

MPCViT: Searching for Accurate and Efficient MPC-Friendly Vision Transformer with Heterogeneous Attention

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Abstract

Secure multi-party computation (MPC) enables computation directly on encrypted data and protects both data and model privacy in deep learning inference. However, existing neural network architectures, including Vision Transformers (ViTs), are not designed or optimized for MPC and incur significant latency overhead. We observe Softmax accounts for the major latency bottleneck due to a high communication complexity, but can be selectively replaced or linearized without compromising the model accuracy. Hence, in this paper, we propose an MPC-friendly ViT, dubbed MPCViT, to enable accurate yet efficient ViT inference in MPC. Based on a systematic latency and accuracy evaluation of the Softmax attention and other attention variants, we propose a heterogeneous attention optimization space. We also develop a simple yet effective MPC-aware neural architecture search algorithm for fast Pareto optimization. To further boost the inference efficiency, we propose MPCViT⁺, to jointly optimize the Softmax attention and other network components, including GeLU, matrix multiplication, etc. With extensive experiments, we demonstrate that MPCViT achieves 1.9%, 1.3% and 3.6% higher accuracy with 6.2×, 2.9× and 1.9× latency reduction compared with baseline ViT, MPCFormer and THE-X on the Tiny-ImageNet dataset, respectively. MPCViT⁺ further achieves a better Pareto front compared with MPCViT. The code and models for evaluation are available at <https://github.com/PKU-SEC-Lab/mpcvit>.

1. Introduction

As machine learning models are handling increasingly sensitive data and tasks, privacy has become one of the major concerns during the model deployment. Secure multi-party computation (MPC) [14] can protect the privacy of

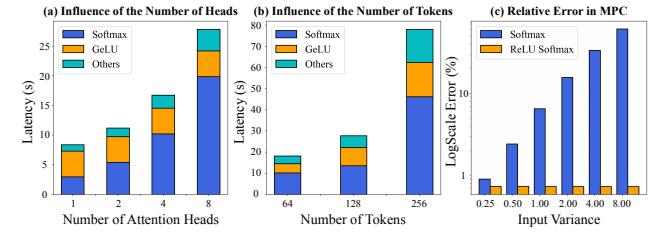


Figure 1. The latency breakdown of a Transformer block w.r.t (a) # heads and (b) # tokens; and (c) the relative error of Softmax and ReLU Softmax with different input variances.

both data and deep neural network (DNN) models and has gained a lot of attention in recent years [42, 51, 60].

However, existing DNN architectures, especially the recently proposed Vision Transformers (ViTs) [2, 11, 64], are not designed or optimized for MPC (the high-level private ViT inference framework in MPC is shown in Figure 2 and Appendix A.1). Although ViTs have achieved superior performance for various vision tasks [2, 15, 16, 64], they face several realistic limitations when directly deployed in MPC:
1) communication overhead: in contrast to regular inference on plaintext, operations like Softmax, GeLU, max, etc, require intensive communication in MPC, which usually dominates the total inference latency [42, 60]. For example, Softmax is usually very lightweight in plaintext inference. However, as shown in Figure 1(a) and Figure 1(b), it accounts for the majority of the Transformer inference latency due to the high communication complexity; **2) approximation error:** operations like exponential, tanh, reciprocal, etc, cannot be computed directly and require iterative approximation, limiting the computation accuracy. For instance, as shown in Figure 1(c), the relative error of Softmax significantly increases when the input variance is large due to its narrow dynamic range [60]. In contrast, replacing exponential in Softmax with ReLU reduces the relative error drastically (denoted as ReLU Softmax in §2.2).

Numerous efficient Transformer variants have been pro-

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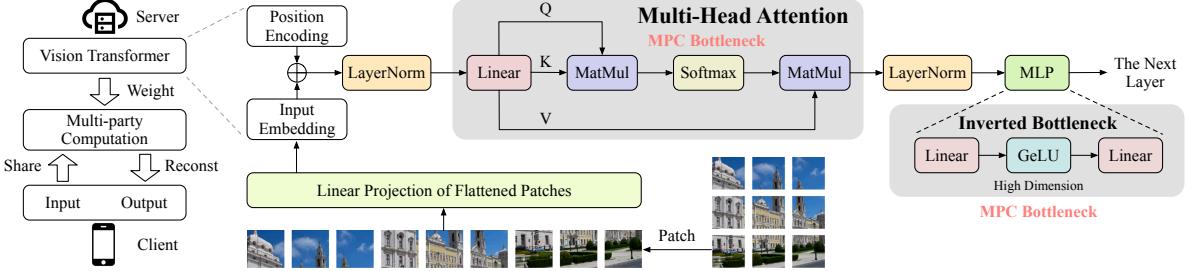


Figure 2. An overall illustration of private Vision Transformer inference in the MPC framework.

posed in recent years [5, 29, 49, 58]. Linear Transformers, including Linformer [58], cosFormer [49], Reformer [29], etc, reduce the quadratic computation complexity of the attentions and significantly accelerate model inference for long sequences. However, these Transformer optimizations have primarily focused on reducing the network computation. Hence, they either retain complex non-linear functions or still require iterative approximation, both resulting in intensive communication overhead in MPC. Recently, MPCFormer [33] and THE-X [6] are proposed to improve the inference efficiency of BERT [28] in MPC. MPCFormer simplifies Softmax by replacing exponential with a more MPC-friendly quadratic operation while THE-X approximates Softmax with a small estimation network. However, their attention variants is not flexible and can still be too expensive for certain latency constraints. Moreover, the network-level optimization suffers from a large accuracy degradation when directly applied to vision tasks.

