∇QDARTS: Quantization as an Elastic Dimension to Differentiable NAS

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Abstract

Differentiable Neural Architecture Search methods efficiently find high-accuracy architectures using gradient-based optimization in a continuous domain, saving computational resources. Mixed-precision search helps optimize precision within a fixed architecture. However, applying it to a NAS-generated network doesn't assure optimal performance as the optimized quantized architecture may not emerge from a standalone NAS method. In light of these considerations, this paper introduces ∇QDARTS, a novel approach that combines differentiable NAS with mixed-precision search for both weight and activation. ∇QDARTS aims to identify the optimal mixed-precision neural architecture capable of achieving remarkable accuracy while operating with minimal computational requirements in a single shot, end-to-end differentiable framework obviating the need for pertaining and proxy. Compared to fp32, ∇QDARTS shows impressive performance on CIFAR10 with (2,4) bit precision, reducing bit operations by 160× with a slight 1.57% accuracy drop. Increasing the capacity enables ∇QDARTS to match fp32 accuracy while reducing bit operations by 18×. For the ImageNet dataset, with just (2,4) bit precision, ∇QDARTS outperforms state-of-the-art methods such as APQ, SPOS, OQA, and MNAS by 2.3%, 2.9%, 0.3%, and 2.7% in terms of accuracy. By incorporating (2,4,8) bit precision, ∇QDARTS further minimizes the accuracy drop to a 1% compared to fp32, alongside a substantial reduction of 17× in required bit operations and 2.6× in memory footprint. In terms of bit-operation (memory footprint) ∇QDARTS excels over APQ, SPOS, OQA, and MNAS with similar accuracy by 2.3× (12×), 2.4× (3×), 13% (6.2×), 3.4× (37%), for bit-operation (memory footprint), respectively. ∇QDARTS enhances the overall search and training efficiency, achieving a 3.1× and 1.54× improvement over APQ and OQA, respectively.

1 Introduction

Neural Architecture Search (NAS) has emerged as a powerful method that reduces the manual and human effort to find optimum network architectures for the target applications. However, traditional NAS methods require complete training of every candidate network, which is computationally prohibitive due to the enormous search space (Kyriakides & Margaritis (2020)). To alleviate this problem, bodies of work suggest different techniques to reduce the NAS search space (Negrinho & Gordon (2017); Liu et al. (2018a; 2017); Kandasamy et al. (2018)). Evolutionary search, Monte-carlo tree search (MCTS) (Negrinho & Gordon (2017)), sequential model-based optimization (SMBO) (Liu et al. (2018a; 2017)), and Bayesian optimization (Kandasamy et al. (2018)) are examples of these approaches. However, even these approaches suffer from inherent search inefficiency, because they treat architecture search as a black-box optimization problem over a *discrete domain*, which leads to a large number of architecture evaluations. These methods are also criticized for their high time complexity, energy consumption, and not being scalable (Elsken et al. (2019); Liu et al. (2018b)).

To address these challenges, weight-sharing methods have been proposed (Ullrich et al. (2017); Cai et al. (2019); Sahni et al. (2021b); Liu et al. (2018b); Xu et al. (2019)). These methods provide the advantage of sharing weights across varied architectures, resulting in a considerable reduction in the compute and memory resources needed to conduct the search. As a result, they have recently attracted significant attention (

Ullrich et al. (2017); Cai et al. (2019); Sahni et al. (2021b); Liu et al. (2018b); Xu et al. (2019); Sahni et al. (2021a); Yu et al. (2020a;a;b); Banbury et al. (2021)).

Among the weight-sharing methods, DARTS (Liu et al. (2018b)) addresses the challenge of scalability of the architecture search through a differentiable search formulation. It relies on *continuous relaxation* of the architectural representation by employing efficient search using gradient descent compared with conventional approaches that use evolution, reinforcement learning, sampling, and random searches over discrete and non-differentiable search spaces.

DARTS has introduced a novel avenue of research in the NAS domain by circumventing the need to traverse discrete and large search spaces (Xu et al. (2019); Wan et al. (2020); Zela et al. (2019); Chu et al. (2020); Liang et al. (2019); Chen & Hsieh (2020); Wang et al. (2021); Zhang et al. (2021); Yang et al. (2021); Zhou et al. (2020); Liu et al. (2021); Zhang et al. (2020a); Chen et al. (2019)). Among DARTS methods, PC-DARTS (Xu et al. (2019)) further reduces the search cost by introducing partial channel sampling during the search operation. As a result of this strategic implementation, the framework has improved memory efficiency and accelerates processing speeds (Elsken et al. (2019)).

Although existing NAS methods can find the suitable architecture for a target device and application, they suffer from computationally expensive floating point operations. These operations are cost-prohibitive, especially for resource-constraint devices. Existing research work demonstrates that lower-bit quantization policy improves the performance of the network in terms of memory footprint, latency, computational cost, bandwidth efficiency, power, and energy consumption (Krishnamoorthi (2018); Choukroun et al. (2019); Wang et al. (2019); Gholami et al. (2021)). However, applying quantization is not straightforward in a NAS setting. First, due to search space explosion, it is non-trivial to incorporate quantization during architecture/weight search (Wang et al. (2019; 2020); Bai et al. (2021)).

Few methods have been proposed to incorporate quantization into NAS. These methods usually exploit proxies (e.g., pretrained neural networks) to estimate the performance of the sampled architecture/quantization search (Wang et al. (2020)). Proxy-based methods usually lack accurate estimation. In addition, proxies need to be treated carefully to ensure that quantized architectures are ranked fairly. Besides, evaluation using a proxy is a time-consuming procedure (Bai et al. (2021)).

Second, it is difficult to predict, in advance, exactly how quantization will affect a neural network found by a NAS method. The reason is that quantization efficiency depends on the neural architecture itself. For instance, Shen et al. show that the accuracy of MobileNetv2 with full precision (fp32) is better than ResNet18. However, with the 2-bit precision, the ResNet18 accuracy is higher than MobileNetv2 (Shen et al. (2021)).

Third, it is unclear how quantization should be applied within NAS architectures. As an example, we can apply quantization to a regiment of potential *SubNets* within a DARTS network that results in a multitude of quantized architectures. However, there is no guarantee that the resultant *SuperNet*, which is formed by combining these *SubNets*, will have the optimal quantized architecture.

In this paper, we introduce ∇**QDARTS**, **a novel framework that integrates architecture and weight optimization along with a comprehensive mixed-precision search for both weights and activations**. The framework is achieved in a single shot, end-to-end, differentiable optimization eliminating the need for any pretraining or proxy. Furthermore, ∇**QDARTS** leverage the complexity-aware training to favor the discovery of lower computational complexity (i.e., lower-bit precision) models during the search phase. In this manner, the model produced by the search stage is optimized for a computational budget determined by a user-specified hyper-parameter where no grid search is required. In addition, ∇**QDARTS** enables to trade-off between bit-operation (*BitOps*) and accuracy to make it a suitable fit for the target edge application with relatively low GPU hours.

In summary, the contributions of the paper are as follows:

- We propose ∇**QDARTS**, which provides a single shot, end-to-end, differentiable framework by integrating architecture and weight search with a mixed-precision quantization policy for both weights and activations, without any need for pretraining and proxies.

- ∇**QDARTS** provides a framework for flexible navigation in accuracy-BitOps trade-off space where the produced model by the search stage is optimized for a complexity budget determined by a user without any grid-search requirement.
- ∇**QDARTS** enables highly efficient and accurate architecture discovery even when ultra low bit-precision is considered (2 and 4) with negligible accuracy loss compared to the full-precision (fp32) networks.

