SCIENCE CHINA
Information Sciences

• PERSPECTIVE •

Autonomous Machine Learning

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Citation Autonomous Machine Learning. Sci China Inf Sci, for review

Machine learning has achieved great success in multiple fields such as natural language processing, computer vision, and robotics, and has become a key technology driving the development of artificial intelligence. To achieve Artificial General Intelligence (AGI), researchers have been striving to reduce the artificial design in the learning process. Unsupervised learning, semi-supervised learning and self-supervised learning methods have made certain progress in reducing manual annotation [1,2], while active learning labels important new data points by interactively querying users or other information sources, thereby reducing the cost of data annotation [3]. In addition, automated machine learning (AutoML) utilizes neural architecture search and hyperparameter optimization to reduce the manual workload in model design and selection [4], while meta-learning rapidly adjusts the learning algorithm through meta-learners to adapt to small amounts of new data and new tasks [5].

On the one hand, although existing methods have reduced human intervention to some extent, the current machine learning paradigms still rely heavily on manual design and human guidance, especially in aspects such as task selection, data annotation, and model setting. For instance, when developing a rescue robot system, human experts still need to design how to train inference models on manually selected datasets and how to automatically build knowledge graphs, etc. This approach relies on manual design, not only consuming a great deal of human resources and time costs, but also lacking sufficient autonomy. On the other hand, the real world environments we encounter tend to change dynamically. Take the process of launching a rocket to the moon as an example, the rocket will go through different stages such as the surface, the blue sky, the space, and then to the moon, which also requires its ability of adapting to different environments, as well as the ability of reacting correctly in a dynamically changing environment. Similarly, we expect machine learning to be capable of adapting to dynamically changing environments. However, traditional machine learning paradigm generally learns from a pre-fixed data distribution, which often faces the challenge of inconsistent training and testing distributions in dynamic environments, making it difficult to adapt towards the new data distribution with manual designs.

To break the bottleneck, exploring whether machines can autonomously select learning tasks, data and models, and control the learning process has become an increasingly concerned research direction in the academic community.

Since the 1970s, self-directed learning, a.k.a., autonomous learning, has been an important topic in the field of educational science [6], especially in scenarios that require a high degree of learning initiative, such as adult education [7] and online education [8] etc. Research shows that individuals who actively engage in autonomous learning can achieve their learning goals better than those who passively wait for guidance [9]. This argument provides us with an enlightenment: Will they bring more autonomy and flexibilities if machines can learn autonomously like humans and actively choose learning tasks, data, models and strategies?

Motivated by this consideration, the new perspective that connects autonomous learning with machine learning to form a new learning paradigm, i.e., **autonomous machine learning**, is presented in this paper. Different from traditional machine learning that relies on manual design, autonomous machine learning realizes a highly autonomous learning process through self-drive, and its core is dynamic self-optimization and autonomous evolution. In this process, the machine can actively explore and sense the environment, autonomously select data, adapt models, and switch tasks without human intervention. At the same time, according to the environmental feedback and self-state, the machine further improves its learning ability through dynamic autonomous evolution. This self-driven learning process not only enables the machine to learn without human intervention, but make it possible to adapt and optimize based on feedback after learning, thus constantly evolving for self-improvement. Therefore, the autonomous machine learning proposed in this paper is not only an extension of traditional machine learning methods, but also a new attempt to realize autonomous learning via self-optimization and self-evolution in machine learning, which provides a new idea for the realization of artificial general intelligence.

Autonomous Machine Learning

Traditional machine learning is mostly human-driven and can only handle well-defined specific tasks, failing to automatically adapt to changing environments. In contrast, autonomous machine learning takes initiative in the learn-

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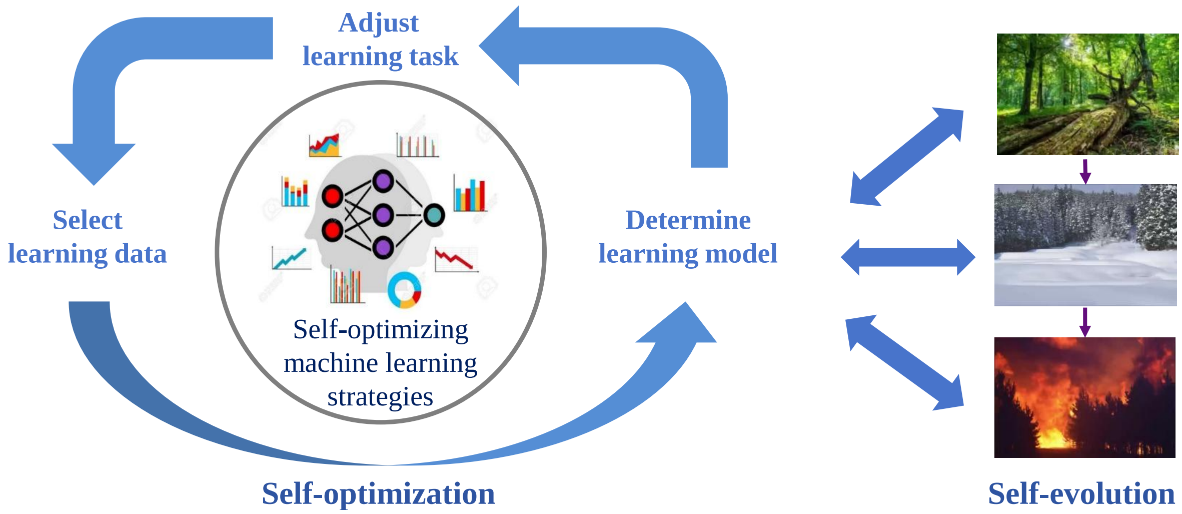

