

Jumping through Local Minima: Quantization in the Loss Landscape of Vision Transformers

Natalia Frumkin

The University of Texas at Austin

nfrumkin@utexas.edu

Dibakar Gope

Arm Inc.

dibakar.gope@arm.com

Diana Marculescu

The University of Texas at Austin

dianam@utexas.edu

Abstract

Quantization scale and bit-width are the most important parameters when considering how to quantize a neural network. Prior work focuses on optimizing quantization scales in a global manner through gradient methods (gradient descent & Hessian analysis). Yet, when applying perturbations to quantization scales, we observe a very jagged, highly non-smooth test loss landscape. In fact, small perturbations in quantization scale can greatly affect accuracy, yielding a 0.5 – 0.8% accuracy boost in 4-bit quantized vision transformers (ViTs). In this regime, gradient methods break down, since they cannot reliably reach local minima. In our work, dubbed Evol-Q, we use evolutionary search to effectively traverse the non-smooth landscape. Additionally, we propose using an infoNCE loss, which not only helps combat overfitting on the small calibration dataset (1,000 images) but also makes traversing such a highly non-smooth surface easier. Evol-Q improves the top-1 accuracy of a fully quantized ViT-Base by 10.30%, 0.78%, and 0.15% for 3-bit, 4-bit, and 8-bit weight quantization levels. Extensive experiments on a variety of CNN and ViT architectures further demonstrate its robustness in extreme quantization scenarios. Our code is available at <https://github.com/enyac-group/evol-q>.

1. Introduction

Quantization is a widespread technique for efficient neural network inference: reducing data precision from 32 bits to ≤ 8 bits is an effective approach to aggressively reduce model footprint and speed up computation. Network quantization is an extremely important tool for deploying models in cloud [28] and edge settings [27], where we aim to maximize accuracy while reducing the computational burden. We consider the post-training quantization (PTQ) setting, where there

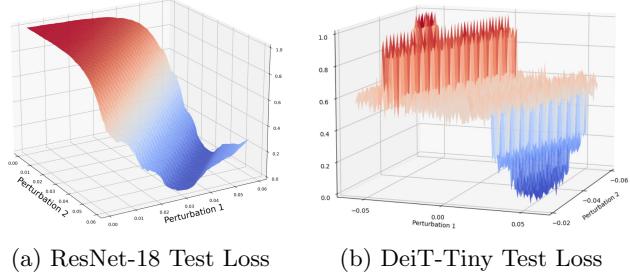


Figure 1: We perturb along two basis vectors of one layer/block’s quantization scales. The test loss landscape during perturbation is smooth in the CNN case (a), and highly non-smooth in the ViT case (b).

is access to a small ($\sim 1,000$ image) calibration dataset but no access to the original training dataset. PTQ is an integral component of model deployment, when a carefully curated full-precision model is too expensive to retrain. Our work, Evol-Q, is a PTQ method for vision transformers which leverages four key observations:

1. **Small perturbations in quantization scale can lead to significant improvement in quantization accuracy.** For example, small adjustments in a self-attention block’s scale can induce a $\pm 1\%$ change in accuracy.
2. As shown in Fig. 1, **quantized vision transformers (ViTs) have an extremely non-smooth loss landscape, particularly with respect to the perturbation in quantization scales**, making stochastic gradient descent a poor choice for optimization. We use evolutionary search to favor nearby local minima to significantly improve accuracy ($\sim 0.5 - 1\%$).
3. In comparison to non-contrastive loss functions such as mean squared error, cosine similarity, and the KL divergence, **contrastive losses tend to**

smooth the loss landscape, as observed in our experiments and supported by recent work [10]. This finding inspires the use of contrastive loss to further facilitate the quantization scale search process. Contrastive losses, specifically the infoNCE loss in this work, also helps in combating overfitting on the small calibration dataset by incorporating negative examples into the loss.

4. The Evol-Q framework generalizes to CNN quantization as well, since the infoNCE loss provides a smoother landscape than other losses.

Combining these observations, we devise a new optimization scheme to adjust the quantization scales of low bit-width ViTs. Instead of using gradient descent to optimize all network parameters or estimating a noisy Hessian, we propose a series of cheap evolutionary search procedures to successively minimize the quantization error. Evol-Q injects small perturbations into the quantization scale at one layer and uses a global infoNCE loss to evaluate them. In the next section, we will show how prior work does not properly address the non-smooth ViT loss landscape.