2 Background and Challenges

2.1 Differentiable NAS Formulation

The key objective of any NAS framework is to find both the optimal architecture, α^*, and its corresponding weights, ω^*, which is a bi-level optimization problem formulated by the following equations:

$$\min_{\boldsymbol{\alpha}} \mathcal{L}_{\text{val}}(\omega^*(\alpha), \alpha), \text{s.t.} \quad \omega^*(\alpha) = \underset{\boldsymbol{\omega}}{\operatorname{argmin}} \mathcal{L}_{\text{train}}(\omega, \alpha) \tag{1}$$

where $\mathcal{L}_{val}(.,.)$ and $\mathcal{L}_{train}(.,.)$ denotes the training and validation loss, respectively. The architecture parameters are optimized over the validation dataset to avoid overfitting (Liu et al. (2018b)). To ensure differentiability, discrete architecture search spaces are converted to continuous ones (Wu et al. (2019); Zhang et al. (2020b); Zela et al. (2019); Cai et al. (2018)). In continuous relation, the architecture search space A is relaxed to $A(\theta)$, where θ is the continuous parameter that presents the distribution of architectures ($A \subseteq A(\theta)$). In this way, we can employ gradient-based methods to find the best weight and architecture (Guo et al. (2020)).

To solve these equations, we can use either single-level or bi-level optimizations. In single-level optimization, α and ω are updated simultaneously in each step. While this is computationally less expensive, they suffer from poor generalization due to overfitting. Bi-level optimization, on the other hand, updates α and ω in an alternative fashion.

2.2 Quantization

The quantization can be fixed-bit, meaning the entire network has a single weight and/or activation precision. Because different layers, filters, and channels have various impacts on the accuracy, a model's accuracy can be significantly degraded when it is uniformly quantized to ultra-low precision. This problem can be addressed with mixed-precision quantization schemes (Dong et al. (2019); Habi et al. (2020); Hu et al. (2021); Zhao et al. (2021)). In mixed-precision, each layer, filter, channel, and/or activation have a separate precision. It has been shown that converting floating-point values to low-precision fixed integer values in four bits or less can reduce memory footprint and latency significantly (Gholami et al. (2021); Dong et al. (2019); Deng et al. (2020)). For instance, ResNet50 inference with INT4 precision can produce a speedup of 50%-60% compared to INT8 inference, emphasizing the importance of using lower-bit precision for optimal performance (Salvator et al. (2019)). However, when the bit precision goes below 8-bit, reaching high accuracy, especially for large datasets is a challenging task (Sun et al. (2022; 2020)).

2.3 Incorporating Quantization into NAS

Few studies try to incorporate quantization into NAS or employ the idea of the differentiable search for efficient quantization of a fixed architecture.

DNAS (Wu et al. (2018)) proposes a differentiable mixed-precision solution per layer that takes a fixed architecture, like ResNet, and searches over the possible quantization bit precision per layer. The method assigns a probability weight to the quantization 'path' per layer such that the entire network is fully differentiable. DNAS is not like a NAS architecture, rather it employs NAS formula for a fixed architecture to find a proper mixed-precision solution.

HAQ (Wang et al. (2019)) proposes a Hessian-aware mixed-precision quantization technique that finds the optimum bit-precision for each output channel within every layer. The importance and bit precision of each

Table 1: Comparing ∇**QDARTS** with state-of-the-art quantization methods. "Weight-sharing" means whether the method is utilizing a weight-sharing solution. "Single-shot mixed-precision" quantization policy refers to using QAT to train the *SuperNet* with arbitrary mixed-precision quantization policies. "Mixed-precision" means that the method supports different precisions. "No training during search" means during the search phase there is no need for re-training the sampled network candidate. As ∇**QDARTS** doesn't need any sampling mechanism, we do not need to train and evaluate the selected *SubNet*. The research community has set a standard for evaluating NAS methods, using "DARTS Search Space" that has been widely used. It has larger search space compared to the MobileNet search space (Mehta et al. (2022); Zhang & Ding (2023)). "Proxies Avoidance" refers to the fact that the employed technique avoids employing a trained neural network to estimate the accuracy of a sampled architecture. "Pretraining Avoidance" means the method can avoid any required pertaining.

Property	**DNAS**	**HAQ**	**EdMIPS**	**APQ**	**OQA**	**BatchQuant**	**SPOS**	**AutoNBA**	**MNAS**	**UDC**	**∇QDARTS**
Joint DNN & Quan Search				✓	✓	✓		✓	✓	✓	✓
Weight Sharing				✓	✓	✓	✓	✓	✓	✓	✓
Mixed Precision We. Quan	✓	✓	✓	✓		✓	✓		✓	✓	✓
Mixed Precision Act. Quan	✓	✓	✓	✓		✓	✓		✓		✓
Single-shot Mixed Precision						✓	✓				✓
Differentiable Quan	✓	✓	✓							✓	✓
DARTS Search Space											✓
No Training During Search				✓	✓	✓	✓		✓	✓	✓
Proxies Avoidance					✓	✓				✓	✓
Pretraining Avoidance					✓					✓	✓
Relatively Low Train Time	✓	✓	✓	✓	✓				✓	✓	✓

output channel is recognized based on the Hessian values of the channel. To make this method works, it is necessary to have an already trained, fixed architecture network.

EdMIPS (Cai & Vasconcelos (2020)) opts for mixed-precision search strategies for the different filters in a fixed architecture and achieves high efficiency by sharing weights for all mixed-precision operations. It employs the idea of DARTS for finding the best precision of predefined architecture. EdMIPS employs a block that is weighted sums of all quantized weights for a single convolution. With N different precisions, this reduces the complexity of the forward and backward passes by nearly a factor of N. Similar to DNAS, it does not perform an architecture search on the layer types and just optimizes mixed-precision for a fixed architecture.

APQ (Wang et al. (2020)) applies a joint search for NAS, pruning, and quantization policies. This technique enables mixed-precision architecture search but relies on a proxy to decide the best precision and pruning scheme. It employs an already trained 32-bit precision predictor as a proxy. For training the accuracy predictor, APQ performs QAT on 5000 architectures and quantization policies for 0.2 GPU hours each. Producing this predictor is expensive in terms of time and resource consumption.

OQA (Shen et al. (2021)) develops Once Quantized for All, which achieves training efficiency by gradually shrinking the bit-width of the supernetwork after it trains via bit-inheritance to enable efficient searching for different quantization bit widths. However, this approach lacks the support of mixed-precision search.

BatchQuant (Bai et al. (2021)) proposes a mixed quantization for OFA-like architecture (and not differentiable architectures). However, it needs pretraining the supernet at the beginning, otherwise, the accuracy will drop. BatchQuant first trains *SuperNet* with bit width options 2, 3, 4, 32 for the first 65 epochs and then continue training the *SuperNet* with 2, 3, 4 bit width options for the rest of the training to reach high accuracy.

Besides, due to retraining, the total GPU hours are significantly high. Unlike ∇QDARTS, it was proposed for MobileNet search space.

SPOS (Guo et al. (2020)) employs uniform path sampling for supernet training, conducting random sampling of block and weight bit widths. The evolutionary step determines the final values. However, under SPOS, only channel searches are permitted, reducing the architecture search space size.SPOS targets fixed architecture like ResNet18 and ResNet34.

UDC (Fedorov et al. (2022)) does not support activation quantization. In addition, unlike ∇QDARTS that enables lower bit quantization, UDC utilizes higher bit precision like 8- and 32-bit for the weight quantization.

MNAS (Gong et al. (2019)) combines NAS and quantization over MobileNet search space. MNAS relies on an 8-bit pretrained model and cannot reach high accuracy.

Except for the Batchquant, OQA, and UDC, all of the baselines rely on a proxy estimator. The proxy is usually a trained neural network that predicts the accuracy of the selected architecture. Using proxy increases search space exploration time.

Table 1 shows various features of different techniques. It illustrates how ∇QDARTS is unique compared to the other existing methods. Here, different components of the proposed solutions are explained. As seen, ∇QDARTS **provides a single shot, end-to-end differentiable NAS joint with mixed-precision quantization search for both weight and activation without any need for pretraining or proxy**.

