Spiking Transformer with Experts Mixture

Zhaokun Zhou[1,2]*, **Yijie Lu**[1]*, **Yanhao Jia**[3,7], **Kaiwei Che**[1,2], **Jun Niu**[1], **Liwei Huang**[4,2], **Xinyu Shi**[5,4], **Yuesheng Zhu**[1], **Guoqi Li**[6,2], **Zhaofei Yu**[5,4]†, **Li Yuan**[1,2]†

[1]School of Electronic and Computer Engineering, Shenzhen Graduate School, Peking University
[2]Peng Cheng Laboratory
[3] College of Computing and Data Science, Nanyang Technological University
[4]School of Computer Science, Peking University
[5]Institute for Artificial Intelligence, Peking University
[6]Institute of Automation, Chinese Academy of Sciences
[7]Deep NeuroCognition Lab, I2R and CFAR, Agency for Science, Technology and Research

Abstract

Spiking Neural Networks (SNNs) provide a sparse spike-driven mechanism which is believed to be critical for energy-efficient deep learning. Mixture-of-Experts (MoE), on the other side, aligns with the brain mechanism of distributed and sparse processing, resulting in an efficient way of enhancing model capacity and conditional computation. In this work, we consider how to incorporate SNNs' spike-driven and MoE's conditional computation into a unified framework. However, MoE uses softmax to get the dense conditional weights for each expert and TopK to hard-sparsify the network, which does not fit the properties of SNNs. To address this issue, we reformulate MoE in SNNs and introduce the Spiking Experts Mixture Mechanism (SEMM) from the perspective of sparse spiking activation. Both the experts and the router output spiking sequences, and their element-wise operation makes SEMM computation spike-driven and dynamic sparse-conditional. By developing SEMM into Spiking Transformer, the Experts Mixture Spiking Attention (EMSA) and the Experts Mixture Spiking Perceptron (EMSP) are proposed, which performs routing allocation for head-wise and channel-wise spiking experts, respectively. Experiments show that SEMM realizes sparse conditional computation and obtains a stable improvement on neuromorphic and static datasets with approximate computational overhead based on the Spiking Transformer baselines.

1 Introduction

The spiking neural networks (SNNs) are regarded as the third generation of neural networks [1], distinguished by biological plausibility [2], spike-driven characteristic, and low power consumption. SNNs emulate the dynamics of biological neurons at a microscopic level, utilizing asynchronous binary spikes for information transmission. The membrane potential of spiking neurons in SNNs is only updated upon the arrival of spikes, avoiding calculations of zero values. The inherent features make SNNs promising candidates for low-energy consumption on neuromorphic hardware, such as TrueNorth [3] and Loihi [4]. There are lots of architectures in SNNs include Spiking Recurrent Neural Networks [5], ResNet-like SNNs [6–9], Spiking Graph Neural Networks [10], and Spiking Transformers [11–13]. Spiking Transformers stands at the forefront. Spikformer [11] introduces Spiking Self-Attention (SSA). The Spike-Driven Transformer [12] introduces Spike-driven Self-

*Equal
†Corresponding author

38th Conference on Neural Information Processing Systems (NeurIPS 2024).

 https://doi.org/10.52202/079017-0322

Attention. Other works explore the Spiking Transformer in terms of structural improvements [14–17], training methods [18], and different tasks [19], respectively.

Mixture-of-Experts (MoE) [20, 21] is known for allowing each expert to learn specific tasks or features, showing better performance, conditional computing and dynamic adaptability, which are crucial features in the brain mechanism [22, 23]. In this work, we are committed to exploring the effective integration of MoE and Spiking Transformer. As shown in Fig.1(a), MoE introduces a large number of parameters based on the original Transformer, and the conditional computation is achieved by calculating the routing probability of each token on each expert through the softmax function. Selecting Top-K experts based on the routing probability, MoE achieves hard sparsification. However, SNN calculations need to avoid multiplication and cannot use complex softmax functions. The features in SNNs are dynamically sparse and do not require additional TopK. All the parameters of the expert must be loaded, which aggravates the difficulty of neuromorphic chip deployment. These factors make porting MoE to SNNs non-trivial. To tackle this problem, we develop the Spiking Experts Mixture Mechanism (SEMM), as shown in Fig.1(b), a universal SNN-MoE paradigm with the following three main features. 1) The SEMM is spike-driven. The outputs of the expert and the router are spike sequences, and the element-wise operation between them conforms to the SNN characteristics, i.e., avoiding multiplication. 2) SEMM leverages the sparse spiking activation of SNNs to achieve dynamic conditional computation of MoEs, which is more flexible than the fixed hard sparsification of Artificial Neural Network MoE (ANN-MoE). 3) With reasonable parameter count settings, SEMM enables Spiking Transformers to achieve stable performance gains with negligible overhead.

Based on SEMM, we modify the Spiking Self-attention (SSA) and Multi-layer Perceptron (MLP) of Spiking Transformers to obtain the Experts Mixture Spiking Attention (EMSA) and the Experts Mixture Spiking Perceptron (EMSP). EMSA treats each head of SSA as an expert, computes respective attention, and employs a temporal-aware router to integrate attention. As for Multi-layer Perceptron (MLP), it is common to substitute the entire MLP with MoE [24], which leads to better performance but a significant increase in the overall parameter number. EMSP implements a channel-wise MoE within MLP to overcome the shortcoming. EMSA and EMSP can be inserted directly and seamlessly into existing Spiking Transformer variants [11, 14, 12]. Our work contributes in three main aspects:

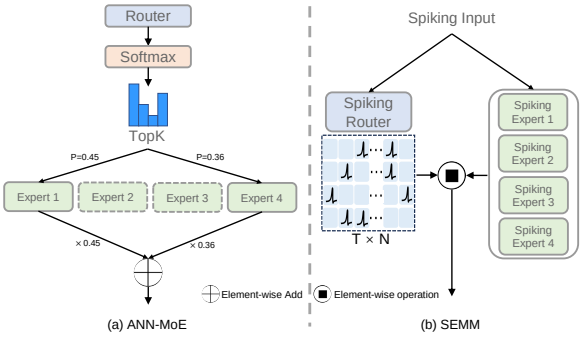

Figure 1: ANN-MoE and Spiking Experts Mixture Mechanism (SEMM). N denotes the length of image patches.

- We introduce the Spiking Experts Mixture Mechanism (SEMM), a universal SNN-MoE paradigm. SEMM is spike-driven, capable of efficient dynamic sparse conditional computation.
- Based on SEMM, we develop the Experts Mixture Spiking Attention (EMSA), whose information from all head-wise experts is selectively integrated through a temporal-aware router. We restructure MLP by a channel-level spiking-sparse SEMM, named the Experts Mixture Spiking Perceptron (EMSP). They can seamlessly replace self-attention and MLP in Spiking Transformers.
- Extensive experiments demonstrate the stable performance improvement of SEMM on both static and neuromorphic datasets. Notably, Spike-driven Transformer-8-512 with SEMM achieves a remarkable 76.62% accuracy on ImageNet with 4 time steps, surpassing the baseline (74.57%).

2 Related Work

Deep Spiking Neural Networks and Spiking Transformers. Spatio-temporal backpropagation(STBP) [25] directly trains SNNs by performing backpropagation on both spatial and temporal domains. Temporal backpropagation [26] computes the gradients of the timings of existing spikes for the membrane potential at the spike timing. Treshold-dependent batch normalization (tdBN) [8] is used to extend the network depth. SEW-ResNet [7] proposed the spiking element-wise residual for SNNs. Spikformer [11] firstly converts all the components of Vision Transformer (ViT) into

https://doi.org/10.52202/079017-0322

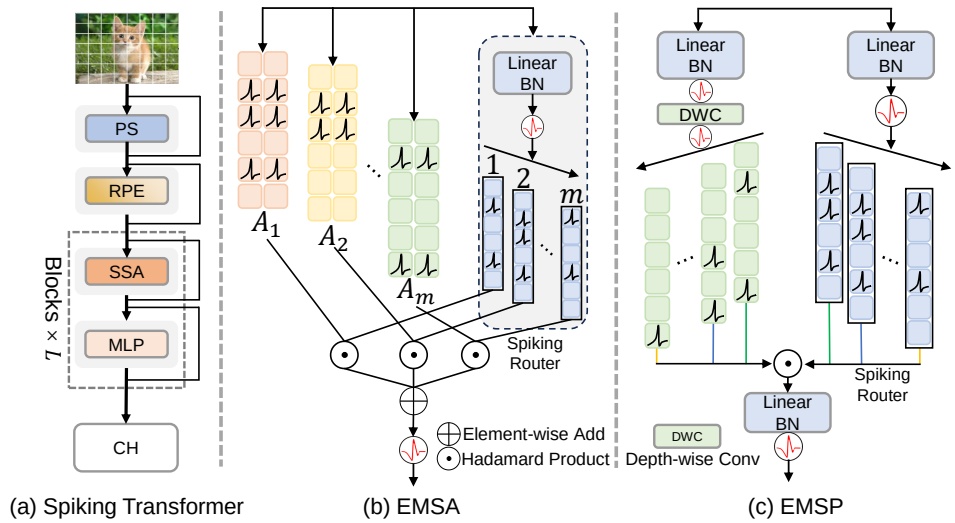

Figure 2: (a) The overview of Spiking Transformer. (b) The Experts Mixture Spiking Attention (EMSA). (c) The Experts Mixture Spiking Perceptron (EMSP). EMSA and EMSP can directly replace SSA and MLP in (a).