2. Related Work

CNN Quantization: When quantizing ViTs, it is natural to borrow techniques from CNN quantization and apply them to vision transformers. In the case of general quantization, one can consider either naive methods (such as MinMax [14] quantization) or complex methods (such as gradient descent) to find the quantization scale. Naive techniques include Min-Max [14], Log2 [3], or Percentile quantization, where we apply some statistical analysis on the values of a model tensor. While simple to implement, these methods can result in unacceptable accuracy degradation, particularly in the 3-bit and 4-bit case. This leads us to employ more advanced strategies to recoup some accuracy lost by quantization.

Complex methods involve techniques such as gradient descent [24], Hessian analysis [15], or knowledge distillation [6] to maximize the quantized model’s accuracy. In particular, many methods employ a layer-wise loss [29, 13, 2]. A layer-wise loss can serve as a good proxy for a smooth global loss [23], yet a local loss is unlikely to resemble the ViT’s highly non-smooth global landscape [1]. While Hessian-based methods [15] can utilize second order information, the ViT loss landscape resembles an “egg carton” with a high density of extremal points. This space cannot be traversed well with only first and second-order gradient information.

Moreover, BRECQ [15] assumes the Hessian is positive semi-definite (PSD) which is a poor assumption for any non-smooth landscape.

ViT Quantization: Some work has already achieved very good accuracy on vision transformers. PTQ-for-ViT [22] learns a quantization scale for each layer by using two loss functions: (1) a ranking loss for each multi-head attention module; and (2) cosine similarity for the MLP layer. The layer-wise loss may achieve good accuracy, but with the non-smooth ViT landscape, this approach may end up at a local maximum and may be very sensitive to initialization. PTQ4ViT [31] also employs a Hessian-guided metric for guided global optimization similar to BRECQ [15]. As we mentioned before, the PSD assumption on the Hessian breaks down for our “egg carton”-shaped loss landscape. In contrast, PSAQ-ViT-V2 [16] uses a student-teacher MinMax game to minimize the KL divergence between the full precision and quantized models. The KL divergence is applied to kernel density estimations which are much more robust than Hessian-based or gradient-based techniques. We believe this technique can traverse the non-smooth ViT landscape, and despite being data-free, it has the best accuracy of all other methods we compare against.

We apply Evol-Q, our quantization scale learning method, on top of the FQ-ViT [20] which incorporates Log2 quantization and an integer Softmax function for end-to-end 8-bit quantization. FQ-ViT [20] is surprisingly effective on ViTs, likely because Log2 quantization can compensate for the asymmetric distributions following the Softmax and GeLU layers.

Quantization-Aware Training (QAT) has shown impressive results on vision transformers [30, 19, 18, 17], yet these methods consider training with the entire dataset rather than an unlabeled calibration dataset.

Contrastive Loss: In this work, we use a global infoNCE loss as our preferred loss function for both CNN and ViT quantization. Since we have such a small calibration dataset, the infoNCE loss helps generalize to the unseen test set. We are the first work to use a infoNCE loss in this manner. Prior work has combined quantization and self-supervised learning in a joint training framework [4, 11] allowing for regularization from both the contrastive loss and a quantization loss in training. In particular, SSQ-L [4] uses a joint SimSiam- L_2 loss during training to improve quantization for all bit-widths, whereas our method considers how the infoNCE loss, in conjunction with an evolutionary search, is used to traverse the highly non-smooth loss landscape and optimize the quantization scale for a specific bit-width at test time. Moreover, SSQ-L [4] uses the loss as regularization and not as a

