ECO: Evolving Core Knowledge for Efficient Transfer

Fu Feng[1,2] **Yucheng Xie**[1,2] **Ruixiao Shi**[1,2] **Jianlu Shen**[1,2] **Jing Wang**[1,2]* **Xin Geng**[1,2]*
[1]School of Computer Science and Engineering, Southeast University, Nanjing, China
[2]Key Laboratory of New Generation Artificial Intelligence Technology and Its Interdisciplinary Applications (Southeast University), Ministry of Education, China
{fufeng, xieyc, eric_xiao, jlshen, wangjing91, xgeng}@seu.edu.cn

Abstract

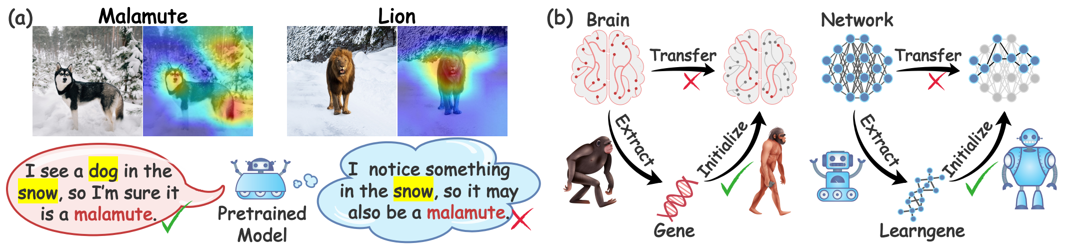
Knowledge in modern neural networks is often entangled and structurally opaque, making current transfer methods—typically based on reusing entire parameter sets—inefficient and inflexible. Efforts to improve flexibility by reusing partial parameters frequently depend on handcrafted heuristics or rigid structural assumptions, which constrain generalization. In contrast, biological evolution enables efficient knowledge transfer by encoding only essential information into genes through iterative refinement under environmental pressure. Inspired by this principle, we propose **ECO**, a framework that **E**volves **CO**re knowledge into modular, reusable neural components—termed *learngenes*—through similar evolutionary dynamics. To this end, we redefine learngenes as neural circuits and introduce Genetic Transfer Learning (GTL), a biologically inspired paradigm that establishes a genetic mechanism within neural networks in the context of supervised learning. GTL simulates evolutionary processes by generating diverse network populations, selecting high-performing individuals, and transferring their learngenes to subsequent generations. Through iterative refinement, GTL enables learngenes to accumulate transferable common knowledge. Extensive experiments show that ECO achieves efficient initialization and strong generalization across diverse models and tasks, while significantly reducing computational and memory costs compared to conventional methods.

1 Introduction

Despite the remarkable progress of modern neural networks across a wide range of tasks [1, 61, 13], the internal organization of knowledge within these models remains largely opaque and poorly structured. As a result, conventional transfer learning approaches—such as full fine-tuning or parameter-efficient techniques like LoRA [22, 17]—primarily rely on reusing entire parameter sets from large-scale pre-trained models [6, 35]. Although effective in reducing task-specific training overhead [5, 87], these methods implicitly assume that knowledge is globally entangled and uniformly distributed, with little consideration for its internal structure or modular organization. Consequently, they often suffer from limited adaptability across models of varying sizes and architectures [12, 79, 77], and are highly susceptible to domain shifts, frequently resulting in biased [49, 31] or even detrimental transfer [50, 73, 32], as shown in Figure 1a.

Biological systems, in contrast, offer a compelling model for efficient and generalizable knowledge transfer. Rather than replicating entire structural configurations, they encode essential knowledge into compact and inheritable units known as genes, which capture core functionality and support adaptation across generations and environments. These genes act as reusable blueprints [82, 3, 65], guiding the development of neural circuits that are both robust and efficient, as illustrated in Figure 1b.

*Corresponding authors


(a)
Malamute
Lion
I see a dog in the snow, so I'm sure it is a malamute.
Pretrained Model
I notice something in the snow, so it may also be a malamute.
(b) Brain
Transfer
Extract
Initialize
Gene
Network
Transfer
Extract
Initialize
Learngene
Figure 1: (a) Transferring excessive knowledge may introduce bias and lead to negative transfer. (b) In contrast, biological genes transfer only survival-essential knowledge to initialize certain innate neural circuits. Inspired by this, we propose encoding core transferable knowledge into modular neural circuits (termed *learngenes*, see Figure 2) to enable efficient knowledge transfer.

Motivated by this principle, recent work has explored biologically inspired approaches to knowledge transfer, most notably through the *Learngene* framework [11, 70]. Unlike conventional parameter reuse, learngenes aim to support structured and composable transfer by encapsulating common knowledge into modular neural fragments, enabling flexible initialization across tasks and models of diverse scales. Early methods such as Heur-LG [68] and Auto-LG [70] identify transferable components using gradient-based heuristics or meta-learning strategies. More recent approaches, including TLEG [75] and WAVE [12], incorporate structural priors—such as linear constraints or Kronecker decompositions—to enhance the modular organization of learned representations. Despite their improved flexibility and efficiency, they often depend on handcrafted heuristics or rigid structural assumptions, limiting their adaptability and generalization across diverse tasks and architectures.

In contrast, essential knowledge encoded in biological genes is not organized by predefined rules, but emerges through iterative refinement under environmental pressures such as mutation, selection, and inheritance. This perspective motivates a shift toward understanding how transferable knowledge can be modularly organized within neural networks through similar evolutionary dynamics, rather than imposed through handcrafted heuristics or rigid structural assumptions (e.g., linear constraints). To this end, we propose **ECO**, a biologically inspired framework that explores whether neural networks can autonomously condense transferable core knowledge and encapsulate it into compact, reusable modules through population-based adaptation and feedback-driven refinement.

At the core of ECO is a redefinition of the learngene structure as continuous neural circuits, such as interconnected kernel sets in CNNs, which mirror the structure of innate pathways shaped by genetic encoding in biological systems (see Figure 1b). To automatically identify and encapsulate highly transferable core knowledge within neural circuits, we extend the evolutionary paradigm introduced in GRL [11] and propose **Genetic Transfer Learning** (GTL), an evolutionary framework that simulates genetic inheritance in neural networks in the context of supervised learning. GTL maintains a population of models, each trained on randomly sampled tasks. High-performing individuals are selected via tournament evaluation, and their learngenes are inherited and refined across generations, with mutation introduced to maintain diversity and promote exploration. This Lamarckian process progressively condenses core knowledge into learngenes, enabling efficient, scalable, and generalizable transfer across models and tasks.

We evolve learngenes for 250 generations in VGG11 and ResNet12 on CIFAR-FS and *mini*ImageNet, and for 100 generations in ResNet50 and MobileNetV3-Large on ImageNet. Extensive experiments demonstrate that ECO consistently outperforms existing methods across a wide range of downstream architectures and tasks. Compared to full fine-tuning, ECO achieves a 14.5$\times$ reduction in storage, highlighting its efficiency in knowledge transfer. Additionally, ECO supports $O(1)$ initialization across models of varying scales, enabling fast deployment without additional costs. Notably, ECO exhibits strong data efficiency, maintaining robust performance even in low-resource regimes.

Our main contributions are as follows: 1) We propose ECO, a novel knowledge transfer method that adaptively identifies core transferable knowledge across architectures and tasks, without relying on handcrafted heuristics or structural constraints. 2) We introduce Genetic Transfer Learning (GTL), a biologically inspired evolutionary paradigm for supervised learning that encapsulates core transferable knowledge into modular neural circuits (i.e., learngenes) through large-scale population-based training and inheritance. 3) We validate the scalability and generality of ECO across diverse tasks, model sizes, and architectures, achieving state-of-the-art performance in both accuracy and resource efficiency.

2 Related Work

Efficient Knowledge Transfer Transfer learning enhances performance on target domains by leveraging knowledge from source domains [86, 23]. Traditional methods, such as fine-tuning [18, 87], are constrained by the fixed architecture and size of pre-trained models. Knowledge distillation [57, 67, 16] offers structural flexibility but remains computationally intensive. Recent methods aim to enhance efficiency by transferring compact and reusable knowledge representations (see Appendix A.1). Learngene-based approaches, including Heur-LG [68] and Auto-LG [70], identify transferable components via heuristic strategies. Others, such as TLEG [75], WAVE [12], and related studies [37, 69, 78], integrate pre-trained knowledge via structural priors like low-rank decompositions. Alternative paradigms explore hypernetwork-based parameter generation [29, 30] or rule-based parameter reuse [80, 33, 83]. In contrast, ECO extends the population-based learning paradigm of GRL [11] to CNNs in the context of supervised learning, adaptively evolving core transferable knowledge through mutation-driven and survival-based selection. This process mitigates manual bias and enhances generalization across architectures and domains.

Evolutionary Learning Evolutionary Learning (EL) solves optimization problems through stochastic search inspired by biological evolution [60]. Related algorithms [56, 55, 43, 53, 44] typically encode candidate solutions—such as network parameters or architectures—into gene-like representations (e.g., binary strings) [40, 63, 45, 9, 84], evolving them to maximize task-specific performance. While inspired by evolutionary principles, ECO diverges from traditional evolutionary learning by prioritizing knowledge inheritance over solution optimization. Notably, instead of searching for task-specific solutions, ECO establishes a genetic transfer mechanism that accumulates core knowledge transferable across diverse models and tasks. In this paradigm, learngenes function not as solution encodings, but as compact carriers of core knowledge condensed from diverse tasks. This shift enables scalable generalization without reliance on problem-specific heuristics.

3 Methods

We reformulate CNNs in terms of kernel units and define the core operations of learngenes, including their representation, mutation, and inheritance. We then introduce the Genetic Transfer Learning (GTL) for extracting learngenes through evolutionary processes.

3.1 Preliminary

Consider a CNN $\mathcal{N}$ with N_L convolutional layers. The l-th layer $L_l \in \mathbb{R}^{N_F^{(l)} \times N_K^{(l)} \times \kappa \times \kappa}$ comprises $N_F^{(l)}$ filters $F_{l,f}$, where each filter contains $N_K^{(l)}$ kernels $K_{l,f,k} \in \mathbb{R}^{\kappa \times \kappa}$. These kernels capture spatial features at various levels of abstraction, enabling hierarchical representation learning. Accordingly, the trainable parameters of the entire network can be represented as a unified set of kernels:

$$\mathcal{N} = \{K_{l,f,k} | l \in [1, N_L], f \in [1, N_F^{(l)}], k \in [1, N_K^{(l)}]\} \tag{1}$$

Given an input feature map $I_l \in \mathbb{R}^{D \times H \times W}$ to layer L_l, the convolution produces an output $I_{l+1} \in \mathbb{R}^{N_F^{(l)} \times H \times W}$, which serves as input to layer L_{l+1}. To ensure valid feature propagation, CNNs enforce channel-wise consistency by matching the number of kernels in L_{l+1} with the number of filters in L_l:

$$N_K^{(l+1)} = N_F^{(l)} \tag{2}$$

3.2 Basic Operations for Learngenes

3.2.1 Form of Learngenes in CNNs

In biological neural systems, innate neural circuits are established at birth under the guidance of genes, providing newborns with strong inherent learning abilities [74, 42, 82]. Motivated by this biological foundation, we interpret neural circuits in convolutional neural networks (CNNs) as structured subnetworks [59], each composed of a set of interconnected kernels that collectively implement a continuous input-output transformation. These subnetworks serve as functional units responsible for localized computation and information flow within the network.