3 Proposed ∇QDARTS

3.1 ∇QDARTS Overview

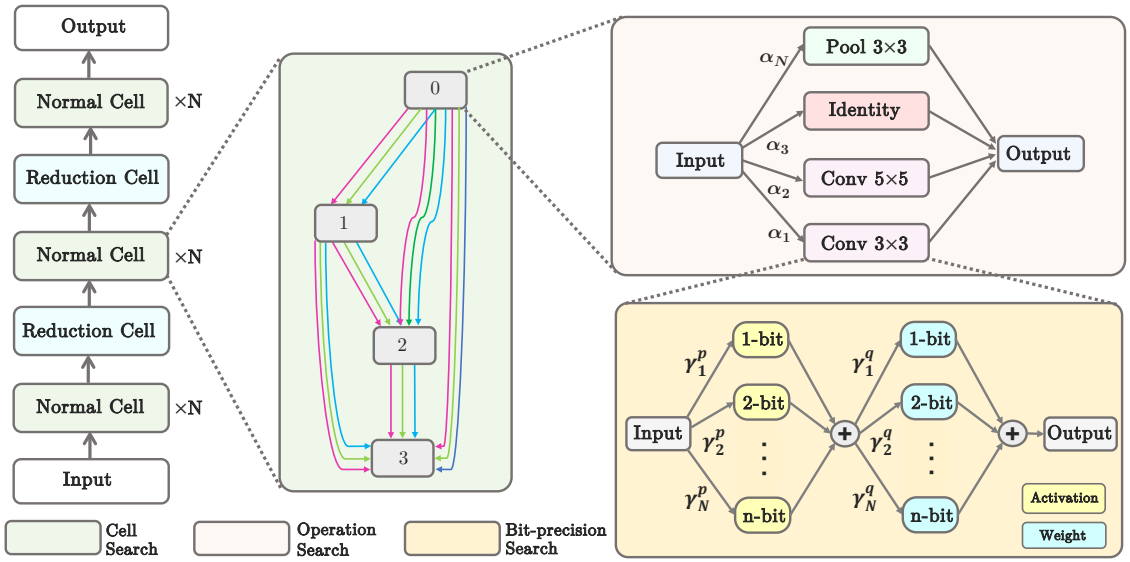

Figure 1: ∇QDARTS brings quantization into DARTS. Each cell consists of the operation search of DARTS while the innermost block shows the mixed precision search candidates. Crucially, the entire *SuperNet* is fully differentiable. Hence, the architecture and mixed precision search can be performed simultaneously in an end-to-end single-shot fashion.

We propose ∇QDARTS, a differentiable NAS framework that jointly finds optimal architecture, weight, and bit-precision of both weight and activation in a single-shot, end-to-end manner. ∇QDARTS extends the existing DARTS (Liu et al. (2018b); Xu et al. (2019)) framework by adding differentiable precision search. Unlike many existing multi-stage methods where architecture search and optimal quantization policy search are explored independently, joint optimization in ∇QDARTS allows for exploring more efficient architecture while preserving its accuracy even in a lower precision regime.

Given a target task, we first follow the fixed architectural macroblocks (or cell) similar to (Liu et al. (2018b)) where each cell has a set of architectural components (i.e., convolution with different kernels, pooling, etc.) $o(.) \in \mathcal{O}$. The output of each cell, c_o, is a weighted summation of all the candidate operations:

$$c_o = \sum_{o \in \mathcal{O}} \alpha'_o o(x) \tag{2}$$

where α'_o is a set of learnable weights defined as:

$$\alpha'_o = \frac{\exp(\alpha_o)}{\sum_{o_i \in \mathcal{O}} \exp(\alpha_{o_i})} \tag{3}$$

Thus the architecture search involves learning this set of continuous variables that define the relative weights of each operation over the same input. Next, consider a specific operation with w weight and a activation with n_a and n_w possible bit precisions for activation and weight, respectively. The output of this operation can be formulated as:

$$\begin{aligned} y &= \sum_{i=1}^{n_a} \gamma_i^p a_i \left(\sum_{j=1}^{n_w} \gamma_j^q w_j(x) \right) \\ \text{s.t. } & \sum \gamma_i^p = 1, \sum \gamma_j^q = 1, \gamma^p, \gamma^q \in [0, 1] \end{aligned} \tag{4}$$

Here γ_i^p and γ_j^q are the weighting hyperparameters for mixed-precision operations (with $\{p, q\}$ as the set of learnable parameters) for the i-th and j-th precision path of activation and weight, respectively, computed through the following equations:

$$\gamma_i^p = \frac{\exp(p_i)}{\sum_k \exp(p_k)}, \quad \gamma_j^q = \frac{\exp(q_j)}{\sum_k \exp(q_k)} \tag{5}$$

Similar to the architectural search, we leverage continuous relaxation of the bit-precision search space. While the most straightforward way is to combine search over architecture and quantization bit precision space in a multi-stage fashion (i.e., find the optimal architecture in full precision, then search over the bit-precisions), we have experimentally shown in Section 4 how such naive integration results in suboptimal performance. The key challenge in incorporating such mixed-precision search into the NAS framework is that simultaneous exploration of different quantization bit-precisions per candidate operations can make the search space computationally intractable. To address this challenge, we extend the originally proposed bi-level optimization in DARTS (Liu et al. (2018b)) to combine both weight and bit-precision as a unified lower variable (details in the following Subsection). Furthermore, to constraint the search space, we leverage the channel-masking mechanism proposed in PC-DARTS (Xu et al. (2019)) to reduce the search cost by 1/K, where K is the number of channels for each convolution operation ($K >> 1$).

Another challenge to search over both architecture and precision parameters is that optimizing them over the same objective function (i.e., the validation loss) would always favor higher precision. Therefore, to penalize the optimization for high compute cost, we additionally add model complexity as a regularizing term to the loss function to incentivize the discovery of model architectures with lower computational complexity during the search phase.

Figure 1 shows the overall perspective of the **∇QDARTS**. The mixed-precision quantization in **∇QDARTS** considers all normal and reduction cells in DARTS search space, where different normal cells and/or reduction cells can have different bit precision for both weight and activation.

3.2 ∇QDARTS Optimizations

Our formulation ideally involves optimization over three levels of variables: architecture parameters (α), weights (w), and bit-precision (γ). While it can be desired to add γ as another level of inner variable to make it a tri-level optimization problem, this would increase the optimization steps exponentially. Instead, we propose an extension of bi-level optimization where we consider architecture parameters as the upper variable while weight and the associated bit-precision as a joint set of lower variables. It has been shown that a single update to both weight and quantization parameters can preserve similar performance while

enjoying half the complexity of their alternating (i.e., update the weights first, then the next step involves updating bit precision parameters while keeping the weights fixed, hence twice the update steps) updates (Cai & Vasconcelos (2020)).

We reformulate Eq. 1 to introduce the mixed-precision search weighting parameter, γ, as follows:

$$\begin{aligned} &\min_{\alpha} \quad \mathcal{L}_{val}(\omega^*(\alpha), \gamma^*(\alpha), \alpha) \\ \text{s.t.} \quad &\omega^*(\alpha), \gamma^*(\alpha) = \underset{\omega,\gamma}{\mathbf{argmin}} \quad \mathcal{L}_{train}(\omega, \gamma, \alpha) \end{aligned} \tag{6}$$

The exact solution to Eq. 6 involves expensive inner optimization of $\{w, \gamma\}$ over the whole training dataset. This can be avoided by approximating the gradient over a single training step (instead of the whole dataset) as follows (Liu et al. (2018b)):

$$\begin{aligned} &\nabla_\alpha \mathcal{L}_{\text{val}}(w^*(\alpha), \gamma^*(\alpha), \alpha) \\ &\quad \approx \nabla_\alpha \mathcal{L}_{\text{val}}\left(w - \xi_\omega \nabla_w \mathcal{L}_{\text{train}}(w, \gamma, \alpha),\right. \\ &\qquad \left.\gamma - \xi_\gamma \nabla_\gamma \mathcal{L}_{\text{train}}(w, \gamma, \alpha), \alpha\right) \end{aligned} \tag{7}$$

where ξ_ω and ξ_γ denote the learning rate of inner step optimization for weight and bit-precision, respectively. Effectively, this implies that updates on α and $\{w, \gamma\}$ occur in an alternating manner.

3.3 Complexity-aware Loss

Another challenge in joint architecture, weight, and precision search is that the existing methods predominantly rely on validation loss as its search parameter. This would always lead the **∇QDARTS** mixed-precision search to converge to a uniform bit-precision (i.e., the highest available bit-precision in the search space) for all the operations.