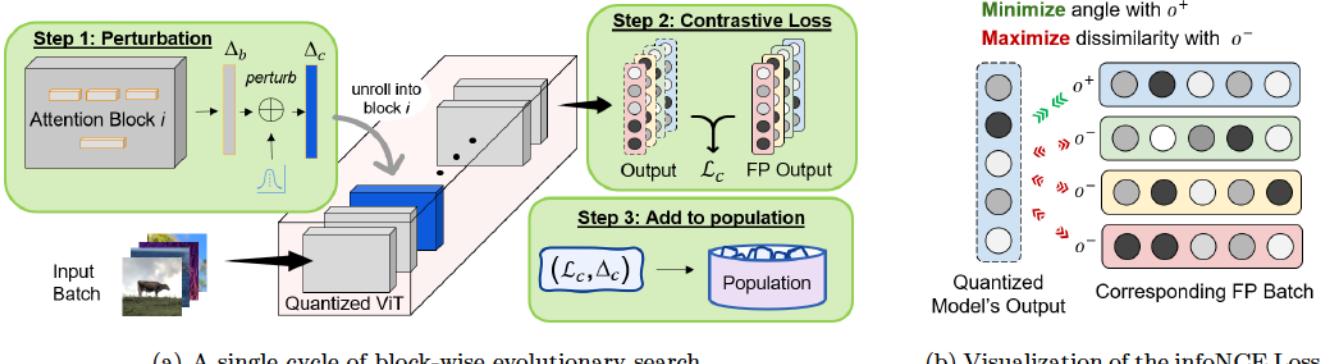


Figure 2: An overview of Evol-Q. On the left, we show one cycle completed on a single block. Each block has C cycles of evolutionary search, and we perform P passes over all blocks. On the right, we provide intuition for the infoNCE loss (Step 2), where we encourage similarity between the quantized and corresponding predictions while simultaneously maximizing dissimilarity between unlike predictions.

proxy for the test loss. Another work [26] applies contrastive learning to binarized ResNet and VGG models. They apply a layer-wise infoNCE loss, showing that it achieves good results for the 2-bit loss landscape of small CNNs. While a layer-wise loss is sub-optimal, the ability for the infoNCE loss to perform well on a binary loss landscape is great motivation for our work.

In summary, prior work has migrated CNN quantization techniques to ViT quantization without addressing the non-smooth ViT loss landscape. In the coming section, we present Evol-Q as an effective solution to this problem.

3. The Evol-Q Framework

In the non-smooth ViT quantization landscape, first and second-order gradient methods are not effective and cannot handle the large number of local minima. In such a regime, small perturbations in quantization scale can lead to a significant boost in accuracy. We apply evolutionary search using an infoNCE loss to evaluate these perturbations, enabling Evol-Q to traverse a non-smooth surface and minimize overfitting on the calibration dataset.

We begin with an overview of uniform quantization and then dive into the core components of our method: traversing perturbations using evolutionary search and evaluating them using an infoNCE loss.

3.1. Uniform, End-to-End Quantization

We consider uniform quantization, where full precision values are mapped to a uniform range based on the quantization bit-width (b). Uniform quantization is formally defined as:

from a uniform ball centered around Δ :

self-supervised setting [10] (see supplementary materials for details). Inspired by Chen et al. [5], we use the infoNCE [25] loss:

4-bit weights, 8-bit activations (4W8A)				
Method	DeiT-T	DeiT-S	DeiT-B	ViT-B
PSAQ-ViT	65.57	73.23	77.05	25.34
PTQ4ViT	-	-	64.39	-
FQ-ViT	66.91	76.93	79.99	78.73
PSAQ-ViT-V2 [†]	68.61	76.36	79.49	-
Evol-Q (ours)	67.29	77.06	80.15	79.50

[†] Does not quantize Softmax/GELU layers

Table 3: Top-1 Accuracy on ImageNet using 4W8A quantization.

3-bit weights, 8-bit activations (3W8A)				
Method	DeiT-T	DeiT-S	DeiT-B	ViT-B
FQ-ViT	35.79	60.58	72.11	55.33
Evol-Q (ours)	39.45	61.16	72.41	65.63

Table 4: Top-1 Accuracy on ImageNet with 3W8A quantization.

By reducing the precision from 32 to 3 bits, we achieve a $>10X$ reduction in memory footprint while still maintaining a reasonable accuracy for DeiT-Base. We refer to supplementary materials for ablations on using OMSE [7] and bias correction [2] for 3W8A which dramatically improves our method’s performance.

4.5. Extending to Swin & LeViT Models

We run our experiments on additional model families to ensure that our method is applicable to different types of attention blocks. Swin transformers [21] have the same macro-architecture as DeiT and ViT models, with the exception that the Swin transformer block is a windowed attention. We see results for 4-bit Swin transformers in Tab. 5.