spike-form and pioneers the field of SNN-Transformer. Spike-driven Transformer [12] goes further by introducing linear spike-driven self-attention. Spikingformer [14] proposes a hardware-friendly spike-driven residual learning architecture. Besides, Masked Spiking Transformer [27] combines SNNs and Transformers from the perspective of the ANN-to-SNN conversion. However, the SNN Transformer architecture that can bring SNNs' superiority into full play is still ongoing research.

Mixture-of-Experts. The Mixture-of-Experts (MoE) [28, 29] combines the predictions of multiple specialized experts, which is effective in handling high-dimensional data and complex problems. Researchers explore diverse gating mechanisms [30, 31], optimizing expert allocation strategies [32, 33], and enhancing the scalability of MoE models [34, 35]. Sparsely-Gated Mixture-of-Experts [30] adopted MoE into architectures such as the Long Short-Term Memory (LSTM) [36], showcasing effectiveness in Language Modeling. The Transformer also benefits from MoE with the substitution of the Multi-layer Perceptron (MLP) [24, 37]. Switch Transformer [35] has scaled the models with trillions of parameters. Currently, there is no existing work on MoE with Spiking Transformers.

3 Methodology

3.1 Preliminaries and Overall Architecure

Spiking neuron is the basic unit of SNNs. For the dynamics of the Leaky Integrate-and-Fire (LIF) neuron used in this work, the $t-th$-time-step membrane potential $U[t]$ is equal to the sum of the state potential $H[t-1]$ at the previous time step and the input $X[t]$. When membrane potential exceeds the threshold u_{th}, the neuron will fire a spike, otherwise, it remains inactive. Consequently, the output $S[t]$ only contains binary values, either 1 or 0. $\mathrm{Hea}(\cdot)$ is a Heaviside function that satisfies $\mathrm{Hea}\,(x) = 1$ when $x \geq 0$, otherwise $\mathrm{Hea}\,(x) = 0$. $H[t]$ is the temporal state output, and V_{reset} denotes the reset potential after a spiking event. $\beta < 1$ determines the rate of decay. If the neuron remains inactive, the potential $U[t]$ decays towards $H[t]$ over time. LIF can be described as:

$$U[t] = H[t-1] + X[t], \tag{1}$$

$$S[t] = \mathrm{Hea}\,(U[t] - u_{th})\,, \tag{2}$$

$$H[t] = V_{reset} S[t] + (\beta U[t])\,(1 - S[t])\,. \tag{3}$$

Spiking Transformer[11, 14, 12] baselines contain Patch Splitting (PS), Relative Position Embedding (RPE), Spiking Self Attention (SSA) (e.g., Spiking Self-Attention [11] and Spike-driven Self-Attention[12]), MLP and linear classification head, as shown in Fig. 2(a). Given a 2D image sequence $\mathbf{I} \in \mathbb{R}^{T \times C \times H \times W}$, where T, C, H, and W denote time-step, channel, height and width, the PS splits it into a sequence of N flattened spike patches $\mathbf{x}$ with D dimensional channel. A Convolution-BatchNorm-LIF block generates Relative Position Embedding (RPE):

https://doi.org/10.52202/079017-0322

$$\mathbf{X}_0 = \mathrm{PS}\left(\mathbf{I}\right) + \mathrm{RPE}, \tag{4}$$

$$\mathbf{X}_l^{'} = \mathrm{SSA}(\mathbf{X}_{l-1}) + \mathbf{X}_{l-1}, \tag{5}$$

$$\mathbf{X}_l = \mathrm{MLP}(\mathbf{X}_l^{'}) + \mathbf{X}_l^{'}, \tag{6}$$

$$\mathbf{Y} = \mathrm{CH}(\mathrm{GAP}(\mathbf{X}_L)), \tag{7}$$

where the $\mathbf{X}_0$ is fed into the L-blocks and each block consists of a SSA and a MLP. $\mathbf{X}_l^{'}, \mathbf{X}_l$ are spike sequences and $l = 1...L$ is layer. A Global Average-pooling (GAP) is utilized on the $\mathbf{X}_L$ and the linear Classification Head (CH) to output the prediction $\mathbf{Y}$. See Appendix. A for more details.

3.2 Spiking Experts Mixture Mechanism

Before exploring the adaptation of spiking MoE in SNNs, we first review MoE in ANNs. An ANN-MoE layer typically comprises a set of m experts $\mathbf{E}_\mathrm{A} = \{\mathbf{E}_1, \mathbf{E}_2, ..., \mathbf{E}_m\}$, along with a router $\mathcal{R}_\mathrm{A}$ for selecting the corresponding experts. Given an input sequence $\mathbf{X}_\mathrm{A}$, the resulting output can be expressed as the sum of the Top-K selected experts from m candidates using a router:

$$\mathrm{y} = \sum_{k=1}^{K} \mathcal{R}_k(\mathbf{X}_\mathrm{A}) \cdot \mathbf{E}_k(\mathbf{X}_\mathrm{A}), \tag{8}$$

$$\mathcal{R}(\mathbf{x}) = \mathrm{TopK}(\mathrm{softmax}(\mathbf{X}_\mathrm{A}\mathbf{W}_\mathcal{R}, K)), \tag{9}$$

$$\mathrm{TopK}(\boldsymbol{v}, K) = \begin{cases} \boldsymbol{v} & \text{if } \boldsymbol{v} \text{ is in the top } K \text{ elements} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where $\mathbf{W}_\mathcal{R}$ is the router weight matrix. The $\mathrm{TopK}(\cdot, K)$ together with the $\mathrm{softmax}(\cdot)$ sets all elements of the routing vector to zero except the largest top K values. The sparse conditional computing is obtained from the selecting of TopK and the different routing weights of the softmax, while K is usually taken as $0.5 * m$. We argue that the ANN-MoE is not suitable for SNN for two main reasons. First, the float-point routing-expert and the softmax which involve exponentiation and division, do not adhere to the computation principles of SNNs. Second, SNN experts are inherently highly sparse, so the hard sparsification approach of additional TopK is unnecessary. An event-triggered spike-based sparse conditional computation on asynchronous neuromorphic chips is needed more than TopK. To bridge these gaps, we introduce a generalized representation of the Spiking Experts Mixture Mechanism (SEMM), which is as follows,

$$\mathrm{SEMM}(\mathbf{E}, \mathcal{R}, \mathrm{F}(\cdot)) = \mathrm{F}(\mathbf{E}, \mathcal{R}), \tag{11}$$

where $\mathbf{E} = \{\mathbf{E}_1, \mathbf{E}_2, ..., \mathbf{E}_m\}$ represents the spiking sequence of m spiking experts in the Spiking Transformer, and $\mathcal{R} \in \{0, 1\}^{T \times N \times m}$ represents the spiking router for allocating computation. $\mathrm{F}(\cdot)$ denotes the element-wise form of the operation between the router and the expert output spiking sequence, i.e., Hadamard product and addition.