In this work, we first breakdown Softmax into more atomic operations and analyze their impact on the inference accuracy and efficiency, based on which we propose and compare a set of attention variants comprehensively. The comparison enables us to find MPC-friendly attention variants, which are either highly accurate or highly efficient. We further observe not all attentions are equally important within a ViT. Based on these observations, we propose the first MPC-friendly ViT architecture, dubbed MPCViT. MPCViT features a heterogeneous attention design space to explore the trade-off between accuracy and efficiency, and an MPC-aware differentiable neural architecture search (NAS) algorithm for effective Pareto optimization. Our contributions can be summarized as follows:

- We breakdown Softmax and reveal the impact of atomic operations on the inference accuracy and efficiency, based on which a heterogeneous attention design space is proposed.
- We propose an effective MPC-aware differentiable NAS algorithm to explore the attention design space based on real latency measurements instead of proxies. To the best of our knowledge, we make the first

attempt to introduce the MPC-aware NAS to optimize ViT inference in MPC.

- Our MPC-friendly ViT model family, MPCViT, outperforms prior-art models in MPC in terms of both accuracy and efficiency. MPCViT achieves 1.9% and 1.3% higher accuracy with 6.2 \times and 2.9 \times latency reduction compared with baseline ViT and MPCFormer on Tiny-ImageNet dataset, respectively.
- We further extend MPCViT to optimize other Transformer components simultaneously with Softmax, named MPCViT⁺, achieving an even better Pareto front compared with MPCViT.

2. Preliminaries and Related Works

2.1. ViT and Efficient Attention

ViT architecture. ViT [11] has demonstrated a great potential to capture the 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 layer consists of a multi-head attention (MHA) layer and an MLP block. The core computation is the Softmax attention:

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

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. The detailed explanation of ViT architecture is shown in Figure 2 and Appendix A.2.

Linear attention. Linear attention has been widely studied in previous works [5, 29, 38, 49]. These works aim at reducing the quadratic increase of compute and memory by leveraging special kernel functions. Different kernel functions have been proposed in existing works [4, 49, 53, 58]. UFO-ViT [53] proposes to use ℓ_2 -Norm as the kernel function while CosFormer [49] leverages the cosine distance kernel. Linformer [58] approximates self-attention by a low-rank matrix. Hydra Attention [4] proposes to use as many heads as possible to further reduce the computation

Table 1. Comparison among existing network optimizations for the efficient private inference.

Method	Model	Technique	Optimized Component	Granularity	Linear Fusion
Delphi [42]	CNN	ReLU-aware NAS	ReLU	Layer	✗
DeepReDuce [25]	CNN	Manually removal	ReLU	Layer	✗
CryptoNAS [13]	CNN	ReLU-aware NAS	ReLU	Layer	✗
SNL [8]	CNN	ReLU-aware NAS	ReLU	Channel, pixel	✗
Sphynx [7]	CNN	Block-level NAS	ReLU	Block	✗
SENet [31]	CNN	Sensitivity-aware alloc.	ReLU	Layer, pixel	✗
RRNet [48]	CNN	Hardware-aware NAS	ReLU	Layer	✗
DeepReShape [26]	CNN	ReLU-equalization	ReLU	Stage	✗
SAFENet [37]	CNN	Mixed-precision poly. approx.	ReLU	Channel	✗
THE-X [6]	BERT	Polynomial approx.	GeLU, Softmax, LayerNorm	Network	✗
MPCFormer [33]	BERT	Polynomial approx.	Softmax, GeLU	Network	✗
MPCViT (ours)	ViT	MPC-aware NAS	Softmax	Layer, head, row	✗
MPCViT ⁺ (ours)	ViT	Heterogeneous attention MPC-aware NAS	Softmax, GeLU, MatMul	Layer, head, row, token	✓

complexity of the linear attention. However, these works primarily focus on reducing the network computation rather than the communication overhead and are not beneficial for ViT inference in MPC.

Non-local neural networks and Scaling attention.

[59] presents a generic non-local operation to capture long-range dependencies. The formulation is defined as $\frac{1}{C(x)} \sum_{\forall j} f(x_i, x_j)g(x_j)$, 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 $C(x)$ 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). ScaleAttn is an extremely simple attention and only involves linear operations like multiplication and addition. ScaleAttn can be further re-parameterized to accelerate computation¹ as below:

$$\text{ScaleAttn}(Q, K, V) = \frac{1}{n} (QK^T)V = \frac{Q}{\sqrt{n}} \left(\frac{K^T}{\sqrt{n}} V \right).$$

2.2. Multi-Party Computation

MPC [14] is a cryptographic technique that offers a promising solution to protect the privacy of both data and model during deep learning inference. Appendix B depicts the cryptographic primitives for MPC, including Secret Sharing, Oblivious Transfer and Garble Circuit. [14] proposes an efficient MPC protocol for addition and multiplication. [44] proposes efficient two-party computation protocols for various arithmetic operations and approximations for non-linear functions in DNN. For example, [44]

¹In this work, we do not focus on computational overhead in MPC since communication dominates the overhead.

approximates Softmax with ReLU Softmax, i.e.,

$$\text{ReLUSoftmax}(x) = \frac{\text{ReLU}(x_i)}{\sum_i \text{ReLU}(x_i) + \epsilon},$$

where ϵ is a very small value to avoid the zero denominator. ABY3 [43] is proposed to enable efficient conversion between different secret sharing schemes in three-party computation. Delphi [42] develops a hybrid MPC protocol and optimizes the network to explore the performance-accuracy trade-off. Iron [18] proposes a set of protocols to reduce the communication overhead of matrix-matrix multiplications (MatMuls), LayerNorm, etc for Transformer-based models.

