A Survey of Meta-learning: Paradigms, Applications, and Challenges

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Abstract

Meta-learning is a transformative approach in machine learning that enables models to learn how to learn, allowing rapid adaptation to new tasks with minimal data. This capability is achieved through four core paradigms—metric-based, model-based, optimization-based, and unsupervised or self-supervised methods—each offering distinct strategies for efficient generalization across diverse scenarios. These approaches have found practical applications across critical domains including cybersecurity, computer vision, natural language processing, and reinforcement learning, where they effectively address the persistent challenges of data scarcity and dynamic environments. Building on these foundations, emerging directions such as continual, causal, and generative meta-learning are further expanding the boundaries of adaptive artificial intelligence. To assess these methods, recent research has utilized diverse benchmark datasets, emphasizing robustness and cross-domain generalization. However, significant challenges remain, including diverse task distributions, computational complexity, and limited labeled task families, which this survey examines alongside recent solutions and promising research directions.

Keywords: Meta-learning, Transfer-learning, learning to learn, Continual-learning, Model-agnostic methods, Metric-based learning, Optimization-based learning

1 Introduction

Traditional machine learning algorithms have achieved remarkable success in static environments, excelling at tasks like image classification, speech recognition, and predictive modeling when provided with abundant labeled data [1, 2]. However, as real-world applications grow more complex, these methods often struggle in scenarios where data is scarce, noisy, or highly variable. For instance, consider medical diagnostics with limited patient records [3], robots navigating unpredictable terrains, or natural language processing for low-resource languages—these challenges expose the limitations of conventional approaches. Moreover, the high computational cost of training models from scratch for each new task highlights the need for more flexible and efficient solutions.

To address these challenges, several paradigms have emerged that aim to improve generalization across tasks. Transfer learning, for example, bridges knowledge from source tasks to related target tasks, typically through pre-training on large datasets and fine-tuning on smaller ones, and is particularly effective where structural similarities—such as image or text features—exist between tasks [4, 5]. Multi-task learning enhances learning efficiency by training models on multiple tasks simultaneously, encouraging shared representations such as embeddings or parameters across related domains [6, 7]. Meanwhile, continual learning addresses the issue of sequential task learning, aiming to retain performance on earlier tasks as new ones are learned—mitigating the problem of catastrophic forgetting [8, 9].

Meta-learning, commonly known as "learning to learn," enhances these methods by allowing models to quickly adapt to new and unfamiliar tasks using only a small amount of data. This is particularly effective even when there are significant differences between the source and target task distributions [10, 11]. This adaptability is especially useful in data-scarce or resource-constrained settings, unlocking practical applications in dynamic environments. For example, in intrusion detection systems, meta-learning enables models to recognize and respond to novel threats based on limited prior exposure, without the need for extensive retraining or risking vulnerability to adversarial manipulation. Despite its promise, meta-learning is not without limitations. High computational costs during meta-training, sensitivity to task diversity, and a lack of standardization in benchmarks and evaluation protocols remain key challenges. Furthermore, integrating meta-learning effectively with other paradigms such as transfer or continual learning is still an open area of research.

Addressing these challenges, particularly the standardization of evaluation protocols, requires robust benchmarks that can comprehensively assess meta-learning capabilities. While early work relied on a handful of classic datasets such as Mini-ImageNet and Omniglot, the field has evolved toward more diverse and challenging benchmarks that better capture real-world variability and cross-domain generalization requirements.

In this survey, we begin by exploring the foundational paradigms of meta-learning, including metric-based, model-based, optimization-based, and unsupervised/self-supervised approaches. We then review real-world applications spanning computer vision, natural language processing, and reinforcement learning. Next, we provide a detailed overview of benchmark datasets and evaluation protocols that have shaped

recent research. Finally, we discuss emerging directions, ongoing challenges, and promising solutions in the field.
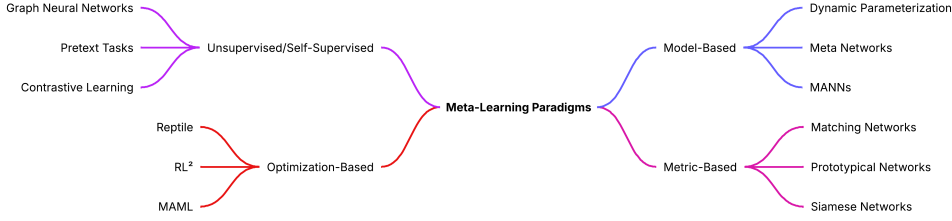

Fig. 1 Comparison of Meta-Learning Paradigms. This figure illustrates the four core approaches to meta-learning, their key methods, strengths, and limitations, showing how they differ in their mechanisms for rapid adaptation to new tasks.