As a MoE mechanism specifically designed for SNNs, SEMM has the following three significant advantages. i) **Spike-driven.** The SEMM is spike-driven, which is important for SNNs. Due to the spike-driven computation mode of experts, i.e., Spiking Self-attention and Spiking-MLP, SEMM computations are triggered by sparse spikes of experts and require only synaptic manipulation. For example, the Hadamard product between the spiking signals $\mathcal{R}$ and $\mathbf{E}$ is equivalent to mask. ii) **Sparse-spiking conditional computation.** The SEMM subtly utilizes the sparse activation of the spiking routers for the conditional computation of MoE. SEMM has a variable sparsity when dealing with different data. Additionally, SEMM does not suffer from the load imbalance problem in ANN-MoE, i.e., TopK selects fixed number of experts. The sparse conditional computation is distributed to each expert. iii) **Efficient computation.** Unlike loading with multiple heavy expert modules of ANN-MoE, the SEMM has comparable parameters and operations to the previous SSA and MLP of Spiking Transformers. These are further discussed in Sec. 3.5. Without loss of generality, we use the mainstream architecture of Spiking Transformer for SEMM embedding in Sec. 3.3 and Sec. 3.4.

3.3 Experts Mixture Spiking Attention

We begin by reviewing the processing of Spiking Self-Attention (SSA). Different from vanilla ANN-Transformers [38], it discards the softmax normalization for the attention map. The SSA mechanism

can be described by the following equation:

$$\mathbf{Q} = \mathcal{SN}_{\mathbf{Q}}(\text{L-BN}_{\mathbf{Q}}(\mathbf{X})), \mathbf{K} = \mathcal{SN}_{\mathbf{K}}(\text{L-BN}_{\mathbf{K}}(\mathbf{X})), \mathbf{V} = \mathcal{SN}_{\mathbf{V}}(\text{L-BN}_{\mathbf{V}}(\mathbf{X})), \tag{12}$$

$$\mathbf{A} = \text{SSA}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \begin{cases} \mathcal{SN}(\mathbf{Q}\mathbf{K}^{\text{T}}\mathbf{V} * s), \text{for Spiking Self-Attention} \\ \mathcal{SN}\left(\text{SUM}_{\text{c}}\left(\mathbf{Q} \odot \mathbf{K}\right)\right) \odot \mathbf{V}, \text{for Spike-Driven Self-Attention} \end{cases} \tag{13}$$

where $\mathcal{SN}$ represents the spiking neuron and L-BN represents that the features pass sequentially through Linear and BatchNorm. s is the scaling factor and $\mathbf{Q}, \mathbf{K}, \mathbf{V} \in \{0,1\}^{T\times N\times D}$ are in spike-form. $\mathbf{A} \in \{0,1\}^{T\times N\times D}$ is the spiking output of SSA. $\odot$ is the Hadamard product, and $\text{SUM}_{\text{c}}(\cdot)$ denotes the sum of each column. As shown in Fig 2(b), the Experts Mixture Spiking Attention (EMSA) based on SEMM and SSA is formulated as:

$$\mathbf{A_m} = \text{SSA}(\mathbf{Q_m}, \mathbf{K}, \mathbf{V}), \tag{14}$$

$$\mathbf{E} = \{\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_m\}, \tag{15}$$

$$\mathcal{R} = \mathcal{SN}(\text{BN}(\mathbf{X}\mathbf{W}_{\mathcal{R}})) = \{\mathbf{r}_1, \mathbf{r}_2, ..., \mathbf{r}_m\}, \tag{16}$$

$$\text{SEMM}(\mathbf{E}, \mathcal{R}, \text{F}(\cdot)) = \sum_{i=1}^{m} \mathbf{r}_i * \mathbf{A}_i, \tag{17}$$

$$\text{EMSA} = \mathcal{SN}(\text{BN}(\text{SEMM}(\mathbf{E}, \mathcal{R}, \text{F}(\cdot)))\mathbf{W}_o), \tag{18}$$

where $\mathbf{A}_m \in \{0,1\}^{T\times N\times d}$ is the output of each SSA experts, and $\mathbf{W}_{\mathcal{R}} \in \mathbb{R}^{D\times m}$ is the router weight matrix. $\mathcal{R} \in \{0,1\}^{T\times N\times m}$ is the routing sequence. We set $d \leq D$ by default to avoid introducing too many parameters. The operation $\text{F}(\cdot)$ between expert-router is computed by masking the expert using router pair-by-pair and then summing them up. The output of EMSA is obtained by performing matrix multiplication between $\text{SEMM}(\mathbf{E}, \mathcal{R}, \text{F}(\cdot))$ and synaptic weight $\mathbf{W}_o \in \mathbb{R}^{d\times D}$, the same as the last layer of SSA block in Spiking Transformers.

3.4 Experts Mixture Spiking Perceptron

As illustrate in Fig. reffig:method, the Experts Mixture Spiking Perceptron (EMSP) launches the channel-wise SEMM within MLP. The architecture can be written as follows:

$$\mathbf{E} = \mathcal{SN}(\text{DWC}(\mathcal{SN}(\text{BN}(\mathbf{X}\mathbf{W}_1)))) \in \{0,1\}^{T\times N\times m} \tag{19}$$

$$\mathcal{R} = \mathcal{SN}(\text{BN}(\mathbf{X}\mathbf{W}_{\mathcal{R}})) \in \{0,1\}^{T\times N\times m}, \tag{20}$$

$$\text{SEMM}(\mathbf{E}, \mathcal{R}, \text{F}(\cdot)) = \mathbf{E} \odot \mathcal{R}, \tag{21}$$

$$\text{EMSP} = \mathcal{SN}(\text{BN}((\text{SEMM}(\mathbf{E}, \mathcal{R}, \text{F}(\cdot))\mathbf{W}_o)) \in \{0,1\}^{T\times N\times D}, \tag{22}$$

where $\mathbf{W}_1, \mathbf{W}_{\mathcal{R}} \in \mathbb{R}^{D\times m}$ is the weight matrix of first layer in MLP and router, respectively. We integrate a 3×3 Depth Wise Convolution layer DWC to capture local features on each channel expert, which has fewer parameters and is computationally efficient compared to original convolution. $\mathbf{W}_o \in \mathbb{R}^{m\times D}$ is the wight matrix of output layer. The original Spiking Transformer's MLP would have a D to $4 * D$ channel dimension increase after the first layer and the second layer would reduce the dimension back to D. In EMSP we set m to $(8//3) * D$ to try to match the parameter number of the original MLP. EMSP integrates sparse routing of multiple channel-wise experts. It can also be viewed as the channel-wise gating, which is suitable for temporal information processing, allowing information to flow unimpeded through potentially many time steps [39]. The gate (router) branch and expert branch can be also regarded as incorporating the Spike Element-Wise (SEW) [7] residual block into EMSP. Channel-wise convolution and element-wise (Hadamard) products only introduce a minor increase in computational cost. By appropriately configuring the number and dimensions of expert networks, our EMSP achieves more efficient computation compared to the original spiking MLP. More details of the computational overhead are given in the next sub-section.

3.5 Characteristics of SEMM

We explain each of the three advantages of SEMM, i.e., Spike-driven, Sparse-spiking conditional computation and efficient computation.

Spike-driven has the following formal definition, meaning that the gathering of input current is initiated by sparse spikes released from presynaptic neurons:

https://doi.org/10.52202/079017-0322

Definition 1. *In SNN, the operation is spike-driven if the input currents satisfy the following form,*

$$I_i[t] = \sum_j w_{i,j} s_j[t] = \sum_{j, s_j[t] \neq 0} w_{i,j}, \tag{23}$$

where $I_i[t]$ is the input current of the i-th postsynaptic neuron at time step t, $s_j[t] \in \{0, 1\}$ is the spike output of the j-th pre-synaptic neuron, $w_{i,j}$ is the weight of the synaptic connection from j to i.

