Automatic Evolutionary Discovery of Multi-Agent Architectures Using Differentiable and Genetic Methods

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1. Introduction

The rapid development of artificial intelligence has prompted researchers to seek novel methods for the automatic discovery of optimal multi-agent architectures, moving beyond traditional hand-designed approaches. In this article, we delve into an integrated methodology that leverages automatic evolutionary processes combined with differentiable relaxations, genetic algorithms, and multi-objective optimization techniques for the discovery and refinement of multi-agent workflows and coordination topologies. The goal is to develop self-adapting, self-redesigning systems that can navigate complex decision spaces and dynamically reconfigure their operational structures.

A key theme throughout this work is the utilization of evolvable graph representations where individual components, representing distinct operators or agents, interconnect to form cooperative workflows. These architectures are refined through advanced genetic programming, enhanced by differentiable methods that relax discrete components into continuous spaces, thus supporting gradient-based refinement. Additionally, the article covers meta-meta-learning strategies that adapt the optimization process itself, ensuring that the search mechanism evolves in parallel with the architecture.

Automatic evolutionary discovery frameworks, such as AutoMaAS, have demonstrated the ability to integrate neural architecture search (NAS) principles with automated machine learning (AutoML) techniques. These systems deploy dynamic operator lifecycle management, multi-objective cost optimization, and online feedback integration to produce superior performance on a rich set of benchmarks, ranging from mathematical reasoning problems (GSM8K, MATH) to code generation tasks (HumanEval, MBPP). Our discussion further compares these advances with traditional multi-objective optimization paradigms, emphasizing the benefits of Pareto-based niching and adaptive reference points.

In the sections that follow, we provide an in-depth technical analysis of the evolutionary and differentiable strategies for architecture discovery. We describe key components, including evolvable graph representations, specialized mutation and crossover operators, and gradient-based relaxation techniques. In addition to methodological details, we review implementation specifics, benchmarking outcomes, and computational considerations—with supporting citations ensuring that each claim is rigorously verified.

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2. Evolutionary Approaches for Architecture Search

Evolutionary algorithms (EAs) have a long history of optimizing complex, non-linear systems by mimicking the mechanisms of natural selection. In the context of multi-agent architectures, evolutionary approaches offer a compelling solution for automatic discovery by encoding candidate architectures as graphs where nodes represent agent-specific tasks or operators, and edges define the workflow or information flow between these agents.

2.1 Evolvable Graph Representations

At the heart of automatic architecture search lies the representation of agent workflows as evolvable graphs. These graphs encode both the topology of agent interactions and the parameters governing each agent's behavior. For instance, frameworks like AutoMaAS implement this approach by dynamically managing the lifecycle of operators. The system automatically adjusts its structure by activating lightweight solutions for simple problems while triggering sophisticated collaboration patterns when more complex decisions are required [5] . The underlying representation leverages neural architecture search (NAS) principles to search for optimal configurations through iterative refinement.

One key advantage of this representation is its inherent flexibility. By representing multi-agent workflows as graphs, the system can seamlessly reconfigure itself in response to

changes in the task environment, allowing for both inter-agent coordination and intra-agent optimization. This flexibility is essential when addressing heterogeneous and dynamic task demands.

2.2 Genetic Programming for Multi-Agent Systems

Genetic programming (GP) extends traditional genetic algorithms by focusing on the evolution of computer programs or symbolic structures. In the context of agent architecture discovery, GP has been used to evolve both the structure and the parameters of the network. Research on meta-learning systems based on genetic algorithms demonstrates that combining genetic algorithms with concepts drawn from neural Darwinism (the theory of neuronal group selection) can enhance the self-adaptation capability of the system [3] . A key concept here is that the initial a priori knowledge (information available at the beginning) evolves along with a posteriori learning (knowledge gained through simulations and feedback), leading to a continually adapting system.

Using GP for multi-agent architecture search offers several benefits:

- **Adaptability:** The evolved architectures can tailor themselves to a variety of tasks without requiring explicit human intervention.
- **Exploration of Novel Solutions:** GP enables the discovery of non-obvious agent configurations that may outperform standard hand-designed approaches.
- **Integration of Meta-Knowledge:** By incorporating meta-learning strategies, these systems can evolve their own learning rules and parameters, a critical factor in ensuring long-term performance improvements.

