MPCViT: Searching for MPC-friendly Vision Transformer with Heterogeneous Attention

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Abstract—Secure multi-party computation (MPC) enables computation directly on encrypted data on non-colluding untrusted servers and protects both data and model privacy in deep learning inference. However, existing neural network (NN) architectures, including Vision Transformers (ViTs), are not designed or optimized for MPC protocols and incur significant latency overhead due to the Softmax function in the multi-head attention (MHA). In this paper, we propose an MPC-friendly ViT, dubbed MPCViT, to enable accurate yet efficient ViT inference in MPC. We systematically compare different attention variants in MPC and propose a heterogeneous attention search space, which combines the high-accuracy and MPC-efficient attentions with diverse structure granularities. We further propose a simple yet effective differentiable neural architecture search (NAS) algorithm for fast ViT optimization. MPCViT significantly outperforms prior-art ViT variants in MPC. With the proposed NAS algorithm, our extensive experiments demonstrate that MPCViT achieves 7.9\times and 2.8\times latency reduction with better accuracy compared to Linformer and MPCFormer on the Tiny-ImageNet dataset, respectively. Further, with proper knowledge distillation (KD), MPCViT even achieves 1.9\% better accuracy compared to the baseline ViT with 9.9\times latency reduction on the Tiny-ImageNet dataset.

I. INTRODUCTION

As machine learning models are handling increasingly sensitive data and tasks, privacy has become one of the major concerns in deploying machine learning models. In recent years, as a privacy-enhancing technique, secure multi-party computation (MPC) \cite{1} has shown its ability for private deep learning inference that protects the privacy of both data and deep neural network (NN) models \cite{2} \cite{3} \cite{4}.

Vision Transformers (ViTs), as a state-of-the-art (SOTA) DNN architecture, has demonstrated superior accuracy for various vision tasks. \cite{5}. However, ViTs are not designed or optimized for MPC protocols. Directly deploying ViTs in MPC suffers from several realistic limitations: 1) communication overhead: in contrast to regular inference on plaintext, operations, e.g., multiplication, max, etc, involve intensive communication in MPC, which usually dominates the inference latency \cite{2} \cite{3}. For example, the max operation, which is widely used in ReLU and Softmax functions, is usually very lightweight in plaintext inference but requires two rounds of communication and high latency overhead in MPC; 2) approximation error: operations like exponential, reciprocal, etc, cannot be computed directly and require iterative approximation, leading to extra communication overhead and a limited dynamic range \cite{3}. For exponential operations in Softmax, they are usually approximated as $e^x = \lim_{n \to \infty} (1 + \frac{x}{n})^n$ and reciprocal operations are approximated with the Newton-Raphson iterative method \cite{3}.

While numerous efficient Transformer variants have been proposed in recent years \cite{6} \cite{7} \cite{8} \cite{9}, they cannot directly improve the performance and efficiency of ViT inference in MPC. Linear Transformers, including Linformer \cite{7}, cosFormer \cite{8}, Reformer \cite{9}, etc, reduce the quadratic computation complexity and significantly accelerate the plaintext Transformer training or inference for long sequences. DARTFormer \cite{9} further proposes to combine different linear attentions for accuracy improvements. However, these Transformer optimizations have primarily focused on reducing the network computation. Hence, they either retain complex non-linear functions, e.g., Softmax, cosine, max, etc, or still require iterative approximation, both resulting in intensive communication overhead when deployed in MPC. The vacancy of MPC-friendly ViT optimization motivates us to ask an intriguing question: “How can we develop MPC-friendly ViTs to accelerate the ViT inference in MPC?”