Method	Swin-T	Swin-S	Swin-B
PSAQ-ViT	71.79	75.14	-
PSAQ-ViT-V2 [†]	76.28	78.86	-
FQ-ViT	80.73	82.13	82.73
Evol-Q (ours)	80.43	82.63	83.07

[†] Does not quantize Softmax/GELU layers

Table 5: Top-1 Accuracy for 4W8A Swin Models.

Prior quantization techniques do not consider LeViT models, a family of ViTs that improve the inference speed of existing transformers. Using a longer convolutional backbone, they can achieve similar results to classic ViTs while also reducing the complexity of the transformer blocks in favor of ResNet-like stages. We include the LeViT family in our experiments to illustrate how our method can be extended beyond the standard block size. We can see 4W8A results for the LeViT model family in Tab. 6. Across the board, we

see a significant improvement in LeViT quantization as compared to FQ-ViT, our baseline.

Method	LeViT -128S	LeViT -192	LeViT -256	LeViT -384
FQ-ViT	14.90	17.00	61.33	64.60
Evol-Q (ours)	29.20	30.37	64.57	69.50

Table 6: Top-1 Accuracy for 4W8A LeViT models.

In fairness, we have not applied any other techniques to boost LeViT’s accuracy (doing so may inflate our method’s improvement), so we leave it to future work to incorporate other quantization techniques on top of our framework.

5. Analysis

In the following section, we support the three observations set forth in the introduction. First, we show how **the non-smooth ViT loss landscape compares with the CNN one**, and discuss how a variety of loss functions perform in the Evol-Q framework. Next, we visualize the layer-wise weight distributions to illustrate how small perturbations can yield a significant jump in accuracy. Finally, we report runtime and various ablations to contextualize our method in the broader space of quantization techniques. For more ablations and analysis, please refer to the supplementary materials.

5.1. The Test Loss Landscape of ViTs

In Fig. 3, we show that perturbing quantization scale yields a smooth test loss landscape for ResNet-18 and a jagged, non-smooth landscape for DeiT-Tiny. This loss landscape illustrates how the test loss is related to the Δ_{10} scale at block #10. **We perturb along two basis vectors for the Δ_{10} and observe the effect on the test loss.** The DeiT-Tiny loss landscape is very complex and highly non-linear, whereas the ResNet-18 landscape is comparatively smooth. Intuitively, we hypothesize that the presence of many GeLUs and Softmax functions induces in the DeiT loss landscape many more extreme points than in the ResNet loss landscape.

For the smooth landscape in Fig. 3a, the infoNCE loss is clearly optimal since it is closest to the global minimum. If we plot the MSE, Cosine (Cossim), and Fisher loss landscapes, we find that they are not as smooth as the infoNCE loss in the CNN case (see supplementary materials, Sec A). The infoNCE loss helps to provide a smoother loss with respect to the calibration dataset by incorporating negative samples to reduce bias [10].