To overcome this, **∇QDARTS** introduces a pivotal enhancement: the integration of a complexity-aware loss function denoted in Eq. 8. This augmentation allows for a more nuanced and refined search, considering not just validation loss but also the intricate complexities inherent in the network operations. As a result, the optimization process becomes more capable of discerning varying levels of precision for different operations, leading to a more efficient search solution:

$$L[F] = R_E(F) + \nu R_C(F) \tag{8}$$

where $R_E[F]$ is categorical cross-entropy loss and $R_C[F]$ represents the total computational cost of the given architecture. $R_C(F)$ is computed as follows:

$$R_C(F) = \sum_{i=1} OPs * BitA * BitW \tag{9}$$

$$BitA = \gamma_i^p a_i \quad BitW = \gamma_i^q w_i \tag{10}$$

$$\begin{aligned} OPs = InChannel \times OutChannel \times (kerSize)^2 \\ \times \left(\frac{InW \times InH}{stride^2}\right) \end{aligned} \tag{11}$$

The hyperparameter ν determines the complexity of the final architecture. A higher ν will result in an architecture that favors lower mixed-precision architectures.

3.4 Increasing Model Capacity

In PC-DARTS, the training stage needs an increase in employed cells compared to the search stage to increase the capacity of the architecture to reach better accuracy. Usually, the same normal/reduction cells discovered during the search stage are stacked together. However, the straightforward stacking approach will not work in **∇QDARTS** due to variations in bit-precision among the discovered cells. This brings a challenge in selecting the appropriate cells to add to the stack, thereby increasing the capacity of the final architecture. Addressing

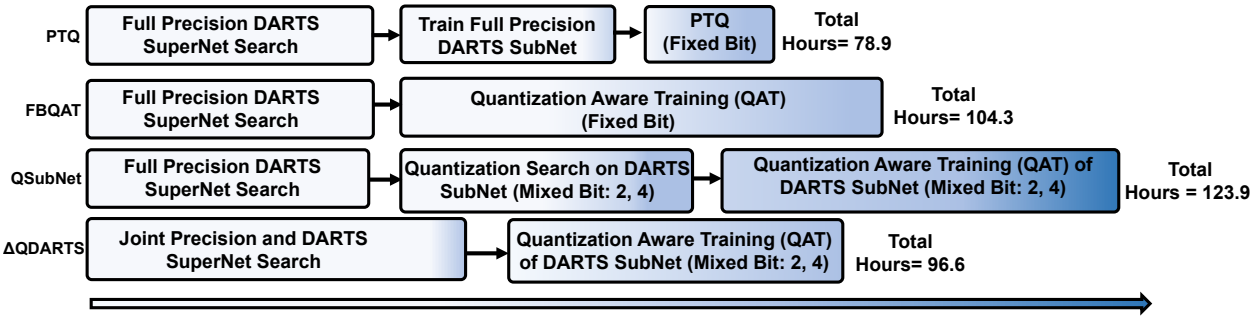

Figure 2: Comparing the total cost (both search and finetune/retrain time) of various baselines against ∇QDARTS cost to evaluate the effectiveness of ∇QDARTS. We show the total cost in terms of GPU hours for the ImageNet dataset.

this challenge necessitates a smart approach to identify cells that ensure optimal performance in expanding the architecture's capacity.

Through exploring various methods, we realized a technique to enhance the architecture of ∇QDARTS during the training phase. By duplicating the first cells and placing them at the top of the found cells, we effectively increase the capacity of the underlying architecture. This approach is motivated by the recognition that initial layers often possess weights and activations that are more sensitive to quantization and play a significant role in the final accuracy. Leveraging this understanding, ∇QDARTS strategically employs the first cell and stacks multiple copies of it on top of other discovered cells. As a result, the architecture's capability is expanded, leading to improved accuracy. We explored alternatives such as selecting cells from the last, the middle, and employing random selection, but it was the replication of the first cells that yielded the most promising results.

4 Experimental Setup and Evaluation

4.1 Setup

We have opened the source code on the GitHub [1], where one can get the code and run the whole experiments we describe in this section. We perform ∇QDARTS experiments on CIFAR10 and ImageNet, as the two most popular datasets for evaluating the efficiency and scalability of the NAS algorithm.

We employ HWGQ (Cai et al. (2017)) as a quantization scheme for 2- and 4-bit and channel-wise min-max (Zmora et al. (2019); Gholami et al. (2021)) for 8-bit quantization. We used ffcv-based accelerator data loading (Leclerc et al. (2022)) to reduce the training time of all baselines and ∇QDARTS.

Unless we explicitly mention it, we use the same setting of PC-DARTS for the DARTS-based baselines and ∇QDARTS. For APQ (Wang et al. (2020)), OQA (Shen et al. (2021)), SPOS (Guo et al. (2020)), and MNAS (Gong et al. (2019)) baselines, we use the best setting introduced in the manuscripts.

The experiments are carried out on 8(1) A40 GPUs on our internal clusters for ImageNet (CIFAR10) datasets. The training batch size is 2048(256) for ImageNet (CIFAR10) datasets. We consider 500 epochs for finetuning the searched architecture for all our experiments.

During the search phase, we use different optimizers for the ω, α, and γ. For the ω, an SGD optimizer with a learning rate of 0.5 (0.1 for CIFAR10), momentum 0.9, and weight decay of 3×10^{-4} is used. For the α, Adam optimizer with learning rate 6×10^{-3} (6×10^{-4} for CIFAR10), beta1 0.5, beta2 0.999, and weight decay of 10^{-3} is used. Finally, for γ, an SGD optimizer with a learning rate of 0.01, momentum of 0.9, and weight decay of 10^{-3} is used.

4.2 Baselines

Unfortunately, there is no direct SOTA work that is comparable to our work as mentioned in Table 1. However, we show how much ∇QDARTS can reduce the Bitops compared to the full-precision PC-DARTS

[1] https://anonymous.4open.science/r/QwDaRkTZ1

(32-bit) at the cost of negligible accuracy drop. In addition, we consider assorted baselines that can be employed to be compared against ∇QDARTS as shown in Figure 2.

Post Training Quantization (PTQ): A simple alternative to ∇QDARTS is applying post-training quantization (PTQ) on the final trained architecture with fp32 precision (i.e., *SubNet*) discovered by PC-DARTS. This requires no additional fine-tuning and therefore is highly computationally efficient. We employ asymmetric linear post-training quantization for this purpose (Gholami et al. (2021)).

Fixed-bit Quantized Aware Training (FBQAT): The high accuracy drop of lower-bit quantization is usually alleviated with quantization-aware training (QAT) (Shen et al. (2021)). It is well known that quantization-aware training outperforms post-training quantization, especially in low-bit regimes (Gholami et al. (2021)). Therefore, we apply QAT to the PC-DARTS full precision searched architecture using the HWGQ (Cai et al. (2017)) technique with a uniform, fixed-bit quantization policy (e.g., three experiments with 2-, 4-, and 8-bit).

Quantization on *SubNet* (Q*SubNet*): To understand if ∇QDARTS is better than a multi-staged optimization that involves a NAS followed by a mixed precision architecture search, we apply differentiable mixed-precision quantization technique (i.e., EdMIPS) on the output of search stage of PC-DARTS. We call this baseline Q*SubNet*. After 50 epochs of EdMIPS search on the architecture produced by PC-DARTS, we apply 450 epochs of fine-tuning so that it is a fair comparison against ∇QDARTS.

Existing Baselines: From the literature, we compare against APQ (Wang et al. (2020)), OQA (Shen et al. (2021)), SPOS (Guo et al. (2020)), and MNAS (Gong et al. (2019)) as the closet work to ∇QDARTS. We also compare ∇QDARTS with state-of-the-art non-NAS methods such as EMQ (Dong et al. (2023)), HAWQ (Yao et al. (2021)), OMPQ (Ma et al. (2023)).