2 Meta-Learning Paradigms

Meta-learning can be broadly categorized into four core paradigms, each offering a unique approach to enabling rapid adaptation across tasks (see Figure 1):

2.1 Metric-Based Meta-Learning

Metric-based meta-learning methods focus on learning a similarity function that enables rapid classification. This is done by comparing new, unseen samples to a small set of labeled examples, known as the support set. Rather than learning task-specific parameters from the ground up, these methods embed data into a feature space where distances between samples of the same class are minimized, while distances between samples of different classes are maximized. Classic examples of these methods include Siamese Networks [12] and Prototypical Networks [13]. Siamese Networks utilize twin neural networks with shared weights to assess whether two inputs belong to the same class by learning a similarity score. On the other hand, Prototypical Networks compute a class prototype by averaging the embeddings of support examples for each class, and they classify query samples based on their proximity to these prototypes in the embedding space. Another notable approach is Matching Networks [14], which uses attention mechanisms and memory to rapidly adapt to new tasks. These approaches are known for their computational efficiency and are particularly effective for few-shot classification scenarios, such as in medical imaging or facial recognition, where labeled data is scarce but general visual similarity can be leveraged. The evolution of metric-based methods shows a clear progression from simple distance metrics to more sophisticated, learnable, and context-aware similarity functions, frequently combined with generative models or attention mechanisms. For example, in few-shot text classification, recent research has proposed creating task-adaptive metric spaces using attention mechanisms. This approach dynamically reduces intra-class differences while amplifying inter-class differences, thus enhancing classification performance even with

limited examples. Another notable advancement is the Hierarchical Gaussian Mixture based Task Generative Model (HTGM) [15], which is an encoder-agnostic framework that extends metric-based meta-learning by modeling the density of task instances. It learns task embeddings and fits mixture distributions of tasks, introducing only a small overhead to the encoder for parameterizing its distributions, making it efficient even with large backbone networks. This evolution suggests that while the core concept of "similarity" remains central, the methods for learning and applying this similarity have become increasingly complex and adaptive. Instead of relying on static embeddings or fixed distance functions, contemporary methods dynamically construct optimal metric spaces or generate task-specific prototypes from intricate mixture distributions, allowing them to capture more nuanced relationships in diverse and complex data.

2.2 Model-Based Meta-Learning

Model-based meta-learning methods are distinguished by their ability to incorporate rapid adaptation directly into the model's architecture. Instead of relying on iterative gradient descent for adaptation, these approaches utilize learned internal mechanisms—such as memory modules, gating mechanisms, or dynamic parameterization—to efficiently encode and recall prior knowledge. Notable examples of this include Memory-Augmented Neural Networks (MANNs) [16], which integrate external memory modules to store past experiences, allowing for quick retrieval and adaptation to new tasks. Similarly, Meta Networks [17] are designed to generate task-conditioned fast weights for the base learner, enabling the model to dynamically reconfigure itself based on specific task inputs. These model-based methods are particularly effective in low-latency environments, such as robotics or real-time decision systems, where rapid task switching is essential and full retraining is impractical.

2.3 Optimization-Based Meta-Learning

Optimization-based meta-learning methods focus on enhancing the learning algorithm itself. This is typically achieved by discovering favorable initialization points for model parameters or learning update rules that effectively generalize across a variety of tasks. A prominent example is Model-Agnostic Meta-Learning (MAML) [11], which optimizes the initialization of model parameters to allow for rapid fine-tuning with just a few gradient steps. Another method, Reptile [18], simplifies MAML by utilizing first-order gradient information, which avoids the need for computationally expensive second-order derivatives and reduces overall computational overhead. Additionally, RL^2 (Reinforcement Learning Squared) [19] treats the entire learning process as a recurrent system, allowing the agent's internal hidden state to accumulate experience over episodes, enabling adaptation without explicit parameter updates. These optimization-based methods are particularly valuable in settings where rapid adaptation and strong generalization capabilities are critical, such as in autonomous navigation systems and personalized recommendation systems. Recent work, such as Scalable And Modular Algorithms (SAMA) [20], directly addresses scalability challenges in meta-learning for large models and datasets by leveraging advancements in implicit differentiation algorithms—techniques that compute gradients efficiently