For EMSA, the input current for the LIF in Eq. 18 at a specific time step t is given by:

$$\mathbf{I}[t] = \mathrm{SEMM}(\mathbf{E}[t], \mathcal{R}[t], \mathrm{F}(\cdot))\mathbf{W}_o = \sum_{i=1}^{m} r_i[t] * \mathbf{A}_i[t]\mathbf{W}_o, \tag{24}$$

$$I_{p,q}[t] = \sum_{i=1}^{m} r_i[t] \sum_l a_{i,p,l}[t] w_{l,q} = \sum_{\substack{i,l \\ (r_i[t] \wedge a_{i,p,l}[t]) \neq 0}} w_{l,q}, \tag{25}$$

where $\mathbf{I}[t]$ has a dimension of $P \times Q$, with p and q represent the p-th row and q-th column, respectively. EMSA is essentially spike element-wise addition after masking operation on SSA, consistent with the characteristics of spike-driven. For EMSP, the operation between two spiking sequences $\mathbf{E}$ and $\mathcal{R}$ corresponds to the logical AND function [7], which also conforms to the spike driven,

$$\mathbf{I}[t] = \mathrm{SEMM}(\mathbf{E}[t], \mathcal{R}[t], \mathrm{F}(\cdot))\mathbf{W}_o = (\mathbf{E}[t] \odot \mathcal{R})[t]\mathbf{W}_o, \tag{26}$$

$$I_{p,q}[t] = \sum_l e_{p,l}[t] r_{p,l}[t] w_{l,q} = \sum_{\substack{l \\ (e_{p,l}[t] \wedge r_{p,l}[t]) \neq 0}} w_{l,q}. \tag{27}$$

Sparse-spiking conditional computation means using spiking routers to dynamically allocate the computation in temporal and spatial dimension. More analysis is detailed in experiments.

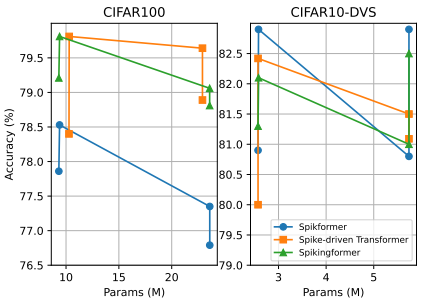

Figure 3: Comparison of parameters-accuracy for different MoEs. Methods of each line from left to right correspond to: 1. the baseline, 2. EMSP, 3. ANN-router with four heavy MLP experts, 4. Spiking-router with four heavy MLP experts, respectively. The last two use softmax and TopK ($K = 2$).

Efficient computations means that SEMM approximates SSA and MLP in terms of number of parameters and theoretical synaptic operations. Tab. 1 demonstrates the computation load for EMSA, EMSP versus SSA and MLP. In terms of parameter number, despite having a routing layer mD, EMSA has a smaller number of parameters than SSA when the number of experts is within a reasonable range (≥ 2). EMSP additionally introduces a 3×3 depthwise convolution, and the number is slighter higher than MLP. Due to the similarity of the actual spiking rates, EMSA is smaller than SSA on the TND^2 term, while the calculation of the additional introduced by SEMM is on the TND term (much smaller than TND^2) and therefore can be ignored. The situation is similar on EMSP, with depth-wise convolution adding a slight computational overhead. The design of EMSP is different from ANN-MoE, which selects multiple heavy MLPs as experts. We demonstrate it's validity in Fig. 3, i.e., it performs better while the number of parameters is much smaller than ANN-MoE.

4 Experiments

4.1 Sparse Conditional Computation Analysis

We analyze the average spiking rate (ASR) of routers for EMSA and EMSP on the ImageNet validation set, which is shown in Tab. 2. The SD-Transformer-8-512 is used for the analysis. The ASR of EMSA is around 0.5, which is comparable to the regular TopK setting of ANN-MoE. The ASR of EMSP is low and gradually decreases as the block deepens, compared to the fixed TopK hard sparse in ANN-MoE, SEMM fully reflects the advantage of SNN dynamic sparse conditional computation. To further verify the spiking router, we ablate it, i.e., cancel it in EMSA and EMSP, as

Table 1: Number of parameters and theoretical synaptic operations. $\overline{R}$, $\widehat{R}$, $\tilde{R}$ and R denote the average spike firing rates (the proportion of non-zero elements in the spike matrix) in various spike matrices. T, N, and D are the time step, sequence length, and channel dimension of the input features, respectively. d is the channel dimension of $\mathbf{A}_m$ and m is the number of experts. The details are provided in the Appendix. B.

	Param	OPs
SSA	$4D^2$	$4\overline{R}TND^2 + 2\widehat{R}TN^2D$
EMSA	$(1+1/m)D^2 + (2d+m)D$	$(1+1/m)\overline{R}TND^2 + (2d+m)\tilde{R}TND + (D+md)RTN^2$
MLP	$8D^2$	$8\overline{R}TND^2$
EMSP	$8D^2 + 24D$	$8\overline{R}TND^2 + 24\tilde{R}TND$

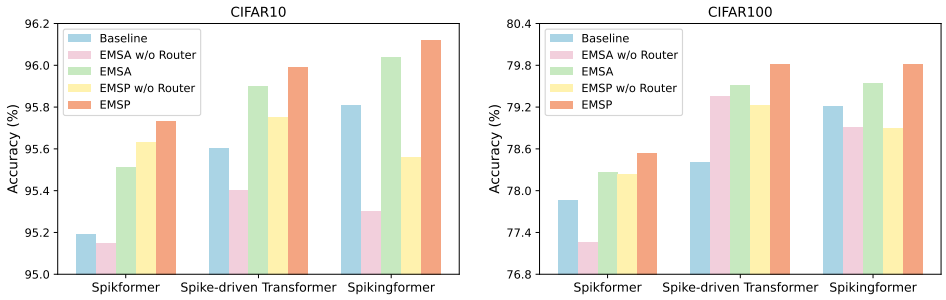

Figure 4: Ablation study on the EMSA and EMSP router.

shown in Fig. 4, the accuracy decreases significantly after canceling the router, and it is even lower than the baseline model on the Spikingformer. Directly analyzing the conditional computation of SEMM is challenging, we therefore use visualizations to illustrate this intuitively. As show in Fig. 5, for the same image, each expert's router assigns a different computational region, e.g., the third router filters the background of the expert's features, while the second router assigns the computation to the foreground target. The computation allocation of the spiking router to the irregular object "snake" can be seen that the router is highly dynamic and effective. See Appendix. D for more samples. In addition, as shown in Fig. 6, we also report the ASR of spatial-temporal locations of routers in different kinds of images. As can be seen by the difference in average firing rates, spiking router has a dynamic adjustment of ASR processing different kinds of images, further illustrating its data-dependent conditional computation property.

Table 2: The average spike rate of EMSA and EMSP router in 8 blocks testing on the ImageNet.

	Block0	Block1	Block2	Block3	Block4	Block5	Block6	Block7
EMSA	0.64	0.68	0.49	0.52	0.47	0.43	0.51	0.50
EMSP	0.25	0.30	0.33	0.27	0.20	0.10	0.05	0.02

4.2 Results on various Datasets

We conduct experiments on static datasets, i.e., ImageNet [40] and CIFAR [41], and neuromorphic datasets, i.e., CIFAR10-DVS [42], DVS128 Gesture [43] to verify the effectiveness of SEMM. See Appendix. C for more details. **ImageNet** results are shown in Tab. 3 which mainly compares SEMM with the Spiking Transformer baselines. At slightly lower model parameter counts, SEMM is steadily superior to baselines. For instance, Spikformer-8-512 with SEMM is 2.55% higher than the baseline with 28.22M parameters, Spike-driven Transformer-8-384 with SEMM obtain 2.05% improvement. SEMM on Spikingformer presents similar findings.

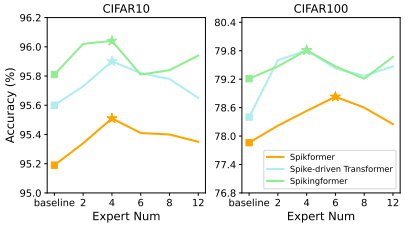

Figure 8: Accuracy with different experts number.

https://doi.org/10.52202/079017-0322

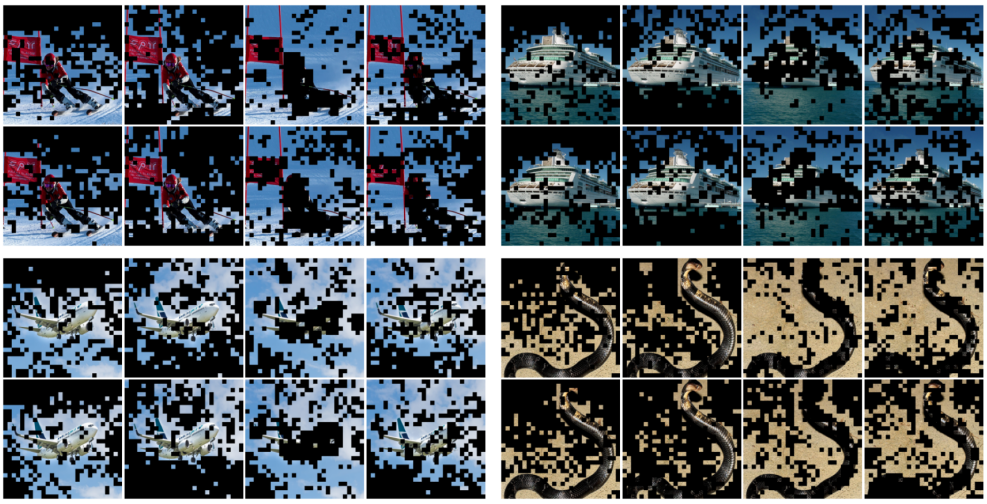

Figure 5: Visualization of routers as masks. The mask position (black) indicates router of 0 here and the background image is the same for each subplot. We show the dynamic sparsity of spiking router for different experts (horizontal direction) and time steps (vertical direction).

