is also called base-learning [18]. Usually, it generates meta knowledge which describes the learning process to build meta models. Using this knowledge, the meta learner is able to adapt the base-learner according to observed changes [20].

Active Learning: In general, machine learning (ML) is based on data. *Active learning (AL)* is a machine learning paradigm, which is based on the idea that a system can learn faster and better if it is allowed to ask questions. AL starts with a rather small knowledge base and extends it by asking an information source (also known as *oracle*) "the right question(s)" [9], [21]. The various possibilities and strategies (see [22] for a review of different query startegies) to gather knowledge from an information source fall outside the scope of this article. However, the information sources are multifarious: (A) On the one hand, there are systems that continuously deliver information, such as sensors that deliver measurements. (B) On the other hand, there are knowledge sources that have to be explicitly queried for information. Other smart systems with similar tasks, the Internet (as a collection of diverse, heterogeneous data bases), simulation systems, humans with different levels of expertise (domain experts [21] as well as non-domain experts [23]), or any combination of the above may serve as knowledge source. Moreover, these queries generate costs (e.g., monetary, time, etc.), thus the learner has to carefully select and combine them.

Autonomous Learning: Biological entities are able to continuously learn in our ever changing and unpredictable world. They have the ability to create an internal representation of the environment that helps them to select the events from which they learn, set their goals, and evaluate their performances [24]. Analogously, a machine learning entity should be able to create a representation of the environment during the learning process, select the most informative knowledge sources, set their own objective functions, and be aware of its own performance. Namely, it should be able to learn autonomously. Research fields such as data mining, Organic Computing, fuzzy logic, reinforcement learning, or pattern recognition deal with questions that address some of the properties and demands of autonomously learning systems [8].

Design of self-adaptive systems: From a system perspective, self-adaptive and self-organising (SASO) systems are typically conceptualised as a combination of distributed autonomous entities, sometimes with additional centralised elements (i.e., a hierarchical composition). In this context, initiatives such as Organic Computing (OC) [3] and Autonomic Computing (AC) [4] have proposed a variety of blueprints. For instance, the generalised observer/controller framework with several distribution variants (ranging from fully distributed to hybrid and to fully centralised concepts) [25] is a popular representative from the OC domain. In addition, AC has developed the Monitor-Analyse-Plan-Execute(-Knowledge) cycle, typically referred to as MAPE(-k) [4]. Hierarchical extensions have been proposed as well as system-of-system concepts. Another important domain in this context deals with multi-agent systems [26]. Here, especially design schemes for autonomous agents have been considered, with the Belief-Desire-Intention model as probably most prominent variant. In [27], a current overview and classification of design approaches for self-adaptive systems has been presented. One particular aspect of the taxonomy proposed in this context deals with the utilisation of learning: The authors found that adaptation is done using different concepts, ranging from static policies to pre-trained models (e.g., using Neural Networks), and to reinforcement learning.

III. Autonomous Meta Learning

Autonomous meta learning has the goal to analyse the behaviour of the underlying adaptive system and to continuously improve the behaviour. In contrast to traditional learning concepts in self-adaptive systems (see, e.g., [27] for an overview), the learning perspective is shifted: from applying one technique with a perfectly defined scope of the learning problem towards an exploitation of various heterogeneous knowledge sources and learning paradigms. In principle, this

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also means to shift the focus from a static, dedicated learning behaviour to a dynamic, opportunistic one. The approach is called "autonomous" since it should act without or with only minimal intervention from users or other systems that aim at controlling the learning process.

In addition, a self-adaptive system will most probably exist in the context of an overall system composition, i.e., in the sense of a system-of-systems composition [5], [28]. This means that it interacts with other autonomous entities during operation – which in turn means that learning is not only passive but also demands for interactions. This idea of interaction can be taken further towards the insight that during the own learning process (i.e., making use of knowledge accessed from other external knowledge sources) this knowledge source may learn from the interaction as well: in terms of modelling knowledge gaps of the questioner or by analysing the questions that are asked. For instance, concepts can be derived that the questioner may possess, goals it fulfils with the question, or the "language" it speaks, to name just a few.

In this section, we present a system model for such a meta learning mechanism, discuss knowledge sources and access models, and highlight the implications for the utilised learning paradigms.