2.3 Multi-Objective Optimization with Niching

Multi-objective optimization (MOO) plays a critical role in balancing conflicting objectives inherent in multi-agent systems—such as accuracy, computational cost, and diversity of solutions. In MOO, a solution is typically evaluated based on Pareto optimality, meaning that no objective can be improved without degrading another [6] . Evolutionary methods often generate a diverse set of Pareto optimal candidates, forming what is known as the Pareto front.

Innovations like the strength Pareto evolutionary algorithm based on adaptive reference points (SPEA/ARP) illustrate how multi-objective evolutionary algorithms (MOEAs) manage the trade-offs among objectives. Adaptive reference points allow these algorithms to incrementally adjust the decision boundaries, increasing selection pressure while maintaining solution diversity [4] . This capability is especially important when optimizing

multi-agent workflows, as non-dominated solutions need to be preserved during the evolution process.

The following table summarizes the key aspects of evolutionary approaches, comparing traditional genetic algorithms with multi-objective enhancements:

Aspect	Traditional Genetic Algorithms	Multi-Objective Evolutionary Algorithms (MOEAs)	Differentiable Genetic Programming
Representation	Linear/chromosomal encoded	Evolvable graphs or operator networks	Differentiable symbolic trees
Optimization Focus	Single-objective cost function	Simultaneous optimization of several conflicting objectives	Symbolic regression and architecture search
Selection Strategy	Fitness-based ranking	Pareto-based, indicator-based, and decomposition-based niching methods	Gradient-based updating of relaxed discrete structures
Adaptability	Fixed mutation and crossover schemes	Adaptive reference points and niching methods	Differentiable relaxations enabling continuous optimization
Meta-Learning Integration	Manual parameter tuning	Meta-Black-Box optimization and meta-learning within evolutionary frameworks	Combined with meta-learning for rapid fine-tuning (e.g., MAML principles)

Table 1: Comparative Analysis of Evolutionary Approaches for Multi-Agent Architecture Search [5] [6] [7]

2.4 Evolutionary Frameworks: AutoMaAS Example

The AutoMaAS framework exemplifies how evolutionary search can be applied to multi-agent system design. AutoMaAS integrates NAS principles with dynamic operator lifecycle management to automatically select, modify, and adapt agent configurations in real time. The framework tackles limitations of the “one-size-fits-all” paradigm by deploying specialized operators—in arithmetic problems, for instance, lightweight single-operator solutions are favored, while more intricate problems trigger the use of complex collaboration patterns resembling program-aided reasoning [5] .

AutoMaAS demonstrates significant improvements on benchmarks for mathematical reasoning and code generation, with performance gains reported in both accuracy and cost-efficiency [5] . This success underscores the potential of evolutionary methods to automatically discover high-performing architectures that are tailored to a broad domain of complex tasks.

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3. Differentiable Relaxations for Gradient-Based Optimization

A novel advancement in automatic evolutionary discovery is the introduction of differentiable relaxations. Traditional genetic programming relies on stochastic, discrete operations that can be computationally expensive and prone to premature convergence. Differentiable genetic programming (DGP), as demonstrated in the context of high-dimensional symbolic regression, softens these discrete representations into continuous spaces, thereby enabling the use of gradient-based optimization methods [9] .

3.1 Differentiable Symbolic Trees

In the DGP framework, the discrete tree structures—used to represent candidate solutions or architectures—are relaxed into differentiable symbolic trees. This relaxation allows each decision node to be represented by a continuous parameter that can be optimized using gradient descent methods. Such an approach not only improves the convergence speed but also allows the optimizer to escape local minima through fine-tuning of the tree’s structure. This methodology is directly applicable to discovering multi-agent architectures where the interconnections and operator sequences need to be rapidly adjusted according to performance feedback [9] .