without storing intermediate computations—and systems. SAMA has demonstrated improvements in computational efficiency and memory consumption, showcasing its practical applicability in language and vision domains through experiments with large language models and image classification tasks.

2.4 Unsupervised and Self-Supervised Meta-Learning

When labeled data is scarce or expensive to obtain, unsupervised and self-supervised meta-learning offer practical alternatives to traditional supervised approaches. These methods learn to adapt across tasks without requiring manual annotations.

2.4.1 Unsupervised Meta-Learning

Unsupervised meta-learning learns from collections of unlabeled datasets, where each dataset represents a different task [21]. The goal is to discover common patterns and structures across tasks that enable rapid adaptation to new, unlabeled tasks. For example, when learning to classify different types of objects without labels, the system must identify shared features that distinguish between categories. The key challenge is learning meaningful representations that transfer well across diverse tasks. Success depends on having sufficiently diverse training tasks that provide the meta-learner with broad, transferable knowledge.

2.4.2 Self-Supervised Meta-Learning

Self-supervised meta-learning generates its own supervision signals from the data structure, eliminating the need for manual labels. This is achieved through "pretext tasks"—carefully designed challenges that force the model to learn useful patterns. Common examples include predicting missing parts of images, reconstructing shuffled text sequences, anticipating future video frames, and contrastive learning on graph structures. These artificial tasks create pseudo-labels that guide the learning process. When well-designed, pretext tasks help models develop generalizable knowledge that transfers to real-world applications. However, poor alignment between pretext tasks and target applications can limit performance. Recent advances in contrastive learning and graph neural networks have shown particular promise, addressing the fundamental challenge of labeled data scarcity by extracting meaningful patterns from raw, unlabeled data.

3 Applications of Meta-Learning

This section explores the potential applications of meta-learning in cybersecurity, computer vision, natural language processing (NLP), and reinforcement learning (RL).

3.1 Cybersecurity

Cybersecurity encompasses strategies and technologies aimed at protecting systems from threats such as unauthorized access, data breaches, malware, and other malicious activities. Key areas within cybersecurity include intrusion detection, cyber resource
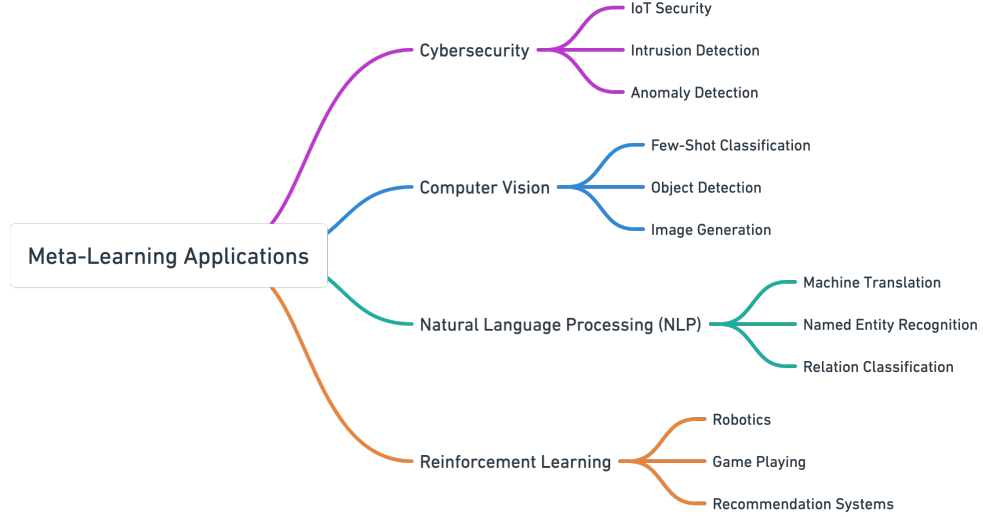
Fig. 2 Meta-learning applications in cybersecurity, computer vision, NLP, and reinforcement learning.