Although MPC protocols have been improved significantly in recent years, DNN inference in MPC still suffers from intensive communication and latency overhead compared to the plaintext inference. To reduce the latency, different algorithms have been proposed to optimize convolutional NNs (CNNs) with a focus on ReLU. We compare the important characteristics of our methods with existing related work in Table 1. SNL [8] and DeepReDuce [25] propose to remove ReLUs and linearize a subset of neurons selectively. SAFENet [37], Delphi [42], RRNet [48] and PolyMPCNet [47] replace ReLUs with polynomial functions that are more MPC-friendly via NAS for CNNs. Sphynx [7] further develops an MPC-friendly architecture search space for CNNs and leverages NAS to optimize the accuracy given different latency constraints. However, these works mainly focus on the ReLU counts in CNNs, and accelerating ViTs with latency consideration is still a challenge. MPCFormer [33] and THE-X [6] recently propose to replace Softmax with more MPC-friendly operations for BERT, but the network-level method incurs limited latency reduction and a large accuracy degradation. As shown in Table 1, our work proposes an MPC-aware NAS to explore a fined-grained heterogeneous attention optimization space, and further presents a GeLU linearization

Table 2. Top-1 accuracy and latency comparison of different attention variants on CIFAR-10. The rows in grey are attention variants with the lowest latency and the highest accuracy, respectively. We also show the properties and remaining operations of each variant.

Attention Variant	Monotonicity	Non-negativity	Normalization	Exponential	Max	Reciprocal	Acc. (%)	Lat. (s)
Softmax Attention [11]	✓	✓	✓	✓	✓	✓	92.69	6.82
Linformer Attention [58]	✓	✓	✓	✓	✓	✓	90.85	5.44
ReLU Attention	✓	✓	✗	✗	✓	✗	fail	fail
ReLU6 Attention	✓	✓	✗	✗	✓	✗	90.50	3.02
Sparsemax Attention [40]	✓	✓	✗	✗	✓	✗	91.23	3.23
XNorm Attention [53]	✓	✗	✗	✗	✗	✓	91.24	13.25
Square Attention	✗	✓	✗	✗	✗	✗	91.27	0.72
2Quad Attention [33]	✗	✓	✓	✓	✗	✓	91.86	4.22
Scaling Attention (ScaleAttn) [59]	✓	✗	✗	✗	✗	✗	91.52	0.66
ReLU Softmax Attention (RSAAttn) [44]	✓	✓	✓	✗	✓	✓	92.31	5.32

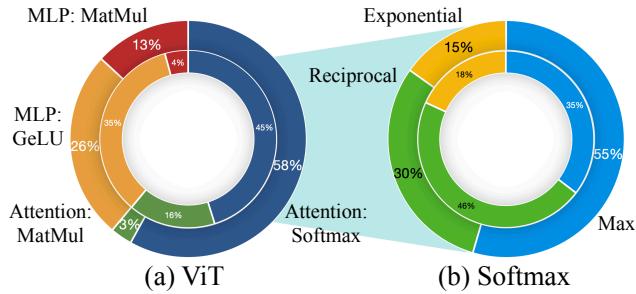


Figure 3. (a) Latency breakdown of a 4-head ViT with 256 hidden dimension and 65 tokens on CIFAR-10 dataset; (b) latency breakdown of Softmax. Both (a) and (b) consist of SEMI-2K (outside) and Cheetah (inside) protocols.

technique to reduce the latency of MLP.

3. Motivating Inspiration of MPCViT

In this section, we breakdown Softmax for accuracy and efficiency evaluation and compare two ways of building MPC-friendly ViTs. The analysis serves as our motivation of proposing MPCViT, which features heterogeneous attention and NAS-based Pareto optimization.

Motivation 1: ViT latency bottleneck in MPC. In Figure 1, we profile the latency of a Transformer block with different number of heads and tokens. We now further dive into Softmax and evaluate its latency breakdown. We profile a 4-head ViT with 65 tokens and 256 hidden dimension assuming the WAN setting as defined in §5.1. We consider two widely used protocols, including SEMI-2K [9] and Cheetah [22]. From both Figure 1 and Figure 3, we make the following observations: 1) Softmax is the major latency bottleneck in most cases. The latency of GeLU and MatMuls also becomes non-negligible when the number of heads or tokens is small; 2) Softmax mainly involves three operations, including exponential, reciprocal and max. All of the operations are important for the latency overhead. Therefore, we are motivated to get rid of these expensive operations as many as possible, and we propose to first focus on optimizing the Softmax and only consider GeLU and MatMul when the number of heads or tokens is small.