A. System Model

Independently of the underlying application domain, we assume a technical system to comprise two different parts: a) a productive part that fulfils the technical purpose and b) a control mechanism that adapts the behaviour of the productive part to changing conditions. Following the ideas of the OC initiative in terms of the Observer/Controller pattern, the basic system is defined as follows (see lower part of Figure 1):

- System under Observation and Control (SuOC): The productive part of the system is equipped with sensors (to gather environmental information) and actuators (to interact with its environment). It provides interfaces for observation (i.e., status description) and control (i.e., parameters to steer the behaviour).
- Adaptation Layer: An observer component is responsible for analysing the current conditions and the behaviour of the SuOC. It augments this information with experiences, predictions, and indicators (such as emergence) to derive a sophisticated situation description. Based on this description, the controller component decides about necessary adaptations. The controller typically contains a learning component that improves the parameter adaptation process over time.

To this end, Figure 1 resembles OC's design concept [25] (and the ideas of AC's MAPE cycle [4]). In principle, the Adaptation Layer may be refined into more than one layer to distinguish between different aspects of the control problem (corresponding to different abstraction layers of the control task). We propose to add a novel layer – the *Meta Learning Layer* – on top of such a self-adaptive system that allows for a self-improvement of the Adaptation Layer's behaviour. This layer is structured as follows (see upper part of Figure 1):

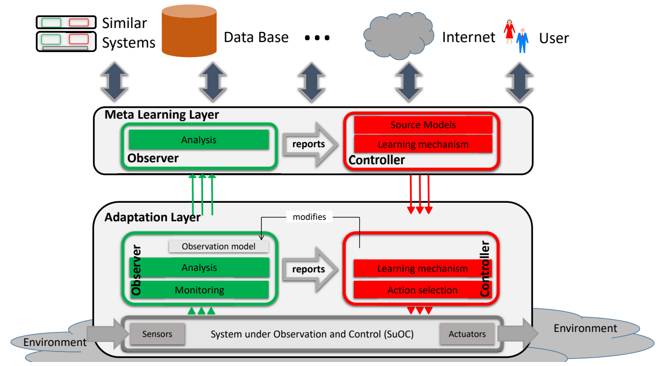

Fig. 1. Architectural blueprint of a meta learning system based on the Observer/Controller approach [25] from the OC domain.

- The current state of the Adaptation Layer is perceived by the **Observer**. The task of the observer is to "reflect" about the environment and the behaviour of the Adaptation Layer, and to analyse the particular inputs provided by the knowledge sources as well as their behaviour. Through the broader understanding of the environmental settings (by that we mean both the environment in which the Adaptation Layer operates, as well as the setting of the knowledge sources) it reports the necessary information to the controller. Thus, on the one hand, it learns how to reason and, on the other hand, how to react on short and long term decisions. The underlying time horizon for reflection may differ considerably from the one of the Adaptation Layer (i.e., is significantly longer).
- The **Controller** is the decision-making entity that controls the Adaptation Layer. Its choices are based on the learned *source models* for each knowledge source. These models contain learned information about the availability, reliability, and the set of possible questions and expected type of answers. Based on the knowledge models, it decides (i) when is the right time to gather new information, (ii) which knowledge source or sources should be inquired, (iii) and how (which pair of question-answer type) to query the knowledge sources.
  The second import part of the controller is the *learning mechanism*, which not only provides answers to the previous three questions, but also learns how to regulate and supervise the Adaptation Layer.

Conceptually, the Meta Learning Layer adds an additional, higher-level control loop on-top of the self-adaptive system. In the following, we discuss the knowledge sources, the underlying access functions and cost as well as the resulting learning paradigms in more details.

B. Knowledge Sources

Firstly, we categorise the different knowledge sources and, secondly, present their potential applications. The potential sources of information are:

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- **Human** or humans, which may be domain expert (e.g., operators of machines or process engineers) or non-domain experts. Furthermore, the humans can contribute with implicit or explicit input.
- **Other productive systems** of the same kind that perform the same or similar functions.
- **Context and environment** of the learning system in which the system operates, the environment of the productive system according to Fig. 1, also known as SuOC [25]. Additional knowledge may be queried from a simulation system, which reflect a virtual interaction form. Still, further information may be gathered from a real, deployed (online) system, or from a real test stand in a lab environment.
- **Free, open data** or data that is not cost intensive, such as the Internet, social media, or data bases. One issue of the open data is that it lacks structure and straightforwardness.
- **Collateral knowledge** about the specific application, such as previously used knowledge (practical), knowledge from related domains, or knowledge related to previous observations (empirical knowledge).