In this work, we propose the first MPC-friendly ViT architecture, dubbed MPCViT, to solve the aforementioned problems. We first profile a ViT in MPC and observe the Softmax function is the latency bottleneck, especially for a multi-head ViT. By further looking into the latency breakdown, we find reciprocal and exponential operations contribute to almost 70\% latency of Softmax. Hence, we systematically study different MPC-friendly attention variants in MPC and propose a heterogeneous attention search space with different structure granularities. In specific, we mix both high-accuracy attention and MPC-efficient attention to build MPCViT. We further propose a differentiable neural architecture search (NAS) algorithm for MPCViT optimization and determine the Pareto front between inference accuracy and latency. The contributions of our work can be summarized as follows:

- We reveal the ViT latency overhead introduced by the reciprocal and exponential operations besides the max operation through detailed ViT profiling, and further study different attention variants in MPC to design a heterogeneous attention search space with different structure granularities.
- We propose a simple yet effective differentiable NAS algorithm to explore the heterogeneous search space. We further introduce token-wise knowledge distillation (KD) to improve the accuracy of the MPC-friendly ViTs.
- Our MPC-friendly ViT model family, MPCViT, outperforms prior-art models in MPC, e.g., Linformer, MPCFormer, in both accuracy and efficiency. MPCViT even achieves 1.9\% better accuracy compared to the baseline ViT with 9.9\times latency reduction on the Tiny-ImageNet dataset.

II. BACKGROUND AND PRELIMINARIES

A. Vision Transformer (ViT) and Efficient Attention

\textbf{ViT architecture.} ViT has shown great potential to capture long-range visual dependencies. It takes image patches as input and is composed of an input projection layer, a stack of transformer layers, and a task-specific multi-layer perceptron (MLP) head. Each transformer layer consists of a multi-head attention layer and a feed-forward layer. The core computation is the Softmax-based attention:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V,$$

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\textsuperscript{1}Max operation is used in Softmax to improve the numerical stability \cite{3}.
where \(Q, K, V\) are queries, keys and values, respectively. \(d_k\) denotes the embedding dimension of each key, and Softmax normalizes the attention map. Computing \(QK^T\) leads to \(O(n^3)\) complexity, w.r.t. the sequence length \(n\).

**Linear attention.** Linear attention has been widely studied in previous works \([6, 8, 9]\). These works aim at solving the quadratic compute and memory increase problems. Let \(\phi(\cdot)\) denote a kernel function with the following property: \(\phi(QK^T)V = \phi(Q)\phi(K^T)V = \phi(Q)(\phi(K^T)V)\). Then, the complexity of the attention operation can be reduced and increases only linearly. Different kernel functions have been proposed in existing works \([7, 8, 10, 11]\). UFO-ViT \([10]\) proposes to use \(\ell_2\)-Norm as the kernel function to replace the Softmax function while CosFormer \([8]\) leverages the cosine distance kernel. Linformer \([7]\) approximates self-attention by a low-rank matrix. Hydra Attention \([11]\) proposes to use as many heads as possible to further reduce the computation complexity of the linear attention. However, these works are not optimized for MPC protocols and they primarily focus on reducing the network computation rather than the communication overhead in MPC.

**Non-local neural networks and Scaling attention.** Wang et al. \([12]\) present a generic non-local operation to capture long-range dependencies. The formulation is defined as \(\frac{1}{n} \sum_{j=1}^{n} f(x, x_j)g(x_j)\), where \(x\) denotes the input feature map and \(f(\cdot)\) is a similarity function, e.g., cosine or Euclidean distance. \(g(\cdot)\) computes a certain input representation, and \(C(\cdot)\) is a normalization factor. By setting \(f(\cdot)\) as the dot-product similarity and \(C(x) = n\), where \(n\) is the sequence length, we get an attention variant, named Scaling Attention (ScaleAttn for short). ScaleAttn is an extremely simple attention function, e.g., cosine or Euclidean distance. ScaleAttn can be further linearized as below: \(\text{ScaleAttn}(Q, K, V) = \frac{1}{n} (QK^T)V = \frac{Q}{\sqrt{n}} (\frac{K^T}{\sqrt{n}})V\).

**B. Multi-Party Computation**

MPC \([1]\) is a cryptographic technique that allows computation on untrusted non-colluding servers without revealing the data to the servers. Compared with other cryptographic techniques such as homomorphic encryption \([13]\), MPC is a promising solution for privacy-preserving due to its relatively high performance. Goldreich \([1]\) proposes an efficient MPC protocol for addition and high multiplications. Mohassel and Zhang \([14]\) propose efficient two-party computation protocols for various arithmetic operations and approximations for non-linear functions in NN. For example, \([14]\) approximates the Softmax function with ReLU Softmax, i.e., \(\text{ReLUSoftmax}(x) = \frac{\text{ReLU}(x)}{\sum_i \text{ReLU}(x_i) + \epsilon}\), where \(\epsilon\) is a very small value to avoid the zero denominator.