Motivation 2: comparison of different attention variants. To reduce the latency of Softmax in the attention module, there are two different ways, i.e., 1) reducing the dimension of QK^T such as Linformer [58], which approximates QK^T with a low rank matrix; and 2) simplifying Softmax by replacing exponential, reciprocal or max with other operations. For the second method, while the possible activation variants can be abundant, we observe the following three important properties of Softmax, which helps us to select promising candidates: *monotonicity*, *non-negativity*, and *normalized sum to 1*. The first two properties are related to the exponential while the last one is achieved with reciprocal. We propose and evaluate the following variants, including ReLU, ReLU6, Sparsemax [40], XNorm [53], Square, Scaling [59], 2Quad [33], Linformer [58] and ReLU Softmax [44]. We define the attention with ReLU Softmax as RSAAttn for short. The formulation of these attention variants is described in Appendix C.

To compare these attention variants, we train each model for 300 epochs on CIFAR-10 and compare the latency, accuracy, remaining operations, and how they satisfy the properties of Softmax in Table 2. We make the following observations: 1) Attention with more expensive operations can be more inefficient. For instance, 2Quad has an extra reciprocal compared with Square such that 2Quad suffers from a higher latency; 2) Linformer suffers from a high accuracy degradation ($\sim 1.8\%$ compared with Softmax attention) as it significantly reduces the matrix dimensions such that the model learning capability is degraded, and the computation reduction of this optimization cannot benefit latency reduction a lot. Hence, the first method is not preferred; 3) ReLU Softmax and 2Quad achieve higher accuracy among other variants and we hypothesize this is because they both normalize the sum to 1, which is realized with reciprocal and also leads to relatively higher latency. ReLU Softmax is more preferred over Softmax and 2Quad due to its small approximation error and small accuracy degradation; 4) Scaling is equivalent to directly removing the Softmax. Although it is the fastest, directly linearizing all the Softmax leads to a large accuracy degradation; 5) it is interesting to notice that although XNorm attention has linear com-

putation, it incurs the highest latency because computing ℓ_2 -norm involves both reciprocal and square root, both of which are expensive in MPC.

Motivation 3: Not all attentions are equally important. As observed in [5, 36, 41, 46, 54, 56], not all attentions are equally important and different layer prefers different attention type. For instance, [46] identifies the minor contribution of the early attention layers in recent ViTs, while [34] demonstrates the second head shows higher importance than other heads. Thus, the importance of attentions among different layers or even the attentions within the same layer can be different. It indicates we can safely replace the expensive Softmax or ReLU Softmax with the cheaper Scaling without compromising the network accuracy.

Remark The analysis above provide us with the following intuitions when designing an MPC-friendly ViT:

- 1) ReLU Softmax is more preferred over Softmax and more MPC-friendly, and Scaling has the highest inference efficiency;
- 2) by selectively replacing the ReLU Softmax with the cheaper Scaling, it is possible to reduce the inference latency without compromising the inference accuracy;
- 3) when the latency of GeLU and Softmax are comparable, we have an opportunity to further simplify GeLU along with Softmax.

4. The Proposed MPCViT Algorithm

In this section, we introduce MPCViT, which for the first time optimizes the ViT architecture with NAS-based algorithm for a fast private inference in MPC.

4.1. Overview of Optimization Flow

Based on the motivations described above, we now describe our MPC-aware ViT optimization flow as shown in Figure 4. We propose to replace the Softmax with the accurate yet MPC-friendly ReLU Softmax in the ViT first and then, linearize the relatively “unimportant” ReLU Softmax with efficient Scaling. To find the “unimportant” ReLU Softmax, we first design a heterogeneous search space that includes both ReLU Softmax and Scaling attentions. Architecture parameters are defined to measure the importance of ReLU Softmax and enable the selection between the two attention variants with different structure granularities (§4.2). Then, we propose an MPC-aware differentiable NAS algorithm to learn the architecture parameters and model parameters simultaneously. We select between the attention variants based on the architecture parameters and the latency constraints (§4.3). In the last step, we retrain the ViT with heterogeneous attentions from scratch. We leverage knowledge distillation (KD) to improve the accuracy of the searched networks (§4.4). Appendix D depicts the complete algorithm flow of MPCViT.

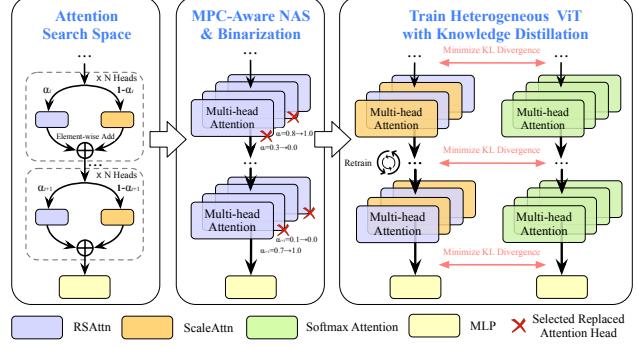


Figure 4. Overview of our proposed MPCViT pipeline.

4.2. Heterogeneous Attention Search Space

Our heterogeneous search space combines two candidate attention variants, i.e., MPC-efficient ScaleAttn and high-accuracy RSAttn and has the following three different structural granularities as shown in Figure 5:

- *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 (i.e., token-wise) is the most fine-grained and mixes the two attention variants along each row of the attention map.

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 algorithm.

4.3. MPC-Aware Differentiable NAS

Many research efforts have been made to NAS including reinforcement learning method (RL) [17, 24, 57], however, RL-based NAS requires significant overhead during searching. Recent years, [10, 27, 55, 61] explore hardware-aware NAS algorithms to make model fit the rigorous hardware requirement. For private ViT inference, we also need a NAS algorithm that takes MPC conditions into consideration.