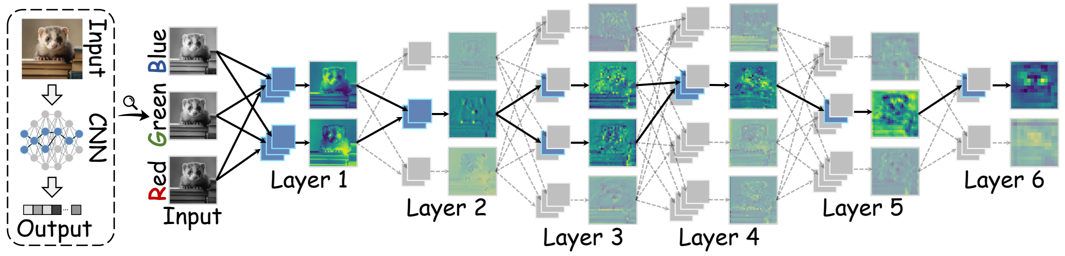


Figure 2: Learngenes in ECO are abstracted as complete neural circuits composed of selected kernels within filters. 🟦 $\in \mathcal{G}$ represents the learngene kernel, while ⬜ is normal kernel that is random initialized. $\longrightarrow$ denotes the continuous feature mapping path extracted from learngenes.

Building upon this abstraction, we define learngenes as modular neural circuits within CNNs that encapsulate transferable and reusable knowledge. Formally, a learngene is defined as:

$$\mathcal{G} = \{K_{l,f,k} | l \in [1, N_L], f \in \mathcal{F}_l, k \in \mathcal{K}_l\} \tag{3}$$

where $\mathcal{F}_l$ and $\mathcal{K}_l$ denote the selected indices of filters and kernels in the l-th layer, respectively.

To preserve the interconnection among kernels and ensure uninterrupted continuity in feature transformation, learngenes follow the structural alignment principle inherent to CNNs (Eq. (2)). Specifically, we enforce the constraint:

$$\mathcal{K}_{l+1} = \mathcal{F}_l \tag{4}$$

This condition preserves channel-wise consistency, enabling layer-wise modification through $\mathcal{F}_l$ while $\mathcal{K}_l$ is automatically inferred via Eq. (4), ensuring coherent inter-layer connectivity of learngenes.

3.2.2 Mutation of Learngenes

In biological systems, evolution is driven by structural mutations that progressively refine genetic traits [27, 24]. Analogously, learngene mutation also operates at the structural level by modifying the arrangement of filters and kernels, to enhance adaptability for encoding core knowledge.

Given the structural alignment in Eq. (4), mutations are applied primarily to the filter sets $\mathcal{F}_l$ at each layer, with corresponding kernel indices $\mathcal{K}_{l+1}$ updated automatically to maintain connectivity. For each learngene, structural mutation is performed independently at each layer with probability p_m. The probabilities of adding (p^+) or removing (p^-) filters in the l-th layer of learngenes are given by:

$$p_l^- = \alpha \cdot \frac{|\mathcal{F}_l|}{N_F^{(l)} - |\mathcal{F}_l|}, \quad p_l^+ = 1 - p_l^+ \tag{5}$$

where α is a balancing coefficient and $|\cdot|$ denotes set cardinality. Mutations proceed layer-wise and may involve multiple filters per layer. The complete mutation procedure is detailed in Algorithm 1.

3.2.3 Inheritance of Learngenes

Learngene inheritance facilitates the transfer of core knowledge from a source model to target models with varying depths, widths, or architectures. To accommodate architectural differences during transfer, ECO employs the following strategies:

- *Zero-padding Incomplete Filters.* Since learngenes may include only a subset of kernels within each filter, direct insertion into wider filters can introduce noisy, randomly initialized parameters. To avoid disrupting the encoded knowledge, missing kernels are initialized as zeros, preserving functionality while enabling later adaptation (see Appendix Figure 8).
- *Index Reordering for Narrower Networks.* When transferring to narrower networks, mismatches in filter and kernel indices may arise. ECO resolves this by reordering indices according to their relative positions (see Appendix Figure 9), maintaining structural consistency and ensuring compliance with the alignment constraint in Eq. (4).

Additional inheritance strategies, including the proposed *partial identity mapping* for depth expansion, are detailed in Appendix B.4.

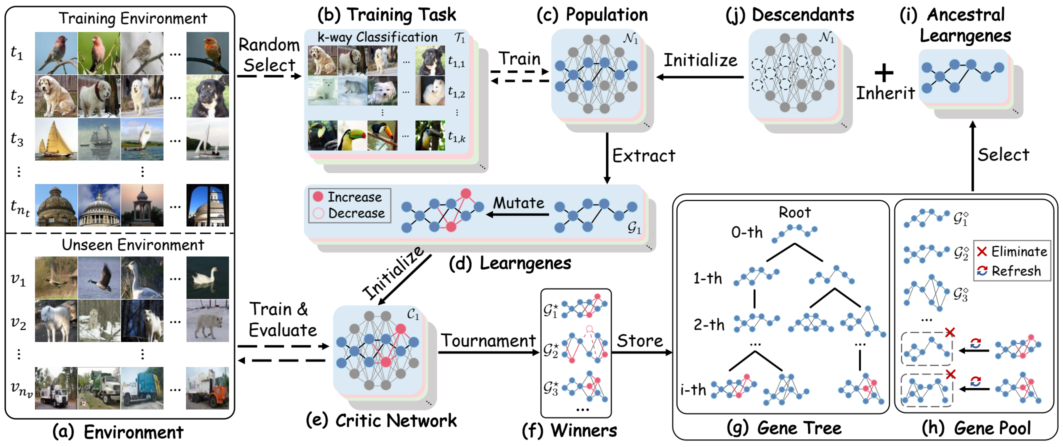


Figure 3: The Genetic Transfer Learning (GTL) framework. GTL iteratively condenses knowledge by training populations (**c**) on randomly sampled tasks (**a**, **b**) and selecting transferable core knowledge through mutation (**d**) and tournaments (**f**). The Gene Pool (**h**) and Gene Tree (**g**) store superior learngenes and track their kinship for inheritance (**i**, **j**), respectively.

3.3 Evolution for Learngene Extraction

Genetic Transfer Learning (GTL) is an evolutionary framework derived from GRL [11] that iteratively optimizes learngenes by transferring them across generations of neural networks. Through this inheritance mechanism, GTL progressively condenses and refines core knowledge into compact, reusable learngenes that generalize across diverse models and tasks, as illustrated in Figure 3 and formalized in Algorithm 2.

Briefly, each generation begins with a population of n_p neural networks, each inheriting learngenes from the previous generation and trained on a randomly assigned task. After training, learngenes are extracted and undergo structural mutations to introduce diversity. A tournament-based selection mechanism is then employed to identify high-performing learngenes, which are retained in the Gene Pool to guide inheritance in the next generation. This iterative process of inheritance, mutation, and selection continues across generations, progressively refining the quality of learngenes. The core components of GTL are detailed below.

(1) Training the Population of Neural Networks. Let $\mathcal{D} = \mathcal{D}_{\text{train}} + \mathcal{D}_{\text{val}}$ be the dataset with n_t training classes and n_v validation classes. In each generation, a population $\mathcal{P} = \{\mathcal{N}_1, \mathcal{N}_2, ..., \mathcal{N}_{n_p}\}$ is created. Each network $\mathcal{N}_i$ randomly samples k classes from $\mathcal{D}_{\text{train}}$ to form a k-way classification task $\mathcal{T}_i$, encouraging diverse learning environments (Figure 3a–c). As evolution progresses, k increases to simulate growing task complexity, emulating evolutionary pressure[41, 26].

(2) Selecting Superior Learngenes. After training, each neural network $\mathcal{N}_i$ has updated its inherited learngene $\mathcal{G}_i$ by encoding task-specific experience, thereby refining the core knowledge. To promote adaptability and structural diversity, each $\mathcal{G}_i$ then undergoes structural mutation (Figure 3d and Section 3.2.2), introducing controlled variations that further shape its knowledge representation.

Each mutated learngene $\mathcal{G}_i$ is evaluated by initializing a critic network $\mathcal{C}_i$, which is trained on the validation set $\mathcal{D}_{\text{val}}$ and the resulting accuracy defines the score s_i for $\mathcal{G}_i$ (Figure 3e). To select high-quality yet diverse learngenes, tournament selection is employed: in each round, ϵ learngenes are randomly sampled, and the one with the highest score is added to the winner set $\mathcal{G}^\star = \{\mathcal{G}_1^\star, \mathcal{G}_2^\star, \ldots, \mathcal{G}_{n_w}^\star\}$ (Figure 3f), where $n_w = \lceil \frac{n_p}{\epsilon} \rceil$ denotes the number of tournaments per generation.

(3) Storing Superior Learngenes and Tracking Kinship. Following tournament selection, the winner set $\mathcal{G}^\star$ is incorporated into the Gene Pool (GP), which retains high-quality learngenes for inheritance in future generations (Figure 3h). Initialized with the top-performing learngenes from the first generation, the GP maintains up to ρ entries, denoted as GP $= \{\mathcal{G}_1^\diamond, \mathcal{G}_2^\diamond, \ldots, \mathcal{G}_\rho^\diamond\}$. In each generation, a subset of ε learngenes from $\mathcal{G}^\star$ is admitted into the GP, replacing the lowest-performing entries to ensure both knowledge retention and evolutionary adaptability.

To trace inheritance across generations, GTL constructs a Gene Tree (GT) that records the evolutionary lineage of selected learngenes (Figure 3g). Each node in GT represents a superior learngene, with root nodes originating from the initial generation. New entries in GP are appended as leaf nodes, and the path length between nodes encodes their degree of kinship.

(4) Updating Learngene Scores. To preserve ancestral excellence and guide future evolution, the scores of learngenes in the GP are updated after each generation. For every selected learngene $\mathcal{G}_i^\star$ with score $s_i^\star$, its kinship is traced back from its corresponding leaf node to the root according to GT. Each ancestral learngene $\mathcal{G}_{\text{anc}}$ along this path receives a score update:

$$s_{\text{anc}} \leftarrow s_{\text{anc}} + \eta^\tau s_i^\star \tag{6}$$

where η is the decay coefficient and τ is the path length. See Algorithm 3 for more details.