4.3 Accuracy/BitOps/Memory Footprint Results

Table 2 and Table 3 compare accuracy, required bit operations (Bitops), and memory footprint of different baselines with ∇QDARTS. The first column shows the employed method. The number of employed cells in the search and training stages is shown in the second and third columns. The fourth column displays bit-precision, which pertains to both weight and activation, unless explicitly stated otherwise. The accuracy results (Top-1 for ImageNet) are shown in the fifth column. The sixth and seventh columns show the improvement in terms of bit operations normalized to the PC-DARTS values. The last column indicates the amount of improvement in memory footprint normalized to PC-DARTS. The absolute values of PC-DARTS are shown in parentheses in the first row (i.e., in terms of Gigabits for the required bit operations and mega bytes(MB) for memory footprint). The difference between the two versions of ∇QDARTS (2,4) is the complexity-aware loss values. By changing this parameter (ν in Eqn.8) we can push for higher accuracy at the cost of higher BitOps.

Table 2: Comparing the impact of different methods on Accuracy, BitOps, and Memory Footprint over CIFAR10 dataset

Method	#Cells-search	#Cells-train	Precision	Accuracy	BitOps (G)	Memory Footprint (MB)
PC-DARTS	8	20	32	96.25%	1(634.712)	1(218.977)
PTQ	8	20	8	95.59%	0.0625	0.250
PTQ	8	20	4	18.19%	0.0150	0.125
PTQ	8	20	2	9.99%	0.0039	0.063
FBQAT	8	20	8	95.86%	0.0611	0.236
FBQAT	8	20	4	62.68%	0.0157	0.125
FBQAT	8	20	2	38.45%	0.0039	0.063
Q*SubNet*	8	20	2, 4	70.05%	0.0039	0.063
∇QDARTS	8	8	2,4	93.43%	**0.0056**	**0.047**
∇QDARTS	8	8	2,4	**94.68**%	0.0062	0.062
∇QDARTS	8	8	2,4,8	95.95%	0.0185	0.081
∇QDARTS	8	20	2, 4, 8	**96.20**%	0.0556	0.198

4.4 CIFAR10 Results

As demonstrated in Table 2, the effectiveness of ∇QDARTS shines for CIFAR10 dataset. With a mere utilization of 2- and 4-bit operations, ∇QDARTS manages to achieve remarkable reductions in required bit operations by a staggering 160×, along with substantial savings in memory footprint of 16× while the accuracy drop is 1.57%.

∇**QDARTS** showcases its capacity to attain the same level of accuracy as PC-DARTS while simultaneously reducing the required operations by 18× and the memory footprint by 5×.

As can be observed, ∇**QDARTS** achieves remarkable accuracy in CIFAR10 without having to increase training capacity as compared to search capacity. (i.e., merely 0.3% lower accuracy than fp32 with PC-DARTS). This exemplifies the efficiency of ∇**QDARTS** in determining the optimal architecture and weight configurations, which enables us to reach high accuracy with less capacity. The last row in Table 2 shows that ∇**QDARTS** reaches the same accuracy as PC-DARTS with 18× less BitOps and 5× less memory footprint.

Comparing against the best outcomes achieved by other baselines, (i.e., Q*SubNet*), it is worth noting that ∇**QDARTS** excels. With 1.58× the bit operations required by Q*SubNet*, ∇**QDARTS** improves the accuracy by an impressive 24.63% while outperforming Q*SubNet* in terms of consumed GPU hours by 28%. This further highlights the superiority of ∇**QDARTS** in optimizing accuracy while maximizing efficiency in comparison to other baselines.

4.5 ImageNet Results

For the ImageNet dataset, we observe a significant accuracy degradation (i.e., 25.1%) for the Q*SubNet* when utilizing 2- and 4-bit operations compared to PC-DARTS. In contrast, ∇**QDARTS**, with 1.5× less required BitOps reaches 21% higher accuracy than Q*SubNet*. Although ∇**QDARTS** with only 2- and 4-bit precision for both activation and weights experience an accuracy drop of 1.7% compared to PC-DARTS, it reduces the required bit operations by an outstanding 65.36× and the memory footprint by 5×.

Moreover, by incorporating 2-, 4-, and 8-bit operations, ∇**QDARTS** further mitigates the accuracy drop to a mere 1%. Particularly, this is achieved by reducing the required bit operations to a notable 17×, underscoring the superior performance of ∇**QDARTS** in optimizing accuracy and reducing computational requirements on the ImageNet dataset.

4.5.1 Compare with SOTA

We also compare ∇**QDARTS** with APQ (Wang et al. (2020)), MNAS (Gong et al. (2019)), OQA (Shen et al. (2021)), and SPOS (Guo et al. (2020)) as the closest state-of-the-art baselines to ∇**QDARTS**. APQ, SPOS, OQA, and MNAS converge at the accuracy of 72.1%, 71.5%, 74.1%, and 71.77% while APQ and MNAS methods use even 8-bit weight/activation. In contrast, by only using 2- and 4-bit, ∇**QDARTS** outperforms APQ, SPOS, OQA, and MNAS by 2.3%, 2.9%, 0.3%, and 2.7% in terms of accuracy. By involving 8-bit, ∇**QDARTS** outclasses APQ, SPOS, OAQ, and MNAS by 3%, 3.6%, 1%, and 3.4%, respectively. In terms of BitOps (memory footprint), by considering almost the same accuracy, ∇**QDARTS** outperforms APQ, SPOS, OQA, and MNAS by 2.3×(12×), 2.4×(3×), 13%(6.2×), 3.4×(37%).

Table 3: Comparing the impact of different methods on Accuracy, BitOps, and Memory Footprint over ImageNet dataset

Method	#Cells-search	#Cells-train	Precision	Accuracy	BitOps (G)	Memory Footprint (MB)
PC-DARTS	8	14	32	76.1%	1(536.552)	1(172.102)
PTQ	8	14	8	67.47%	0.0625	0.254
PTQ	8	14	4	1.0%	0.0157	0.127
FBQAT	8	14	8	74.01%	0.0622	0.244
FBQAT	8	14	4	50.27%	0.0156	0.127
FBQAT	8	14	2	33.57%	0.0039	0.063
Q*SubNet*	8	14	2,4	50.70%	0.0156	0.127
APQ	(21 blocks)	(21 blocks)	4,6,8	72.1%	0.0239	1.284
MNAS	(22 blocks)	(22 blocks)	2,4,6,8	71.77%	0.0347	0.147
OQA	(21 blocks)	(21 blocks)	4	74.1%	0.0173	1.245
SPOS	(20 blocks)	(20 blocks)	1,2,3,4	71.5%	0.0244	0.321
∇QDARTS	8	14	2,4	71.70%	**0.0101**	**0.107**
∇QDARTS	8	14	2,4	**74.41**%	0.0153	0.199
∇QDARTS	8	14	2,4,8	**75.10**%	0.0587	0.385

4.6 Total Cost

Figure 2 and Table 4 offer a comprehensive depiction of the total needed time (i.e., search and training), measured in GPU hours, for various methods on the ImageNet dataset on 8 A40 GPUs. Upon observation, it is evident that ∇QDARTS takes 28% (8%) shorter runtime compared to Q*SubNet* (FBQAT), and longer runtime compared to PTQ. PTQ takes less time since it assumes that an expensive fully trained network is available to be quantized with fixed-bit and no extra fine-tuning is required. Compared with state-of-the-art methods ∇QDARTS improves the total cost significantly. ∇QDARTS improves the total search and training cost by 3.1×, 1.54×, compared with APQ, OQA, respectively. SPOS has less GPU hours at the cost of low accuracy, high BitOps, and large memory footprint.

Table 4: Comparing the total GPU hours (8,A40) of ∇QDARTS and other methods on ImageNet dataset

Method	**APQ Wang et al. (2020)**	**OQA Shen et al. (2021)**	**SPOS Guo et al. (2020)**	∇QDARTS
GPU Hours	302.6	149.4	73.5	96.6

4.7 Compare with Non-NAS Quantization Methods

We compare ∇QDARTS with non-NAS state-of-the-art quantization schemes in Table 5. The numbers are the highest accuracy that these methods can reach with their corresponding BitOps(i.e., normalized to PC-DARTS). Among them, only HAWQ supports mixed-precision for both weight and activation.