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

Search formulation. Inspired by [5], we introduce an architecture parameter α ($0 \leq \alpha \leq 1$) for each head, which is an auxiliary learnable variable that helps to choose between RSAttn and ScaleAttn. Then, each head implements the computation below:

$$\alpha \cdot \text{ReLUSoftmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V + (1-\alpha) \cdot \frac{\text{ScaleAttn}(Q, K, V)}{\sqrt{d_k}}$$

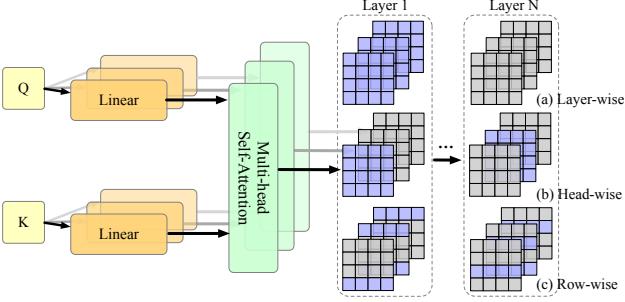


Figure 5. An illustration of our proposed search space with different structure granularities: (a) layer-wise search space with the size of $2^{\# \text{layers}}$; (b) head-wise search space with the size of $2^{\# \text{layers}} \times \# \text{heads}$ and; (c) row-wise search space with the size of $2^{\# \text{layers}} \times \# \text{heads} \times \# \text{tokens}$. The blocks in blue represent RSAtn and the blocks in grey represent ScaleAttn.

Note that we also add $\frac{1}{\sqrt{d_k}}$ for ScaleAttn to make the search process more stable and robust.

Search objective function. We aim at training ViTs with high accuracy but as few RSAtn as possible. We introduce ℓ_1 -penalty into the objective function and formulate the NAS as a one-level optimization problem. To take MPC overhead into consideration, we incorporate realistic inference latency constraints into objective function to construct the MPC-aware NAS algorithm as

$$\begin{aligned} \text{Cost}(\alpha_{ij}) &= \alpha_{ij} \cdot \text{Lat}(\text{ATTN}_{ij}), \\ \min_{\theta, \alpha} \ell(f_{\theta, \alpha}(x), y) + \lambda \cdot \left(\sum_{i=1}^L \sum_{j=1}^N \|\text{Cost}(\alpha_{ij})\|_1 \right), \end{aligned}$$

where x and y are the input-label pairs, $\ell(\cdot)$ is the loss function, λ is a hyper-parameter to control the weight of inference overhead, N is the number of heads in one layer, and L is the number of layers. $\|\cdot\|_1$ means ℓ_1 -norm, and ATTN_{ij} means the candidate attention of i -th layer and j -th head. We initialize α for each head to 1.0 and jointly optimize the network parameter θ and architecture parameter α during searching. Note that our differentiable algorithm computes the gradients of α for all the attention heads across different layers in ViT simultaneously.

Architecture parameter binarization. After the network searching, we obtain α for each attention head in all layers. To select either RSAtn or ScaleAttn for each head, we binarize α based on the following rule: we use the *top-k* rule according to the ratio of RSAtn budget μ , which is defined as $\#\text{RSAtn}/\#\text{Heads}$. Specifically, we first find the $\mu L N$ -th largest α , denoted as α^* , and then we binarize α for each attention head following $\mathbb{1}(\alpha \geq \alpha^*)$. Our proposed search method does not need to train candidate networks, but only needs to train once and then select, which accelerates our search process. Now, we obtain a heterogeneous ViT, and by changing μ , we can obtain a family of

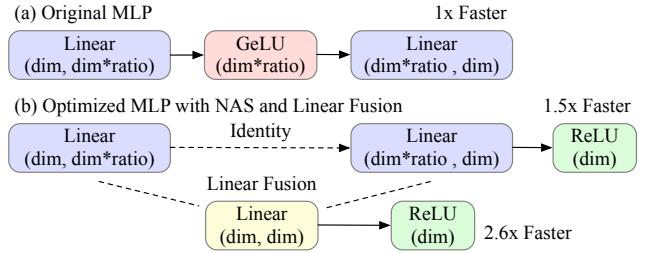


Figure 6. MPCViT⁺: The optimization of our proposed GeLU linearization and linear fusion for the MLP block.

ViTs with different accuracy and efficiency trade-off.

4.4. Train the Searched ViT for Better Performance

After binarization, RSAtn with a small α 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 an important question for us.

Token-wise feature-based KD. KD [21] 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 token-wise feature-based self-distillation along with a logits-based KD, which uses 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 \mathcal{L}_{KL} for the logits-based KD, denoted as $\mathcal{L}_{\text{logits}}$. Combining distillation loss with the task-specific cross-entropy (CE) loss \mathcal{L}_{CE} , we obtain the final training objective under a distillation temperature \mathcal{T} as follows:

$$\begin{aligned} \mathcal{L}_{\text{train}} &= \chi \mathcal{L}_{CE} + \beta \mathcal{L}_{\text{logits}} + \gamma \mathcal{L}_{\text{feature}} \\ &= \chi \mathcal{L}_{CE} + \beta \mathcal{L}_{KL}\left(\sigma\left(\frac{z_s}{\mathcal{T}}\right), \sigma\left(\frac{z_t}{\mathcal{T}}\right)\right) + \gamma \|z_s - z_t\|_2, \end{aligned}$$

where χ , β and γ are training hyper-parameters to balance different loss functions in the training objective, z_s and z_t are feature maps from student and teacher, and σ is Softmax. This self-distillation requires no extra model and only introduces negligible training cost, and has no influence on inference latency or communication overhead in MPC.