(5) Generating the Next Generation of Learngenes. After refreshing the GP and updating learngene scores, the next generation of learngenes is sampled from the GP according to a score-proportional probability:

$$p_i = \frac{s_i^\diamond}{\sum_{i=1}^{\rho} s_i^\diamond} \tag{7}$$

where p_i is the probability of selecting $\mathcal{G}_i^\diamond$ as a parent based on its score $s_i^\diamond$ (Figure3i).

The selected learngenes are then inherited by a new population of networks $\mathcal{P}$ (see Figure 3j and Section 3.2.3), initiating the next cycle of evolution.

4 Experiments

Datasets. We conduct evolutionary experiments on three datasets of increasing scale. CIFAR-FS [2] and *mini*ImageNet [64] each contain 100 classes, split into 64 for training ($\mathcal{D}_{\text{train}}$), 16 for validation ($\mathcal{D}_{\text{val}}$), and 20 for novel evaluation. ImageNet-1K [10] contains 1,000 classes, divided into 640, 160, and 200 for the same purposes. We further evaluate the extracted learngenes on four downstream datasets: Oxford Flowers [46], CUB-200-2011 [66], Stanford Cars [15], and Food-101 [4].

Network Architectures. We evaluate four representative convolutional architectures: VGG11 [52], ResNet12 [20], ResNet50 [20], and MobileNetV3-Large [21]. To assess the scalability and adaptability of learngenes in initializing models of varying capacity, we additionally evaluate width-adjusted variants of ResNet50 and MobileNetV3-Large, with widths scaled from $0.5W$ to $0.9W$, where W denotes the original width.

Training Details. Evolutionary training is conducted independently across networks to support parallelism. For VGG11 and ResNet12, learngenes evolve over 250 generations, each comprising 20 networks trained for 15 epochs. For MobileNetV3-Large and ResNet50, evolution proceeds for 100 generations, with 6 networks per generation trained for 5 epochs. All experiments are executed on NVIDIA GeForce RTX 4090 GPUs, with total computational cost comparable to training a typical medium-scale model. Full hyperparameter configurations are detailed in Appendix C.1.

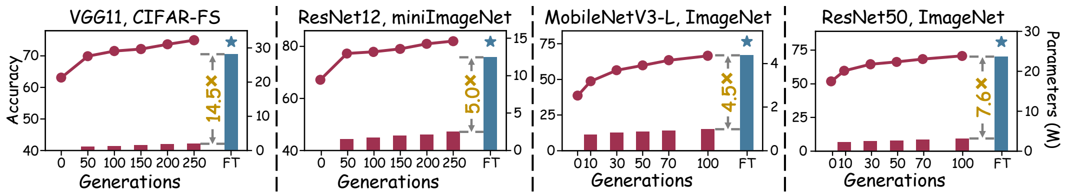


Figure 4: Accuracy (red curves) of networks on validation classes and parameter (red bars) of corresponding learngenes during evolution. Blue stars and bars represent performance and parameter transfer via direct fine-tuning. Notably, models inheriting learngenes achieve comparable or superior results, especially in smaller networks, with a significant reduction in transferred parameters.

5 Results

5.1 Evolutionary Performance of Learngenes Extracted by ECO

In biological evolution, beneficial mutations accumulate through natural selection, leading to the progressive refinement of genes [24, 28]. Similarly, ECO evolves learngenes by gradually refining core knowledge across generations.

As shown in Figure 4, learngenes accumulate dominant mutations, reflected in the steady growth of their parameter counts. Consequently, networks initialized with evolved learngenes demonstrate consistently improved performance over time. Notably, ECO significantly outperforms models trained from scratch, achieving performance comparable to pre-trained models while transferring significantly fewer parameters (14.5× reduction in VGG11).

Table 1 provides a quantitative comparison across generations against baseline methods. Taking ResNet12 on *mini*ImageNet as an illustrative example, early-generation learngenes already outperform direct initialization approaches (e.g., GradInit [85]) and hypernetwork-based methods (e.g., GHN-3 [30]), benefiting from inherited transferable knowledge. At mid-generation, ECO surpasses advanced transfer methods such as Heur-LG [68] and Auto-LG [70], transferring 4.8× fewer parameters—highlighting its advantage in preserving convolutional feature hierarchies.

In later stages, ECO achieves a 2.6 performance gain over re-initialization methods like KE [59], while reducing training time by 3×. Compared to pre-training-based approaches (e.g., Weight Selection [80]), ECO reduces parameter transfer over 5.0×, with performance gains of 3.85, demonstrating both efficiency and the superior transferability of its core knowledge.

Table 1: Performance of networks inheriting learngenes on validation and novelty classes across various datasets. Para.(M) represents the number of transferred parameters. N/A denotes that the criterion is not applicable to the respective method.

	VGG, 28.18M			ResNet12, 12.44M		
Dataset	CIFAR FS			*mini*ImageNet		
Methods	Para.	Valid	Novel	Para.	Valid	Novel
He-Init [19]	0	63.13	66.05	0	67.19	65.55
GradInit [85]	N/A	65.19	66.80	N/A	67.75	68.90
ECO-10th	0.83	**65.44**	**67.75**	1.17	**73.31**	**72.80**
GHN-2 [29]	N/A	59.63	62.10	N/A	68.56	66.05
GHN-3 [30]	N/A	57.56	61.45	N/A	77.56	77.55
ECO-50th	1.08	69.94	71.70	1.47	77.25	77.45
ECO-100th	1.30	**71.56**	**73.25**	1.71	**77.88**	**78.15**
Heur-LG [68]	7.09	65.25	68.35	9.43	70.75	69.45
Auto-LG [70]	9.19	68.00	71.15	9.51	75.25	75.55
ECO-150th	1.51	**72.19**	**74.50**	1.96	**79.00**	**78.90**
KE$_{N_3}$ [59]	N/A	69.81	74.10	N/A	75.94	77.60
ECO-200th	1.81	**73.69**	**76.30**	2.09	**80.94**	**80.20**
Wt Select [80]	28.09	63.31	65.75	12.41	76.81	77.75
ECO-250th	1.94	**75.00**	**76.95**	2.47	**82.00**	**81.60**
	Mobile-L, 4.37M			ResNet50, 23.66M		
Dataset	ImageNet			ImageNet		
Methods	Para.	Valid	Novel	Para.	Valid	Novel
He-Init [19]	0	38.54	38.70	0	51.85	53.48
GradInit [85]	N/A	41.86	41.13	N/A	52.06	51.94
ECO-10th	0.74	**48.66**	**49.21**	2.22	**59.70**	**60.05**
GHN-2 [29]	N/A	31.93	30.72	N/A	47.30	46.27
GHN-3 [30]	N/A	37.28	37.18	N/A	54.13	52.89
ECO-30th	0.82	**56.41**	**55.28**	2.47	**64.54**	**64.99**
Heur-LG [68]	1.76	43.55	43.07	14.99	52.89	54.54
Auto-LG [70]	1.77	50.76	50.13	15.21	55.10	55.60
ECO-50th	0.86	**59.81**	**58.60**	2.63	**66.29**	**66.32**
KE$_{N_3}$ [59]	N/A	54.58	54.52	N/A	65.93	67.02
ECO-70th	0.92	**63.39**	**62.08**	2.82	**68.35**	**67.92**
Wt Select [80]	2.94	56.03	55.84	23.45	69.91	69.29
ECO-100th	0.98	**66.50**	**65.22**	3.13	**70.73**	**69.91**

5.2 Performance of ECO in Initializing Models of Variable Sizes

Neural networks deployed in diverse hardware environments often require models of varying sizes due to differing computational and storage constraints, but pre-trained models are typically fixed in size, making it impractical to have one for every possible configuration.

ECO addresses this challenge through scalable and size-agnostic learngenes, enabling efficient initialization of networks with variable sizes. As shown in Table 2, ECO consistently achieves superior accuracy across variable-sized models, significantly outperforming existing transfer methods.

Compared to direct pre-training (i.e., Direct PT), ECO reduces training time by at least 2×, while transferring up to 2.5× and 3.7× fewer parameters than Weight Selection [80], highlighting its transfer efficiency. Moreover, ECO achieves a 3× reduction in FLOPs relative to STKD [57]. Unlike distillation-based approaches whose computational cost scales linearly with the number of target models ($O(n)$), ECO directly initializes each model independently with no additional training overhead, enabling scalable deployment across diverse resource constraints.

Table 2: Performance of ECO and other methods for variable-sized model initialization. “Com.” refers to the complexity of initializing n models, while “Time”, “Para.(M)”, and “FLOPs(G)” represent training time, transferred parameters, and computational overhead, respectively. N/A denotes that the criterion is not applicable to the respective method.

			MobileNetV3-Large, 5.04M, ImageNet, Train														
			0.70W			0.75W			0.80W			0.85W			0.90W		
Methods	Com.	Time	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.
He-Init [19]	O(1)	1.0×	0	0.75	32.71	0	0.87	34.48	0	0.92	34.54	0	1.04	36.13	0	1.15	37.07
GradInit [85]	O(n)	1.0×	N/A	0.75	37.07	N/A	0.87	38.26	N/A	0.92	35.68	N/A	1.04	40.01	N/A	1.15	40.58
Direct PT	O(n)	2.0×	0	0.75	42.35	0	0.87	44.61	0	0.92	44.52	0	1.04	46.54	0	1.15	47.97
Wt Select [80]	O(1)	1.0×	1.48	0.75	42.87	1.70	0.87	44.83	1.90	0.92	45.30	2.16	1.04	46.88	2.41	1.15	47.85
STKD [57]	O(n)	1.0×	N/A	2.14	46.03	N/A	2.40	46.78	N/A	2.51	45.13	N/A	2.78	47.66	N/A	3.02	48.08
ECO	O(1)	1.0×	0.98	0.75	**46.07**	0.98	0.87	**48.09**	0.98	0.92	**48.15**	0.98	1.04	**48.73**	0.98	1.15	**49.13**
			ResNet50, 24.87M, ImageNet, Train														
			0.50W			0.55W			0.60W			0.65W			0.70W		
Methods	Com.	Time	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.	Para.	FLOPs	Acc.
He-Init [19]	O(1)	1.0×	0	6.82	39.26	0	8.00	41.32	0	9.33	42.68	0	10.84	44.31	0	12.40	45.68
GradInit [85]	O(n)	1.0×	N/A	6.82	37.28	N/A	8.00	39.28	N/A	9.33	41.09	N/A	10.84	42.68	N/A	12.40	43.97
Direct PT	O(n)	2.0×	0	6.82	49.85	0	8.00	51.66	0	9.33	53.59	0	10.84	54.54	0	12.40	55.89
Wt Select [80]	O(1)	1.0×	5.88	6.82	49.97	7.06	8.00	51.21	8.41	9.33	52.86	9.87	10.84	54.23	11.46	12.40	55.89
STKD [57]	O(n)	1.0×	N/A	23.16	51.86	N/A	25.78	53.00	N/A	28.76	52.91	N/A	32.09	52.99	N/A	35.58	54.39
ECO	O(1)	1.0×	3.13	6.82	**52.23**	3.13	8.00	**53.12**	3.13	9.33	**53.79**	3.13	10.84	**54.88**	3.13	12.40	**55.93**

Table 3: Performance of ECO and other methods when transferring to downstream datasets. “Para.” refers to the transferred parameters, with total parameters and FLOPs recorded for various architectures. N/A denotes that the criterion is not applicable to the respective method.