ABY3 \([15]\) is proposed to enable efficient switching back and forth between different secret sharing schemes in three-party computation. Delphi \([2]\) develops a hybrid cryptographic protocol as well as a planner that can adjust the deep learning algorithm to explore the performance-accuracy trade-off.

Although MPC protocols have improved significantly in recent years, DNN inference in MPC still suffers from intensive communication and latency overhead compared to the inference in plaintext. To reduce the inference latency, different algorithms have been proposed to optimize convolutional NNs (CNNs) with a focus on the ReLU function. Cho et al. \([16]\) and Jha et al. \([17]\) propose to remove the ReLU functions and linearize a subset of neurons selectively.

**SAFENet** \([18]\) replaces ReLUs with polynomial functions that are more MPC-friendly via NAS. Sphytx \([19]\) further develops an MPC-friendly architecture search space for CNNs and leverages NAS to optimize the CNN accuracy given different latency constraints. For Transformer models, \([20]\) proposes a set of protocols to reduce the communication overhead of matrix-matrix multiplications, LayerNorm, etc. However, how to develop MPC-friendly ViTs are not yet well studied.

**III. Our Proposed MPCViT Algorithm**

In this section, we first describe our motivation of proposing MPCViT by profiling a ViT model in MPC and revealing its latency bottleneck. We then introduce MPCViT, which for the first time optimizes ViTs for MPC to improve the inference efficiency while preserving accuracy.

### A. Motivation and Insights of MPCViT

**Motivation from ViT latency bottleneck in MPC.** To improve the ViT latency in MPC, we aspire to figure out which part of Transformer is most time-consuming. We profile a 4-head ViT following the settings in Section \([3]\). As shown in Figure \([1]\)a, the multi-head attention accounts for 80% of the total latency of Transformer. In the multi-head attention, the Softmax function takes the most latency while the matrix multiplication (MatMul) operation can be neglected. With the increase of the number of attention heads, attention latency increases drastically, leading to an unacceptable overhead, as shown in Figure \([1]\)a. By further diving into the Softmax latency as shown in Figure \([1]\)b, we observe the max operation, which has been the focus of existing works \([3, 22]\), accounts for 32% of the total latency. In contrast, reciprocal and exponential operations are also very time-consuming, taking almost 70% latency. The main reason for the statistical result is the high communication overhead of max, exponential, and reciprocal operations in MPC. Hence, to develop MPC-friendly ViTs, we are motivated to reduce these MPC-inefficient operations as much as possible.

**Motivation from Softmax approximation error in MPC.** Another concern about the Softmax attention in MPC is that the reciprocal and exponential operations in Softmax cannot be computed directly. Instead, iterative approximations are needed, which not only involve multiple rounds of extra communication, but also limit the dynamic range of the computation and render accurate inference very hard \([3]\). While reciprocal can be approximated more accurately, \([3]\) observes the exponential operation incurs a much narrower dynamic range and larger error, which is also confirmed in our experiments in Table \([1]\). The narrow dynamic range and large error also motivate us to get rid of the exponential operation.

To deal with the aforementioned problems, we systematically study different attention variants by replacing Softmax with different activation functions, including ReLU, ReLU6, Sparsemax \([22]\).

\(^2\)We use ReLU activation throughout the paper since we find GeLU does not provide extra accuracy benefits as observed in \([27, 22]\).
MLP: computing XNorm attention has linear computation, it incurs the highest latency.

Table II. Result shows that the ScaleAttn has the lowest inference latency along with the best accuracy.

Fig. 1. (a) Latency breakdown of the 4-head ViT with 192 hidden dimension and 192 tokens; (b) latency breakdown of the Softmax function; and (c) latency growth of single layer attention with the number of attention heads.