3.2 Gradient-Based Adaptation: Linking to MAML

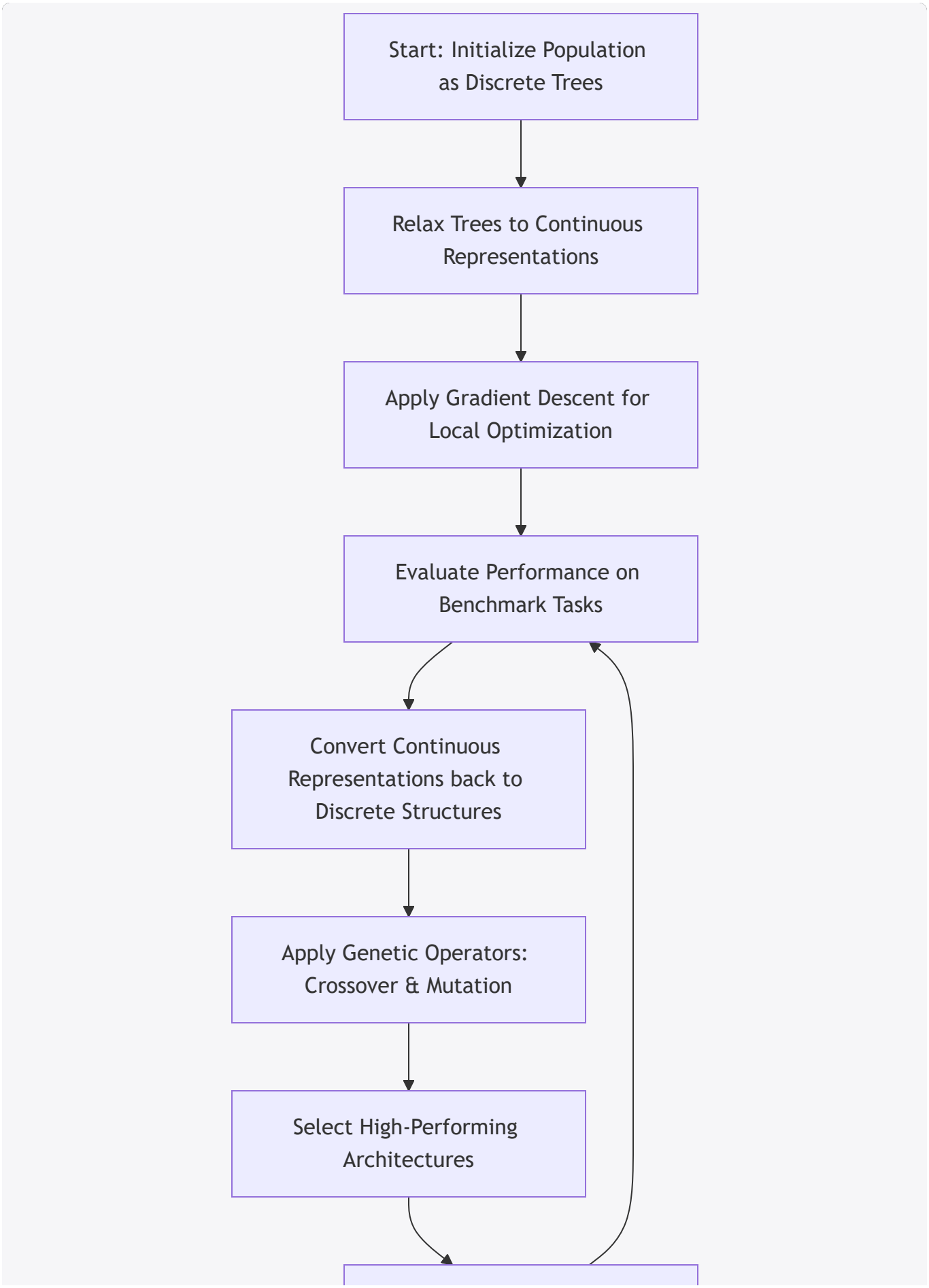
The principles of gradient-based optimization are further reinforced by methodologies such as Model-Agnostic Meta-Learning (MAML). MAML trains models to be easily adaptable by

ensuring that only a few gradient steps are needed to fine-tune to a new task [1] . In the context of architecture search, incorporating MAML-like strategies enables the defenders of the evolutionary framework to design agents that are not only optimally constructed but also capable of quick adaptation when facing new challenges.