Secondly, we address some deployment methods for querying the previously presented knowledge sources. Obviously, tapping into knowledge depends on the knowledge sources. Thus, we categorise the methods of knowledge acquisition according to the type of application:

- **Human**: Systems can actively query human domain experts (e.g. operators of machines or process engineers) to ask for appropriate actions (or, more general: to assign labels to provided situations). Such a process is typically challenging due to the sparse availability of human interaction or due to the risk of annoying humans quickly when continuously asking for input. Consequently, the underlying research field of dedicated collaborative interactive learning [21], which is related to active learning [9] investigates efficient utilisation schemes of the restrained human feedback resource.
  In some complex or easy problems, either there are no experts, or there is no need for domain experts, or the learning task takes a long time, such that the number of humans varies over time. These opportunistic [23] systems can crowdsource human input.
- **Other productive systems**: The productive system may cooperate and collaborate with other productive systems in order to improve its knowledge. By "cooperation" we mean that the systems exchange knowledge that helps both of them to reach their goals, whereas "collaboration" means that the systems share the same goal.
- **Context and environment**: The learning system interacts with the environment through its actions. Depending on the current situation and the performed action the system receives a reward. The goal is to find the behaviour (actions) that maximise the long-term reward of the system. Such scenarios are the research subject of reinforcement learning [29], which is based on the trial-and-error idea. The main challenge, that is still under active research, is how to decide when and if to explore new action policies.
- **Free, open data**: An alternative to direct human feedback are data bases containing generalised knowledge – which is available already at design-time of the system. In addition, it can be extended at runtime by users and systems in a reactive and proactive manner. The contained knowledge can be accessed on demand. A specific example is a data base containing collections of "best practices" that have been generated by humans based on their experiences.
  Aside from structured data bases, unstructured sources of information are available. The Internet is the most prominent example for a large amount of information that is distributed, heterogeneous and unstructured. But, the major challenge here is to discover and locate that piece of information that is needed to solve the current problem, combined with mechanisms to deal with the underlying uncertainty about the appropriateness.
  Another possible source of information is the social media. For example, sudden, unexpected events lead to a high number of entries, that are posted with high frequency (e.g. tweets). This can trigger an update of the optimisation function, such that the productive system can react accordingly on time.
- **Collateral knowledge**: The productive system can boost its learning of new tasks if it uses the experience gathered by solving past similar problems. Thus, the system should posses the ability to recognise and use knowledge from previous tasks to similar domains. The objective of transfer learning [30] is to learn what, how, and when to *transfer*.
  A system is typically considered to learn if it is able to improve its behaviour based on experience [31]. During runtime, a system faces varying conditions and has to react to these observations accordingly. The resulting experiences (e.g. taking feedback in the sense of reinforcement learning into account) are quantified in terms of answering the question: How successful was my action A in situation X? This source of experiences can be used to generalise situation-action mappings, to select actions from similar situations, or to identify correlations.
- **Hybrid methods**: In general, combinations of these sources are possible. In addition, ensembles can be generated to accessing the task in parallel and combining the answers in varying results.

C. Decision functions

The meta learning algorithm aims at maximising the performance of the base-learner (i.e., the learning mechanism at the Adaptation Layer). The definition of performance depends on the learner's type (reinforcement learning, classification, regression), the accessibility of its performance (e.g., utility, accuracy, etc.) and the properties of the available knowledge sources. Depending on the learning scenario, the meta learner

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might operate online, offline or in a combination of both. The adaptations, initialised by the meta learning algorithm, might influence the long-term or short-term performance of the model and we therefore need information about sensitivity of the system. In this context, the lifetime of a certain information has to be discussed. When and how should knowledge be forgotten (i.e., stability-plasticity dilemma [32]) or in case the environment changes between two varying states (reoccurring concepts), how can we maintain the knowledge from temporarily obsolete information? Other factors that influence the meta learning algorithm which are independent from the choice of knowledge sources are:

- Performance of productive system and environmental status
- Change in the environment: detection of anomalies, disturbances or novel information (knowledge that deviates from expected or tolerated behaviour), concept drift/shift
- Persistence of knowledge (lifetime of information)
- Safety constraints (e.g., in medical systems)
- Theoretical guarantees of the base-algorithm
- Number of evaluation cycles (reinforcement learning)

Additionally, the objective function of the meta learning algorithm has to include the specific properties of each knowledge source. The meta learner permanently has to answer the questions: What do I ask? When do I ask? Who do I ask? and Why do I ask? The last question refers to the motivation of the learner's actions because each action has to be justified with a measurable benefit. Actions might target the exploration, exploitation or validation of knowledge. Ranking the importance of the actions still is an open challenge.