TABLE II
PERFORMANCE AND LATENCY COMPARISON OF DIFFERENT ATTENTION VARIANTS. THE ROWS IN GREY COLOR ARE ATTENTION VARIANTS WITH THE LOWEST LATENCY AND THE HIGHEST ACCURACY, RESPECTIVELY.

| Type                  | Top-1 Acc. (%) | Latency (s) |
|-----------------------|----------------|-------------|
| Softmax Attention     | 92.09          | 6.68        |
| ReLU Attention        | 90.50          | 13.17       |
| Sparsemax Attention   | 91.24          | 24.67       |
| XNORM Attention       | 91.42          | 59.42       |
| Square Attention      | 91.27          | 99.95       |
| 2Quad Attention       | 91.13          | 11.21       |
| ScaleAttn             | 91.52          | 120.14      |
| ReLU Softmax Attention| 92.31          | 5.32        |

XNorm, square, Scaling, 2Quad and ReLU Softmax. We train each model for 300 epochs on CIFAR-10 and report both their top-1 accuracy and inference latency in MPC in Table II. Result shows that the ScaleAttn has the lowest inference latency while ReLU Softmax attention (RSAttn) has the highest accuracy. It is also interesting to notice that although XNORM attention has linear computation, it incurs the highest latency as computing $\ell_2$-norm involves both reciprocal and square root operations, both of which are expensive in MPC. Moreover, as shown in Table II, ReLU Softmax and Scaling operations can both be accurately implemented in MPC. Therefore, our key insight of MPCViT is to mix MPC-efficient ScaleAttn and high-accuracy RSAttn together to improve the inference efficiency while preserving the accuracy.

B. MPCViT: MPC-friendly ViT Architecture

Based on the motivation described above, we now describe our MPC-aware ViT optimization flow as shown in Figure 2. We first design a heterogeneous search space that includes both the high-accuracy RSAttn and MPC-efficient ScaleAttn. Architecture parameters $\alpha$’s are defined to enable the selection between the two attention variants with different structure granularities (described in Section III-C). Then, we propose a differentiable NAS algorithm to learn the architecture parameters as well as model parameters simultaneously. We select between the attention variants based on the architecture parameters and the target latency (described in Section III-D). In the last step, we re-train the ViT with heterogeneous attention from scratch. We leverage KD to improve the accuracy of the searched networks (described in Section III-E).

C. Heterogeneous Attention Search Space

Our heterogeneous search space combines both MPC-efficient ScaleAttn and high-accuracy RSAttn and has the following three different structural granularities as shown in Figure 2:

- **Layer-wise** search space is coarse-grained, with each layer using either ScaleAttn or RSAttn. The total number of possible architectures in the search space can be limited, especially for shallow ViT models.
- **Head-wise** search space selects ScaleAttn or RSAttn for each attention head of each layer.
- **Row-wise** search space is most fine-grained and mixes the two attention variants along each row of the attention map. Although it has the largest search space which comprises of the head-wise and layer-wise search space, it may incur difficulties in NAS and leads to network architecture with inferior accuracy or efficiency. Though the search spaces have different granularities, they share very similar NAS formulation. In the rest of the explanation, we will use the head-wise search space as an example to explain our NAS algorithm. We show the comparison of different search spaces in the experimental results.

D. Differentiable NAS

Given the heterogeneous attention search space, we now introduce our simple yet effective differentiable NAS algorithm.

**NAS formulation.** Inspired by Brown et al. [9], we introduce an architecture parameter $\alpha$ ($0 \leq \alpha \leq 1$) for each head, which is an auxiliary learnable variable that helps to choose between RSAttn and ScaleAttn. Then, each head implements the computation below:

$$\alpha \cdot \text{ReLU Softmax}(\frac{QK^TV}{\sqrt{dk}}) + (1 - \alpha) \cdot \text{ScaleAttn}(Q, K, V)$$

Note that we also add $\frac{1}{\sqrt{dk}}$ for ScaleAttn following RSAttn to make the searching process more stable and robust.