Methods	Para.	Flower	CUB	Cars	Food	*Aver.*	Para.	Flower	CUB	Cars	Food	*Aver.*
	VGG11, FLOPs=45.14G, Para=28.72M						**ResNet12, FLOPs=154.04G, Para=12.52M**					
He-Init [19]	0	34.22	49.81	60.94	78.67	*55.91*	0	50.74	46.89	61.27	81.10	*60.00*
GradInit [85]	N/A	36.38	49.36	66.86	78.07	*57.67*	N/A	50.92	55.61	72.45	81.39	*65.09*
GHN-2 [29]	N/A	46.32	49.05	68.18	67.57	*57.78*	N/A	54.92	49.36	59.21	74.10	*59.40*
GHN-3 [30]	N/A	44.09	50.55	69.39	66.49	*57.63*	N/A	61.33	56.06	71.30	75.28	*65.99*
Heur-LG [68]	7.09	38.84	55.54	71.67	78.65	*61.18*	9.43	54.69	55.68	76.37	81.93	*67.17*
Auto-LG [70]	9.19	50.64	58.54	74.93	78.60	*65.68*	9.51	61.90	58.99	81.68	82.15	*71.18*
Wt Select [80]	28.09	62.87	60.08	76.21	78.26	*69.36*	12.41	55.26	57.92	77.74	81.68	*68.15*
ECO	1.94	**64.42**	**60.20**	**78.12**	**79.47**	***70.55***	2.47	**81.48**	**64.14**	**84.28**	**82.41**	***78.08***
	MobileNetV3-Large, FLOPs=1.33G, Para=4.39M						**ResNet50, FLOPs=24.62G, Para=23.81M**					
He-Init [8]	0	51.05	56.08	74.88	74.81	*64.21*	0	27.53	46.34	46.96	73.66	*48.62*
GradInit [85]	N/A	56.38	56.33	71.67	54.49	*59.72*	N/A	46.09	48.15	53.84	75.48	*55.89*
GHN-2 [29]	N/A	46.07	47.53	56.96	66.35	*54.23*	N/A	61.68	55.66	66.91	66.79	*62.76*
GHN-3 [30]	N/A	42.75	45.06	54.40	58.54	*50.19*	N/A	49.18	52.69	71.58	71.26	*61.18*
Heur-LG [68]	1.76	56.12	58.23	75.43	74.31	*66.02*	14.99	53.78	54.95	67.08	72.83	*62.16*
Auto-LG [70]	1.77	56.77	59.15	77.98	74.69	*67.15*	15.21	55.42	57.11	71.14	73.28	*64.24*
Wt Select [80]	2.94	61.81	61.56	79.17	74.77	*69.33*	23.45	57.16	52.42	62.58	75.54	*61.93*
ECO	0.98	**64.45**	**62.17**	**79.90**	**75.04**	***70.39***	3.13	**77.02**	**65.12**	**82.61**	**76.13**	***75.22***

5.3 Performance of ECO on Downstream Tasks

The core knowledge encapsulated in learngenes exhibits strong generalizability, enabling effective transfer across a wide range of downstream tasks. As shown in Table 3, ECO consistently outperforms baseline methods, confirming its robust adaptability and transfer efficiency.

Hypernetwork-based approaches (e.g., GHN-2 [29], GHN-3 [30]) achieve competitive results on small datasets but often underperform on larger ones due to their coarse architecture-level parameter modeling. Methods like Heur-LG [68] and Auto-LG [70] transfer pre-trained knowledge layer-wise, but this localized mapping can disrupt global feature hierarchies, especially in compact architectures. Notably, Auto-LG lags behind ECO by 4.87 on average with VGG11, despite transferring 4.7× more parameters, reflecting inefficiencies in knowledge utilization.

Pre-trained model-based approaches offer extensive knowledge transfer, but their reliance on task-agnostic optimization can lead to suboptimal adaptation. On Food-101 with VGG11, Weight Selection achieves 78.26, in contrast to ECO’s 79.47, highlighting the need for more targeted transfer mechanisms. These results underscore ECO’s ability to retain and apply transferable core knowledge more efficiently, offering a scalable and task-adaptive solution for downstream model initialization.

Table 4: Accuracy of few-shot classification. “-N” indicates narrower networks than normal ones.

	CIFAR-FS, VGG11			*mini*Imagenet, ResNet12		
Methods	5-shot	10-shot	20-shot	5-shot	10-shot	20-shot
MAML[14]	63.4±0.86	68.2±0.74	70.5±0.77	61.1±0.78	66.4±0.68	68.4±0.62
RelationNet[58]	64.2±0.79	68.9±0.71	72.9±0.71	65.4±0.69	70.3±0.66	72.9±0.63
MatchingNet[64]	59.9±0.78	63.8±0.78	69.3±0.81	66.3±0.66	70.9±0.63	74.7±0.59
ProtoNet[54]	65.9±0.85	69.3±0.79	73.1±0.69	66.5±0.71	72.4±0.60	74.9±0.59
Baseline++[7]	64.9±0.78	71.3±0.73	75.3±0.67	67.5±0.67	74.0±0.60	78.2±0.51
ECO	69.9±0.78*	75.5±0.69*	78.5±0.63*	69.4±0.71*	75.4±0.61*	80.2±0.52*
ECO$_{\text{-N}}$	**70.5±0.73**	**76.6±0.65**	**80.5±0.58**	**71.3±0.70**	**76.8±0.59**	**81.7±0.53**

Table 5: Ablation study results across various architectures.

	VGG11		ResNet12		MobileNetV3-L		ResNet50	
Methods	Valid	Novel	Valid	Novel	Valid	Novel	Valid	Novel
He Init [19]	63.13	66.05	67.19	65.55	38.54	38.70	51.85	53.48
Direct Select	70.06	72.30	77.50	76.85	52.46	52.14	60.63	61.23
w/o Tournament & GP	72.31	74.55	80.94	80.25	62.06	60.79	65.79	65.97
w/o Mutation	72.25	73.25	80.88	79.80	63.08	62.11	69.00	68.72
ECO	**75.00**	**76.95**	**82.00**	**81.60**	**66.50**	**65.22**	**70.73**	**69.91**

5.4 Improved Data Efficiency of ECO

Models initialized with learngenes demonstrate strong data efficiency, particularly in few-shot learning scenarios. As shown in Table 4, ECO consistently outperforms conventional few-shot learning methods, including those built upon fully pre-trained models such as Baseline++ [7], underscoring the effectiveness of core knowledge encapsulated in learngenes under limited data conditions.

Notably, a narrower variant (“-N”), initialized with the same learngenes, achieves even higher accuracy. This can be attributed to reduced parameter redundancy and stochasticity, indicating that learngenes in ECO not only encapsulate transferable representations but also enable more stable and efficient adaptation under both architectural and data constraints, thereby reinforcing its practicality and robustness in real-world, resource-constrained scenarios.

5.5 Ablation and Analysis

5.5.1 Effects of Mutation

Mutations are essential to the selection and refinement of core knowledge, as they dynamically reshape the structure and semantics of learngenes. By introducing controlled variations, mutations promote population diversity and enhance the effectiveness of tournament-based selection.

As illustrated in Figure 5, learngenes within ResNet12 undergo continual structural evolution, progressively condensing transferable knowledge while eliminating redundant components, facilitating the emergence of more generalizable representations. Thus, the absence of mutation leads to static learngene structures, which constrain learngene diversity and hinder knowledge accumulation, as demonstrated in Table 5.

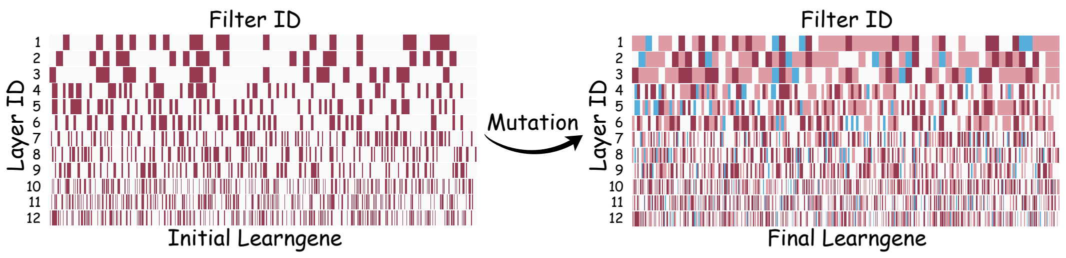


Figure 5: Visualization of learngenes in ResNet12 pre- and post-evolution. 🟥 is the filter of the initial learngenes. ▨ is the filter that becomes a new part of learngene through mutation. 🟦 indicates redundant filters removed during the evolution.

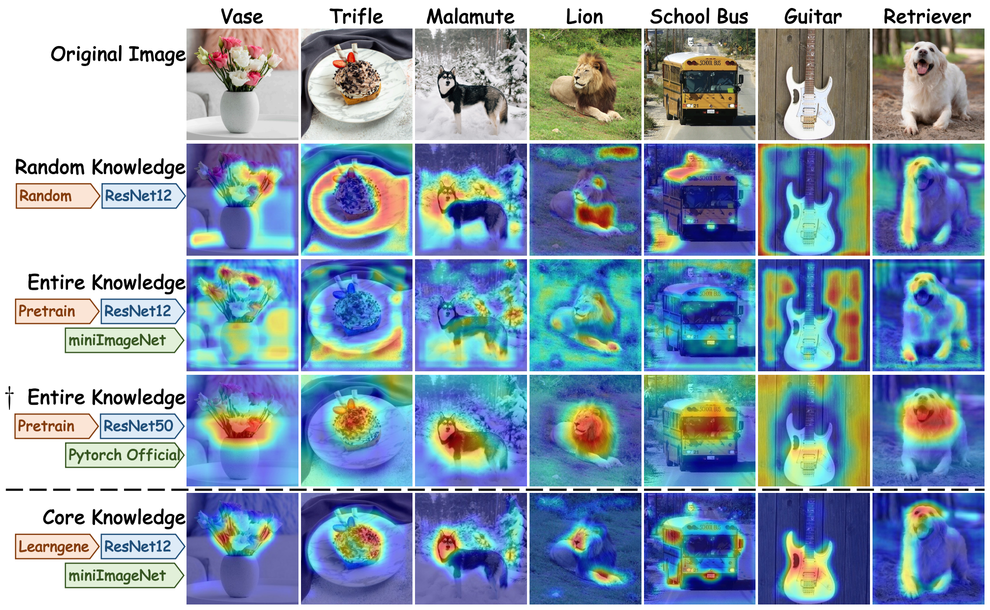


Figure 6: Visualization of core knowledge in learngenes. Networks have not undergone any learning or fine-tuning. † ResNet50 (pre-trained on ImageNet) already contains these classes.