management, and Internet-of-Things (IoT) [22] security. Intrusion detection focuses on identifying suspicious activities in real time and triggering defensive mechanisms to mitigate potential threats. At the same time, cyber resource management aims to reduce computational overhead while ensuring high-performance and energy-efficient operations, particularly for on-device applications. With the proliferation of connected devices, IoT security has become increasingly vital, as it involves protecting communication across vast networks of heterogeneous, often resource-constrained, devices. Artificial intelligence and deep learning have been extensively studied for cybersecurity applications, particularly in detecting anomalous network behavior based on known attack signatures [2]. However, conventional deep learning models struggle with evolving cyber threats, such as zero-day attacks and novel exploit variations. These models depend on predefined task structures and prior knowledge of attack patterns, limiting their adaptability to real-world challenges. Additionally, training deep learning models from scratch requires significant computational power and storage, making them impractical for deployment on resource-limited devices.

Meta-learning offers a promising alternative by enabling models to quickly adapt to new cyber threats using only a few examples—a process known as few-shot detection [23]. This capability allows models to generalize more effectively within a limited number of iterations. Recent research has explored applying meta-learning algorithms to IoT security, where models must detect anomalies across diverse device types and network configurations with limited labeled examples from each device category.

Additionally, Xu et al. [24] developed FC-Net, a continual few-shot learning approach that uses knowledge distillation for network intrusion detection. Their method achieved an average detection rate of 98.88% on training and testing datasets, with even higher accuracy (99.62%) when detecting previously unseen malicious patterns.

As real-time applications continue to grow, so does the need for low-latency network edge communication, particularly with the advancement of 5G technology. Mobile Edge Computing (MEC) [25] has gained significant attention as a key component of 5G infrastructure. In 2020, Huang et al. [26] introduced MELO, a meta-learning-based computation offloading technique designed to optimize resource allocation by shifting computational tasks closer to end-users. By leveraging the MAML algorithm [11], MELO trains a deep neural network (DNN) on multiple tasks, enabling rapid adaptation to new workloads and enhancing efficiency. Empirical results validate the effectiveness of MELO, achieving 99% accuracy with one-shot training using only 10 training samples.

3.2 Computer Vision

Computer vision is a key area that has greatly benefited from the advancement of deep learning models designed to analyze visual content and perform recognition tasks. For instance, convolutional neural networks (CNNs) [27] have shown excellent results in extracting features from images layer by layer and have become the foundation for many object detection models [2]. However, the scarcity of labeled samples, which require substantial time and resources to obtain, poses challenges for most deep-learning models.

Meta-learning has emerged as a promising solution to address this limitation, with few-shot learning (FSL) being its most common application in computer vision. Few-shot learning enables models to perform multi-class classification with minimal labeled examples [13]. Building on advancements in few-shot learning, few-shot object detection has been developed, leveraging hypernetworks to synthesize classifier weights for base learners [28].

In image generation, amortized meta-learning enables the synthesis of different object views from a single image. Similarly, in few-shot video generation, weight generators learn to synthesize videos from only a few example images. Meta-learning also enhances generative models, which typically require substantial amounts of data to learn underlying distributions for high-quality outcome synthesis. For example, PixelCNN has been adapted to few-shot settings, using gradient-based meta-learning to predict pixel values effectively, even with limited training samples [29].

3.3 NLP

With the advancement of deep learning models, particularly transformers [30], NLP has gained more attention than ever. NLP encompasses a broad range of domains, including text classification, sequence labeling, machine translation, speech recognition, relation classification, and graph relation completion. However, conventional deep learning models struggle to achieve reasonable performance when given only a limited number of labeled training examples, making it difficult to generalize underlying patterns and dependencies.

For instance, personal assistants like Siri and Alexa rely on multiple conversation systems, each designed for a specific task. These systems require extensive task-specific labeled data to perform effectively across diverse domains. However, collecting

and annotating such data is both costly and time-consuming, particularly in chatbot applications that involve real human interaction.