Furthermore, each knowledge source has different properties and the meta learner has to decide which question to which knowledge source at what time will improve the base-learner the most. Possible knowledge source specific decision functions might be:

- Availability and maximal / minimal request frequency of a knowledge source
- Reliability and trust
- Expertise of knowledge source
- Uncertainty / certainty of the answer
- Cost in terms of money
- Cost in terms of communication overhead
- Delay of the answer, transmission speed
- Abstraction level of questions / answers
- Privacy (and security) of knowledge exchange

Most of these properties are unknown in the beginning and have to be determined at runtime. Hence, some information may just be acquired to estimate one of the above properties (e.g., asking questions to a human to verify its expertise). Hence, we are faced to multiple exploration-exploitation problems when designing the meta learner. On top of that, privacy and safety constraints have to be fulfilled in real world applications (such as encrypted transmission lines, or the guarantee that such a system will not harm humans) which are often ignored in simulations.

D. Learning paradigms (functions of the meta learner):

After having proposed the design of the system model, the knowledge sources and the decision function, we discuss the mechanics of a meta learning system. In contrast to related research fields, autonomous meta learning only works by combining various learning paradigms to complete its knowledge base, to detect change in the environment, and to improve the base learner. It therefore uses well-known techniques for the specific tasks or uses a combined approach.

Possible learning paradigms are

- pre-training (static at runtime),
- anomaly, novelty and change detection,
- active learning
- reinforcement learning, classification, regression,
- stream and online learning,
- and hybrid mechanisms as a combination of the above.

IV. Research Agenda

Solutions towards the realisation of meta learning concepts have to consist of multiple and partially orthogonal perspectives that also allow for the combination of existing methodologies with new approaches. We suggest to distinguish between four distinct perspectives: the Learning Perspective (LP), the Knowledge Source Perspective (KSP), the Knowledge Perspective (KP), and the Performance Perspective (PP). In the following, we outline the resulting challenges for these perspectives – without the claim of completeness and without prioritisation:

Learning Perspective (LP):

- *How can the meta learner decide which learning paradigm it follows?* – The decision depends on various aspects including, e.g., the behaviour of the Adaptation Layer, the availability and the current costs of the sources, the necessity of deriving new knowledge, and the current goal that is followed. Priorities will change at runtime and a decision mechanism has to dynamically consider these aspects.
- *At which time horizon does the meta learner operate?* – As outlined before, the meta learner's goal is a long-term monitoring and improvement of the Adaptation Layer and its knowledge base. This means that the observation/control cycles are significantly longer as for the Adaptation Layer. However, it may not necessarily rely on a fixed cycle only – instead, it may also be triggered actively in case of missing or insufficient knowledge.
- *How can we integrate domain knowledge of designers into the meta learning mechanism?* – Meta learning is mostly performed at runtime. However, starting from scratch will unnecessarily delay an appropriate functioning. Consequently, concepts to pre-train the learner at design-time, to initially insert human knowledge, and to allow for restricting the search space are needed. This also implies that the learning concept needs interfaces that allow for an access in a human understandable manner.
- *How can an evolution of the underlying control problem be covered by the learning mechanism?* – Controlling a

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certain productive system may result in changing goals and utilities. In particular, this means that the meta learner has to deal with concept drifts or, even worse, with complete concept shifts [33].

- *How does the meta learner switch between exploration and exploitation mode?* – Already in the case of just one learning method and knowledge source, answering this question results in different solutions. However, the challenges become even more complex if combinatorics comes into play: a variety of sources has to be explored and exploited at the same time.

Knowledge Source Perspective (KSP):