4.5. MPCViT⁺: Support for GeLU Linearization

The above design of MPCViT leverages NAS algorithm to build the efficient yet effective attention mechanism. Besides attention, in MLP blocks, non-linear GeLU also impacts the communication cost in some protocols, e.g., Cheetah when the number of heads or tokens is small. And two linear layers near GeLU are also costly because

the inverted-bottleneck structure of MLP leads to high-dimensional MatMul, which is shown in Figure 1 and Figure 3(a). To further improve the efficiency of ViTs, we propose an extended version called MPCViT⁺. Specifically, MPCViT⁺ searches and removes relatively “unimportant” GeLUs. Given architecture parameter β for GeLU, the NAS algorithm is similar to the attention optimization:

$$(\beta \cdot \text{GeLU}(x) + (1 - \beta) \cdot x) \cdot \mathcal{W}.$$

The architecture parameters α and β are jointly learnt during the search, thus the NAS loss is defined along with the classification loss $\min_{\theta, \alpha, \beta} \ell(f_{\theta, \alpha, \beta}(x), y)$:

$$\begin{aligned} \text{Cost}(\beta_{ij}) &= \beta_{ij} \cdot \text{Lat}(\text{Act}_{ij}), \\ \lambda \cdot (\sum_{i=1}^L \sum_{j=1}^N \|\text{Cost}(\alpha_{ij})\|_1) + \eta \cdot (\sum_{i=1}^L \sum_{j=1}^T \|\text{Cost}(\beta_{ij})\|_1), \end{aligned}$$

here, we take token-wise linearization as an example, and $\text{Lat}(\text{Act}_{ij})$ denotes the latency of either GeLU or identity of i -th layer and j -th token, T denotes the number of tokens in each layer. We can consider the balance between λ and η through the private inference latency: $\frac{\lambda}{\eta} = \frac{\text{Lat}(\text{ATTN})}{\text{Lat}(\text{GeLU})}$.

Fuse two linear layers together. After GeLU linearization, we observe an opportunity for further latency reduction. As shown in Figure 6, we fuse the linear layer before and after GeLU of a certain token, which reduces the communication associated with the MLP. Denote the input of a MLP block of i -th layer as $X^{(i)} \in \mathbb{R}^{B \times H \times W \times C}$, the linear layers as $\mathcal{W}_1^{(i)} \in \mathbb{R}^{C \times K}$ and $\mathcal{W}_2^{(i)} \in \mathbb{R}^{K \times C}$, the output of MLP as $X^{(i+1)} \in \mathbb{R}^{B \times H \times W \times C}$. The input dimension of GeLU is $B \times H \times W \times K$, and C, K are channel numbers of linear layers. Note that we generally set the ratio of MLP (i.e., $\frac{K}{C}$) to 2 or 4 in ViT models. The linearized MLP can be formulated as $X^{(i+1)} = (X^{(i)} \mathcal{W}_1^{(i)}) \mathcal{W}_2^{(i)} = X^{(i)} (\mathcal{W}_1^{(i)} \mathcal{W}_2^{(i)})$. In this way, $\mathcal{W}_1^{(i)} \mathcal{W}_2^{(i)}$ is fused into $\mathcal{W}_f^{(i)} \in \mathbb{R}^{C \times C}$, which optimizes two high-dimensional MatMuls to only a single low-dimensional MatMul, further reducing the latency of MLP.

Adding additional activations. After GeLU removal and linear fusion, there is no non-linearity in these tokens. To boost the accuracy, we additionally add a non-linear function after the fused linear positions. Here, we choose to add ReLU which incurs a cheaper cost than GeLU.

5. Experiments

5.1. Experimental Setup

Experimental and MPC settings. In our experiments, we leverage the SecretFlow (SPU [39] V0.3.1b0)² framework for private inference, which is popular for privacy-

²<https://github.com/secretflow/secretflow>

preserving deep learning. We adopt the SEMI-2K [9] protocol, which is a semi-honest two-party computation protocol³. We follow Cheetah [22] and use the WAN mode for communication. Specifically, the communication bandwidth between the cloud instances is set to 44 MBps and the round-trip time is set to 40ms. Our experiments are evaluated on an Intel Xeon CPU@2.40 GHz with 62 GB RAM.

Model architectures and datasets. Many researches have studied training ViTs on small datasets [12, 19, 23, 32, 35]. We consider two ViT architectures on three commonly used datasets following [19]. For the CIFAR-10/100 dataset, we set the ViT depth, # heads, hidden dimension, and patch size to 7, 4, 256, and 4, respectively. For Tiny-ImageNet dataset, we set the ViT depth, # heads, hidden dimension, and patch size to 9, 12, 192, and 4, respectively.

Searching settings. We run the 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 $\lambda = 10^{-5}$.

Training settings. Following [19], we train the searched heterogeneous ViTs for 600 epochs on CIFAR-10/100 and 300 epochs on Tiny-ImageNet. We leverage data augmentations as [19]. For KD, we set the temperature \mathcal{T} to 1, and set χ, β, γ to 1 as well. To explore the trade-off between inference accuracy and latency, we set μ to $\{0.1, 0.3, 0.5, 0.7\}$.