Meta-learning has emerged as a promising solution to these challenges by addressing the scarcity of annotated text data and enabling rapid adaptation [31]. By leveraging knowledge from multiple tasks, meta-learning allows models to generalize to unseen tasks with minimal supervision.

In machine translation and speech recognition, meta-learning enhances adaptability to new languages and improves recognition of non-native speakers by adjusting to different accents. For sequence labeling tasks, meta-learning aids in named entity recognition (NER) [32], where the goal is to identify entities such as names, locations, and organizations using only a small labeled context, while also improving slot tagging, which extracts key information from user queries across different domains. Additionally, in few-shot relation classification, meta-learning enhances the ability to identify relationships between entities in a sequence using a few labeled relations [33], helping to overcome the long-tail dependency problem where certain relations are absent or rare in the training set. These improvements also contribute to knowledge graph relation completion, where entity relationships are often sparse, as meta-learning enhances the robustness and coverage of knowledge graphs by effectively harnessing limited available information.

3.4 RL

RL is a branch of machine learning where an agent learns to make decisions by interacting with an environment. The agent receives feedback in the form of rewards or penalties and aims to learn a policy that maximizes cumulative rewards over time. Rather than being explicitly taught what actions to take, the agent discovers optimal behaviors through trial and error.

When combined with meta-learning, RL can become even more powerful as we can train agents across multiple environments or tasks, so they can quickly adapt their strategies when faced with new, unseen situations. For instance, MAML has been applied to RL [11], allowing agents to quickly fine-tune novel policies using just a few gradient steps.

The practical applications of meta-RL include: robotics [34, 35], where agents must adapt to changing dynamics, such as varying payloads or different terrains, while requiring minimal retraining; in game playing, particularly in Meta-Q Learning, agents generalize across multiple game scenarios and efficiently adjust their strategies; personalized recommendation systems must keep pace with evolving user preferences, necessitating agents that can learn from sparse feedback; in the healthcare field, treatment policies need to be tailored to individual patient responses, often with limited historical data available.

With promising results and broad applicability of meta-learning across multiple domains, it is expanding its effects and encourages more research to be done on its further advancements and practical implementations. Figure 2 provides a comprehensive overview of these diverse application areas.

4 Emerging Directions in Meta-Learning

Beyond the foundational categories and established applications, the field of meta-learning is witnessing the emergence of new paradigms and interdisciplinary approaches that push the boundaries of adaptive AI.

4.1 Continual and Online Meta-Learning

Continual learning and online learning are fields focused on the incremental updating of models with streaming data [8]. Online learning typically assumes a stationary data stream, while continual learning specifically aims to alleviate the problem of catastrophic forgetting when learning from non-stationary streams [9]. The convergence of these fields with meta-learning has led to the emergence of "meta-continual learning," which is the concept of "learning to continually learn." This advanced idea seeks to develop robust continual learning capabilities over extended periods, closely resembling the lifelong learning observed in human intelligence. Similarly, online meta-learning aims to imitate sequential meta-learning processes by presenting learning episodes in a streaming manner, enabling the underlying learning algorithm to continuously adapt to new data. A central challenge in Continual Meta-Learning (CML) is addressing the "stability-plasticity dilemma" [36]. This dilemma involves finding the right balance between maintaining stability—preventing catastrophic forgetting of previously learned tasks—and retaining plasticity—effectively learning generalizable concepts from new, incoming tasks. This issue is more complex than simply preventing forgetting; it necessitates a principled approach to managing the trade-off between retaining old knowledge and acquiring new, generalizable knowledge. To tackle this challenge, a unified theoretical framework for CML has been proposed, which is applicable in both static and shifting environments. This framework includes a novel algorithm that dynamically adjusts meta-parameters and learning rates in response to changes in the environment, thereby striving to achieve the optimal trade-off. Additionally, Automated Continual Learning (ACL) [37] represents an innovative approach that trains self-referential neural networks to meta-learn their own in-context continual (meta)learning algorithms. Future directions in this area include expanding beyond meta-learning initializations to explore model-based and metric-based meta-learning within online and continual frameworks. Researchers are also considering incorporating an additional meta-learning loop, creating a "triple-loop learning framework" (which may be called meta-online-meta-learning, or meta-continual-meta-learning), potentially leading to even more efficient learning mechanisms.