- *How can novel knowledge sources be discovered at runtime?* – Continuous evolution of systems means to adapt to changing conditions, and it also means to adapt to changing system compositions. This includes the availability of knowledge sources. For instance, more systems of the same kind may be available as interaction partners. Consequently, techniques for runtime (self-) integration [34] are needed.
- *How can knowledge sources provide a self-explanation of their capabilities?* – Obviously, a self-description using ontologies and semantics is a possibility to provide a solution for this challenge. However, we may face dynamics in the underlying concepts as well – and consequently need additional mechanism to cover these dynamics.
- *How can source-inherent constraints be taken into consideration (e.g., frequency of querying humans is limited)?* – Especially if no reliable self-description of a source is available, we need concepts to exploit the capabilities and constraints of a source by simultaneously taking safety considerations into account.
- *How can we estimate the reliability and trustworthiness of a knowledge source?* – Assuming an (at least in principle) open system composition means to accept the participation of interaction partners that are at least acting selfishly. We may estimate various aspects of reliability and trustworthiness according to concepts as discussed in [35]. This has to be augmented with a detection of abnormal or novel behaviour of the source, e.g., by means of [36].
- *How can the various cost and access aspects of knowledge sources be estimated at runtime with only limited (or even missing) a-priori information?* – The learning mechanism has to continuously rate the source, but it also has to come up with appropriate models of the source after only a few interactions.
- *How can the quality of information provided by a source be estimated (i.e., the expertness of a source)?* – If several sources are available that provide the same information, testing of sources and their expertness can be done by replication of queries. However, the goal is to model the expertness of a source in relation to the type of query, the domain of expertise, and the abstraction level, for instance. This information has to be aggregated towards an estimation of how the expected behaviour of the source is – and adapt this models as a result of experience.
- *How can an adequate communication protocol between the different sources and the Meta Learning Layer be learned?* – Suitable protocols that restrict the exchange of information to only what is essential and necessary are critical for an efficient communication between the knowledge sources.

Knowledge Perspective (KP):

- *How can we efficiently memorise the learned knowledge?* – It is important for the meta learner to be able to access a large history of observed experiences. Thus, past actions, decisions, observations of the environment, communications with the different knowledge sources, or, eventually, even decisions that were considered to be gainful but were discarded should be memorised. Moreover, fast access to the stored information has to be ensured despite the large amount of data.
- *How to decide when to forget?* – Over time, new findings will certainly arise. At this moment, the meta learner has a valid knowledge, which is based on the previous, now obsolete or incorrect, perceptions. Thus, the process of learning has to consider if it keeps only the new information and discards the old one or it continues to keep both of them (stability-plasticity dilemma).
- *What is the necessary initial knowledge?* – The system has to be able to self evaluate and determine which knowledge it has to query at the very beginning of the learning process.

Performance Perspective (PP):

- *How can we evaluate the success of the meta learning approach?* – The basic idea of the meta learner is to exploit knowledge that is uncertain, has limited availability, may come with dynamic cost, etc. Assuming that no ground truth is available, however, raises the question of how we can measure the success of the approach. Obviously, metrics concerning robustness against disturbances and achievement of utility have the highest priority. However, an integrated framework for behaviour analysis will need further metrics: privacy, efficiency, or discovery of knowledge, to name just a few.
- *How can meta learning mechanisms be tested?* – Dealing with knowledge discovery that just occurs at runtime also implies that testing the estimations for a particular source and the interactions cannot be done at design-time in a traditional manner. Here, novel paradigms in testing are needed.
- *How can we compare different meta learning strategies?* – Besides application-specific behaviour analysis of a particular meta learner, benchmarks that compare the behaviour of different learning strategies under the same conditions will be needed.

V. Exemplary Use Cases

For illustration purposes, we conceptually apply the presented meta learning approach to two different use cases: one

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from the urban traffic management and one from the industry automation domain.

A. Urban Traffic Management

Imagine an autonomous traffic control and management solution such as the Organic Traffic Control (OTC) system [37]. In OTC, an intersection-based controller self-improves the signal plan (i.e., the green duration for the controlled traffic lights) in accordance with the current traffic conditions based on a reinforcement approach. In addition, techniques such as Neural Networks are used to predict the upcoming traffic conditions and adapt the control strategy proactively. Besides the pure intersection-wide scope, OTC controllers agree on coordination schemes to form progressive signal systems and exchange link status information to derive route guidance recommendations.

All these aspects of the adaptive and self-organising solution are based on knowledge that is available in the system, either in terms of pre-trained models or as feedback calculated from situation analysis for reinforcement purposes. However, disturbances such as severe emergencies within the city pose novel challenges that cannot be addressed with the existing knowledge. For instance, a large-scale incident situated in the city centre requires a fast reaction in terms of a) clearing main roads towards the incident site for ambulance services, police, fire brigade, and technical emergency response teams and b) simultaneously reduce individual traffic in the surroundings of the incident site or necessary links towards this site. This requires a shift in the underlying goal function: Instead of the typically utilised goal to reduce waiting times, travel times, and emissions, individual traffic should be actively kept away from the incident site and rerouted spaciously. Therefore, a meta learner may consider further sources of knowledge: i) continuously monitor social media sources and emergence channels to identify such cases, ii) query other devices to identify route recommendations that bypass the area, and iii) actively ask traffic administrators for options to guide traffic participants, for instance.