5.5.2 Effects of Evolution

ECO leverages evolution to extract and refine core knowledge, enhancing transferability across model sizes and tasks. In contrast, traditional pre-trained models are optimized for specific objectives and lack mechanisms for isolating generalizable components. As a result, methods that directly extract fragments from such models (i.e., Direct Select) fail to capture broadly applicable knowledge, as shown in Table 5.

Tournament selection plays a critical role in identifying high-quality learngenes for preservation in the Gene Pool (GP), thereby facilitating the accumulation and iterative refinement of transferable core knowledge across generations. As evidenced in Table 5, the removal of tournament selection and GP (i.e., w/o Tournament & GP) disrupts this process, resulting in the retention of redundant or suboptimal knowledge and weakening the influence of superior candidates across generations.

5.6 Visualization of Core Knowledge in Learngenes

To illustrate the core knowledge encapsulated in learngenes, we visualize model attention using CAM [51] on sample images from novel classes in *mini*ImageNet, which are not involved during learngene evolution.

As shown in Figure 6, randomly initialized models tend to focus on diffuse or irrelevant regions, while pre-trained models, though more focused, often highlight background areas. For instance, pre-trained ResNet12 fails to localize novel objects, and ResNet50, despite identifying relevant regions, exhibits background activation that may introduce bias (see Figure 1a).

In contrast, models initialized with learngenes produce compact, focused attention maps, concentrating on semantically meaningful and discriminative regions, even to unseen categories.

6 Conclusion

Inspired by biological knowledge transfer, we propose ECO, a method that condenses core knowledge into learngenes for efficient transfer across models. Built upon the Genetic Transfer Learning (GTL) framework, ECO enables the evolution of neural networks and the inheritance of learngenes in supervised tasks. Experiments show that learngenes impart strong learning capabilities, while ensuring scalability and adaptability across model sizes and tasks, providing an efficient and generalizable alternative for knowledge transfer through the inheritance of core knowledge.

Acknowledgement

We sincerely appreciate Freepik for contributing to the figure design. This research was supported by the Jiangsu Science Foundation (BG2024036, BK20243012), the National Natural Science Foundation of China (62125602, U24A20324, 92464301, 62306073), China Postdoctoral Science Foundation (2022M720028, 2025T180432), the Xplorer Prize, the Fundamental Research Funds for the Central Universities (2242025K30024), and SEU Innovation Capability Enhancement Plan for Doctoral Students (CXJH_SEU 26023).

References

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

[2] Luca Bertinetto, Joao F. Henriques, Philip Torr, and Andrea Vedaldi. Meta-learning with differentiable closed-form solvers. In *Proceedings of the International Conference on Learning Representations (ICLR'19)*, pages 1–13, 2019.

[3] Johannes Bohacek and Isabelle M Mansuy. Molecular insights into transgenerational non-genetic inheritance of acquired behaviours. *Nature Reviews Genetics*, 16(11):641–652, 2015.

[4] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101–mining discriminative components with random forests. In *Proceedings of European Conference on Computer Vision (ECCV'14)*, pages 446–461, 2014.

[5] Shuvam Chakraborty, Burak Uzkent, Kumar Ayush, Kumar Tanmay, Evan Sheehan, and Stefano Ermon. Efficient conditional pre-training for transfer learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'22)*, pages 4241–4250, 2022.

[6] Tianlong Chen, Sijia Liu, Shiyu Chang, Yu Cheng, Lisa Amini, and Zhangyang Wang. Adversarial robustness: From self-supervised pre-training to fine-tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'20)*, pages 699–708, 2020.

[7] Wei-Yu Chen, Yen-Cheng Liu, Zsolt Kira, Yu-Chiang Frank Wang, and Jia-Bin Huang. A closer look at few-shot classification. In *Proceedings of the International Conference on Learning Representations (ICLR'19)*, pages 1–12, 2019.

[8] Xinlei Chen, Saining Xie, and Kaiming He. An empirical study of training self-supervised vision transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV'21)*, pages 9640–9649, 2021.

[9] Ashraf Darwish, Aboul Ella Hassanien, and Swagatam Das. A survey of swarm and evolutionary computing approaches for deep learning. *Artificial Intelligence Review*, 53(3):1767–1812, 2020.

[10] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV'09)*, pages 248–255, 2009.

[11] Fu Feng, Jing Wang, Xu Yang, and Xin Geng. Learngene: Inheritable "genes" in intelligent agents. *Artificial Intelligence*, page 104421, 2025.

[12] Fu Feng, Yucheng Xie, Jing Wang, and Xin Geng. Wave: Weight template for adaptive initialization of variable-sized models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'25)*, pages 4819–4828, 2025.

[13] Fu Feng, Yucheng Xie, Xu Yang, Jing Wang, and Xin Geng. Redefining <creative> in dictionary: Towards an enhanced semantic understanding of creative generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'25)*, pages 18444–18454, 2025.

[14] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of International Conference on Machine Learning (ICML'17)*, pages 1126–1135, 2017.

[15] Timnit Gebru, Jonathan Krause, Yilun Wang, Duyun Chen, Jia Deng, and Li Fei-Fei. Fine-grained car detection for visual census estimation. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI'17)*, pages 4502–4508, 2017.

[16] Yuxian Gu, Li Dong, Furu Wei, and Minlie Huang. Minillm: Knowledge distillation of large language models. In *Proceedings of the International Conference on Learning Representations (ICLR'24)*, 2024.

[17] Soufiane Hayou, Nikhil Ghosh, and Bin Yu. Lora+: Efficient low rank adaptation of large models. In *Proceedings of the International Conference on Machine Learning (ICML'24)*, 2024.

[18] Kaiming He, Ross Girshick, and Piotr Dollár. Rethinking imagenet pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'19)*, pages 4918–4927, 2019.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'15)*, pages 1026–1034, 2015.

[20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'16)*, pages 770–778, 2016.

[21] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for mobilenetv3. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'19)*, pages 1314–1324, 2019.

[22] Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. In *Proceedings of the International Conference on Learning Representations (ICLR'22)*, 2022.

[23] Mohammadreza Iman, Hamid Reza Arabnia, and Khaled Rasheed. A review of deep transfer learning and recent advancements. *Technologies*, 11(2):40, 2023.

[24] Eva Jablonka, Marion J Lamb, and Eytan Avital. 'Lamarckian' mechanisms in Darwinian evolution. *Trends in Ecology & Evolution*, 13(5):206–210, 1998.

[25] Khurram Javed and Martha White. Meta-learning representations for continual learning. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'19)*, pages 1–11, 2019.

[26] Marc TJ Johnson and Jason Munshi-South. Evolution of life in urban environments. *Science*, 358(6363):eaam8327, 2017.

[27] Motoo Kimura. The neutral theory of molecular evolution. *Scientific American*, 241(5):98–129, 1979.

[28] Motoo Kimura. *The neutral theory of molecular evolution*. Cambridge University Press, 1983.

[29] Boris Knyazev, Michal Drozdzal, Graham W Taylor, and Adriana Romero Soriano. Parameter prediction for unseen deep architectures. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'21)*, pages 29433–29448, 2021.

[30] Boris Knyazev, Doha Hwang, and Simon Lacoste-Julien. Can we scale transformers to predict parameters of diverse imagenet models? In *Proceedings of International Conference on Machine Learning (ICML'23)*, pages 17243–17259, 2023.

[31] Zhiqiang Kou, Si Qin, Hailin Wang, Mingkun Xie, Shuo Chen, Yuheng Jia, Tongliang Liu, Masashi Sugiyama, and Xin Geng. Label distribution learning with biased annotations by learning multi-label representation. In *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI'25)*, pages 5545–5553, 2025.

[32] Zhiqiang Kou, Jing Wang, Yuheng Jia, and Xin Geng. Inaccurate label distribution learning. *IEEE Transactions on Circuits and Systems for Video Technology*, 34(10):10237–10249, 2024.

[33] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations. In *Proceedings of the International Conference on Learning Representations (ICLR'20)*, pages 1–14, 2020.

[34] Shiyu Li, Edward Hanson, Hai Li, and Yiran Chen. Penni: Pruned kernel sharing for efficient cnn inference. In *Proceedings of International Conference on Machine Learning (ICML'20)*, pages 5863–5873, 2020.

[35] Suichan Li, Dongdong Chen, Yinpeng Chen, Lu Yuan, Lei Zhang, Qi Chu, Bin Liu, and Nenghai Yu. Improve unsupervised pretraining for few-label transfer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'21)*, pages 10201–10210, 2021.

[36] Mingbao Lin, Bohong Chen, Fei Chao, and Rongrong Ji. Training compact cnns for image classification using dynamic-coded filter fusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(8):10478–10487, 2023.

[37] Shuxia Lin, Miaosen Zhang, Ruiming Chen, Xu Yang, Qiufeng Wang, and Xin Geng. Linearly decomposing and recomposing vision transformers for diverse-scale models. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'24)*, 2024.

[38] Lin Liu, Lingxi Xie, Xiaopeng Zhang, Shanxin Yuan, Xiangyu Chen, Wengang Zhou, Houqiang Li, and Qi Tian. Tape: Task-agnostic prior embedding for image restoration. In *Proceedings of European Conference on Computer Vision (ECCV'22)*, pages 447–464, 2022.

[39] Yen-Cheng Liu, Chih-Yao Ma, Junjiao Tian, Zijian He, and Zsolt Kira. Polyhistor: Parameter-efficient multi-task adaptation for dense vision tasks. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'22)*, pages 36889–36901, 2022.

[40] Yuqiao Liu, Yanan Sun, Bing Xue, Mengjie Zhang, Gary G Yen, and Kay Chen Tan. A survey on evolutionary neural architecture search. *IEEE Transactions on Neural Networks and Learning Systems*, 34(2):550–570, 2021.