4.2 Causal Meta-Learning

Traditional machine learning methods often focus on modeling correlations within data rather than identifying causal relationships. This limitation can result in suboptimal performance and even systematic errors, particularly in high-stakes applications where understanding the underlying mechanisms is essential. Causal machine learning aims to overcome this limitation by developing models that can directly infer causal effects from observational data. Integrating causal inference with meta-learning represents a significant advancement toward creating more robust, generalizable, and

trustworthy AI [38]. This integration enables models to understand not just what happens, but why things happen, which is crucial for reliable decision-making in various applications where mere correlation is insufficient. Recent research in causal meta-learning focuses on improving flexibility by effectively handling high-dimensional, time-series, and multi-modal data, enhancing efficiency with optimized learning algorithms, and increasing robustness through methods that perform well even when standard assumptions are violated. Specific developments include causal transformers for estimating counterfactual outcomes [39]. Researchers are also exploring model-agnostic meta-learners for estimating heterogeneous treatment effects over time. A notable advancement is DiffPO [40], a causal diffusion model that learns the distribution of potential outcomes. Additionally, meta-learners are being developed for partially identified treatment effects across multiple environments, and conformal meta-learners—which combine conformal prediction (a framework for quantifying prediction uncertainty) with meta-learning to provide statistically valid confidence intervals for treatment effect predictions—have been proposed for the predictive inference of individual treatment effects [41]. This synergy allows models to learn how to infer causal relationships across different contexts or when data is limited. This development indicates that meta-learning is not just about making existing machine learning tasks more efficient; it is enabling AI to tackle a more fundamental issue: understanding the underlying mechanisms of data generation. This leads to models that are not only more accurate and robust to distribution shifts—since they can learn invariant causal relationships—but also more interpretable, as they can explain the causal basis of their predictions.

4.3 Generative Meta-Learning

Generative models are powerful tools for synthesizing high-quality outcomes, but they typically require substantial amounts of data to effectively learn underlying distributions. Meta-learning enhances these models by allowing them to adapt to few-shot learning scenarios. An early example of this is the adaptation of PixelCNN for few-shot pixel value prediction, enabling it to perform well even with limited training samples. The convergence of meta-learning and generative models is resulting in new paradigms for data augmentation and semi-supervised learning, effectively addressing data scarcity through the synthesis of new, relevant training data. Recent advancements in generative meta-learning include methods for generative transfer learning [42], which utilize pre-trained large generative models for situations where the source datasets or the pre-trained weights for target tasks are unavailable. A notable contribution in this area is a method that generates synthetic samples from pre-trained generative models to regularize only the feature extractors of neural networks. This approach employs meta-learning of latent variables to identify and utilize the most useful synthetic samples for the regularization process. Another significant development introduces "real unlabeled-dateless semi-supervised learning" by leveraging foundational generative models as sources of unlabeled data. This method proposes a meta-optimization-based sampling algorithm to extract synthetic unlabeled data from these models, along with a cosine similarity-based unsupervised loss function to update the classifier's feature extractor using these synthetic samples. Additionally,

the Hierarchical Gaussian Mixture based Task Generative Model (HTGM) [15] models task instance density, learns task embeddings, and fits mixture distributions. This framework is efficient for large backbone networks and allows for density-based scoring of novel tasks. These advancements demonstrate that the focus is not just on generating realistic outputs, but on creating data that enhances learning. By integrating meta-learning into generative models, we can produce synthetic data that is optimally suited to improving performance on new, data-scarce tasks, transforming the challenge of data scarcity into an opportunity for intelligent data generation.

5 Benchmarks and Evaluation

Benchmark datasets play a central role in evaluating and comparing meta-learning algorithms. While earlier studies predominantly relied on standard datasets like Mini-ImageNet and Omniglot, recent research has expanded to include more diverse, realistic, and challenging benchmarks. This shift reflects a growing emphasis on robustness, cross-domain generalization, and real-world applicability. Table 1 summarizes key benchmarks used in recent studies from 2023 to 2025.