5.2. Comparison with Prior-Art Efficient Attentions

Baselines. We compare MPCViT with prior-art models on the inference accuracy and efficiency. We compare with MPCFormer [33], Linformer [58, 60], THE-X [6] and ViT variants in Table 2. Linformer is studied in [60] as an efficient Transformer variant for MPC and the compression rate of attention dimension is also defined as μ . For networks compared with MPCViT, we only modify attention layer and keep MLP unchanged as the baseline ViT. For MPCViT⁺, we optimize attention and MLP simultaneously.

Results and analysis. The main results are shown in Figure 7, 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. Without KD, on Tiny-ImageNet, MPCViT with $\mu = 0.1$ outperforms Linformer with $\mu = 0.7$ by 0.57% better accuracy with $4.9 \times$ latency reduction; Compared with THE-X, MPCViT achieve 3.6% accuracy improvement with $1.9 \times$ latency reduction;
- 2) with proper KD, MPCViT even achieves 1.9% and 1.3% better accuracy with $6.2 \times$ and $2.9 \times$ latency reduction with $\mu = 0.1$ and 0.3, compared with baseline ViT and MPCFormer on Tiny-ImageNet, respectively;

³Although the actual latency of each operator may be different for different MPC protocols, our proposed algorithm can be generally applied.

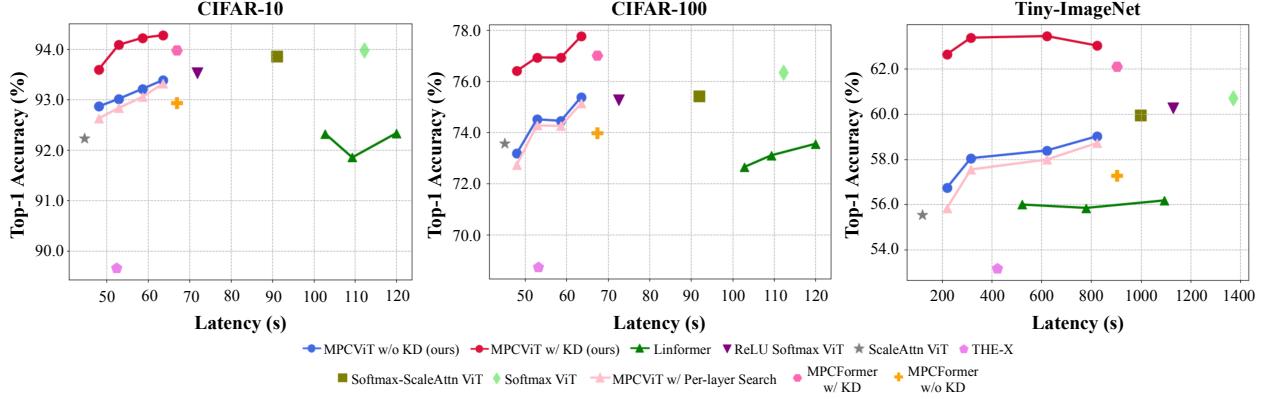


Figure 7. Top-1 Accuracy and inference latency comparison with baseline ViTs across three datasets.

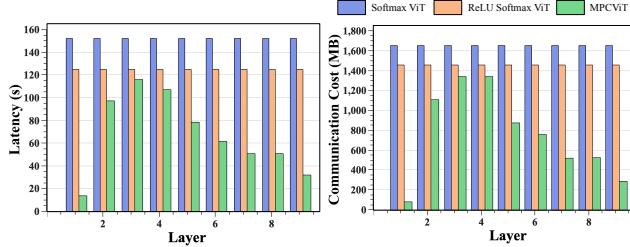


Figure 8. Latency and communication cost comparison of different layers in the 9-layer 12-head ViT with $\mu = 0.5$.

3) we mix Softmax attention and ScaleAttn. Although it has a slightly higher accuracy in plaintext inference, it incurs at least $1.4\times$ and $1.2\times$ latency on CIFAR-10/100 and Tiny-ImageNet compared with MPCViT.

We visualize the latency and communication cost comparison of Softmax ViT, ReLU Softmax ViT, and MPCViT in Figure 8. We can observe the latency changes proportionally with the communication. Also, we observe for MPCViT, RSAtn in middle layers (e.g., layer 2 to layer 5) tend to be preserved while RSAtn in early and final layers are likely to be replaced with ScaleAttn.

5.3. Comparison on Structure Granularities

The choice of search space is important for MPCViT, so we compare different structure granularities of search space proposed in §4.2. We use the CIFAR-10 dataset for the comparison. As shown in Table 3, the head-wise search space achieves the best accuracy. We hypothesize although row-wise structure leads to the largest search space, such a fine-grained search space may introduce difficulties in NAS, and hence, leads to network architecture with inferior accuracy. Head-wise search space achieves the right balance between flexibility and optimizability.

5.4. Ablation Study of MPCViT

Contribution of KD. One of our key techniques for training heterogeneous ViT is KD. We enumerate different

Table 3. Top-1 accuracy (%) comparison with different structure granularities of attention search space with different μ .

Granularity	Layer-wise	Row-wise	Head-wise
$\mu = 0.5$	93.01	93.16	93.21
$\mu = 0.7$	93.32	93.13	93.38

Table 4. Top-1 Accuracy (%) comparison of different combinations of training loss function with $\mu = 0.7$.