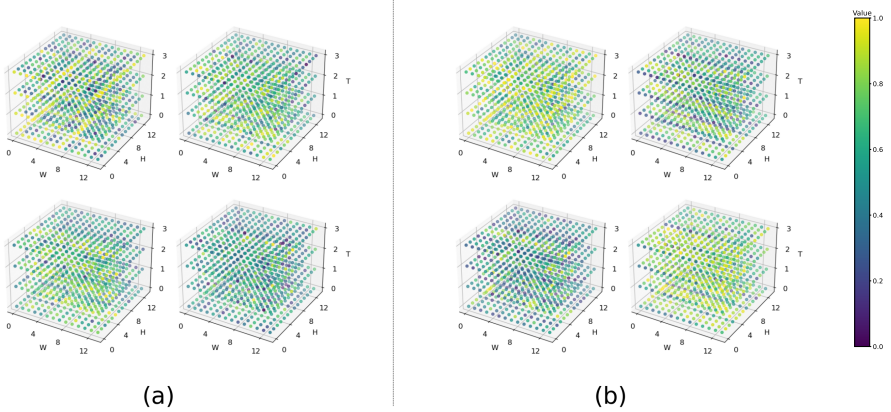

Figure 6: Average spiking rate of different kinds of images in the ImageNet validation set in the spatial-temporal dimension. The height of the cube is the time step. (a) Japanese spaniel. (b) Volcano.

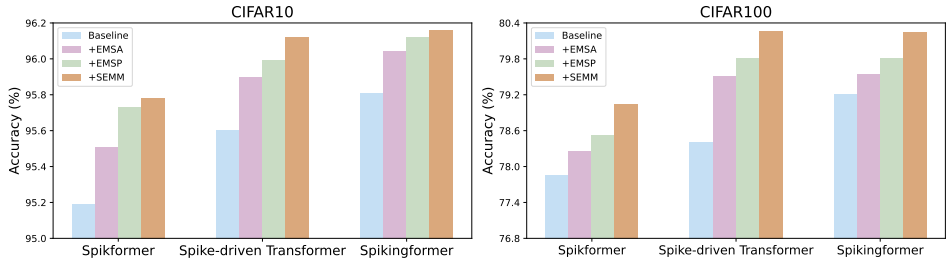

Figure 7: Ablation study of EMSA and EMSP module.

The experimental results on CIFAR, CIFAR10-DVS, and DVS128 Gesture are shown in Tab. 4. These four datasets are relatively small. We basically keep the experimental setup in [11, 12, 14], including the network structure, training settings, etc., and details are given in the Appendix. C.1. SEMM has demonstrated stable performance improvements across various datasets when integrated

Table 3: Results on ImageNet-1k. Model-L-D represents a model with L encoder blocks and D channels.

Methods	Architecture	Param (M)	Time Step	Top-1 Acc (%)
SEW ResNet[7]	SEW-ResNet-34	21.79	4	67.04
	SEW-ResNet-101	44.55	4	68.76
	SEW-ResNet-152	60.19	4	69.26
MS-ResNet[9]	MS-ResNet-18	11.69	6	63.10
	MS-ResNet-34	21.80	6	69.42
	MS-ResNet-104*	77.28	5	76.02
Spikformer[11]	Spikformer-8-384	16.81	4	70.24
	Spikformer-8-512	29.68	4	73.38
Spikformer + SEMM	Spikformer-8-384	**16.05**	4	**72.86**
	Spikformer-8-512	**28.22**	4	**75.93**
Spike-driven Transformer[12]	SD-Transformer-8-384	16.81	4	72.28
	SD-Transformer-8-512	29.68	4	74.57
SD-Transformer + SEMM	SD-Transformer-8-384	**16.05**	4	**73.93**
	SD-Transformer-8-512	**28.22**	4	**76.62**
Spikingformer[14]	Spikingformer-8-384	16.81	4	72.45
	Spikingformer-8-512	29.68	4	74.79
Spikingformer + SEMM	Spikingformer-8-384	**16.05**	4	**73.58**
	Spikingformer-8-512	**28.22**	4	**76.03**

Table 4: Results on CIFAR10-DVS, DVS128 Gesture, and CIFAR.

Methods	CIFAR10-DVS		DVS128 Gesture		CIFAR-10		CIFAR-100	
	T	Acc	T	Acc	T	Acc	T	Acc
tdBN [8]	10	67.80	40	96.90	6	93.20	-	-
PLIF [44]	20	74.80	20	97.60	8	93.50	-	-
DIET-SNN [45]	-	-	-	-	5	92.70	5	69.70
Dspike [46]	10	75.40	-	-	6	94.30	6	74.20
DSR [47]	10	77.30	-	-	20	95.40	20	78.50
Spikformer [11]	10	78.90	10	96.90	4	95.19	4	77.86
	16	80.90	16	98.30				
Spikformer + SEMM	10	**82.32**	10	**97.56**	4	**95.78**	4	**79.04**
	16	**82.90**	16	**98.63**				
Spike-Driven Transformer [12]	10	78.90	10	96.90	4	95.60	4	78.40
	16	80.00	16	99.30				
Spike-Driven Transformer + SEMM	10	**81.10**	10	**97.56**	4	**96.12**	4	**80.26**
	16	**82.42**	16	**99.30**				
Spikingformer [14]	10	79.90	10	96.20	4	95.81	4	79.21
	16	81.30	16	98.30				
Spikingformer + SEMM	10	**80.70**	10	**96.88**	4	**96.16**	4	**80.24**
	16	**82.10**	16	**98.56**				

into different Spiking Transformer baselines. Specifically, SEMM achieves SOTA on CIFAR-10 (96.16%), CIFAR-100 (80.26%), CIFAR10-DVS (82.9%) and DVS128 Gesture (99.3%).

4.3 Ablation Study and Hyperparameter Sensitivity

Module ablation. EMSA and EMSP together improve the performance of the baseline, as shown in Fig. 7. The use of both EMSA and EMSP alone is better than baseline, illustrating their respective superiority.

Experts number. We examine the utility brought by different numbers of experts of EMSA. The results of Spiking Transformer baselines on CIFAR are presented in Fig. 8. It indicates that within a certain range of expert numbers, the results can still be competitive and robust. Among these, we select 4 experts as the parameter setting for our final application.

https://doi.org/10.52202/079017-0322

5 Conclusion

In this work, we explored the feasibility of adapting MoE in Spiking Neural Networks and formulated an SNN-MoE paradigm named the Spiking Experts Mixture Mechanism. Unlike the vanilla MoE, which uses softmax and TopK hard sparse, SEMM implements dynamic conditional computation from the viewpoint of spiking sparse activation. With redesigned Router-Expert pairs and element-wise spike-driven operations, SEMM is computation-efficient and SNN-compatible. Embedded in Spiking Transformers, SEMM-based EMSA and EMSP can bring stable performance improvement on static and neuromorphic datasets. SEMM paradigm can inspire future exploration of high-performance, high-capacity Spiking Transformers. We hope SEMM can bring vitality to dynamic conditional computation and the design of next-generation architecture for SNNs. Future work will explore SEMM implementation in a wider range of tasks and larger SNN models.