Table 1 Summary of Benchmarks Used in Recent Meta-Learning Research

Benchmark	Description and Example Use
Mini-ImageNet	A widely used few-shot image classification dataset (100 classes, 84×84 images). Often used for comparing baseline meta-learning methods such as MAML and Meta-AdaM.
Tiered-ImageNet	Larger-scale version of Mini-ImageNet with higher-level class hierarchy. Supports better generalization assessment.
CIFAR-FS	Few-shot version of CIFAR-100. Offers fine-grained classification tasks, used for evaluating model robustness.
Omniglot	Handwritten character dataset, popular in early meta-learning work. Still included for historical comparison.
Meta-Dataset	A comprehensive benchmark combining multiple datasets to test cross-domain generalization. Used in domain-robust meta-learning (e.g., Qin et al., CVPR 2023).
WILDS	Real-world distribution shift benchmark suite (e.g., iWildCam, FMoW). Commonly used in recent studies focused on robustness (e.g., Jain et al., CVPR 2024).
MetaCoCo	Synthetic few-shot benchmark introduced to study spurious correlations. Proposed in ICLR 2024.
XLand-MiniGrid	A new JAX-based environment for meta-RL. Enables scalable, diverse task evaluation, introduced at NeurIPS 2024.

6 CHALLENGES AND SOLUTIONS

In this section, we examine the potential challenges raised while working with conventional and novel meta-learning approaches. We also review some of the corresponding solutions found to address these weaknesses.

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6.1 Diverse Task Distributions

In meta-learning, tasks are often treated as instances labeled by different classes within a domain-specific dataset or a single problem that comes from various domains. For example, in NLP, tasks can involve sentiment analysis, machine translation, or part-of-speech tagging applied to a specific dataset, or sentiment analysis conducted across various datasets. However, in meta-learning, significant challenges can arise when the task distributions differ considerably between the meta-training and meta-testing phases. This issue stems from the fact that a shared model receives gradients from different modes, each corresponding to a different task. This can lead to conflicts in the learning process. To overcome this weakness, recent papers have explored multi-modal meta-learning which typically performs clustering or projecting each task into task-specific subspaces [10]. Other studies have focused on incorporating a regularization parameter to reduce the dependence of the meta-parameters in the meta-model on the training-task distribution. Additionally, others have employed data augmentation to enhance the diversity during the training phase, which helps improve generalization. These approaches help to discriminate tasks and guide the learning process more adaptively.

6.2 Scarcity of Labeled Task Families

One of the critical challenges in meta-learning is the limited availability of diverse and well-structured labeled task families. Research suggests that greater task diversity can improve a model's ability to generalize to unseen tasks by exposing it to a wider range of distributions and objectives. However, collecting such varied task datasets is often labor-intensive, expensive, and time-consuming. Furthermore, if task construction is poorly managed, the model may overfit by memorizing superficial patterns rather than learning transferable representations—especially when tasks are highly similar or lack structural diversity. To address these limitations, several strategies have been proposed. One approach is task augmentation during meta-training, where new tasks are generated from existing ones through techniques such as data transformation or synthetic task creation [43]. While this helps expand the training space, it can also introduce biases if augmented tasks do not faithfully reflect real-world variability. Another promising direction is unsupervised or semi-supervised meta-learning [44, 45], which reduces reliance on labeled data by enabling models to discover underlying task structures based on intrinsic patterns. However, defining coherent task boundaries without labels remains a complex and open problem.

6.3 Computational Complexity

Bilevel optimization algorithms like MAML are computationally demanding due to their inner-loop optimizers, which require multiple back propagation and the storage of intermediate gradients, often exceeding memory constraints [46]. To alleviate these challenges, few-shot meta-learning reduces the number of training examples per task. Conversely, many-shot regimes, while more realistic, are even more resource-intensive. Techniques such as implicit differentiation—which computes gradients by treating the

inner optimization as an implicit function rather than explicitly unrolling all gradient steps—estimate the outer loss gradient without traversing the entire inner loop, making it computationally efficient but potentially less precise due to approximation [47, 48]. In contrast, forward-mode differentiation calculates exact gradients and offers higher fidelity but becomes computationally expensive and less scalable for models with a large number of parameters [49]. Both strategies aim to reduce computational overhead while preserving learning efficacy.