Figure 1 The proposed autonomous machine learning paradigm.

ing process and pursues lifelong self-improvement. Specifically, autonomous machine learning carries out an autonomous learning process with a high degree of autonomy, and its learning results can in turn facilitate further self-improvement, whose core lies in self-optimization and self-evolution. Autonomous machine learning actively explores the perception environment, dynamically optimizes the three core processes of data selection, model adaptation and task switching, and further improves the learning ability through autonomous evolution based on environmental feedback and ego state. As one instantiation in learning data selection, EATA [11] pioneers this direction via developping an entropy-driven scheme for efficient and reliable test-time self-adaptation without human supervision. The proposed autonomous machine learning paradigm is shown in Figure 1.

Core 1: Self-optimization. Autonomous machine learning differs from traditional machine learning paradigms on self-optimization strategies that choose the learning task, data and model in the external dynamic environment, with the results in turn providing feedback for self-improvement. We will detail each component of the self-optimization strategies, namely *data self-selection*, *model self-adaptation*, and *task self-switching*. Putting the above steps together, we have the following multi-level optimization problem.

$$
\begin{aligned}
&\min\nolimits_M \ L_{val}(\{W^*_{s(M)} | s(M) \in S^*(M)\}, F),\\
&s.t.\ W^*_{s(M)} = \operatorname{argmin}_W \ L_{wt}(W_{s(M)}, A^*_{s(M)}, C^*_{s(M)}, o^*_{s(M)}),\\
&\quad o^*_{s(M)} = \operatorname{argmin}_{o_{s(M)} \in \mathcal{O}} \ L_{os}(o_{s(M)}, A^*_{s(M)}, C^*_{s(M)}),\\
&\quad A^*_{s(M)} = \operatorname{argmin}_{A_{s(M)}} \ L_{ms}(A_{s(M)}, s(M)),\\
&\quad C^*_{s(M)} = \operatorname{argmin}_{C_{s(M)} \subseteq D_{s(M)}} \ L_{ds}(D_{s(M)}, C_{s(M)}),\\
&\quad \mathcal{S}^*(B^*(M)) = \operatorname{argmin}_{\mathcal{S} \subseteq \mathcal{T}} \ L_{ts}(\mathcal{T}, \mathcal{S}, E, B^*(M)),\\
&\quad B^*(M) = \operatorname{argmin}_B \ L_{sac}(B, M).
\end{aligned} \tag{1}
$$

Literature [10] provides a representative example of learning in a real dynamic environment that aligns with the autonomous machine learning setting. In this work, graph tasks and data distributions evolve continuously over time, and the model must adapt to newly arriving tasks without access to previous data. To address this, the authors introduce a modular supernet together with a task-module routing mechanism, enabling the system to dynamically select and update suitable architectural modules for different tasks. The architecture parameters and model weights are jointly optimized in a continual manner, while an invariant objective is incorporated to preserve shared knowledge across tasks. In this process, the system not only improves its performance on new tasks but also adjusts its internal architecture organization to mitigate conflicts and forgetting. This demonstrates a form of structural self-optimization under a non-stationary environment, which is consistent with the core idea of autonomous machine learning.

Core 2: Self-evolution. Dynamic environments often require machine learning systems to continuously update their self-awareness to adapt to changing conditions. The core of this challenge lies in enabling machines to autonomously perceive ongoing environmental changes, and adapt their understanding of the world and behavioral patterns accordingly. Specifically, this involves the capability of machines in adjusting training data, task objectives, and model parameters to respond to environmental shifts. One of the key difficulties is the lack of a comprehensive theoretical framework for self-evolution in machine learning—a methodology that allows systems to independently identify environmental changes and optimize their performance without human intervention.