[41] Luis López-Maury, Samuel Marguerat, and Jürg Bähler. Tuning gene expression to changing environments: from rapid responses to evolutionary adaptation. *Nature Reviews Genetics*, 9(8):583–593, 2008.

[42] Liqun Luo. Architectures of neuronal circuits. *Science*, 373(6559):eabg7285, 2021.

[43] Seyedali Mirjalili. Genetic algorithm. In *Evolutionary Algorithms and Neural Networks: Theory and Applications*, pages 43–55, 2019.

[44] Seyedali Mirjalili, Jin Song Dong, Ali Safa Sadiq, and Hossam Faris. Genetic algorithm: Theory, literature review, and application in image reconstruction. pages 69–85, 2020.

[45] Vidyanand Mishra and Lalit Kane. A survey of designing convolutional neural network using evolutionary algorithms. *Artificial Intelligence Review*, 56(6):5095–5132, 2023.

[46] Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *Proceedings of Indian Conference on Computer Vision, Graphics & Image Processing*, pages 722–729, 2008.

[47] Kwanyoung Park, Junseok Park, Hyunseok Oh, Byoung-Tak Zhang, and Youngki Lee. Learning task-agnostic representation via toddler-inspired learning. In *Proceedings of NIPS 2005 Workshop BabyMind*, 2021.

[48] Jathushan Rajasegaran, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan, and Mubarak Shah. itaml: An incremental task-agnostic meta-learning approach. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'20)*, pages 13588–13597, 2020.

[49] Hui Ren, Joanna Materzynska, Rohit Gandikota, David Bau, and Antonio Torralba. Art-free generative models: Art creation without graphic art knowledge. *arXiv preprint arXiv:2412.00176*, 2024.

[50] Michael T Rosenstein, Zvika Marx, Leslie Pack Kaelbling, and Thomas G Dietterich. To transfer or not to transfer. In *Proceedings of NIPS 2005 Workshop on Transfer Learning (NIPSW'05)*, pages 1–4, 2005.

[51] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of International Conference on Machine Learning (ICML'17)*, pages 618–626, 2017.

[52] K Simonyan and A Zisserman. Very deep convolutional networks for large-scale image recognition. In *Proceedings of the International Conference on Learning Representations (ICLR'15)*, 2015.

[53] SN Sivanandam, SN Deepa, SN Sivanandam, and SN Deepa. *Genetic algorithms*. Springer, 2008.

[54] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'17)*, pages 4077–4087, 2017.

[55] Kenneth O Stanley, David B D'Ambrosio, and Jason Gauci. A hypercube-based encoding for evolving large-scale neural networks. *Artificial Life*, 15(2):185–212, 2009.

[56] Kenneth O Stanley and Risto Miikkulainen. Evolving neural networks through augmenting topologies. *Evolutionary Computation*, 10(2):99–127, 2002.

[57] Tongtong Su, Jinsong Zhang, Zhaoyang Yu, Gang Wang, and Xiaoguang Liu. Stkd: Distilling knowledge from synchronous teaching for efficient model compression. *IEEE Transactions on Neural Networks and Learning Systems*, 34(12):10051–10064, 2023.

[58] Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip HS Torr, and Timothy M Hospedales. Learning to compare: Relation network for few-shot learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'18)*, pages 1199–1208, 2018.

[59] Ahmed Taha, Abhinav Shrivastava, and Larry S Davis. Knowledge evolution in neural networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'21)*, pages 12843–12852, 2021.

[60] Akbar Telikani, Amirhessam Tahmassebi, Wolfgang Banzhaf, and Amir H Gandomi. Evolutionary machine learning: A survey. *ACM Computing Surveys*, 54(8):1–35, 2021.

[61] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

[62] Eleni Triantafillou, Hugo Larochelle, Richard Zemel, and Vincent Dumoulin. Learning a universal template for few-shot dataset generalization. In *Proceedings of International Conference on Machine Learning (ICML'21)*, pages 10424–10433, 2021.

[63] Hamit Taner Ünal and Fatih Başçiftçi. Evolutionary design of neural network architectures: a review of three decades of research. *Artificial Intelligence Review*, 55(3):1723–1802, 2022.

[64] Oriol Vinyals, Charles Blundell, Timothy Lillicrap, Daan Wierstra, et al. Matching networks for one shot learning. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'16)*, pages 3630—-3638, 2016.

[65] Conrad H Waddington. Canalization of development and the inheritance of acquired characters. *Nature*, 150(3811):563–565, 1942.

[66] C. Wah, S. Branson, P. Welinder, P. Perona, and S. Belongie. The caltech-ucsd birds-200-2011 dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011.

[67] Can Wang, Defang Chen, Jian-Ping Mei, Yuan Zhang, Yan Feng, and Chun Chen. Semckd: Semantic calibration for cross-layer knowledge distillation. *IEEE Transactions on Knowledge and Data Engineering*, 35(6):6305–6319, 2023.

[68] Qiu-Feng Wang, Xin Geng, Shu-Xia Lin, Shi-Yu Xia, Lei Qi, and Ning Xu. Learngene: From open-world to your learning task. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI'22)*, pages 8557–8565, 2022.

[69] Qiufeng Wang, Xu Yang, Fu Feng, Jing Wang, and Xin Geng. Cluster-learngene: Inheriting adaptive clusters for vision transformers. *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'24)*, 37:26308–26330, 2024.

[70] Qiufeng Wang, Xu Yang, Shuxia Lin, Jing Wang, and Xin Geng. Learngene: Inheriting condensed knowledge from the ancestry model to descendant models. *arXiv preprint arXiv:2305.02279*, 2023.

[71] Xudong Wang and X Yu Stella. Tied block convolution: Leaner and better cnns with shared thinner filters. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI'21)*, pages 10227–10235, 2021.

[72] Yunhe Wang, Chang Xu, Chunjing Xu, Chao Xu, and Dacheng Tao. Learning versatile filters for efficient convolutional neural networks. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'18)*, pages 1–11, 2018.

[73] Zirui Wang, Zihang Dai, Barnabás Póczos, and Jaime Carbonell. Characterizing and avoiding negative transfer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'19)*, pages 11293–11302, 2019.

[74] Dongyu Wei, Vaishali Talwar, and Dayu Lin. Neural circuits of social behaviors: innate yet flexible. *Neuron*, 109(10):1600–1620, 2021.

[75] Shiyu Xia, Miaosen Zhang, Xu Yang, Ruiming Chen, Haokun Chen, and Xin Geng. Transformer as linear expansion of learngene. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI'24)*, pages 16014–16022, 2024.

[76] Guotian Xie, Kuiyuan Yang, and Jianhuang Lai. Filter-in-filter: low cost cnn improvement by sub-filter parameter sharing. *Pattern Recognition*, 91:391–403, 2019.

[77] Yucheng Xie, Fu Feng, Ruixiao Shi, Jing Wang, and Xin Geng. Fine: Factorizing knowledge for initialization of variable-sized diffusion models. *arXiv preprint arXiv:2409.19289*, 2024.

[78] Yucheng Xie, Fu Feng, Ruixiao Shi, Jing Wang, Yong Rui, and Xin Geng. Divcontrol: Knowledge diversion for controllable image generation. *arXiv preprint arXiv:2507.23620*, 2025.

[79] Yucheng Xie, Fu Feng, Jing Wang, Yong Rui, and Xin Geng. Kind: Knowledge integration and diversion in diffusion models. In *Proceedings of the International Conference on Machine Learning (ICML'25)*, 2025.

[80] Zhiqiu Xu, Yanjie Chen, Kirill Vishniakov, Yida Yin, Zhiqiang Shen, Trevor Darrell, Lingjie Liu, and Zhuang Liu. Initializing models with larger ones. In *Proceedings of the International Conference on Learning Representations (ICLR'24)*, pages 1–13, 2024.

[81] Yingzhen Yang, Jiahui Yu, Nebojsa Jojic, Jun Huan, and Thomas S Huang. Fsnet: Compression of deep convolutional neural networks by filter summary. In *Proceedings of the International Conference on Learning Representations (ICLR'20)*, pages 1–10, 2020.

[82] Anthony M Zador. A critique of pure learning and what artificial neural networks can learn from animal brains. *Nature Communications*, 10(1):3770, 2019.

[83] Jinnian Zhang, Houwen Peng, Kan Wu, Mengchen Liu, Bin Xiao, Jianlong Fu, and Lu Yuan. Minivit: Compressing vision transformers with weight multiplexing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'22)*, pages 12145–12154, 2022.

[84] Xun Zhou, A Kai Qin, Maoguo Gong, and Kay Chen Tan. A survey on evolutionary construction of deep neural networks. *IEEE Transactions on Evolutionary Computation*, 25(5):894–912, 2021.

[85] Chen Zhu, Renkun Ni, Zheng Xu, Kezhi Kong, W Ronny Huang, and Tom Goldstein. Gradinit: Learning to initialize neural networks for stable and efficient training. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'21)*, pages 16410–16422, 2021.

[86] Fuzhen Zhuang, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Hui Xiong, and Qing He. A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43–76, 2020.

[87] Barret Zoph, Golnaz Ghiasi, Tsung-Yi Lin, Yin Cui, Hanxiao Liu, Ekin Dogus Cubuk, and Quoc Le. Rethinking pre-training and self-training. In *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS'20)*, pages 3833–3845, 2020.

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: Please refer to the Introduction (Section 1), which clearly states the paper's contributions and scope.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: Please see Appendix E.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate "Limitations" section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [NA]

Justification: The paper does not include theoretical results.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

   Answer: [Yes]

   Justification: Please see Section 4 and Appendix C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
   - If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
   - Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
   - While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
     (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
     (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
     (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
     (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: The datasets used in the paper are all public datasets, which are described in the Section 4 and Appendix C.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: We provide experimental setting and hyperparameters in Section 4 and Appendix C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [Yes]

   Justification: We provided variance and 95% confidence intervals in Table 4 and Figure 10.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
   - The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
   - The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
   - The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification: Please see Section 4.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: The research strictly conforms to the NeurIPS Code of Ethics.

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [Yes]

    Justification: Please see Appendix F.

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

    Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

    Answer: [NA]

    Justification: The paper does not involve the release of models or data, hence there are no associated risks requiring safeguards.

    Guidelines:

    - The answer NA means that the paper poses no such risks.
    - Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
    - Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
    - We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

    Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

    Answer: [Yes]

    Justification: Data and experimental setup details, including source citations and licensing compliance, are thoroughly documented in the experiments section and supplementary materials.

    Guidelines:

    - The answer NA means that the paper does not use existing assets.
    - The authors should cite the original paper that produced the code package or dataset.
    - The authors should state which version of the asset is used and, if possible, include a URL.
    - The name of the license (e.g., CC-BY 4.0) should be included for each asset.
    - For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
    - If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.

- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [NA]

    Justification: The paper does not release new assets.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: The paper does not involve crowdsourcing or research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: The paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

    Answer: [NA]

    Justification: LLMs were not used as an essential, original, or non-standard component in the core methodology of this research. All research methods and analyses were conducted independently of LLMs.

    Guidelines:

    - The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.

A Additional Related Work

A.1 Common Knowledge in Neural Networks

Common knowledge refers to transferable representations that can be shared across neural networks. It typically falls into two categories: size-agnostic knowledge, which generalizes across network architectures of different scales, and task-agnostic knowledge, which transfers across tasks.

Size-agnostic Knowledge. The modular nature of neural networks (e.g., convolutional filters and Transformer blocks) enables knowledge sharing across models of varying widths and depths. For example, Filter-in-Filter [76], versatile filters [72], and TBC [71] show that filters can be reused to detect multiple patterns or reduce redundancy. Other works [36, 81, 34] compress CNNs through cross-filter weight sharing. Similarly, in Transformer-based models, reusable blocks [75] and parameter-sharing techniques [33, 83] achieve efficient scaling without performance degradation.

Task-agnostic Knowledge. Task-agnostic knowledge captures general visual features that are transferable across domains. Tape [38] encodes such priors for image restoration, while Park et al.[47] and Polyhistor[39] learn generalizable representations and reusable adapters for multi-task learning. The idea of a universal backbone, as in Universal Template [62], improves generalization in few-shot settings. Meta-learning approaches like OML [25] and iTAML [48] enhance transferability by decoupling task-specific heads from shared representations.

ECO integrates and condenses such size- and task-agnostic knowledge into adaptive neural fragments called learngenes, which encapsulate what we refer to as core knowledge. These learngenes enable flexible adaptation across network scales and task types.

B Additional Details of Methods

B.1 Learngenes in ResNets

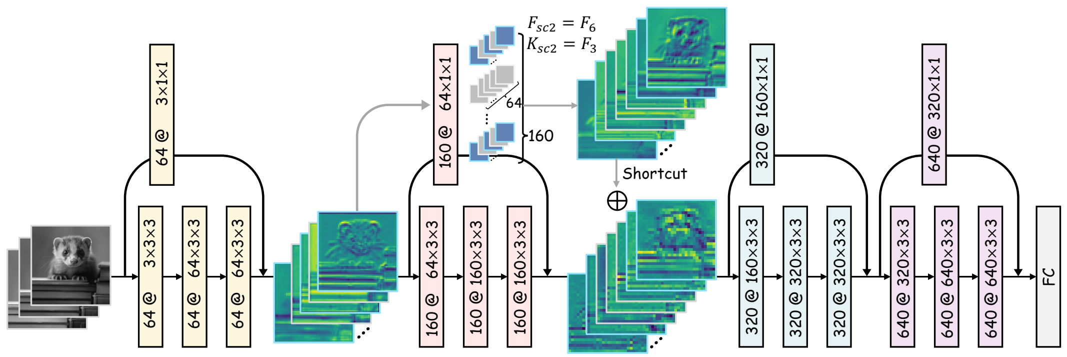


Figure 7: The form of the learngenes in ResNet12, where the kernels in skip connection layers are also integrated as components of the learngenes.

ResNets enhance traditional CNN architectures by introducing skip connections, typically realized through 1×1 convolutions. These connections enable feature propagation across non-adjacent layers, promoting representational reuse.

To accommodate this architectural feature, the formulation of learngenes in ResNets should extended beyond standard convolutional layers to explicitly incorporate skip connections. Let L_i and L_j denote the source and target layers of a skip connection, where $L_j > L_i$, and let the corresponding skip layer be denoted as L_{sc}. To ensure structural alignment with the main pathway, the number of kernels and filters in the learngenes at L_{sc} are defined as:

$$N_K^{(L_{\text{sc}})} = N_F^{(L_i)},\ N_F^{(L_{\text{sc}})} = N_F^{(L_j)} \tag{8}$$

Accordingly, the selected kernel and filter index sets of learngenes are given by:

$$\mathcal{K}_{\text{sc}} = \mathcal{F}_i,\ \mathcal{F}_{\text{sc}} = \mathcal{F}_j \tag{9}$$

This configuration ensures that learngenes encapsulate both primary and residual pathways, forming complete kernel-level circuits essential for effective knowledge transfer, as illustrated in Figure 7.

Algorithm 1 Mutation of the Learngene

Input: Learngene $\mathcal{G}$, Mutation probability p_m, Number of layers N_L and number of filters $N_F^{(l)}$ in l-th layer

```
1: # Mutation layer by layer
2: for $l = 1$ to $N_L$ do
3:     # Whether to mutate in $l$-th layer
4:     Randomly generate a number $r \sim U(0, 1)$.
5:     while $r \leq p_m$ do
6:         # Mutate!
7:         # Whether to increase and decrease a filter of $\mathcal{G}$ in layer $l$
8:         Randomly generate a number $s \sim U(0, 1)$.
9:         if $s \leq p_l^+$ then
10:            # Random increase a filter
11:            Randomly select a filter index $f$ from $[1, N_F^{(l)}] - \mathcal{F}_l$
12:            # Update the corresponding sets $F_l$ and $K_l$
13:            $\mathcal{F}_l \leftarrow \mathcal{F}_l \cup \{f\}$
14:            $\mathcal{K}_{l+1} \leftarrow \mathcal{K}_{l+1} \cup \{f\}$
15:        else
16:            # Random decrease a filter
17:            Randomly select a filter index $f$ from $\mathcal{F}_l$
18:            # Update the corresponding sets $\mathcal{F}_l$ and $\mathcal{K}_l$
19:            $\mathcal{F}_l \leftarrow \mathcal{F}_l - \{f\}$
20:            $\mathcal{K}_{l+1} \leftarrow \mathcal{K}_{l+1} - \{f\}$
21:        end if
22:        # Whether to continue mutating in layer $l$
23:        Randomly generate $r \sim U(0, 1)$.
24:    end while
25: end for
```

Algorithm 2 Genetic Transfer Learning

Input: Training dataset $\mathcal{D}_{\text{train}}$ with n_t classes, Validate dataset $\mathcal{D}_{\text{val}}$ with n_v classes, Population number n_p, and total number of generation N_G

```
1: for $g = 0$ to $N_G$ do
2:     # Initialize population with learngenes
3:     Randomly initialize population $\mathcal{P}_g$ with $n_p$ networks $\mathcal{N}_i$
4:     if $g \neq 0$ then
5:         Select ancestry learngenes $\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, ..., \mathcal{G}_{n_p}\}$ from the Gene Pool for each $\mathcal{N}_i$ using Eq. (7). Then
           initialize each $\mathcal{N}_i$ by inheriting $\mathcal{G}_i$
6:     end if
7:     # Train population $\mathcal{P}$ on $\mathcal{D}_{train}$
8:     for each network $\mathcal{N}_i$ do
9:         Sample $k$ classes from $\mathcal{D}_{\text{train}}$ to form task $\mathcal{T}_i$
10:        Train $\mathcal{N}_i$ on $\mathcal{T}_i$
11:    end for
12:    # Learngene extraction and evaluation
13:    for each learngene $\mathcal{G}_i$ do
14:        Mutate $\mathcal{G}_i$ according to Appendix Algorithm 1
15:        Initialize critic networks $\mathcal{C}_i$ with mutated $\mathcal{G}_i$
16:        Train $\mathcal{C}_i$ on a $n_v$-way classification task on $\mathcal{D}_{\text{val}}$
17:        Calculate learngene score $s_i$ based on the accuracy of $\mathcal{C}_i$
18:    end for
19:    # Update Gene Pool and Gene Tree
20:    Perform learngene competition and select winners $\mathcal{G}^{\star}$
21:    Take winners as leaf nodes of the Gene Tree
22:    Update scores of ancestral learngenes according to Eq. (6)
23:    Refresh Gene Pool by adding winners and eliminating learngenes with lower scores
24: end for
```

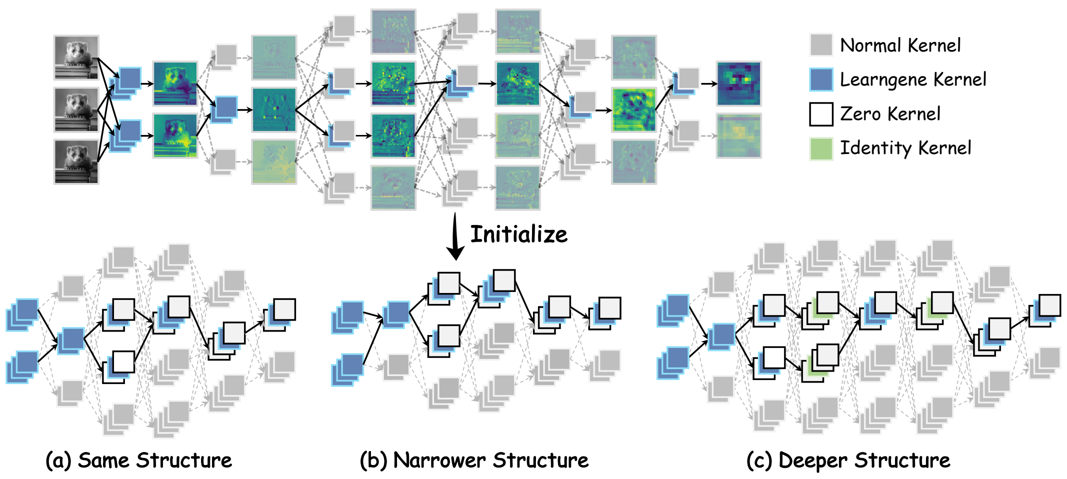


Figure 8: The learngenes exhibit scalability, enabling the initialization of networks with the same structures and the flexibility to initialize networks with narrower/wider and deeper structures. The normal kernels in networks are randomly initialized, while the zero kernels and identity kernels are initialed by $\mathbf{0}$ (i.e., zero matrix) and $\mathring{\mathbf{1}}$, respectively.

B.2 Further Details on Learngene Mutation

Learngene mutation serves not only to alter structural configurations but also to refine the condensed core knowledge. This process increases structural diversity while maintaining a broad reservoir of "raw material" for subsequent selection, thereby facilitating the identification of core knowledge most suitable for transfer.

The complete mutation procedure is outlined in Algorithm 1.

B.3 Further Details of Genetic Transfer Learning (GTL)

The complete GTL procedure is presented in Algorithm 2, complementing the illustration in Figure 3.

A key component of GTL is the recursive update of learngene scores, which begins at a selected high-performing learngene (i.e., a leaf node in the current generation) and proceeds upward along its lineage to the root node. This process ensures that the performance feedback of descendants is reflected in the evaluation of their ancestors. The specific score update strategy is described in Algorithm 3.