B. Industry Automation

Imagine an autonomous production cell that is part of a production site (and maybe even of an interconnected and spatially distributed production system). Figure 2 illustrates such a setting. In comparison to the previous example, where we discussed a change in the underlying goal function (and an identification of appropriate behaviour according to the new priorities), we consider missing knowledge for the standard process in this example.

This cell processes incoming workpieces and moves them to the next cell for postprocessing or to logistics for shipping. The goal of such a production cell may be twofold: maintain a certain production quality and process the incoming tasks as efficiently as possible. A learning mechanism may be responsible for ensuring the quality of the machined workpieces and for steering the process accordingly. However, deviations from specifications may occur and the cell has to adapt its behaviour.

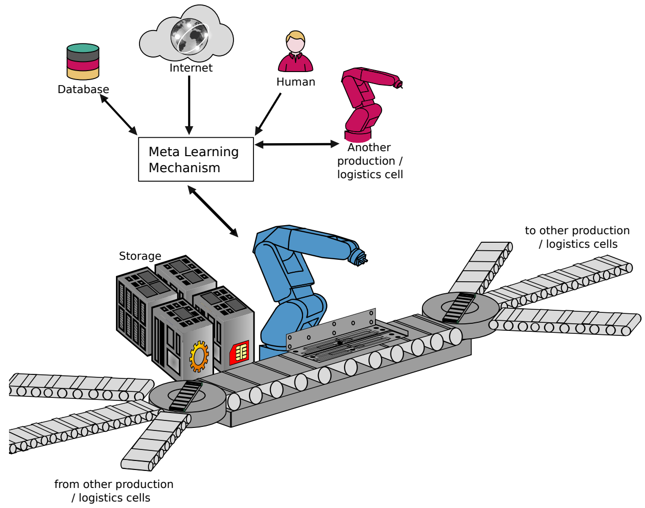

Fig. 2. Schematic illustration of a production cell equipped with meta learning capabilities.

At this point, the meta learning mechanism is used as it has to identify the most appropriate knowledge source. For instance, the behaviour adaptation can be triggered based on knowledge accessed through the following sources: i) querying human knowledge (i.e., the responsible engineer), ii) accessing data bases with known countermeasures, iii) searching the Internet for (unstructured) information (e.g., based on error codes), or iv) query cells of the same kind that may have experienced the particular event before.

Already in this simple scenario, the interplay of different learning paradigms is visible: An initial AC/OC-based solution for controlling the production cell may consist of a knowledge model that is trained based on sample data to allow for, e.g., an appropriate classification of the processed workpieces into successful/suspicious ones. In addition, the forwarding decision of workpieces (to which successor) may be subject to reinforcement techniques (based on feedback derived from production times). However, further knowledge sources demand for other learning paradigms: 1) querying a particular user/operator is only feasible during availability and has to be done with low frequency and requires techniques from the Active Learning domain; 2) querying data bases with best practises is restricted to those that have been experienced and generalised before and requires techniques from the field of classification; 3) querying the Internet may result in unreliable and faulty information and requires techniques from data mining; and 4) querying other devices may depend on the current status of the communication network and requires mechanisms from the Collaborative Learning domain.

VI. Conclusion

In this article, we proposed and sketched the architecture of a novel meta learning approach that dynamically exploits diverse and heterogeneous combinations or knowledge sources in order to boost the performance of learning at runtime.

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In principle, the proposed approach is able to self-learn the objective function and to self-optimise it at runtime. We presented two use cases that highlight the benefits of the meta learner at least in the fields of urban traffic management and industry automation.

In current and future work, we focus on the research questions as formulated in the corresponding Section IV. More precisely, we will investigate mechanisms to asses the reliability and trustworthiness of the knowledge sources. Based on this, we will examine various methods to handle and select the suitable knowledge sources. In order to study the success of our meta learner we have to develop suitable testing and evaluation methods.

Acknowledgements

The authors would like to thank the German research foundation (Deutsche Forschungsgemeinschaft, DFG) for the financial support in the context of the "Organic Computing Techniques for Runtime Self-Adaptation of Multi-Modal Activity Recognition Systems" project (SI 674/12-1).

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