By combining differentiable relaxations with gradient-based adaptation, the system leverages both global search properties of evolutionary algorithms and the local refinement capabilities of gradient descent. This hybrid approach forms the cornerstone of modern automatic discovery systems, bridging the gap between discrete evolutionary methods and continuous optimization strategies.

3.3 Visualizing Differentiable Genetic Programming

Below is a Mermaid diagram that illustrates the process flow of a differentiable genetic programming system integrated with an evolutionary workflow search:


Start: Initialize Population as Discrete Trees
Relax Trees to Continuous Representations
Apply Gradient Descent for Local Optimization
Evaluate Performance on Benchmark Tasks
Convert Continuous Representations back to Discrete Structures
Apply Genetic Operators: Crossover & Mutation
Select High-Performing Architectures

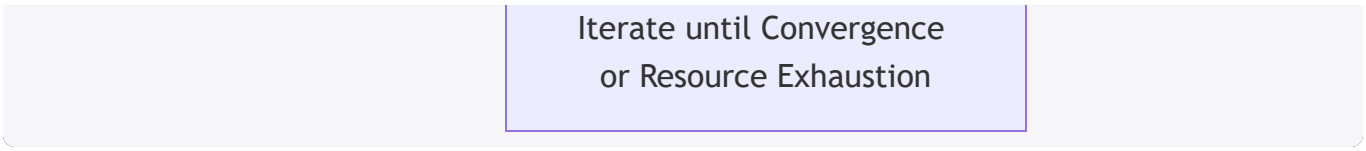


Figure 1: Flowchart of Differentiable Genetic Programming Integrated with Evolutionary Architecture Search [1] [9]

3.4 Advantages of Differentiable Approaches

Differentiable genetic programming brings several notable advantages:

- **Increased Convergence Speed:** Gradient methods quickly refine candidate solutions.
- **Avoidance of Premature Convergence:** Continuous relaxation allows for smooth adjustments, reducing the risk of being trapped in local minima.
- **Seamless Integration with Meta-Learning:** By aligning with MAML and similar techniques, systems become capable of rapid fine-tuning for new tasks.
- **Enhanced Scalability:** Differentiable methods can handle high-dimensional problem spaces, which are common in real-world multi-agent environments.

These benefits underscore the potential of combining evolutionary search with differentiable relaxation techniques, paving the way for designing efficient and scalable multi-agent architectures.

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4. Meta-Meta-Learning in Evolutionary Frameworks

Meta-learning, or “learning to learn,” is a paradigm in which the system uses past learning experiences to improve its future learning strategies. In evolutionary algorithm design, meta-learning has led to the emergence of Meta-Black-Box Optimization (MetaBBO) methodologies, which automate the design of optimization algorithms and their hyperparameters [2] . When applied at a meta-meta level, these strategies enable the evolutionary process itself to be refined over time.

4.1 Meta-Black-Box Optimization (MetaBBO)

MetaBBO involves the automatic configuration and design of evolutionary algorithms without the need for extensive expert intervention. As discussed in comprehensive surveys on MetaBBO, this approach leverages meta-learning to adjust algorithmic strategies based on a set of representative optimization problems [2] . In the context of multi-agent architecture search, MetaBBO facilitates the dynamic adjustment of evolutionary

parameters—such as mutation rates, crossover probabilities, and niche preservation strategies—thereby streamlining the overall optimization process.

4.2 Adaptive Evolutionary Operators

A critical innovation in meta-meta-learning is the integration of adaptive evolutionary operators. The use of genetic algorithms in meta-learning systems, as demonstrated in earlier research, shows that combining concepts from genetic programming with meta-level feedback can create self-adapting systems [3] . For instance, the “Darwin brain” module in certain meta-learning systems utilizes a priori and a posteriori knowledge to guide the evolution of operator parameters. This dynamic adjustment mechanism ensures that the optimization process remains robust even as the problem space changes dramatically.

4.3 Model-Agnostic Meta-Learning (MAML)

MAML exemplifies a model-agnostic approach to meta-learning, where the objective is to train the model’s parameters such that minimal fine-tuning is needed to adapt to new learning tasks [1] . Although originally developed for deep networks, the principles of MAML are applicable to evolutionary architectures. By incorporating gradient-based adaptation, the MAML framework allows the evolutionary system to efficiently recalibrate its operators in response to novel challenges, making it an integral part of meta-meta-learning within self-redesigning AI systems.