6 Acknowledgments and Disclosure of Funding

We sincerely thank Dr. Wei Fang for his assistance with this work. This work is supported by grants from the National Natural Science Foundation of China (62088102, 62202014, 62332002, 62425101, 62236009, U22A20103, 62441606), Shenzhen Basic Research Program (No.JCYJ20220813151736001), the major key project of the Pengcheng Laboratory (PCL2021A13) and National Science Foundation for Distinguished Young Scholars (62325603). Computing support was provided by Pengcheng Cloud Brain.

References

[1] Wolfgang Maass. Networks of spiking neurons: the third generation of neural network models. *Neural networks*, 10(9):1659–1671, 1997.

[2] Roy, Kaushik, Jaiswal, Akhilesh, and Priyadarshini Panda. Towards spike-based machine intelligence with neuromorphic computing. *Nature*, 575(7784):607–617, 2019.

[3] Paul A Merolla, John V Arthur, Rodrigo Alvarez-Icaza, Andrew S Cassidy, Jun Sawada, Filipp Akopyan, Bryan L Jackson, Nabil Imam, Chen Guo, and Yutaka Nakamura. A million spiking-neuron integrated circuit with a scalable communication network and interface. *Science*, 2014.

[4] Mike Davies, Narayan Srinivasa, Tsung-Han Lin, Gautham Chinya, Yongqiang Cao, Sri Harsha Choday, Georgios Dimou, Prasad Joshi, Nabil Imam, Shweta Jain, Yuyun Liao, Chit-Kwan Lin, Andrew Lines, Ruokun Liu, Deepak Mathaikutty, Steven McCoy, Arnab Paul, Jonathan Tse, Guruguhanathan Venkataramanan, Yi-Hsin Weng, Andreas Wild, Yoonseok Yang, and Hong Wang. Loihi: A neuromorphic manycore processor with on-chip learning. *IEEE Micro*, 38(1):82–99, 2018. doi: 10.1109/MM.2018.112130359.

[5] Ali Lotfi Rezaabad and Sriram Vishwanath. Long short-term memory spiking networks and their applications. In *Proceedings of the International Conference on Neuromorphic Systems 2020*, pages 1–9, 2020.

[6] Yangfan Hu, Huajin Tang, and Gang Pan. Spiking deep residual networks. *IEEE Transactions on Neural Networks and Learning Systems*, pages 1–6, 2021. doi: 10.1109/TNNLS.2021.3119238.

[7] Wei Fang, Zhaofei Yu, Yanqi Chen, Tiejun Huang, Timothée Masquelier, and Yonghong Tian. Deep Residual Learning in Spiking Neural Networks. In *Proceedings of the International Conference on Neural Information Processing Systems*, volume 34, pages 21056–21069, 2021.

[8] Hanle Zheng, Yujie Wu, Lei Deng, Yifan Hu, and Guoqi Li. Going Deeper With Directly-Trained Larger Spiking Neural Networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 11062–11070, 2021.

[9] Yifan Hu, Yujie Wu, Lei Deng, and Guoqi Li. Advancing residual learning towards powerful deep spiking neural networks. *arXiv preprint arXiv:2112.08954*, 2021.

[10] Zulun Zhu, Jiaying Peng, Jintang Li, Liang Chen, Qi Yu, and Siqiang Luo. Spiking graph convolutional networks. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence*, pages 2434–2440, 2022. doi: 10.24963/ijcai.2022/338.

[11] Zhaokun Zhou, Yuesheng Zhu, Chao He, Yaowei Wang, Shuicheng YAN, Yonghong Tian, and Li Yuan. Spikformer: When spiking neural network meets transformer. In *The Eleventh International Conference on Learning Representations*, 2023. URL `https://openreview.net/forum?id=frE4fUwz_h`.

[12] Man Yao, Jiakui Hu, Zhaokun Zhou, Li Yuan, Yonghong Tian, Bo Xu, and Guoqi Li. Spike-driven transformer. In *Proceedings of the International Conference on Neural Information Processing Systems*, 2023. URL https://openreview.net/forum?id=9FmolyOHi5&noteId=ShYKrFQugd.

[13] Yuchen Wang, Kexin Shi, Chengzhuo Lu, Yuguo Liu, Malu Zhang, and Hong Qu. Spatial-temporal self-attention for asynchronous spiking neural networks. In Edith Elkind, editor, *Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence*, pages 3085–3093. International Joint Conferences on Artificial Intelligence Organization, 2023. URL https://doi.org/10.24963/ijcai.2023/344.

[14] Chenlin Zhou, Liutao Yu, Zhaokun Zhou, Han Zhang, Zhengyu Ma, Huihui Zhou, and Yonghong Tian. Spikingformer: Spike-driven residual learning for transformer-based spiking neural network. *arXiv preprint arXiv:2304.11954*, 2023. URL https://arxiv.org/abs/2304.11954.

[15] Chenlin Zhou, Han Zhang, Zhaokun Zhou, Liutao Yu, Zhengyu Ma, Huihui Zhou, Xiaopeng Fan, and Yonghong Tian. Enhancing the performance of transformer-based spiking neural networks by improved downsampling with precise gradient backpropagation. *arXiv preprint arXiv:2305.05954*, 2023.

[16] Han Zhang, Chenlin Zhou, Liutao Yu, Liwei Huang, Zhengyu Ma, Xiaopeng Fan, Huihui Zhou, and Yonghong Tian. Sglformer: Spiking global-local-fusion transformer with high performance. *Frontiers in Neuroscience*, 18:1371290, 2024.

[17] Xuerui Qiu, Rui-Jie Zhu, Yuhong Chou, Zhaorui Wang, Liang-jian Deng, and Guoqi Li. Gated attention coding for training high-performance and efficient spiking neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 601–610, 2024.

[18] Ziqing Wang, Yuetong Fang, Jiahang Cao, Qiang Zhang, Zhongrui Wang, and Renjing Xu. Masked spiking transformer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1761–1771, October 2023.

[19] Malyaban Bal and Abhronil Sengupta. Spikingbert: Distilling bert to train spiking language models using implicit differentiation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 10998–11006, 2024.

[20] Carlos Riquelme, Joan Puigcerver, Basil Mustafa, Maxim Neumann, Rodolphe Jenatton, André Susano Pinto, Daniel Keysers, and Neil Houlsby. Scaling vision with sparse mixture of experts. *Advances in Neural Information Processing Systems*, 34:8583–8595, 2021.

[21] Xiaofeng Zhang, Yikang Shen, Zeyu Huang, Jie Zhou, Wenge Rong, and Zhang Xiong. Mixture of attention heads: Selecting attention heads per token. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 4150–4162, 2022.

[22] Changde Du, Kaicheng Fu, Jinpeng Li, and Huiguang He. Decoding visual neural representations by multimodal learning of brain-visual-linguistic features. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(9):10760–10777, 2023. doi: 10.1109/TPAMI.2023.3263181.

[23] O'Doherty JP, Lee SW, Tadayonnejad R, Cockburn J, Iigaya K, and Charpentier CJ. Why and how the brain weights contributions from a mixture of experts. *Neurosci Biobehav Review*, 2021.

[24] Noam Shazeer, Youlong Cheng, Niki Parmar, Dustin Tran, Ashish Vaswani, Penporn Koanantakool, Peter Hawkins, HyoukJoong Lee, Mingsheng Hong, Cliff Young, Ryan Sepassi, and Blake Hechtman. Mesh-tensorflow: Deep learning for supercomputers. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Proceedings of the International Conference on Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018. URL https://proceedings.neurips.cc/paper_files/paper/2018/file/3a37abdeefe1dab1b30f7c5c7e581b93-Paper.pdf.

[25] Yujie Wu, Lei Deng, Guoqi Li, Jun Zhu, and Luping Shi. Spatio-temporal backpropagation for training high-performance spiking neural networks. *Frontiers in neuroscience*, 12:331, 2018.

[26] Saeed Reza Kheradpisheh and Timothée Masquelier. Temporal backpropagation for spiking neural networks with one spike per neuron. *International journal of neural systems*, 30(06):2050027, 2020.

[27] Ziqing Wang, Yuetong Fang, Jiahang Cao, Qiang Zhang, Zhongrui Wang, and Renjing Xu. Masked spiking transformer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1761–1771, October 2023.

[28] Robert A. Jacobs, Michael I. Jordan, Steven J. Nowlan, and Geoffrey E. Hinton. Adaptive mixtures of local experts. *Neural Computation*, 3(1):79–87, 1991. doi: 10.1162/neco.1991.3.1.79.

 https://doi.org/10.52202/079017-0322

[29] Michael I Jordan and Robert A Jacobs. Hierarchical mixtures of experts and the em algorithm. *Neural computation*, 6(2):181–214, 1994.