**Architecture search objective function.** We aim at training ViTs with high accuracy but as few RSAttn as possible. Motivated by [23], we introduce $\ell_1$-penalty into the objective function and formulate the NAS as a one-level optimization problem:

$$\min_{\theta, \alpha} \ell(f_{\theta, \alpha}(x), y) + \lambda \sum_{i=1}^{N} \|\alpha_i\|_1$$
granularities: (a) layer-wise search space with the size of $2^{\text{#layers}}$, (b) head-wise search space with the size of $2^{\text{#layers}} \times \text{#heads}$, and (c) row-wise search space with the size of $2^{\text{#layers}} \times \text{#heads} \times \text{#tokens}$. The blocks in blue represent RSAttn and the blocks in grey represent ScaleAttn.

where $x$ and $y$ are the input-label pairs, $\ell$ is the loss function, $\lambda$ is a hyper-parameter, and $N$ is the total number of heads in the ViT. We initialize $\alpha$ for each head to 1.0 and jointly optimize the network parameter $\theta$ and architecture parameter $\alpha$ during searching. Note that our differentiable algorithm computes the gradients of $\alpha$ for all the attention heads across different layers in ViT simultaneously. Compared to the per-layer architecture search, our method achieves a better Pareto front for inference accuracy and latency, and we show the comparison in our experimental results.

**Architecture parameter binarization.** After the network training, we obtain $\alpha$ for each head in all attention layers. To select either RSAttn or ScaleAttn for each head, we binarize $\alpha$ based on the following rule. We use the top-k rule according to the compression rate $\mu$, which is defined as $\#\text{RSAttn}/\#\text{Heads}$ in this paper. And for Linformer, $\mu$ is defined as projected dimension/original dimension. Specifically, we first find the $\mu N$th largest $\alpha$, denoted as $\alpha^*$, and then we binarize $\alpha$ for each attention head as below:

$$\alpha = \begin{cases} 1.0, & \text{if } \alpha \geq \alpha^*; \\ 0.0, & \text{otherwise.} \end{cases} \tag{1}$$

Now, we can obtain a heterogeneous ViT by combining both RSAttn and ScaleAttn. By changing $\mu$, we can obtain a family of ViTs with different accuracy and efficiency trade-off.

**E. How to Train a Heterogeneous ViT**

After binarization, RSAttn with a small $\alpha$ are replaced with ScaleAttn. We find that directly training a heterogeneous ViT results in an accuracy drop. So, how to effectively train the heterogeneous ViT and restore the model accuracy is important for us.

**Token-wise feature-based KD.** KD~\cite{KD} is a powerful tool for a student network to learn from a teacher network, which is usually larger and more complex with a higher learning capacity. To improve the accuracy of MPCViT, we leverage a token-wise feature-based KD along with a logits-based KD. We use the baseline ViT as the teacher network while other larger networks can be easily plugged in and used in our framework. For the feature-based KD, we take the output features of the last ViT layer from both the student and the teacher networks and compute the $l^2$ distance, denoted as $\mathcal{L}_{\text{feature}}$. We also use KL-divergence loss for the logits-based KD, denoted as $\mathcal{L}_{\text{logits}}$. Combining distillation loss with the task-specific cross-entropy loss $\mathcal{L}_{\text{CE}}$, we obtain the final training objective as follows:

$$\mathcal{L}_{\text{train}} = \chi \mathcal{L}_{\text{CE}} + \beta \mathcal{L}_{\text{logits}} + \gamma \mathcal{L}_{\text{feature}} \tag{2}$$

where $\chi$, $\beta$ and $\gamma$ are training hyper-parameters to balance different losses in the training objective.

**IV. Experiments**

**A. Experimental Setup**

**MPC settings and experimental environment.** In our experiments, we leverage the SecretFlow~\cite{SecretFlow} framework for private inference, which is a popular framework for privacy-preserving deep learning. We adopt the SEMI-2K protocol, which is a semi-honest two-party computation protocol.~\cite{SecretFlow} We follow~\cite{SecretFlow} and use the WAN mode for communication. Specifically, the bandwidth between the cloud instances is set to 44 MBps and the round-trip time is set to 40ms. Our experiments are evaluated on a 2.40 GHz Intel Xeon CPU with 62 GB RAM.