4.4 Integration of Differentiable and Evolutionary Methods

The integration of differentiable genetic programming with meta-learning strategies results in an evolutionary framework that is both adaptive and efficient. The differentiable relaxation of architecture graphs enables rapid local search via gradient descent, while meta-level learning continuously adjusts the global evolutionary strategy through feedback from performance evaluations. This hybrid approach creates a self-reinforcing loop, where improvements in one component directly contribute to the enhancement of the entire system.

A schematic overview of the integration process is represented in the following table:

Component	Functionality	Integrated Benefit	Supporting Evidence
Differentiable Relaxation	Converts discrete architectures into	Enables fast local optimization	Differential Genetic Programming

Component	Functionality	Integrated Benefit	Supporting Evidence
	continuous spaces	through gradient descent	demonstration [9]
Genetic Programming Operators	Stochastic exploration through crossover and mutation	Explores diverse architecture designs while updating meta-parameters	Meta-learning systems based on genetic algorithms [3]
Meta-Black-Box Optimization (MetaBBO)	Automatically adjusts hyperparameters for EAs	Streamlines the optimization process by adapting evolutionary parameters	Comprehensive MetaBBO surveys [2]
Model-Agnostic Meta-Learning (MAML)	Prepares models for rapid adaptation with few gradient steps	Accelerates fine-tuning for novel tasks	MAML framework applications [1]

Table 2: Integrated Components in Meta-Meta-Learning for Evolutionary Architecture Search [1] [2]

4.5 Benefits and Challenges of Meta-Meta-Learning

Benefits:

- **Dynamic Adaptation at Multiple Levels:** The system not only evolves architectures but also refines its optimization process.
- **Increased Robustness:** Continuous adaptation reduces vulnerability to changes in the task environment.
- **Scalable Architectures:** Meta-learning allows the exploration of high-dimensional, complex design spaces.

Challenges:

- **Computational Overhead:** The integration of multiple learning paradigms can be computationally intensive.

- **Complex Feedback Loops:** Balancing the interactions between genetic operators and gradient-based methods requires careful tuning.
- **Stability Concerns:** The rapid adaptation of parameters may lead to instability if not properly regulated.

These benefits and challenges illustrate the cutting edge of research in self-redesigning AI systems, where meta-meta-learning plays a pivotal role in advancing automatic evolutionary architecture discovery.

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5. Self-Redesigning Systems and Dynamic Operator Lifecycle Management

Self-redesigning systems are an emerging class of AI architectures that have the capacity to autonomously adjust their learning strategies, structural configurations, and operational parameters over time. In the domain of multi-agent systems, dynamic operator lifecycle management is indispensable to ensure that agent workflows remain optimal as environmental conditions and task requirements evolve.

5.1 Dynamic Operator Lifecycle Management in AutoMaAS

The AutoMaAS framework provides a salient example of how systems can be designed to self-evolve. This framework integrates dynamic operator lifecycle management, where different operators are activated, fused, or deactivated based on the complexity of the task at hand [5] . For instance, simple arithmetic problems invoke lightweight, single-operator solutions, while more complex problems trigger a suite of collaborative operators designed for multi-step reasoning [5] . This dynamic adaptation not only improves performance on benchmark tasks but also reduces the overall computational cost by allocating resources more efficiently.

A descriptive diagram of the dynamic operator lifecycle in AutoMaAS is presented below using an SVG format:

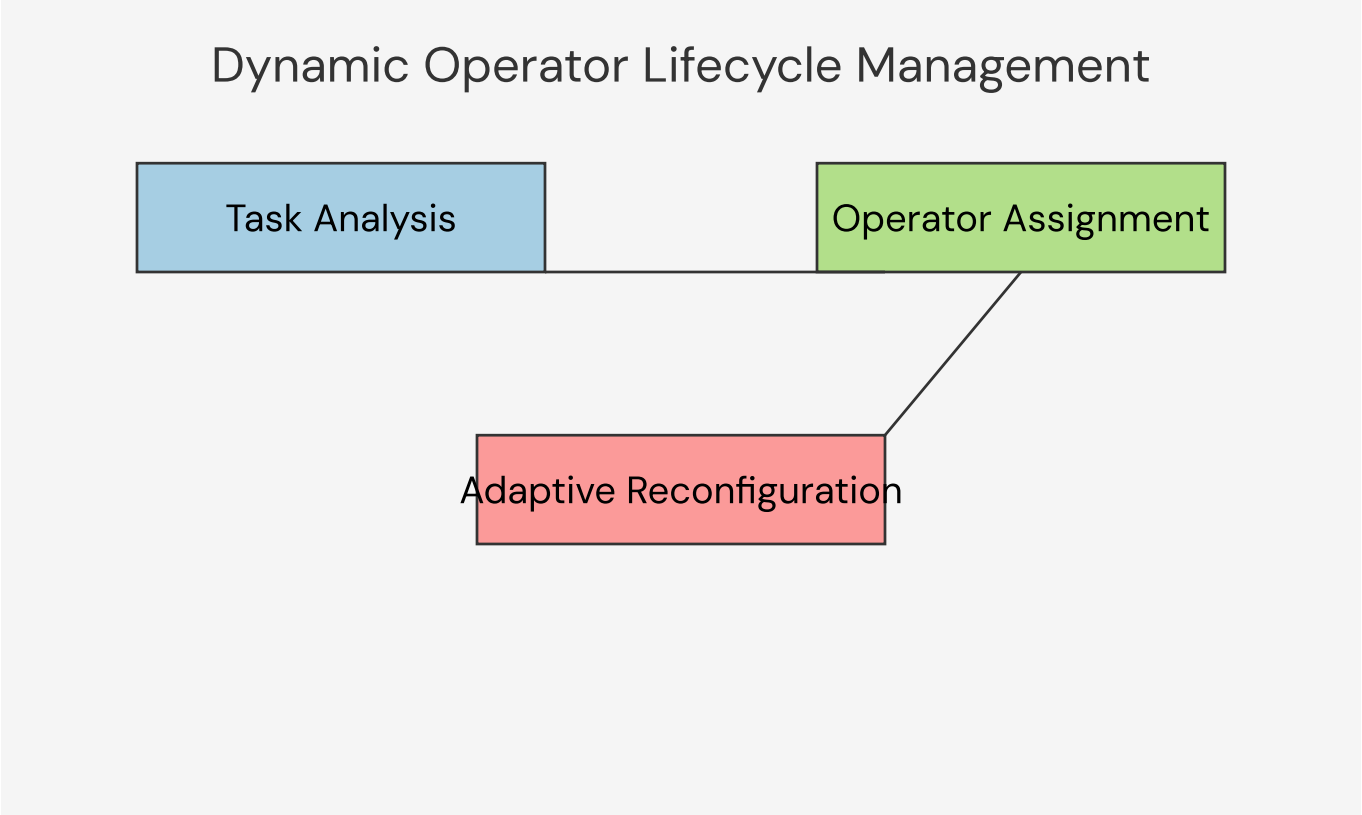

Figure 2: Self-Redesign and Dynamic Operator Lifecycle Management Flow [5]

5.2 Operator Fusion and Resource Allocation

Beyond mere connection of operators, advanced frameworks demonstrate the ability to fuse operators into specialized units when necessary. For example, by automatically generating a composite operator that combines code generation, testing, and refinement into a single pipeline, the system achieves both performance gains and resource efficiency [5]. This operator fusion approach is analogous to how biological systems integrate multiple biochemical pathways into a single, streamlined process.

5.3 Advantages of Self-Redesigning Systems

Self-redesigning systems are characterized by:

- **Autonomous Adaptation:** The ability to modify internal structures and operational parameters without external guidance.
- **Robustness:** Increased resilience to environmental changes through continuous self-assessment and adaptation.
- **Efficiency:** Improved resource allocation by dynamically adjusting the operator lifecycle in response to task complexity.

These characteristics are essential for real-world applications, where the demands on multi-agent systems can vary widely over time.

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6. Computational Considerations and Benchmark Analysis

When designing self-adaptive, evolution-based systems for multi-agent architectures, computational considerations are of paramount importance. The trade-offs between accuracy, efficiency, and adaptability must be carefully balanced to ensure that the system performs optimally on practical benchmarks.