Algorithm 3 Update of the Learngene Score

```
Input: Winner learngenes $\mathcal{G}^\star$, Parental decay coefficient $\eta$, Path length $\tau$ and Gene Tree (GT)
1: for each $\mathcal{G}_i^\star$ in $\mathcal{G}^\star$ do
2:     Initialize node pointer $pt \leftarrow \mathcal{G}_i^\star$
3:     Set path length $\tau \leftarrow 0$
4:     # Recursively traverse Gene Tree for ancestral learngenes
5:     while $pt$ has parent $\mathcal{G}_p$ do
6:         # Increase path length
7:         $\tau \leftarrow \tau + 1$
8:         # Update parental learngene score $s_p$
9:         $s_p \leftarrow s_p + \eta^\tau s_i^\star$
10:        # Move pointer
11:        $pt \leftarrow \mathcal{G}_p$
12:    end while
13: end for
```

B.4 Further Details on Learngene Inheritance

Learngenes possess high structural scalability, enabling the initialization of target networks with varying widths, depths, and architectures, as illustrated in Figure 8.

Identical Model Sizes and Architectures. When the target network shares the same architecture as the source (Figure 8a), initialization is achieved by directly replacing the randomly initialized kernels at the indices specified by the learngenes. Filters containing unassigned kernels are padded with zeros, denoted as white kernels in Figure 8.

Width Adaptation. For target networks that differ in width, index mappings must be adapted to avoid index overflows. Specifically, the filter and kernel indices in the l-th layer are re-indexed as $\mathcal{F}'_l = [1, |\mathcal{F}_l|]$ and $\mathcal{K}'_l = [1, |\mathcal{K}_l|]$, ensuring compatibility with the narrower or wider target network (Figure 8b and Figure 9).

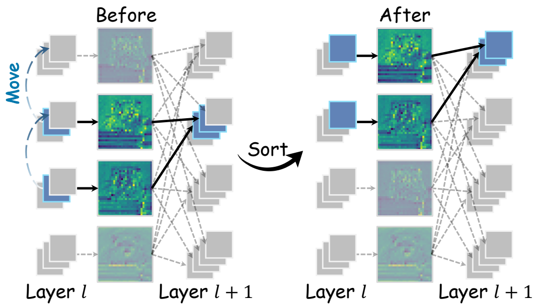


Figure 9: Sorting the positions of learngene filters and kernels. To prevent index overflow when initializing a narrower model, the indices of learngene kernels and filters are rearranged starting from 1.

Depth Extension. When the number of layers in the target network $N_L^{(d)}$ exceeds that in the learngene $N_L^{(a)}$, additional *Partial Identity Mapping* (PIM) layers are inserted to preserve feature continuity (Figure 8c). Each PIM layer bridges adjacent layers L_l and L_{l+1} by introducing an intermediate mapping: $L_l \to L_{\text{pim}} \to L_{l+1}$, where the filter set is defined as:

$$\mathcal{F}_{\text{pim}} = \mathcal{F}_l \tag{10}$$

For each filter $f \in \mathcal{F}_l$, the corresponding kernel in the PIM layer is initialized as:

$$\mathcal{K}_{k,f,\text{pim}} = \begin{cases} \mathring{\mathbf{1}} & \text{if } k = f \\ \mathbf{0} & \text{otherwise} \end{cases}, \quad \mathring{\mathbf{1}}_{3\times 3} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \mathbf{1} & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{11}$$

This identity-preserving initialization ensures seamless propagation of core features across expanded network depths.

C Implementation Details

C.1 Hyperparameters for Evolution

Table 6 provide the hyperparameters used for evolving the learngenes using GTL.

Table 6: Hyperparameters in evolution.

Hyperparameter	**VGG11**	**ResNet12**	**ResNet50**	**MobileNetV3-Large**
Training Class Number n_t	64	64	640	640
Validation Class Number n_v	16	16	160	160
Novel Class Number	20	20	200	200
Init Class k_{init}	5	5	50	50
Max Class k_{max}	15	15	70	110
Initial Percentage of Learngene Filters	0.3	0.3	0.3	0.4
Mutation Probability p_m	0.1	0.1	0.2	0.2
Population Size n_p	20	20	6	6
Gene Pool Size ρ	8	8	6	6
Obsolete Number ε	4	4	2	2
Generational Decay Coefficient β	0.9	0.9	0.9	0.9
Parental Decay Coefficient η	0.1	0.1	0.1	0.1
Networks Number in Competition s	3	3	3	3
Generation Number	250	250	100	100

Table 7: Performance of ECO across various model sizes and downstream datasets. "Scratch" refers to training from scratch, while "$\mathcal{G}_{\text{vgg11}}$" and "$\mathcal{G}_{\text{res12}}$" represent the initialization using learngenes extracted from VGG11 and ResNet12, respectively. "-N/W" denotes narrower or wider network width. Note that results are given in terms of Top-3 accuracy.

		VGG					ResNet			
Datasets		11	$11_{\text{-N}}$	$11_{\text{-W}}$	16	19	12	$12_{\text{-N}}$	$12_{\text{-W}}$	18
Flower	Scratch	51.41	49.18	53.24	47.32	41.78	56.64	56.16	56.58	56.24
	$\mathcal{G}_{\text{vgg11}}$	69.25*	66.94*	66.97*	72.00*	74.50*	68.99	66.22	66.21	63.15
	$\mathcal{G}_{\text{res12}}$	59.15	56.94	57.65	69.75	60.66	77.33*	**79.83***	74.63*	76.96*
CUB	Scratch	70.75	66.86	73.28	66.60	69.31	63.96	63.72	64.03	67.57
	$\mathcal{G}_{\text{vgg11}}$	79.65*	78.67*	81.57*	82.74	**84.21***	76.67	75.15	76.70	78.24
	$\mathcal{G}_{\text{res12}}$	77.89	75.99	79.58	83.53*	81.15	81.55*	82.24*	80.34*	83.62*
Cars	Scratch	86.01	81.07	88.24	87.14	89.16	80.13	74.43	80.40	82.51
	$\mathcal{G}_{\text{vgg11}}$	92.25*	91.36*	93.04*	94.62	95.29*	92.80	91.74	93.02	93.62
	$\mathcal{G}_{\text{res12}}$	89.78	88.05	91.33	95.20*	94.68	95.63*	95.92*	95.37*	**96.10***
Food	Scratch	80.74	79.73	80.29	79.54	76.23	84.62	84.21	85.28	87.59
	$\mathcal{G}_{\text{vgg11}}$	85.49*	84.73*	84.79*	87.30*	86.85*	88.19	87.32	88.32	89.00
	$\mathcal{G}_{\text{res12}}$	84.69	83.06	84.44	86.46	84.28	89.54*	89.09*	89.74*	**90.57***

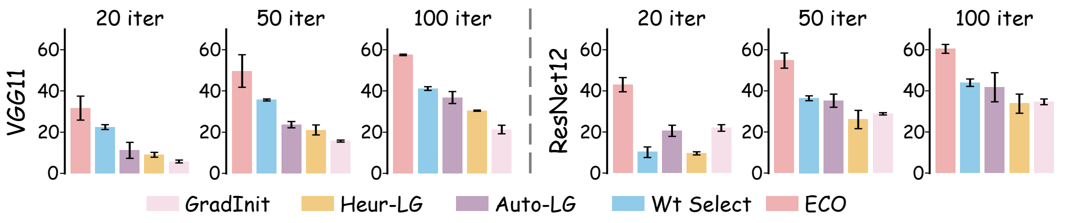


Figure 10: Performance of ECO and other methods on novelty classes with minimal training steps. "iter" indicates parameter update iterations (one iteration equals one optimizer update).

D Additional Results and Analysis

D.1 Scalability and Adaptability of Learngenes

To further evaluate the scalability and adaptability of learngenes, we initialize networks with varying widths (e.g., VGG11-N, VGG11-W, ResNet12-N, ResNet12-W), depths (e.g., VGG16, VGG19, ResNet18), and even across architectures (e.g., VGG$\rightleftharpoons$ResNet). The results on four downstream datasets are presented in Table 7.

Learngenes (i.e., $\mathcal{G}_{\text{vgg11}}$ and $\mathcal{G}_{\text{res12}}$) successfully initialize networks of varying depths (e.g., VGG11, VGG16, VGG19; ResNet12, ResNet18), consistently outperforming models trained from scratch. They also enhance performance when initializing networks with different widths. For example, $\mathcal{G}_{\text{vgg11}}$ initialize a wider VGG11-W, achieving better performance on CUB (81.57% vs. 79.65%), while $\mathcal{G}_{\text{res12}}$ initialize a narrower ResNet12-N, surpassing the standard ResNet12 on Flower (79.83% vs. 77.33%).

Moreover, learngenes demonstrate effective cross-architecture transferability, with $\mathcal{G}_{\text{vgg11}}$ successfully initializing ResNet18 and outperforming models trained from scratch. Despite potential architectural incompatibilities, learngenes show greater flexibility and scalability compared to pre-trained models, which are often limited by architecture. This underscores their capability to transfer core knowledge across varying model sizes and architectures in downstream tasks.

D.2 Instincts of Models Brought by Learngenes

To further explore the initialization ability of learngenes, we extend the concept of "instinct" from reinforcement learning [11] to supervised learning, referring to the innate ability that model initialization provides to neural networks. Figure 10 illustrates the early training performance (within the first epoch) of ECO and other methods on VGG11 and ResNet12, with one iteration represents a single optimizer step.

ECO exhibits notable advantages during early training, requiring only minimal updates to achieve significant performance improvements. Despite transferring more parameters, other methods often struggle to adapt quickly to new classes due to over-transfer of knowledge, which reduces network flexibility. In contrast, ECO selectively transfers only core knowledge via learngenes, enabling descendant networks to quickly adapt to novel tasks. This early-stage capacity for classification with minimal training is referred to as the "instinct" provided by learngenes.

E Limitations and Future Works

ECO demonstrates robust performance on convolutional architectures by integrating size- and task-agnostic knowledge through learngenes. While inherently scalable, current evaluations are limited to small and medium-sized models. Extending ECO to larger architectures remains promising, though it may incur additional training time and computational overhead. Beyond convolutional networks, we also aim to extend ECO to transformer-based models, where the modular representation of learngenes may further facilitate cross-architecture knowledge inheritance and generalization.

F Impact Statement

ECO offers a unified framework for modular knowledge transfer through learngenes, enabling efficient model initialization across architectures and scales. By reducing the need for extensive retraining, ECO lowers computational costs and improves performance in low-data and resource-constrained scenarios. Its architecture-agnostic design supports broad applicability across domains. By promoting the reuse of pre-trained models with minimal overhead, ECO contributes to more sustainable and accessible machine learning, aligning with the goals of green AI.