In terms of accuracy, OMPQ, EMQ, and HAQW3 on ResNet50 have 1.18% (1.87%), 1.6% (2.3%), and 0.29% (0.89%) higher accuracy compared to two versions of ∇QDARTS with (2,4) bit setting. However, their BitOps are 495% (1900%), 460% (1800%), and 489% (1870%) higher than ∇QDARTS (2,4). Notably, PCDARTS in FP32 demonstrates lower accuracy compared to quantized ResNet50 (76.1% vs. 76.7%). This indicates that the higher accuracy of these methods is attributed to the inherent capacity of ResNet50 relative to PCDARTS. However, by increasing the number of cells in PCDARTS, it can reach higher accuracy, at the expense of increased BitOps. Within the same BitOps budget, ∇QDARTS outperforms all these methods in terms of accuracy.

Table 5: Comparing ∇QDARTS with non-NAS quantitation schemes on ImageNet dataset

Method	**W/A**	**Accuracy**	**BitOps(G)**
OMPQ-ResNet18	4-8/8	72.30	0.1808
OMPQ-ResNet18	4-8/6	72.08	0.1398
OMPQ-ResNet50	4-8/5	**76.28**	0.2907
HAWQv3-ResNet18	4,8/4,8	70.22	0.1342
HAWQv3-ResNet18	4,8/4,8	71.56	0.2162
HAWQv3-ResNet50	4,8/4,8	**75.39**	0.2870
EMQ–ResNet18	2,3,4/8	72.31	0.1715
EMQ–ResNet18	2,3,4/6	72.28	0.1323
EMQ–ResNet50	2,3,4/5	**76.70**	0.2758

4.8 Ablation Study

In this subsection, we study different aspects of the proposed ∇QDARTS and perform different experiments to show the impact of various parameters on the proposed methods.

4.8.1 Alternative Update Methods

In the DARTS framework, bi-level optimization concurrently optimizes network weights and architecture parameters using gradient descent. The upper-level optimization targets architecture parameters, whereas the lower level focuses on network weights. Conversely, one-level optimization merges these stages, simplifying the process at the potential expense of architecture quality. In ∇QDARTS, the complexity escalates as it involves three optimization parameters: architecture parameters (α), weights (w), and bit-precision (γ).

As discussed in the main paper, incorporating γ introduces a tri-level optimization challenge, substantially complicating the optimization process. Thus, we propose an efficient bi-level optimization variant in ∇**QDARTS**.

Below, we outline various update mechanisms and their effects on accuracy and BitOps.

∇**QDARTS (Efficient Bi-level Optimization):** In ∇**QDARTS**, the sequence involves forward propagation with a validation dataset, backpropagation on α, a forward pass with the training dataset, and subsequent backpropagation for w and γ.

$$\begin{aligned} \min_{\alpha} \quad & \mathcal{L}_{\text{val}}(\omega^*(\alpha), \gamma^*(\alpha), \alpha) \\ \text{s.t.} \quad & \omega^*(\alpha), \gamma^*(\alpha) = \operatorname*{argmin}_{\omega,\gamma} \quad \mathcal{L}_{\text{train}}(\omega, \gamma, \alpha) \end{aligned} \tag{12}$$

Bi-level-other Optimization: This optimization method (Eq. 13) starts with a forward pass using a validation dataset, followed by backpropagation for α and γ. Then, a forward pass with the training dataset precedes backpropagation for w.

$$\begin{aligned} \min_{\alpha,\gamma} \quad & \mathcal{L}_{\text{val}}(\omega^*(\alpha, \gamma), \gamma, \alpha) \\ \text{s.t.} \quad & \omega^*(\alpha, \gamma) = \operatorname*{argmin}_{\omega} \quad \mathcal{L}_{\text{train}}(\omega, \gamma, \alpha) \end{aligned} \tag{13}$$

Tri-level Optimization: This optimization scenario (Eq. 14) begins with a forward pass using a validation dataset and backpropagation for α. Next, a forward pass with the training dataset is followed by backpropagation for w. Finally, another forward pass with the training set leads to backpropagation for γ.

$$\begin{aligned} \min_{\alpha} \quad & \mathcal{L}_{\text{val}}(\omega^*(\alpha, \gamma), \gamma, \alpha) \\ \text{s.t.} \quad & \omega^*(\alpha, \gamma) = \operatorname*{argmin}_{\omega} \quad \mathcal{L}_{\text{train}}(\omega, \gamma^*(\omega), \alpha) \\ \text{s.t.} \quad & \gamma^*(\omega) = \operatorname*{argmin}_{\gamma} \quad \mathcal{L}_{\text{train}}(\omega, \gamma, \alpha) \end{aligned} \tag{14}$$

One-level Optimization: This optimization procedure (Eq. 15) eliminates the need for a validation dataset, conducting a forward pass with the training dataset and then backpropagating for w, α, and γ.

$$\min_{\alpha,\omega,\gamma} \quad \mathcal{L}_{\text{train}}(\omega, \gamma, \alpha) \tag{15}$$

Figure 3 illustrates the variations in accuracy and BitOPs across different optimization methods where all of them use the same hyperparameter. Each label manifests *(optimization method, BitOps, accuracy)*. It shows that while alternative methods reduce the accuracy, ∇**QDARTS** maintains higher accuracy with less BitOps. Table 6 compares the search time of optimization methods. The One-level needs only one forward pass with the training dataset per mini-batch, per epoch. Hence, it gives the lowest search time and lowest accuracy. Compared to Tri-Level and Bi-Level-other, ∇**QDARTS** improve the search time by 41.8% and 6.6%, respectively. Surely, for the larger datsets, we will see more improvement. For example, for the ImageNet dataset, we observe a time-out issue for Tri-Level optimization (5 days).

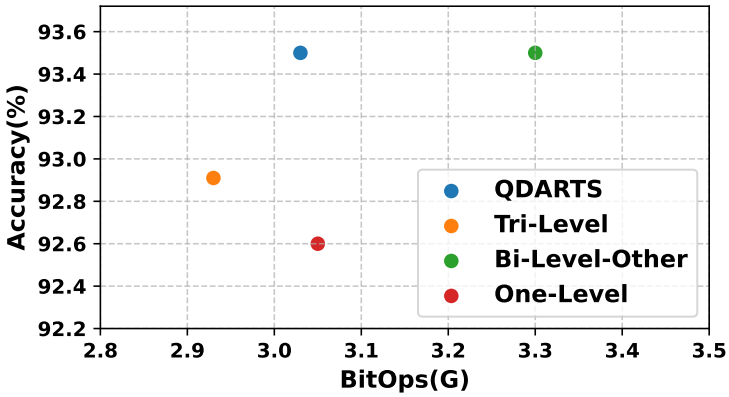

Figure 3: Comparing the impact of various optimization methods on accuracy and BitOps.

Table 6: Comparing search time (minutes) of various optimization methods over CIFAR10 dataset

∇QDARTS	Bi-Level-other	Tri-Level	One-Level
372.28	398.83	640.02	272.08

4.8.2 Validation Accuracy

Figure 4 illustrates how the validation accuracy increases through the first 250 training epochs over the ImageNet dataset. As it has shown, Q*SubNet* and FBQAT (4-bit) achieves almost similar performance and convergence rate throughout the training period and they are significantly better than FBQAT (2-bit). ∇QDARTS outperforms all the baselines extensively from the beginning of the training.

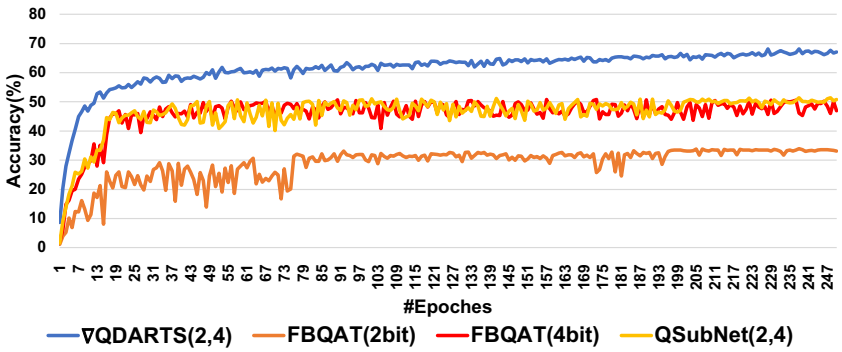

Figure 4: Validation accuracy for different techniques throughout the first 250 training epochs (ImageNet).