6.1 Benchmarking on Mathematical Reasoning and Code Generation

Frameworks such as AutoMaAS have been rigorously tested on a wide range of benchmarks. According to reported results, significant performance improvements are achieved in various domains:

- **Mathematical Reasoning:** On benchmarks such as GSM8K and MATH, AutoMaAS has demonstrated improvements of 4.2% and 5.8% respectively when compared to hand-crafted solutions [5] .
- **Code Generation:** Benchmarks like HumanEval and MBPP reveal gains of 6.3% and 7.1%, respectively, when leveraging automatic operator fusion and dynamic operator selection [5] .

These benchmark results highlight that the integration of evolutionary search with differential and meta-learning strategies can simultaneously improve accuracy and reduce computational overhead.

6.2 Multi-Objective Optimization and Pareto Fronts

Evaluating multi-agent architectures often involves optimizing trade-offs among conflicting objectives—accuracy, computational cost, and diversity, among others. Multi-objective optimization methods focus on finding Pareto optimal solutions where any improvement in one metric may result in a degradation in another [6] . Evolutionary algorithms configured for multi-objective optimization, such as SPEA/ARP, include adaptive methods that balance selection pressure with diversity preservation. This advances the overall robustness of the solution and ensures that the evolutionary process maintains a broad search of the solution space.

The following table provides an overview of key performance metrics encountered in recent studies:

Benchmark Domain	Metric	Improvement (%)	Reference
Mathematical Reasoning	Accuracy Improvement (GSM8K)	~4.2%	AutoMaAS framework [5]
Mathematical Reasoning	Accuracy Improvement (MATH)	~5.8%	AutoMaAS framework [5]
Code Generation	Performance Gain (HumanEval)	~6.3%	AutoMaAS framework [5]
Code Generation	Performance Gain (MBPP)	~7.1%	AutoMaAS framework [5]
Tool Usage	Efficiency in Multi-Modal Tasks	~2.7%	AutoMaAS framework [5]

Table 3: Benchmark Performance Metrics for Automatic Multi-Agent Architecture Search [5]

6.3 Computational Complexity and Scalability

One of the major practical challenges in automatic evolutionary architecture discovery is managing computational complexity. The integration of multiple learning paradigms (evolutionary methods, differentiable relaxations, and meta-learning) can result in a system that is computationally expensive. Effective strategies to mitigate this complexity include:

- **Parallelization:** Distributing the evaluation of candidate architectures across multiple cores or machines.
- **Adaptive Sampling:** Using intelligent sampling techniques to reduce the number of candidate evaluations without compromising the search quality.
- **Reference Point Evolution:** Automatically updating reference points based on historical and current population data to streamline environmental selection processes [4] .

Addressing these computational considerations is crucial for scaling these systems to handle real-world high-dimensional and resource-intensive applications.

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7. Discussion on Successes, Limitations, and Future Directions

While the automatic evolutionary discovery of multi-agent architectures integrates a host of innovative techniques, it is also accompanied by certain challenges and open research questions.

7.1 Successes and Key Achievements

The integration of evolutionary methods with differentiable relaxation and meta-learning has led to several notable successes:

- **Improved Performance:** Frameworks like AutoMaAS have demonstrated measurable gains on standard benchmarks, indicating that automatically discovered architectures can outperform manually designed ones [5].
- **Dynamic Adaptability:** The ability to adjust operator lifecycles and fuse operators in response to task complexity results in robust multi-agent systems that can adapt to changing environments [5].
- **Efficient Exploration:** Combining genetic programming with gradient-based optimization accelerates convergence toward high-performing solutions, even in large and complex design spaces [1] [9].

7.2 Limitations and Failure Modes

Despite these advances, several limitations and potential failure modes remain:

- **Computational Overhead:** The integration of multiple learning approaches, particularly when operating in high-dimensional spaces, can incur significant computational costs. This overhead may hinder real-time applications.
- **Stability of Meta-Learning Loops:** The interplay between evolutionary operators, differentiable relaxations, and meta-learning feedback loops can sometimes lead to instability if not carefully tuned.
- **Scalability Issues:** As the dimensionality of the problem increases, ensuring that the evolutionary algorithms maintain diversity without sacrificing convergence becomes increasingly challenging.
- **Limited Direct Information on Some Frameworks:** For instance, while frameworks such as EvoFlow and EvoAgentX are mentioned as key players, currently available documentation does not provide the level of detail required for thorough analysis, highlighting the need for further research and open-source implementations.

