Adaptation to Unknown Situations as the Holy Grail of Learning-Based Self-Adaptive Systems: Research Directions

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ABSTRACT
Self-adaptive systems continuously adapt to changes in their execution environment. Capturing all possible changes to define suitable behaviour beforehand is unfeasible, or even impossible in the case of unknown changes, hence human intervention may be required. We argue that adapting to unknown situations is the ultimate challenge for self-adaptive systems. Learning-based approaches are used to learn the suitable behaviour to exhibit in the case of unknown situations, to minimize or fully remove human intervention. While such approaches can, to a certain extent, generalize existing adaptations to new situations, there is a number of breakthroughs that need to be achieved before systems can adapt to general unknown and unforeseen situations. We posit the research directions that need to be explored to achieve unanticipated adaptations from the perspective of learning-based self-adaptive systems. At minimum, systems need to define internal representations of previously unseen situations on-the-fly, extrapolate the relationship to the previously encountered situations to evolve existing adaptations, and reason about the feasibility of achieving their intrinsic goals in the new set of conditions. We close discussing whether, even when we can, we should indeed build systems that define their own behaviour and adapt their goals, without involving a human supervisor.

CCS CONCEPTS
• Computing methodologies → Reinforcement learning;
• Software and its engineering → Software design engineering.

KEYWORDS
Self-adaptive systems, Reinforcement learning,

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1 ADAPTING TO UNKNOWN SITUATIONS
Self-adaptive systems are capable of adapting to changes in their execution environment in order to continue meeting their specified goals. Causes of adaptation can be internal or external, and different adaptation mechanisms might be suitable based on the type of adaptation trigger [3]. One of the main challenges in self-adaptation is adapting to previously unknown situations. Approaches distinguish between so-called *known unknowns*, which systems have not previously experienced but have mechanisms to reason about and react to (e.g., by evolving, learning, or involving a human), and *unknown unknowns*, which neither the system nor the designers of the system have foreseen [8]. Learning-based techniques are used to enable self-adaptive systems to adapt to known unknowns [2]. In this position paper we argue that adaptation to unknown unknowns is the ultimate challenge of self-adaptive systems and that learning-based self-adaptation is the key to achieving it. However, this requires building and modifying learning processes at run time. Previous work has started to move towards dealing with unknown situations, however, the main challenges for adaptations to the unknown remain unaddressed. In the rest of this paper we outline the three main research directions required to achieve this goal.

2 LEARNING-BASED SELF-ADAPTIVITY TO UNKNOWN SITUATIONS
While numerous issues in many aspects of self-adaptive system specification, development, and verification need to be addressed to enable adaptation to unknown situations, we focus on aspects unique to learning-based systems, i.e., concerning the learning process itself, as the main driver to achieve adaptation to unknown situations. We focus on three main categories: (i) autonomously building environment representations, (ii) retainment, reuse, and modification of available knowledge required for lifelong learning, and (iii) autonomous goal adaptation.

2.1 Environment observation representation
Software systems are equipped with sensors and monitors which enable them to observe their external and internal environment, together with the structures required to represent relevant environment information. In case of unknown situations in the environment, the system might not have the capabilities to sense the new state space, to represent it, or to classify it as relevant for the fulfillment of its goals. Early work in this area addresses dynamic adaptations of state-space representation in existing learning processes [5], however, currently, the adaptation refers only to the granularity of the sensed information with similar meaning (e.g.,...
cold vs -5 degrees). Together with the state-space granularity representation, the system first needs to identify the relevant dimensions of sensed information (e.g., identifying if weather information is relevant at all), and then which data from each dimension is relevant (e.g., temperature, humidity, or atmospheric pressure). Only then it would be possible for learning processes to incorporate newly sensed information from unknown situations.