4.8.3 Required Bit Operations Per Cell

Figure 5 compares the required bit operations of different cells of ∇QDARTS that have 2-,4-bit and also ∇QDARTS with 2-, 4-, 8-bit against PC-DARTS. The Cell#5 and Cell#8 are *reduction cells* and the rest are *normal cells*.

The nuanced dissimilarities observed among different normal cells in PC-DARTS can be attributed to a fundamental distinction between cells positioned directly after a *normal cell* and those following a *reduction cell*. Notably, the cells immediately succeeding a reduction cell , leading to variations in the computational requirements across normal cells in PC-DARTS. This complex architectural style highlights the detailed design decisions made to improve performance. In the case of ∇QDARTS, the efficacy is exemplified by the substantial reduction in required operations for each cell. Specifically, ∇QDARTS achieves a significant reduction in bit operations of up to 65.5× for the (2,4) bit configuration and a 17× for the (2,4,8) bit configuration. These reductions further emphasize the effective computational optimization achieved by ∇QDARTS.

4.8.4 Sensitivity Analysis of Complexity Decay Parameter (ν)

In this analysis, we explore the effects of altering the complexity decay parameter (ν) within the context of complexity-aware loss on the resulting accuracy. Previously, in Table 2 and Table 3 of the main paper, we present diverse accuracy/BitOps metrics for the same bit precision levels within the ∇QDARTS framework, highlighting the sole variable as the complexity decay parameter (ν). Here we extend this experiment. As shown in Table 7, altering the complexity decay parameter by a factor of 10^{10} results in a 0.58% change in accuracy on the CIFAR10 dataset. However, its impact on the ImageNet data set is significant. By changing this hyperparameter from 10^{-4} to 10^{-9}, the accuracy varies by 6.81%.

Employing Discovered Precision of the first/last Cell for Stacking Cells During Retraining Phase: As we mentioned in Section 3.4, increasing the model capacity in ∇QDARTS is not straightforward as different cells have different precision. Table 8 shows how stacking the cells using the discovered cells will impact the

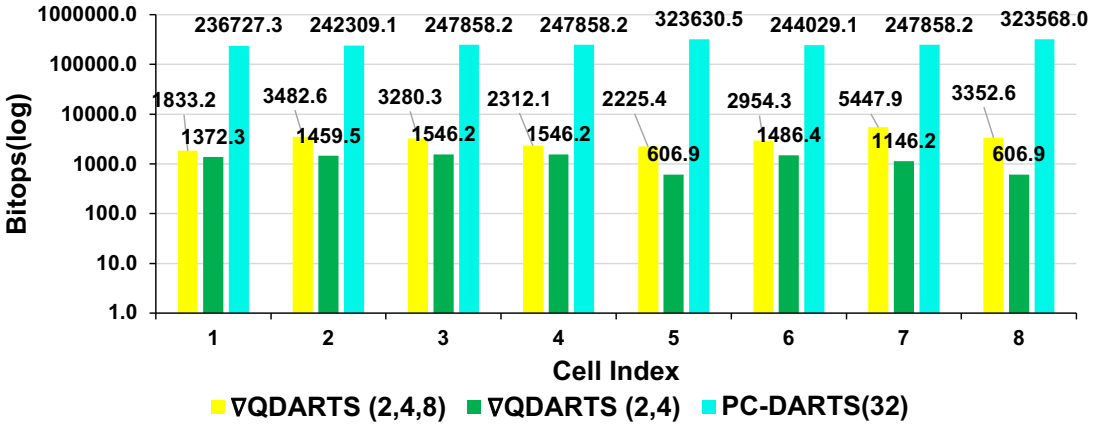

Figure 5: Comparing required bit operations of different cells for PC-DARTS and ∇QDARTS (ImageNet).

Table 7: Comparing the impact of different values of complexity decay (ν) on accuracy over CIFAR10 and ImageNet datasets

Method	#Cells-search	#Cells-train	Precision	Complexity decay	Accuracy	Dataset
∇QDARTS	8	8	2,4	10^{-5}	94.28 %	CIFAR10
∇QDARTS	8	8	2,4	10^{-7}	94.43%	CIFAR10
∇QDARTS	8	8	2,4	10^{-9}	94.49%	CIFAR10
∇QDARTS	8	8	2,4	10^{-15}	**94.86**%	CIFAR10
∇QDARTS	8	14	2,4	10^{-4}	64.45%	ImageNet
∇QDARTS	8	14	2,4	10^{-9}	**71.26**%	ImageNet

accuracy. As seen, by replicating the first cells and positioning them at the top of existing cells, we enhance the capacity of the underlying architecture compared to using the cells discovered at the end.

Table 8: Study the impact of employing discovered precision of first cell and last cell for stacking cells during retraining phase on accuracy over ImageNet dataset

Method	#Cells-search	#Cells-train	Precision	Position	Accuracy
∇QDARTS	8	14	2,4,8	last	74.608%
∇QDARTS	8	14	2,4,8	first	75.04 %

In the appendices, we have provided more ablation studies to show how the bit-precision parameter (γ) evolved during the search phase. Furthermore, we study the impact of the complexity decay parameter, having additional cells in the training phase.

5 Conclusion

The ∇QDARTS method represents a significant advancement in architecture-weight-precision joint search, skillfully integrating weight values, architecture, and bit-precision (for both weight and activation) search into a single-shot and differentiable framework. ∇QDARTS approach not only eliminates the need for proxy and pretraining but also demonstrates its effectiveness through a notable enhancement in accuracy, reducing required bit operations and memory footprint. ∇QDARTS achieves remarkable results on CIFAR10 using (2,4) bit precision compared to fp32, cutting bit operations by 160× while only decreasing accuracy by 1.57%. Enhancing the capacity allows ∇QDARTS to equal fp32 accuracy, decreasing bit operations by 18×. Using (2,4,8) bit precision, ∇QDARTS reduces the accuracy drop to 1% relative to fp32, while significantly cutting bit operations by 17× and memory footprint by 2.6×. Regarding bit operation (memory footprint), ∇QDARTS surpasses APQ, SPOS, OQA, and MNAS with comparable accuracy by APQ, SPOS, OQA, and MNAS with similar accuracy by 2.3× (12×), 2.4× (3×), 13% (6.2×), 3.4× (37%), respectively. ∇QDARTS improves

the total search and training cost by 3.1×, 1.54×, compared with APQ, OQA, respectively. These pieces of evidence show that ∇**QDARTS** hold a promise for efficient and powerful network design, showcasing the potential of joint quantization with NAS in optimizing computational resources while maintaining high accuracy.

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A Appendix

A.1 Visual Analysis of Bit Precision and Architecture Identified by ∇QDARTS

The plots in Fig. 6 showcase the structure of the discovered cells within **∇QDARTS** when employing a (2,4,8) bit configuration for the ImageNet dataset, juxtaposed against PC-DARTS (i.e., first row). A noteworthy observation within the visualization is the strategic selection of bit precision for various convolution blocks. Notably, 2-bit precision is predominantly chosen for many of the 5x5 convolution blocks, while a higher precision of either 4 or 8 bits is judiciously employed for the 3x3 convolution blocks. This representation demonstrates **∇QDARTS**' ability to uncover computationally efficient operations for both weight and activation within each cell, attesting to its optimization capabilities.

A.2 γ Evolution During Search

The plots in Fig. 7 illustrate the evolution of the γ (bit precision) parameter over 50 epochs in the search phase for activation (the first six plots) and weights (the second six plots)for randomly picked cells, running on CIFAR-10 dataset where the bit precision is (2,4,8). The Y-axis shows the probability of a specific bit precision being chosen. The plots show that the proposed framework is able to choose a higher precision to add more capacity to the network and increase the accuracy.