6.4 Episodic Training Forgetting

Meta-learning algorithms employ episodic training, where a task sampler selects a task with multiple class samples for the base learner to train on during each episode. However, this episodic training approach is susceptible to forgetting previous tasks, especially as the range of tasks expands. This can result in underfitting, making it difficult for the model to generalize effectively to unseen tasks. To address this problem, one solution is to incorporate memory-based models, such as Memory-Augmented Neural Networks (MANNs) [16]. These models include a memory module that helps retain and recall tasks across different episodes, thereby addressing the issue of catastrophic forgetting and improving generalization to novel tasks.

6.5 Hyperparameters Optimization

The performance of most meta-learning algorithms heavily depends on selecting appropriate hyperparameters, as these directly influence both the training and adaptation processes. For example, in methods such as MAML [11] or Prototypical Networks [13], key hyperparameters include the latent space dimensionality, backbone architecture, learning rate, and the number of ways and shots used during training episodes. In the case of MAML, the complexity increases because of its two-step optimization process. The inner loop introduces additional hyperparameters, including its own learning rate and the number of adaptation steps. To address this issue, Alpha-MAML [50] has been proposed as an extension of the original MAML algorithm. It employs a real-time hyperparameter optimization scheme to determine the appropriate learning rate, thereby enhancing the robustness of the training phase.

6.6 Unreliability and Backbone Model Sensitivity

Optimization-based meta-learning approaches, such as MAML, require a deep neural network as their backbone to perform effectively. Therefore, selecting the appropriate model depends on the complexity of the task: the more challenging the task, the deeper the backbone and the more carefully chosen the hyperparameters should be. Moreover, the two-step optimization makes the learning process unreliable. This unreliability manifests in unstable training, where slight changes in the learning rate and the number of adaptation steps can lead to poor performance. To address this issue, Meta-SGD [51] proposes automatically learning the initialization parameters, the gradient direction, and the value of the inner learning rate. Another paper focuses on overcoming the overfitting problem through CAVIA [52], which stands for Fast Context Adaptation via Meta-Learning. Instead of updating all the parameters of the base

model, CAVIA considers a subset of parameters during the inner loop and updates them at test time. By separating task-specific parameters from task-independent ones, CAVIA demonstrates a more efficient training process.

7 Future Research Directions

Based on our analysis of recent advancements and current limitations, we identify several promising directions for future meta-learning research:

The development of robust and trustworthy AI systems represents a critical frontier, requiring meta-learning methods that are inherently robust to noisy data, adversarial attacks, and significant domain shifts for reliable real-world deployment. Equally important is addressing scalability and efficiency challenges by enhancing the computational efficiency of meta-learning algorithms, particularly for large models and dynamic data environments.

The integration of meta-learning with large models presents significant opportunities for applying meta-learning principles to improve the learning, adaptation, and reasoning capabilities of large language models and foundation models. This advancement requires the development of standardized meta-evaluation methods that assess true adaptability beyond task-specific performance metrics.

Another promising direction involves learning what not to learn through the incorporation of negative inductive biases that guide models away from spurious or irrelevant features. Simultaneously, advancing online meta-learning capabilities will enable algorithms to continuously adapt in a streaming fashion to new data episodes.

Finally, the pursuit of human-like learning mechanisms focuses on advancing continual learning capabilities in neural networks to better mimic human learning patterns from non-stationary data streams, ultimately bringing artificial intelligence closer to the adaptive and flexible learning observed in biological systems.

8 Conclusion

In this survey, we have explored the evolving landscape of meta-learning, a paradigm that empowers models to adapt swiftly and effectively to new tasks by leveraging prior knowledge. We began by examining the foundational approaches—metric-based, model-based, optimization-based, and unsupervised or self-supervised methods—that form the core of meta-learning research. We then demonstrated how these paradigms translate into practical applications across cybersecurity, computer vision, natural language processing, and reinforcement learning, showcasing meta-learning's capacity to tackle data-scarce and dynamic scenarios in established domains. Building on this foundation, we reviewed benchmark datasets and evaluation protocols that reflect the growing emphasis on robustness, cross-domain generalization, and real-world applicability. We also explored emerging trends such as continual, causal, and generative meta-learning that push the boundaries of adaptive AI and address unique aspects of learning efficiency and adaptability. Finally, we examined the persistent challenges like computational overhead, task distribution variability, and limited labeled data, alongside innovative solutions such as task augmentation, implicit differentiation, and memory-augmented models that show promise for addressing these issues.

Declarations

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