To handle the above challenges, autonomous machine learning is expected to possess several critical capabilities. i) Robust environmental perception is necessary to accurately and promptly detect changes within the surroundings. ii) Based on the perceived information, self-assessment and dynamical updating of internal model architectures is important to ensure environment understanding and latest environmental condition alignment. iii) It is desirable to autonomously adjust the training datasets, task definitions, and model architectures in response to environmental changes, thus enabling more flexible and efficient operations. Such a dynamically evolving mechanism would not only allow efficient operations in static settings but also demonstrate incremental intelligence improvements when confronted with unknown or changing scenarios.

Autonomous machine learning employs the self-evolution mechanism to comprehensively model and perceive dynamic environments, simultaneously enabling the retention of old knowledge and adaptation to new environments through evolving data-task-model relationships. Formally, through continuous interactions in dynamic environments, the self-evolution mechanism performs task selection $\mathcal{S}$, memory selection $\mathcal{C}$, and model selection A based on self-state B and environmental state $\mathcal{E}$, achieving continuous updates of meta-parameters through evaluation on validation set F:

$$\min_M L_{val}(B, \mathcal{E}, \mathcal{S}, \mathcal{C}, A|F), \tag{2}$$

where L_{val} is the loss function on the validation set. We anticipate that future exploration will focus on developing new theories and techniques to support more advanced self-evolution mechanisms. This includes interdisciplinary collaborative research integrating knowledge from artificial intelligence, biology, psychology and other fields to jointly investigate how organisms achieve self-evolution in natural environments, drawing inspiration for next-generation model designs. Simultaneously, algorithmic innovations are essential to empower machines with the ability to decide when and how to update their internal models without explicit guidance. Furthermore, constructing testbeds that simulate real-world dynamic changes to validate the effectiveness of various self-evolution mechanisms will represent a crucial step in advancing autonomous machine learning. Through such efforts, we expect to witness the emergence of more intelligent and flexible systems capable of operating independently in complex, real-world environments without requiring frequent human intervention.

Relations with Literature

We argue that the proposed autonomous machine learning paradigm is fundamentally distinct from established areas (e.g., automated machine learning (AutoML), reinforcement learning, continual learning, meta-learning, active learning, and agentic systems). The core of AutoML is automation, focusing on using algorithms to automatically execute traditional ML processes (such as hyperparameter tuning, feature engineering, model selection etc.), with the goal of reducing manual intervention. However, its optimization objectives and processes are typically pre-defined and relatively static. The core of reinforcement learning is sequential decision-making, where an agent learns an optimal policy through interaction with the environment based on reward signals to accomplish a specific task. The learning process is usually goal-driven, with the environment model and reward function being designed externally. The core of continual learning is knowledge retention and adaptation under varying data distributions, with emphasis on mitigating catastrophic forgetting across a sequence of predefined tasks. The core of meta-learning is learning to learn, aiming to acquire transferable learning strategies across a group of tasks that is assumed to be given in advance. The core of active learning is data selection, where the model queries the most informative samples to improve performance under a fixed task and model setting. The core of agentic systems is goal-directed behavior through planning, tool use, and interaction, typically operating on top of an existing learning backbone. In contrast, the core of autonomous machine learning lies in "autonomy" and "evolvability". It not only emphasizes the self-optimization of core learning processes such as data, models, and tasks but, more critically, can dynamically evolve its learning architecture, knowledge base, or capability boundaries (e.g., automatically discovering new tasks, defining new objectives, synthesizing data, updating knowledge structures) based on environmental feedback and self-state. This demonstrates stronger intrinsic motivation, environmental adaptability, and continuous evolutionary capability, aiming to construct learning systems that are self-directed and self-improving.

It is noteworthy that the proposed autonomous machine learning paradigm is agnostic to specific machine learning applications and can be broadly applied to enhance various machine learning tasks. These include, but are not limited to: classification, regression, clustering, text generation, dialogue systems, machine translation, document summarization, object detection, semantic segmentation, visual question answering, time series forecasting, as well as link and node prediction in graphs.

Conclusion

Inspired by the autonomous learning ability of humans, we derive the foundational concept of autonomous machine learning paradigm. The objective of autonomous machine learning is to achieve a high degree of autonomy via jointly optimizing data self-selection, model self-adaptation and task self-switching without manual human intervention. Furthermore, autonomous machine learning realizes self-improvement through continual evolution based on environmental feedback and internal state. As such, autonomous machine learning consists of two key components: self-optimization and self-evolution. We propose a possible mathematical formulation based on bi-level optimization and reinforcement feedback for autonomous machine learning. In case studies involving autonomous rescue robots, unmanned driving, and intelligent drones, we demonstrate how to utilize autonomous machine learning to autonomously solve complex real-world problems.

Acknowledgements This work is supported by Beijing National Research Center for Information Science and Technology under Grant No.BNR2026TD03005.

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