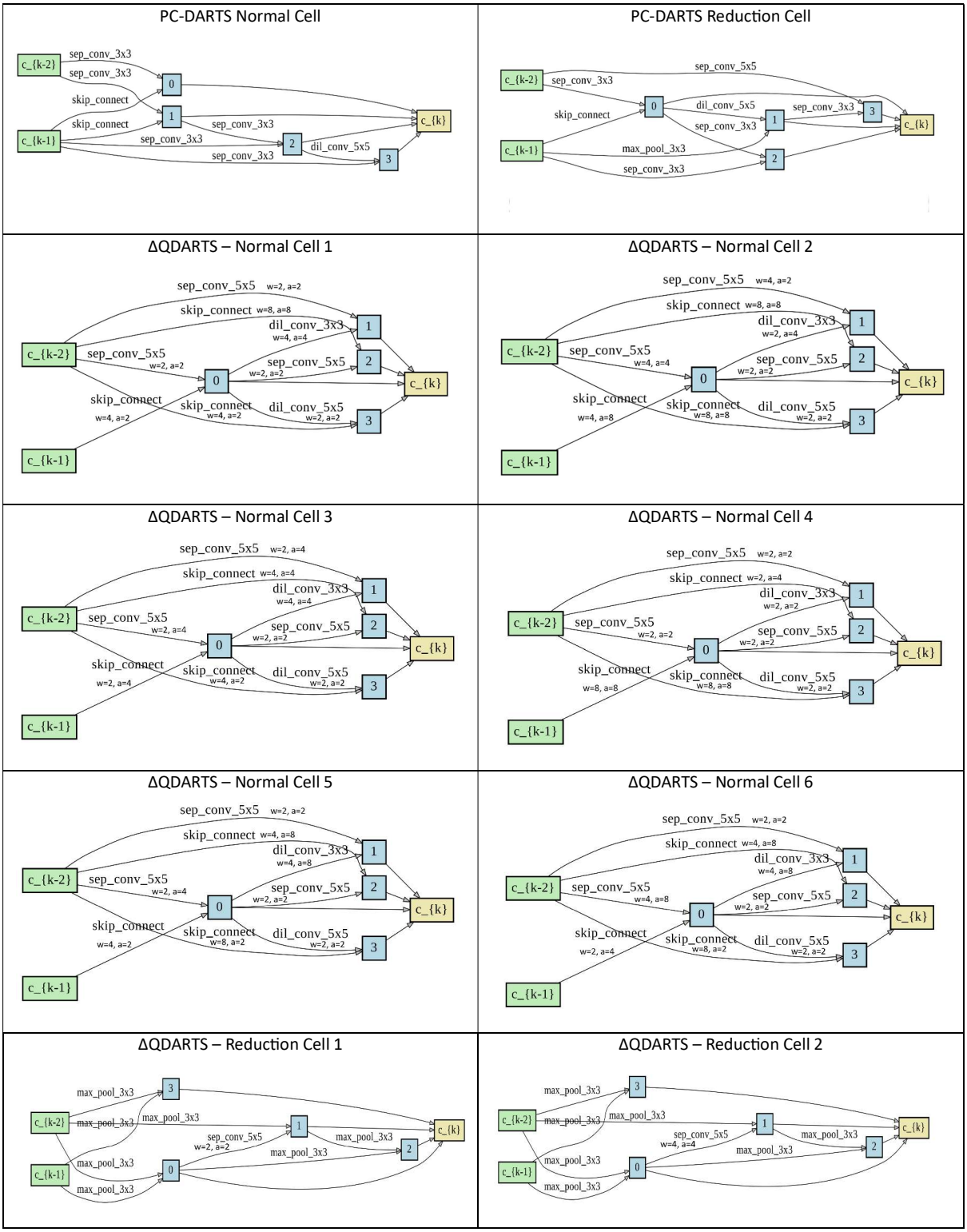

Figure 6: Comparing the discovered cell structures with bit precision of all normal and reduction cells (i.e., row 2-5) with PC-DARTS (i.e., row 1) for ImageNet dataset. Due to mixed-precision, unlike PC-DARTS, the cells in ∇QDARTS are not similar.

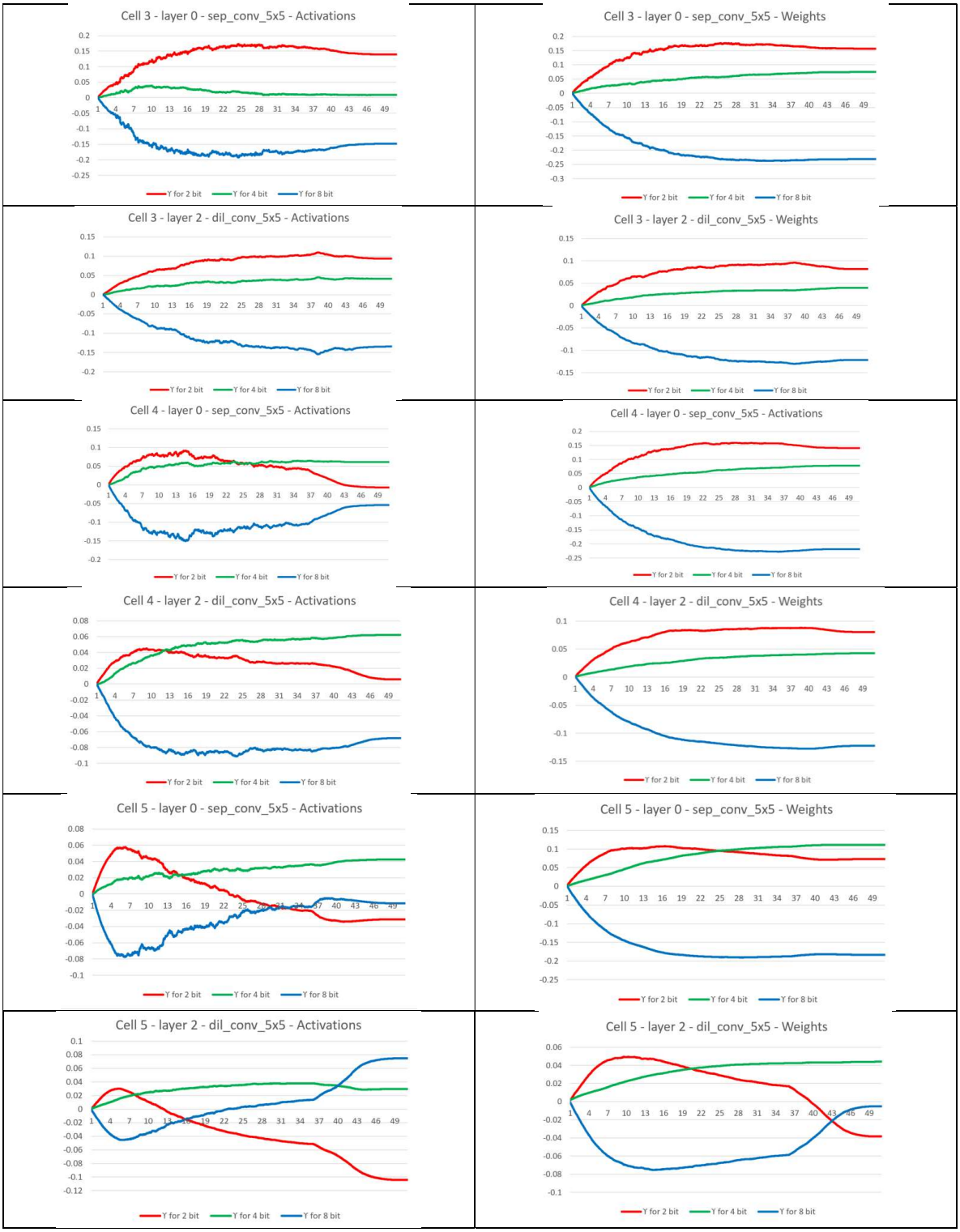

Figure 7: Evolution Illustration of the γ (bit precision) parameter over 50 epochs in the search phase for activation (the first six plots) and weights (the second six plots) for randomly picked cells, for CIFAR-10 where the bit precision is (2,4,8).