2.2 Lifelong learning and adaptation evolution
After successfully sensing and representing new situations, self-adaptive systems need to generate brand new behaviour to adapt to such situations. Using learning processes to learn this from scratch at run time could be detrimental to system performance. Various approaches are being explored to derive new behaviour from previously experienced situations but advancements will need to be made in multiple research sub-areas depending on the level of similarity of the new situations. In simpler cases, new behavior might be a composition of existing adaptations [1] (which requires managing potential conflicts between adaptations’ behaviour), or might only require parameter evolution to adapt previously seen situations. A repository of behaviour classified by environment conditions can be maintained, using similarity metrics to identify the closest matches, and initiate a new learning process bootstrapped with ‘close-enough’ existing behaviour for online fine-tuning [7]. However, scaling this to the execution of a self-adaptive system with multiple dissimilar situations, requires complex continual (life-long) learning techniques [6]. Existing open issues to address include identifying similarities between situations, transfer learning between tasks, and limiting forgetting of previous useful behaviour as numerous new situations arise.

2.3 Goal adaptation and fulfillment
Environment changes may also give rise to situations in which one or more of the system goals cannot be met successfully, regardless of its capabilities and knowledge. Similarly, new observations might require modifications or additions to the existing system goals. There are a number of considerations here that need to be addressed. First, the system needs to identify that it is not able to attain the goal. Second, the system must identify whether the goal is partially obtainable from explored states ‘close enough’ to the goal, and whether partial fulfilment is preferable to system failure. Third, the system must identify suitable substitute goals, and proceed to learn to fulfil them, or interact with a human to propose newly defined goals. Flexibility of goals can be expressed within goal specification, i.e., whether it is permitted for the system to modify a given goal. Online goal adaptation, as well as generation of the associated learning process to meet the adapted goal is likely to require significant research progress, given that even dynamic specification of individual parts of the learning process (e.g., states, as discussed earlier) is in its early stages. However, progress is already being made on agents autonomously generating their own goals using generative adversarial networks [4] in order to identify a range of tasks/skills that are possible to achieve. In the context of self-adaptive systems, such goals can be initially used as suggestions to human in the loop (e.g., “I cannot currently reach the goal, but these are the states I can reach”), or for fully autonomous goal adaptation where such feedback can come from interaction with environment.

3 FINAL REMARKS
Special consideration should be given to how to incorporate ethical rules into self-adaptive systems, if we equip them with the technical capabilities to fully operate, adapt and even modify their own goals without the human in the loop. Similarly to having to generate new behaviour to adapt to new situations, adapting to unknown situations might also involve making ethical choices that were not foreseen or that have not been previously encountered by the system, and therefore the system does not have human guidance on how to proceed. Efforts on enabling self-adaptation to unknown situations should progress hand-in-hand with efforts on developing a set of ethical principles of self-adaptive systems [9]. Addressing research and technical challenges of encoding ethical aspects into self-adaptive systems should take priority before equipping them with capabilities to fully guide their own performance in all circumstances.

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REFERENCES
[1] N. Cardozo and I. Dusparic. Learning run-time compositions of interacting adaptations. In proceedings of the International Symposium on Software Engineering for Adaptive and Self-Managing Systems. ACM, 2020.
[2] M. D’Angelo et al. On learning in collective self-adaptive systems: state of practice and a 3d framework. In International Symposium on Software Engineering for Adaptive and Self-Managing Systems, pages 13–24. ACM, 2019.
[3] R. de Lemos et al. Software engineering for self-adaptive systems: a second research roadmap. In Software Engineering for Self-Adaptive Systems II. Springer, 2013, pages 1–32.
[4] C. Florensa et al. Automatic goal generation for reinforcement learning agents. In Proceedings of International Conference on Machine Learning, pages 1515–1528, 2018.
[5] M. Guériau, N. Cardozo, and I. Dusparic. Constructivist approach to state space adaptation in reinforcement learning. In International Conference on Self-Adaptive and Self-Organizing Systems. IEEE, 2019.
[6] K. Khetarpal et al. Towards continual reinforcement learning: a review and perspectives, 2020.
[7] A. Marinescu, I. Dusparic, and S. Clarke. Prediction-based multi-agent reinforcement learning in inherently non-stationary environments. Transactions on Autonomous and Adaptive Systems, 12(2):9, 2017.
[8] D. Weyns. Engineering self-adaptive software systems - an organized tour. In IEEE International Workshop on Foundations and Applications of Self* Systems, pages 1–2. IEEE, 2018.
[9] D. Weyns. Towards a code of ethics for autonomous and self-adaptive systems. In Proceedings of the IEEE/ACM International Symposium on Software Engineering for Adaptive and Self-Managing Systems, pages 163–165. ACM, 2020.