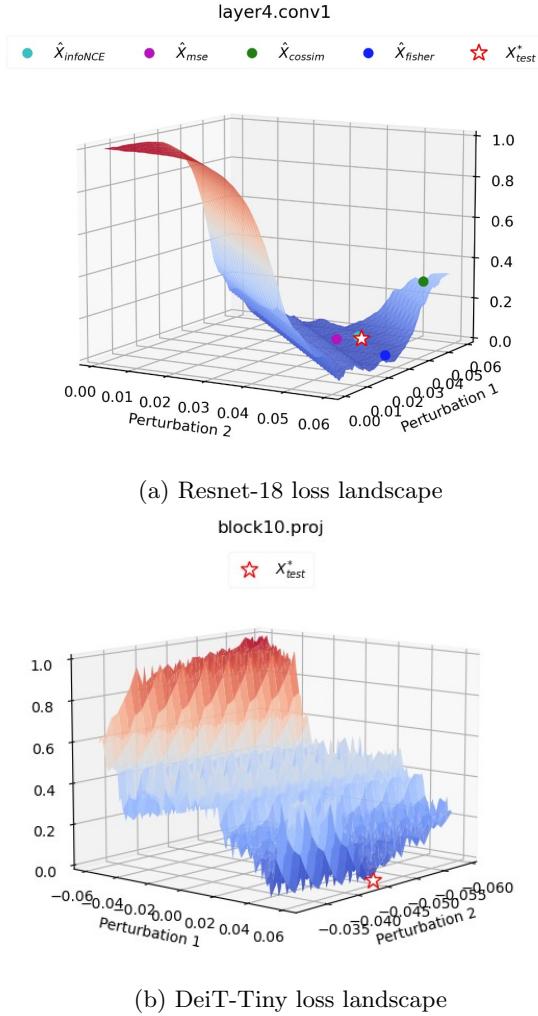


Figure 3: A comparison of the test loss landscapes for 4-bit quantized CNNs and ViTs. In Fig. 3a, we show how small perturbations in the 4th convolutional layer yields a smooth test loss landscape. In Fig. 3b, we apply perturbations to attention block #10 and the resultant loss landscape is highly non-smooth.

In the non-smooth landscape, Fig. 3b, the global minimum is very hard to find. In fact, proximity to the global loss in this landscape is not a good indicator of loss function quality, since there are many local maxima in close proximity (with an ϵ - ball) of the global minimum. In Sec. 5.3, we provide an empirical justification that the infoNCE loss prevents overfitting and is superior to other loss functions.

5.2. Gradient Descent vs. Evolutionary Search

In Fig. 4, we show how evolutionary search finds candidates close the local minima, whereas gradient descent breaks down the ViT loss landscape. We show three initial points, where gradient descent either os-

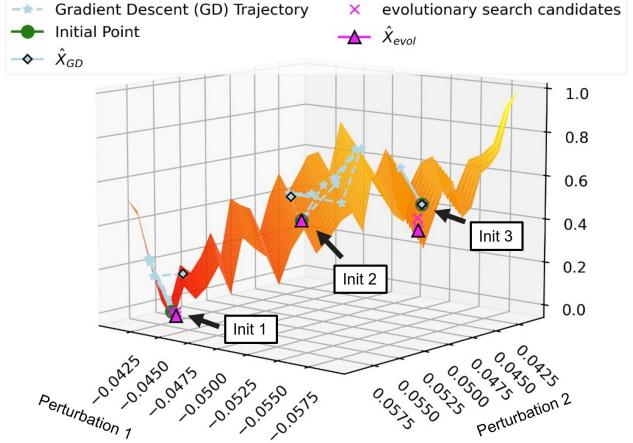


Figure 4: A zoomed in section of the landscape in Fig. 3b, where we perform gradient descent and evolutionary search for three initial points. We show the solutions of evolutionary search (\hat{X}_{evol}) and gradient descent (\hat{X}_{GD}) after 10 iterations.

cillates (init 3) or does not converge to a local minima (init 1 and 2). In contrast, evolutionary search generates a candidate perturbation and steps in the direction of the best candidate. We find that evolutionary search is very good at finding the closest local minima, which is sufficient to get an accuracy boost of $\sim 0.4\%$ in this loss landscape.

In Table 7, we show quantitatively that gradient-based optimizers underperform in comparison to evolutionary search for the same block-wise setting as in Evol-Q. We believe that non-smoothness at the block level is what makes these gradient-based techniques ineffective.

Method	DeiT-T	DeiT-S	DeiT-B	ViT-B
SGD	71.57	79.25	81.24	83.40
Adam	71.29	79.25	81.24	83.25
AdamW	71.37	79.00	81.30	83.36
Evol-Q (ours)	71.63	79.57	82.67	84.40

Table 7: Comparison with gradient-based optimizers using 8-bit weights, 8-bit activations (8W8A).

5.3. Loss Function Choice

We compare the infoNCE (contrastive) loss with other common loss functions in Fig. 6. We find mean-squared error (MSE) to be equally (if not more) effective in the initial iterations of Evol-Q. However, as the number of passes grows, MSE does not perform as well as the infoNCE loss. Both cosine similarity and the Kullback–Leibler divergence (KL) fail to improve performance as the number of iterations increases. We postulate that the poor performance of these traditional loss functions is due to overfitting to the cali-

