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Autonomous machine learning

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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 manual design involved in the learning process. Unsupervised learning, semisupervised learning, and self-supervised learning methods have made some progress in reducing manual annotation [1, 2], while active learning reduces the cost of data annotation by interactively querying users or other information sources to label important new data points [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 reliance on manual design not only consumes considerable human and time resources but also limits the system's autonomy. On the other hand, the real-world environments we encounter tend to change dynamically. Consider, for example, the process of launching a rocket to the moon: the rocket passes through markedly different stages, from the ground to the sky to space and finally to the lunar surface, requiring it to adapt to each new environment and to react correctly as conditions change dynamically. Similarly, we expect machine learning to be capable of adapting to dynamically changing environments. However, traditional machine learning paradigms generally learn from a fixed data distribution, which often leads to inconsistency between training and testing distributions in dynamic environments, making it difficult to adapt to new data distributions through manual design.

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

Since the 1970s, self-directed learning, also known as 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]. 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 observation raises a compelling question: could machines learn more autonomously and flexibly if they, like humans, could actively choose their own learning tasks, data, models, and strategies?

Motivated by this consideration, a new perspective that connects autonomous learning with machine learning to form a new learning paradigm, i.e., **autonomous machine learning**, is presented in this study. Different from traditional machine learning, which relies on manual design, autonomous machine learning achieves a highly autonomous learning process through self-driven mechanisms, 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, based on 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 also makes 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 study 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 AGI.

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 learning process and pursues lifelong self-improvement. Specifically, autonomous machine learning carries out a learning process with a high degree of autonomy, whose results can in turn facilitate further self-improvement. Its core lies in self-optimization and self-evolution. Autonomous machine learning actively perceives and

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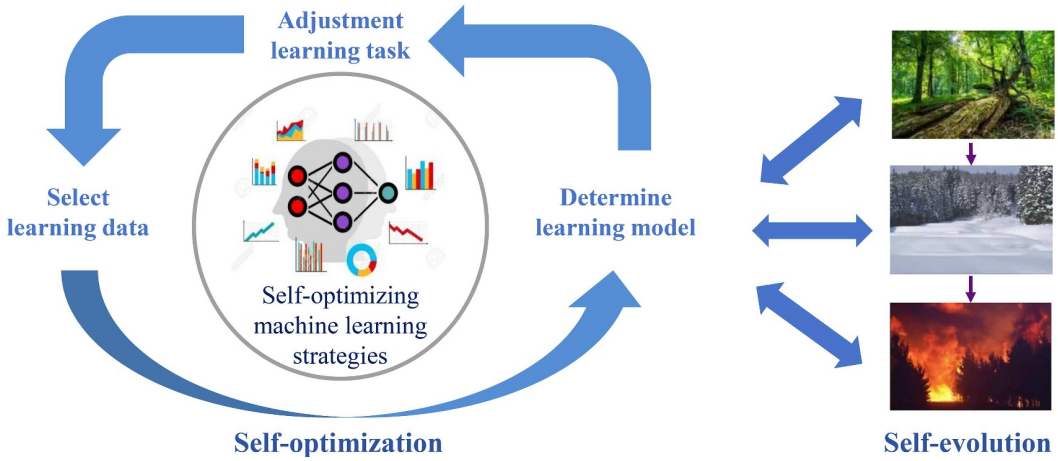

Figure 1 (Color online) The proposed autonomous machine learning paradigm.

explores the 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 self-state. As an example of data selection, EATA [10] pioneers this direction via developing 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 in its self-optimization strategies, which select data, models, and tasks within 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:

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

Prior work [11] provides a representative example of learning in a real dynamic environment that aligns with the autonomous machine learning paradigm. In this work, graph tasks and data distributions continuously evolve over time, requiring the model to adapt to newly arriving tasks without access to previous data. To address this challenge, the authors introduce a modular supernet with a task-module routing mechanism, enabling the system to dynamically select and update appropriate 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. Through this process, the system not only improves performance on new tasks but also reorganizes its internal architecture to mitigate conflicts and forgetting. This demonstrates a form of structural self-optimization in a non-stationary environment, which is consistent with the core principles of autonomous machine learning.

Core 2: Self-evolution. Dynamic environments often require machine learning systems to continuously update their self-awareness and adapt to changing conditions. The core challenge lies in enabling machines to autonomously perceive environmental changes and adjust their knowledge representations and behavioral patterns accordingly. Specifically, this requires machines to modify training data, task objectives, and model parameters in response to environmental shifts. A major difficulty is the lack of a comprehensive theoretical framework for self-evolution in machine learning—a methodology that allows systems to 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 essential to accurately and promptly detect changes in the surrounding environment. (ii) Based on the perceived information, self-assessment and dynamic updating of internal model architectures are important to maintain alignment between the system's learned representations and current environmental conditions. (iii) The system should be capable of autonomously adjusting training datasets, task definitions, and model architectures in response to environmental changes, thereby enabling more flexible and efficient operations. Such a dynamically evolving mechanism would not only allow effective performance in stable environments but also facilitate continual intelligence improvement when encountering unknown or changing scenarios.

Autonomous machine learning employs self-evolution mechanisms to perceive and model dynamic environments while maintaining knowledge retention and adapting to new conditions 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 $\mathcal{E}$, thereby continuously updating model 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 evaluated on the validation set. Future research is expected to focus on developing new theories and techniques to support more advanced self-evolution mechanisms. This includes interdisciplinary research integrating artificial intelligence, biology, psychology, and related fields to investigate how organisms achieve self-evolution in natural environments, thereby inspiring next-generation model designs. Simultaneously, algorithmic innovations are essential to empower machines to autonomously decide when and how to update their internal models

without explicit human guidance. Furthermore, the development of testbeds that simulate real-world dynamic changes will be essential for validating the effectiveness of various self-evolution mechanisms and 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., 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 machine learning processes (such as hyperparameter tuning, feature engineering, and model selection), with the goal of reducing manual intervention. However, its optimization objectives and processes are typically predefined 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 also, more critically, dynamically evolves its learning architecture, knowledge base, or capability boundaries (e.g., automatically discovering new tasks, defining new objectives, synthesizing data, and 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.

Notably, the proposed autonomous machine learning paradigm is agnostic to specific 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 the 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 human intervention. Furthermore, autonomous machine learning achieves self-improvement through continual evolution based on environmental feedback and self-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.

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