[30] Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc V. Le, Geoffrey E. Hinton, and Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. In *The Fifth International Conference on Learning Representations*, 2017. URL https://openreview.net/forum?id=B1ckMDqlg.

[31] Damai Dai, Li Dong, Shuming Ma, Bo Zheng, Zhifang Sui, Baobao Chang, and Furu Wei. StableMoE: Stable routing strategy for mixture of experts. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics*, pages 7085–7095, Dublin, Ireland, May 2022.

[32] Jiaao He, Jiezhong Qiu, Aohan Zeng, Zhilin Yang, Jidong Zhai, and Jie Tang. Fastmoe: A fast mixture-of-expert training system. *arXiv preprint arXiv:2103.13262*, 2021.

[33] Changho Hwang, Wei Cui, Yifan Xiong, Ziyue Yang, Ze Liu, Han Hu, Zilong Wang, Rafael Salas, Jithin Jose, Prabhat Ram, Joe Chau, Peng Cheng, Fan Yang, Mao Yang, and Yongqiang Xiong. Tutel: Adaptive mixture-of-experts at scale. *CoRR*, abs/2206.03382, June 2022. URL https://arxiv.org/pdf/2206.03382.pdf.

[34] Fuzhao Xue, Ziji Shi, Futao Wei, Yuxuan Lou, Yong Liu, and Yang You. Go wider instead of deeper. *Proceedings of the AAAI Conference on Artificial Intelligence*, 36(8):8779–8787, Jun. 2022. doi: 10.1609/aaai.v36i8.20858. URL https://ojs.aaai.org/index.php/AAAI/article/view/20858.

[35] William Fedus, Barret Zoph, and Noam Shazeer. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. *Journal of Machine Learning Research*, 23(120):1–39, 2022.

[36] Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, 11 1997. ISSN 0899-7667. doi: 10.1162/neco.1997.9.8.1735. URL https://doi.org/10.1162/neco.1997.9.8.1735.

[37] Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. Gshard: Scaling giant models with conditional computation and automatic sharding. In *The Ninth International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=qrwe7XHTmYb.

[38] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of the International Conference on Neural Information Processing Systems*, volume 30, 2017.

[39] Yann N Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated convolutional networks. In *International conference on machine learning*, pages 933–941. PMLR, 2017.

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

[41] Alex Krizhevsky. Learning multiple layers of features from tiny images. 2009.

[42] Hongmin Li, Hanchao Liu, Xiangyang Ji, Guoqi Li, and Luping Shi. Cifar10-dvs: an event-stream dataset for object classification. *Frontiers in neuroscience*, 11:309, 2017.

[43] Arnon Amir, Brian Taba, David Berg, Timothy Melano, Jeffrey McKinstry, Carmelo Di Nolfo, Tapan Nayak, Alexander Andreopoulos, Guillaume Garreau, Marcela Mendoza, Jeff Kusnitz, Michael Debole, Steve Esser, Tobi Delbruck, Myron Flickner, and Dharmendra Modha. A low power, fully event-based gesture recognition system. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7243–7252, 2017.

[44] Wei Fang, Zhaofei Yu, Yanqi Chen, Timothée Masquelier, Tiejun Huang, and Yonghong Tian. Incorporating learnable membrane time constant to enhance learning of spiking neural networks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2641–2651, 2021. doi: 10.1109/ICCV48922.2021.00266.

[45] Nitin Rathi and Kaushik Roy. Diet-snn: A low-latency spiking neural network with direct input encoding and leakage and threshold optimization. *IEEE Transactions on Neural Networks and Learning Systems*, 34(6):3174–3182, 2023. doi: 10.1109/TNNLS.2021.3111897.

[46] Yuhang Li, Yufei Guo, Shanghang Zhang, Shikuang Deng, Yongqing Hai, and Shi Gu. Differentiable Spike: Rethinking Gradient-Descent for Training Spiking Neural Networks. In *Proceedings of the International Conference on Neural Information Processing Systems*, volume 34, pages 23426–23439, 2021.

[47] Qingyan Meng, Mingqing Xiao, Shen Yan, Yisen Wang, Zhouchen Lin, and Zhi-Quan Luo. Training high-performance low-latency spiking neural networks by differentiation on spike representation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12444–12453, 2022.

[48] Filipp Akopyan, Jun Sawada, Andrew Cassidy, Rodrigo Alvarez-Icaza, John Arthur, Paul Merolla, Nabil Imam, Yutaka Nakamura, Pallab Datta, Gi-Joon Nam, et al. Truenorth: Design and tool flow of a 65 mw 1 million neuron programmable neurosynaptic chip. *IEEE Transactions on Computer-aided Design of Integrated Circuits and Systems*, 34(10):1537–1557, 2015.

[49] Ole Richter, Yannan Xing, Michele De Marchi, Carsten Nielsen, Merkourios Katsimpris, Roberto Cattaneo, Yudi Ren, Qian Liu, Sadique Sheik, Tugba Demirci, et al. Speck: A smart event-based vision sensor with a low latency 327k neuron convolutional neuronal network processing pipeline. *arXiv preprint arXiv:2304.06793*, 2023.

 https://doi.org/10.52202/079017-0322

A Overall architecture of Spike-driven Transformer/Spikingformer with SEMM

We provide a detailed description of the overall structure of Spike-driven Transformer with SEMM, and Spikingformer with SEMM. Given a 2D image sequence $\mathbf{I} \in \mathbb{R}^{T\times C\times H\times W}$, the Patch Splitting Module (PSM), consisted of three Convolution-Batch Normalization-$\mathcal{SN}$-Maxpooling layers and one Convolution-Batch Normalization-Maxpooling layer, is used to projects and splits $\mathbf{I}$ into a sequence of N flattened spike patches $\mathbf{s}$ with D channels. The Relative Position Embedding (RPE) module, a Convolution-BatchNorm layer, is used to generate position embedding to get $\mathbf{U}_0$. $\mathcal{SN}(\cdot)$ means the spike neuron layer. Then the $\mathbf{U}_0$ is passed to the L-blocks encoder. The encoder block consists of an Experts Mixture Spiking Attention (EMSA) and an Experts Mixture Spiking Perceptron (EMSP) block. Membrane-shortcut residual connections are applied in both the EMSA and EMSP blocks. A global average-pooling (GAP) is utilized on the processed feature from the encoder and outputs the D-dimension feature which will be sent to the fully-connected-layer classification head (CH) to output the prediction Y. The architecture can be written as follows:

$$\mathbf{u} = \mathrm{PSM}\left(\mathbf{I}\right), \qquad \mathbf{I} \in \mathbb{R}^{T\times C\times H\times W}, x \in \mathbb{R}^{T\times N\times D}, \tag{28}$$

$$\mathbf{s} = \mathcal{SN}(\mathbf{u}), \qquad \mathbf{s} \in \mathbb{R}^{T\times N\times D} \tag{29}$$

$$\mathbf{RPE} = \mathrm{BN}(\mathrm{Conv2d}(\mathbf{s})), \qquad \mathrm{RPE} \in \mathbb{R}^{T\times N\times D} \tag{30}$$

$$\mathbf{U}_0 = \mathbf{u} + \mathbf{RPE}, \qquad \mathbf{U}_0 \in \mathbb{R}^{T\times N\times D} \tag{31}$$

$$\mathbf{S}_0 = \mathcal{SN}(\mathbf{U}_0), \qquad \mathbf{S}_0 \in \mathbb{R}^{T\times N\times D} \tag{32}$$

$$\mathbf{U}_l^{'} = \mathrm{EMSA}(\mathbf{S}_{l-1}) + \mathbf{U}_{l-1}, \qquad \mathbf{U}_l^{'} \in \mathbb{R}^{T\times N\times D}, l = 1...L \tag{33}$$

$$\mathbf{S}_l^{'} = \mathcal{SN}(\mathbf{U}_l^{'}), \qquad \mathbf{S}_l^{'} \in \mathbb{R}^{T\times N\times D}, l = 1...L \tag{34}$$

$$\mathbf{S}_l = \mathcal{SN}(\mathrm{EMSP}(\mathbf{S}_l^{'}) + \mathbf{U}_l^{'}), \qquad \mathbf{S}_l \in \mathbb{R}^{T\times N\times D}, l = 1...L \tag{35}$$

$$\mathbf{Y} = \mathrm{CH}(\mathrm{GAP}(\mathbf{S}_L)), \tag{36}$$

Following the Spiking Experts Mixture Mechanism and Spike-driven Self-Attention (SDSA) used in Spike-driven Transformer, the EMSA can be written as:

$$\mathbf{Q} = \mathcal{SN}_{\mathbf{Q}}(\text{L-BN}_{\mathbf{Q}}(\mathbf{X})), \mathbf{K} = \mathcal{SN}_{\mathbf{K}}(\text{L-BN}_{\mathbf{K}}(\mathbf{X})), \mathbf{V} = \mathcal{SN}_{\mathbf{V}}(\text{L-BN}_{\mathbf{V}}(\mathbf{X})), \tag{37}$$

$$\mathbf{A} = \mathrm{SDSA}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathcal{SN}\left(\mathrm{SUM_c}\left(\mathbf{Q} \odot \mathbf{K}\right)\right) \odot \mathbf{V}, \tag{38}$$