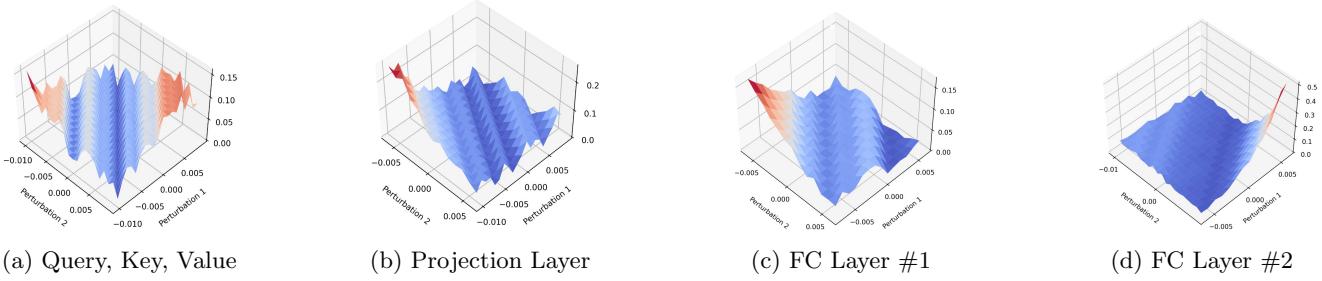


Figure 5: Loss Landscapes for the 4-bit quantized QKV, Projection, and Fully Connected (FC) layers in self-attention block #5. We perturb the the quantization scale along two basis vectors (Perturbation 1 & 2) to visualize the loss landscape. These landscapes capture a zoomed in region around the global minimum of the full landscape. The FC layers exhibit relative smoothness around the global minimum whereas the QKV & Projection layers are not easily traversable. The Projection layer is particularly difficult for gradient methods because it has 4 deep minima in close proximity to the global minimum.

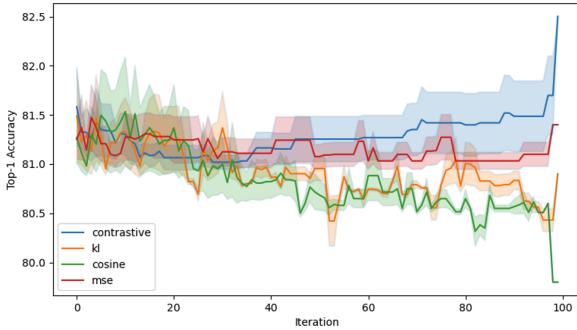


Figure 6: Comparing four loss functions in the Evol-Q framework on ViT-Base. The infoNCE (contrastive) loss prevents overfitting to the calibration dataset, whereas all other loss functions cannot improve accuracy beyond the initialized quantization scheme.

bration dataset. On the other hand, the infoNCE loss is naturally regularized by the negative samples in the batch, allowing for it to preserve the quantization parameters that help discriminate between classes.

5.4. Which layers contribute to non-smoothness?

In Fig. 5, we visualize which layers of the self-attention mechanism yield the non-smooth loss curve. We show that learning the quantization scale for query, key, value (QKV) and projection layers is more difficult because their loss landscape is filled with local minima. We observe this property across different self-attention blocks and advocate for using ES to jump through the field of local minima.

5.5. Layer-wise Weight Distributions

In Fig. 7, we compare the weight distributions of the full precision, FQ-ViT, and Evol-Q quantization schemes. Evol-Q’s quantized values are only a small

adjustment of FQ-ViT’s, yet Evol-Q has a 0.8% improvement. In summary, a small adjustment in scale yields a significant boost in accuracy.

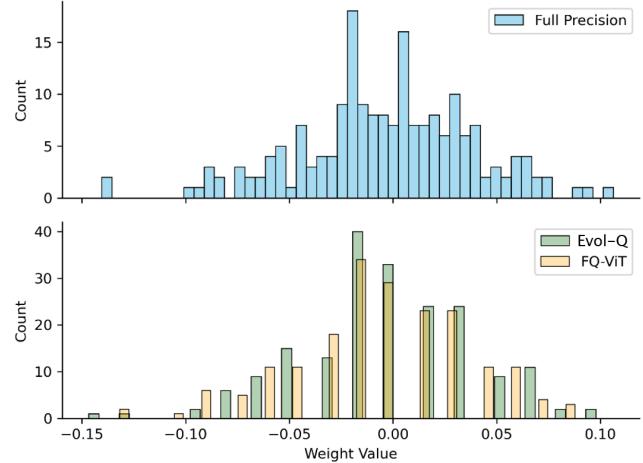


Figure 7: The weight distribution of the projection layer for attention block #1 of ViT-Base. The top plot shows the full precision weight distribution and the bottom plot shows the 8-bit weights using both FQ-ViT and Evol-Q.