**Model architectures and datasets.** We consider two types of ViT architectures on three commonly used datasets following~\cite{MPCFormer}. For the CIFAR-10/100 dataset, we set the ViT depth, # heads, hidden dimension, and patch size to 7, 4, 256, and 8, respectively. For Tiny-ImageNet dataset, we set the ViT depth, # heads, hidden dimension, and patch size to 9, 12, 192, and 16, respectively.

**Searching settings.** We run the differentiable NAS algorithm for 300 epochs with AdamW optimizer and a cosine learning rate across three datasets. We set $\epsilon = 10^{-8}$ to avoid the zero denominator in RSAttn, and set $\lambda = 10^{-5}$.

**Training settings.** Following Hassani et al.~\cite{MPCFormer}, we train the searched heterogeneous ViT for 600 epochs on CIFAR-10/100 and 300 epochs on Tiny-ImageNet. We use the same data augmentations as~\cite{MPCFormer}. For KD, we set the temperature $T$ to 1, and set $\chi, \beta, \gamma$ to 1 as well. To explore the trade-off between inference accuracy and latency, we set compression rate $\mu$ to {0.1, 0.3, 0.5, 0.7}.

**B. Comparison with Prior-art Efficient Attention**

**Baselines.** We first compare MPCViT with prior-art models on the inference accuracy and efficiency. Besides the Softmax ViT, ReLU Softmax ViT, and ScaleAttn ViT, we also compare with MPCFormer~\cite{MPCFormer} and Linformer~\cite{Linformer}. MPCFormer is a recently proposed MPC-friendly transformer for NLP tasks that replaces the Softmax function directly with its proposed 2Quad function. Linformer is studied in~\cite{Linformer} as an efficient transformer variant for MPC. For all the networks, we only modify the attention modules and keep the MLPs unchanged as the baseline ViT.

**Results and analysis.** The main results are shown in Table~\cite{MPCFormer} where we report top-1 accuracy across three datasets and the network inference latency. The main findings are as follows:

1) MPCViT outperforms prior-art methods, including MPCFormer and Linformer. Without KD, on Tiny-ImageNet, MPCViT with $\mu = 0.1$ outperforms Linformer with $\mu = 0.7$ by 0.57% better accuracy with 7.9x latency reduction. MPCViT with $\mu = 0.3$
As shown in Table IV, the latency of three search spaces is very close in Section III-C. We use the CIFAR-10 dataset for the comparison.

**D. Comparison of Different Structure Granularities**

We compare different structure granularities of search space proposed to search and replace RSAttn heads across different layers. It is necessary to include the ScaleAttn in MPCViT and the importance for accuracy compared to the per-layer NAS and the uniform shrink-layer. As shown in Figure 5, MPCViT achieves a better Pareto front uniform shrinking which directly removes the RSAttn heads in each layer uniformly given a certain λ.

We can observe the latency changes proportionally with the total communication. Also, we observe for MPCViT, RSAttn in middle layers (e.g., layer 2 to layer 5) tend to be preserved while RSAttn in early and final layers are likely to be replaced with ScaleAttn.

**C. Comparison with Per-Layer NAS**

We also compare MPCViT with 1) per-layer search which replaces RSAttn heads in each layer uniformly given a certain μ and 2) uniform shrinking which directly removes the RSAttn heads in each layer. As shown in Figure 5, MPCViT achieves a better Pareto front for accuracy compared to the per-layer NAS and the uniform shrinking methods on CIFAR-10/100 datasets. The results demonstrate the necessity of including the ScaleAttn in MPCViT and the importance to search and replace RSAttn heads across different layers.

**D. Comparison of Different Structure Granularities**

The choice of search space is important for MPCViT, so we compare different structure granularities of search space proposed in Section III-C. We use the CIFAR-10 dataset for the comparison. As shown in Table V, the latency of three search spaces is very close to each other. This indicates in MPC, the total number of max and reciprocal operations plays a more important role in inference latency compared to the structure granularities. Meanwhile, though row-wise has the largest search space, such fine-grained search space does not produce a better MPC-friendly ViT model compared to the head-wise search space. We hypothesize this is because mixing different variants within each attention map makes the network training harder.