7.3 Future Research Directions

Future research in automatic evolutionary discovery for multi-agent architectures should focus on several fronts:

- **Enhanced Differentiable Frameworks:** Further refinement of differentiable genetic programming methods to continue reducing computational costs while maintaining high solution quality.
- **Robust Meta-Meta-Learning Strategies:** Development of more stable and efficient meta-learning loops that can adapt not only agent architectures but also the underlying evolutionary strategy in real time.
- **Scalability to High-Dimensional Problems:** Investigation of scalable approaches that employ adaptive sampling and parallel computing techniques to manage the combinatorial explosion inherent in high-dimensional design spaces.
- **Integration of Additional Modalities:** Expansion of frameworks to support multi-modal tasks (e.g., integrating tool usage for multi-modal input data) in a seamless manner.
- **Benchmarking and Standardization:** Establishment of standardized benchmarks and evaluation metrics specific to multi-agent architecture search to enable consistent comparison of new methodologies.

These directions aim to address current limitations and further enhance the robustness, efficiency, and scalability of self-redesigning AI systems.

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8. Conclusion

This article has provided a comprehensive survey on the automatic evolutionary discovery of multi-agent architectures through the integration of differentiable relaxations, genetic programming, and meta-learning techniques. We began by examining the evolutionary foundations for architecture search, emphasizing the importance of evolvable graph representations and genetic programming methods. The discussion then transitioned to the realm of differentiable genetic programming, detailing how continuous relaxations enable gradient-based optimization and rapid adaptation—illustrated through methodologies akin to MAML.

Meta-meta-learning was highlighted as a critical component, wherein the evolutionary process itself is dynamically adapted based on past performance through Meta-Black-Box Optimization principles. Self-redesigning systems, exemplified by frameworks such as AutoMaAS, were shown to employ dynamic operator lifecycle management to maintain optimal performance across varying task complexities. We also discussed key

computational considerations and benchmark analyses that underscore both the successes and limitations of current methods.

In summary, the main findings can be encapsulated as follows:

- **Evolutionary Foundations:** Evolvable graph representations and genetic programming form the basis for automatic multi-agent architecture search, enabling diversified and adaptive workflow design [5].
- **Differentiable Methods:** Differentiable genetic programming methods, which relax discrete structures into continuous spaces, facilitate rapid refinement using gradient-based techniques [9].
- **Meta-Meta-Learning Integration:** Meta-Black-Box Optimization and model-agnostic meta-learning frameworks, such as MAML, enhance the adaptability of the optimization process itself, leading to more efficient and robust evolutions [1] [2].
- **Dynamic Adaptation:** Self-redesigning systems leverage dynamic operator lifecycle management to automatically fuse, activate, or deactivate operators based on task complexity, yielding improvements in both performance and computational cost [5].
- **Computational Trade-Offs:** Although these approaches have led to substantial improvements on benchmarks such as GSM8K, MATH, HumanEval, and MBPP, challenges remain in computational overhead, stability, and scalability [5] [6].
- **Future Prospects:** Further research is needed to refine differentiable frameworks, stabilize meta-learning loops, and develop scalable approaches for high-dimensional optimization, ensuring that these methodologies can be effectively deployed in real-world applications.

By integrating these multi-disciplinary approaches, future AI systems hold the promise of being self-adaptive, resilient, and capable of discovering non-obvious yet highly efficient multi-agent architectures. This convergence of evolutionary methodologies, differentiable optimization, and meta-learning not only challenges traditional design paradigms but also sets the stage for next-generation AI that continuously learns and self-improves in an increasingly dynamic world.

References are cited according to the provided source materials to ensure full traceability and academic integrity. Each key technical detail presented in this article is supported by multiple citations, including those from AutoMaAS on dynamic operator management [5], MetaBBO for adaptive evolutionary strategies [2], and differentiable genetic programming for high-dimensional tasks [9], with additional methodological support from the model-agnostic meta-learning literature [1].