This observation is consistent with results in AdaRound [23], where authors show how choosing the correct rounding scheme can significantly impact performance. Unlike AdaRound [23], our method traverses the global loss landscape (rather than a layer-wise proxy) whereas AdaRound assumes a diagonal Hessian which does not hold in the ViT landscape.

We refer to Sec. F of the supplementary materials for more discussion on layer-wise distributions.

	ResNet-18	ResNet-50	RegNet-3.2GF
BRECQ [16]	69.60	75.05	74.21
Evol-Q [†]	70.10	77.30	76.87

[†] Using BRECQ[16] as pre-quantized model M_Q

Table 8: Top-1 Accuracy on ImageNet using 4W4A quantization.

5.6. Generalization to CNNs

Our method begins with a pre-quantized model, M_Q , and adjusts the quantization scales to improve accuracy. We only require that the model can be abstracted into blocks, which makes our method readily applicable to other types of models such as CNNs, LSTMs, and Graph Neural Networks. In Tab. 8, we show how Evol-Q is run on top of BRECQ to achieve state-of-the-art CNN quantization. In this case, our block is one convolutional layer and Δ is the stacked vector of quantization scales for the one layer’s weight matrix. We find Evol-Q’s method to be suitable for CNN quantization, achieving 1-2.5% accuracy boost over BRECQ for 4-bit quantization. We refer to supplementary material for an explanation of using the infoNCE loss to smooth out the CNN loss landscape.

5.7. Pareto Front for 8-bit Quantized ViTs

Evol-Q improves over existing PTQ techniques for vision transformers. In Fig. 8, Evol-Q is on the Pareto front in terms of both top-1 accuracy and runtime for 8-bit ViT-Base. Current ViT-specific QAT methods [19, 30] do not report 8-bit accuracy, so we do not include them here. These QAT methods are likely to reach the Pareto front, but would take much longer than existing PTQ methods.

All open-source methods are run on a single Nvidia A100 GPU, but some code is not open-sourced at the time of submission. PSAQ-ViT-V2 does not report runtime, so we estimate it to be 60 minutes based on PSAQ-ViT and the relative cost of additional steps.

5.8. Runtime

We run our method on an Nvidia A100-PCIE-40GB Tensor Core GPU and find that all experiments take less than one hour to run. The average runtime is shown in Tab. 9. We use PyTorch 1.9.1, built with the CUDA 11.1 toolkit.

	DeiT-T	DeiT-S	DeiT-B	ViT-B
Runtime (m)	41.5	46.3	41.6	43.2

Table 9: Evol-Q Runtime (in minutes) on one Nvidia A100 GPU

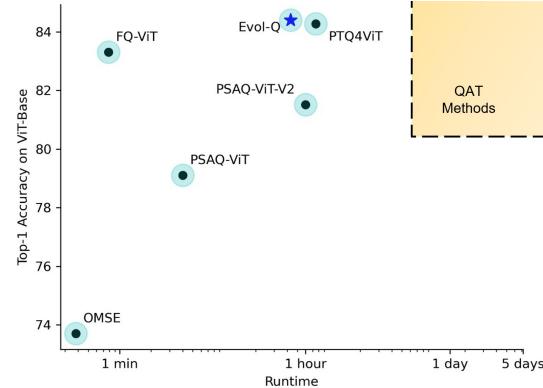


Figure 8: The runtime of 8-bit quantization methods for ViTs. We consider PTQ methods, and show the potential for QAT methods (orange square).

In Fig. 8, we compare runtime with other ViT quantization methods and demonstrate that our method achieves superior accuracy on ViT-Base. Fig. 8 only captures the Top-1 Accuracy of ViT-Base (or, alternatively, DeiT-base if ViT-Base is unavailable). We refer to the supplementary material for a wider discussion on how this plot changes with different models.

6. Conclusion

Evol-Q achieves state-of-the-art results on ViT’s highly non-smooth loss landscape with a high density of extremal points. Prior work on ViT quantization does not address the non-smooth loss landscape, nor how small perturbations in quantization scale can affect performance. Using evolutionary search and an infoNCE loss, Evol-Q evaluates small perturbations in quantization scale, improving accuracy by $\sim 0.5\%$ for 4-bit quantized vision transformers.

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