**E. Ablation Study of MPCViT**

**Contribution of KD.** One of our key techniques for training heterogeneous ViT is KD. In this experiment, we enumerate different combinations of KD and the results are shown in Table V. We find that 1) both logits-based and feature-based KD significantly improve the performance of ViT compared to using cross-entropy loss only; and 2) combining the two KD losses further improves the accuracy of MPCViT slightly. The above findings indicate the indispensability of three parts of $L_{train}$.

**Consistency of our proposed architecture search algorithm.** We hope our NAS algorithm to be robust against hyper-parameters choices. To analyze this consistency of our algorithm, we adjust the coefficient λ to three different values, i.e., $10^{-4}, 10^{-5}, 10^{-6}$, and train a 7-layer ViT with 4 heads. We visualize the distribution of the architecture parameter α in Figure 6 and we find that α in each layer has a quite similar trend under different λ’s. Note that the head indices in the same layer are interchangeable, so we first sort α in each layer and then visualize the distribution. Furthermore, when we change the number of heads to 8, the distribution still shows a similar trend, empirically proving the consistency of our proposed architecture search algorithm.

**V. Conclusion**

In this paper, we propose an MPC-friendly ViT family, dubbed MPCViT, to enable accurate yet efficient ViT inference in MPC. We analyze the inference latency bottleneck for ViT and systematically compare different attention variants, based on which a heterogeneous attention search space is proposed. We also propose a differentiable...
ViT variants with both lower latency and better accuracy. Datasets demonstrate that MPCViT consistently outperforms prior-art and the high-accuracy RSAttn. Extensive experiments on three NAS algorithms to effectively combine the MPC-efficient ScaleAttn [4] D. Rathee, M. Rathee, N. Kumar, N. Chandran, D. Gupta, A. Rastogi, and A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly et al., “An image is worth 16x16 words: Transformers for image recognition at scale,” arXiv preprint arXiv:2010.11929, 2020.

Table III
Top-1 Accuracy and Inference Latency Comparison Across Three Datasets. Note that the left side of “→” means MPCViT w/o KD and the right side means MPCViT w/ KD.

| Architecture   | CIFAR-10          | CIFAR-100         | Tiny-ImageNet     |
|----------------|-------------------|-------------------|-------------------|
|                | Test Acc. (%) ↑   | Latency (s) ↓     | Test Acc. (%) ↑   | Latency (s) ↓ |
| Softmax ViT    | -                 | 93.97             | 76.34             | 60.71         |
| ReLU Softmax ViT | -              | 93.52             | 75.27             | 60.26         |
| ScaleAttn ViT  | -                 | 92.23             | 73.57             | 55.54         |
| Linformer [3, 7]| 0.5               | 91.85             | 72.74             | 56.06         |
| MPCFormer w/o KD [23] | 0.5 | 92.32             | 73.10             | 55.85         |
| MPCViT (Ours)  | 0.5               | 92.33             | 73.55             | 56.18         |

Table IV
Top-1 Accuracy w/o KD Comparison with Different Granularities of Search Space on CIFAR-10 with Different μ.

| Granularity     | μ = 0.5 | μ = 0.7 |
|-----------------|---------|---------|
|                 | Acc. (%) ↑ | Lat. (s) ↓ | Acc. (%) ↑ | Lat. (s) ↓ |
| Layer-wise      | 93.01   | 31.86   | 93.32   | 38.03   |
| Row-wise        | 93.16   | 32.69   | 93.13   | 38.24   |
| Head-wise       | 93.21   | 32.61   | 93.38   | 38.13   |

Table V
Top-1 Accuracy Comparison of Different Combinations of Training Loss on CIFAR-10 with μ = 0.7.

| CE | Logits-based KD | Feature-based KD | Test Acc. (%) ↑ |
|----|-----------------|------------------|-----------------|
| ✓  | ✓               | ✓                | 93.38           |
| ✓  | ✓               | ✓                | 94.18           |
| ✓  | ✓               | ✓                | 94.12           |
| ✓  | ✓               | ✓                | 34.27           |

NAS algorithm to effectively combine the MPC-efficient ScaleAttn and the high-accuracy RSAttn. Extensive experiments on three datasets demonstrate that MPCViT consistently outperforms prior-art ViT variants with both lower latency and better accuracy.

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