CE	Logits-based KD	Feature-based KD	CIFAR-10	Tiny-ImageNet
✓			93.38	59.02
✓	✓		94.18	62.39
✓		✓	94.12	62.26
✓	✓	✓	94.14	61.80
✓	✓	✓	94.27	63.03

combinations of KD and the results are shown in Table 4. 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, especially on a larger dataset. The above findings indicate the importance of KD and the indispensability of three parts of \mathcal{L}_{train} .

Consistency and scalability of NAS algorithm. We hope our NAS algorithm to be robust against hyper-parameter choices and datasets. To analyze this consistency of our algorithm, we adjust the coefficient λ to three different values, i.e., $10^{-3}, 10^{-4}, 10^{-5}$, and train a 7-layer ViT with 4 heads. We visualize the distribution of the architecture parameter α in Figure 9, and we find that α in each layer has a quite similar trend under different λ 's. Furthermore, when we change the number of heads to 8, or even train the same architecture on different datasets like CIFAR-100 and ImageNet, the distribution still shows a similar trend, empirically proving the consistency and scalability of our proposed NAS algorithm. Appendix F shows more distribution trends under other settings.

Comparison with per-layer search. We also compare MPCViT with per-layer search which replaces RSAtn heads in each layer uniformly given a certain μ across three

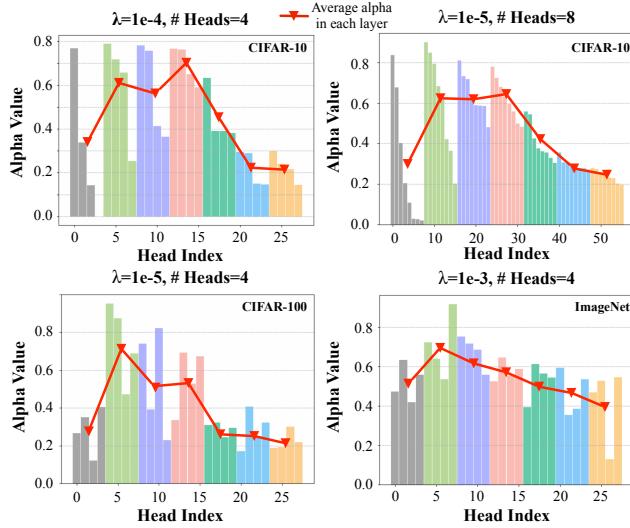


Figure 9. The distribution of architecture parameter α for each head under different λ and different # heads on different datasets. We draw the average α in each layer to show the similar trend.

datasets. As shown in Figure 7, MPCViT achieves a better Pareto front for accuracy and efficiency compared to the per-layer NAS. The results demonstrate the importance to search and replace RSAtn heads across different layers.

5.5. MPCViT⁺ Evaluation

As shown in Figure 7, when μ decreases to 0.1, the major latency bottleneck comes from GeLU in MLP. We evaluate MPCViT⁺ for GeLU reduction on CIFAR-10/100 datasets with KD, which correspond to the ViT models with significant GeLU latency. We take token-wise optimization as an example (exploration for other granularity, i.e., layer-wise is shown in Appendix E), and control the GeLU linearization rate using a threshold σ such that $\beta \leftarrow 0(\beta \leq \sigma)$ while $\beta \leftarrow 1(\beta > \sigma)$. As shown in Figure 10, GeLU linearization leads to a little accuracy degradation, indicating that GeLU plays an important role in ViTs. MPCViT⁺ further reduces the latency on the basis of attention optimization, which proves the effectiveness of MPCViT⁺.

Ablation study of additional ReLU. To analyze the help of adding additional ReLU after the fused linear layer, we fix $\sigma = 0.75$ and perform the ablation study for MPCViT⁺ under different latency constraints on CIFAR-10 dataset in Table 5. The results show that additional ReLU improves the representation ability of MPCViT⁺.

Table 5. Ablation study of adding additional ReLU after the fused linear layer under different latency constraints.

μ	0.3		0.7	
	Accuracy (%)	Latency (s)	Accuracy (%)	Latency (s)
MPCViT ⁺	93.92	43.88	94.27	54.56
w/o ReLU	93.72	41.37	93.81	52.11

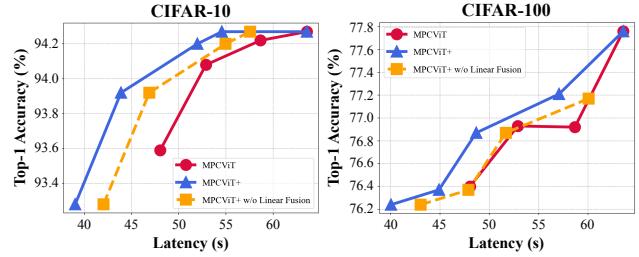


Figure 10. Comparison between MPCViT and MPCViT⁺.

6. Conclusion

In this paper, we present an MPC-friendly ViT family, dubbed MPCViT, to enable accurate yet efficient ViT inference in MPC. We propose a heterogeneous attention optimization space, and design an MPC-aware differentiable NAS algorithm to explore the search space. To further boost the inference efficiency, we propose MPCViT⁺ to jointly optimize attention and MLP. Extensive experiments demonstrate that MPCViT consistently outperforms prior-art ViT architectures with both lower latency and higher accuracy. Our method can be further applied to large language models (LLMs) including BERT and GPT.

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