The rest operate according to standard EMSA 18. The EMSP in Spike Driven Transformer is also much the same as the standard 22, except that no spiking neuron layer in the output layer.

B Computation Overhead Details of SEMM

B.1 EMSA

The linear layers that generates m Query $\mathbf{Q_m}$ have $m(\frac{D^2}{m}) = D^2$ parameters. The linear layer for Key $\mathbf{K}$ has $\frac{D^2}{m}$ parameters. Generating Value $\mathbf{V}$ requires dD parameters. The output linear has dD parameters. The router linear layer transforms D to expert number m, and has mD parameters. The number of total parameters is $(1 + 1/m)D^2 + (2d + m)D$. For operations, obtaining Query and Key needs $(1 + 1/m)\overline{R}TND^2$. Computing Value or the output of EMSA requires $d\tilde{R}TND$. The number of operations between $\mathbf{Q_m}, \mathbf{K}, \mathbf{V}$ is $(D + md)R_{\mathcal{R}}TN^2$. The number of router matrix computation operations is $m\tilde{R}TND$. Due to the sparsity of SEMM and the smaller data dimensions, the number of element-wise operations for the router and expert is negligible.

B.2 EMSP

The parameter number of $\mathbf{W_1}, \mathbf{W}_{\mathcal{R}}, \mathbf{W_o}$ are all $(8//3)D^2$. The number of parameters for 3×3 depthwise convolution is $3 \times 3 \times (8//3)D = 24D$. The all parameter number is $8D^2 + 24D$. The operation number of $\mathbf{W_1}, \mathbf{W}_{\mathcal{R}}, \mathbf{W_o}$ are all $(8//3)TND^2$. The number of operations for depthwise convolution is $24\tilde{R}TND$.

C Experiment Details

C.1 Experimental Setup

Our experimental framework closely aligns with the methodology outlined in [11]. All of Baseline's code is publicly available, and we abide by their credentials. For the ImageNet-1K, we utilize a fixed timestep count of $T = 4$. The optimizer is the AdamW, with a batch size of 128 or 256 over the course of 310 training epochs. The learning rate is governed by a cosine-decay schedule, starting from an initial value of 0.0004. We incorporate a suite of standard data augmentation techniques, including random augmentation, mixup, and cutmix, into our training. For four small datasets, we adapt the SEMM to a variety of baseline models, following the precedents set by [11, 12]. For CIFAR, we maintain a timestep count of $T = 4$. For the neuromorphic datasets, we increase this to $T = 10$ and $T = 16$, respectively. Our experimental setup is consistent with each Spiking Transformer baselines, as detailed below.

Spikformer with SEMM. The training epoch is set to 310 for CIFAR, 200 for DVS128 Gesture, and 106 for CIFAR10-DVS. The batch size is 128 for CIFAR, 16 for DVS128 Gesture and CIFAR10-DVS. The learning rate is initialized to 0.0005 for CIFAR10/100, 0.001 for DVS128 Gesture and CIFAR10-DVS. All of them are reduced with cosine decay. We follow [11] to apply data augmentation on DVS128 Gesture and CIFAR10-DVS. In addition, the network structures used in CIFAR-10, CIFAR10-DVS, and DVS128 Gesture are Spiking Transformer-4-384, Spiking Transformer-2-256 and Spiking Transformer-2-256.

Spike Driven Transformer with SEMM. The training epoch is set to 210 for CIFAR10/100 datasets, 200 for DVS128 Gesture, and 106 for CIFAR10-DVS. The batch size is 32 for CIFAR10/100, 16 for DVS128 Gesture and CIFAR10-DVS. The learning rate is initialized to 0.0005 for CIFAR10/100, 0.0003 for DVS128 Gesture and 0.01 for CIFAR10-DVS. The rest is consistent with Spikformer.

Spikingformer with SEMM The training epoch is set to 410 for CIFAR10/100 datasets, 200 for DVS128 Gesture, and 106 for CIFAR10-DVS. The batch size is 64 for CIFAR10/100, 16 for DVS128 Gesture and CIFAR10-DVS. The learning rate is initialized to 0.0005 for CIFAR10/100, 0.1 for DVS128 Gesture and CIFAR10-DVS. The rest is consistent with Spikformer.

C.2 Model Details

In our experiments, we use 8 NVIDIA-4090 GPUs for ImageNet, and 1 NVIDIA-4090 GPU for other datasets. We adjust the value of membrane time constant τ in spike neuron when training models on DVS datasets. In direct training SNN models with surrogate function,

$$Sigmoid(x) = \frac{1}{1 + \exp(-\alpha x)} \tag{39}$$

We select the Sigmoid function as the surrogate function with $\alpha = 4$ in all experiments.

C.3 Additional Experiments

Table 5: Ablation study results on the time step.

Datasets	Models	Time-Step	Top1-Acc(%)
CIFAR10/100	Spikformer + SEMM	1	94.11/74.67
		2	94.87/78.49
		4	95.78/79.04
		6	95.99/79.29
	Spike Driven Transformer + SEMM	1	94.97/76.77
		2	95.58/78.49
		4	96.12/80.26
		6	96.48/80.87
	Spikingformer + SEMM	1	94.54/77.16
		2	95.42/78.85
		4	96.16/80.24
		6	96.67/81.22

The accuracy regarding different simulation time steps of the spiking neuron is shown in Tab. 5. At all the time steps, our Spiking Transformer with SEMM shows competitive performance. When the

https://doi.org/10.52202/079017-0322

time step is 1, our Spikformer with SEMM is 1.7% lower than the network with $T = 4$ on CIFAR10, and our Spikformer with SEMM with 1 time step still achieves 74.67% on CIFAR100. The above results show that Spikformer with SEMM is robust under fewer time steps.

In EMSP, the role of Deep Wise Convolution layer (DWC) is to independently extract features at the channel-level experts using a 3x3 receptive field, thereby enhancing representational capacity. The ablation study about DWC in Tab. 6 demonstrates its effectiveness.

Table 6: Ablation on Deep Wise Convolution layer.

Model	Module	CIFAR100	CIFAR10-DVS
Spikformer	EMSP	78.53	82.32
Spikformer	EMSP w/o DWC	78.17	81.30
Spike-driven Transformer	EMSP	79.81	81.10
Spike-driven Transformer	EMSP w/o DWC	78.95	80.51
Spikingformer	EMSP	79.81	81.95
Spikingformer	EMSP w/o DWC	79.44	81.20

D Visualization

D.1 Image Samples Visualization

More dynamic allocation visualizations of the spiking router are given in Fig. 9

E Discussion on the Feasibility of Hardware Deployment for SEMM

SEMM can theoretically be deployed on chips that are synchronous within layers and asynchronous between layers, such as TrueNorth [48]. Specifically, multiple spiking router matrices, i.e. $\{r_1, r_2, ..., r_m\}$, can be implemented by one block (Linear-BatchNorm-SpikingNeuron), thus can be mapped to the one core of the neuromorphic chip for computation. Outputs from the same core are considered synchronous. The spiking Hadamard product and addition that occur in SEMM are analogous to the AND and ADD operations in SEW ResNet [7]. These element-wise spiking operations can be adapted on neuromorphics chips that support multiple branches and residuals, such as Speck V2 [49].

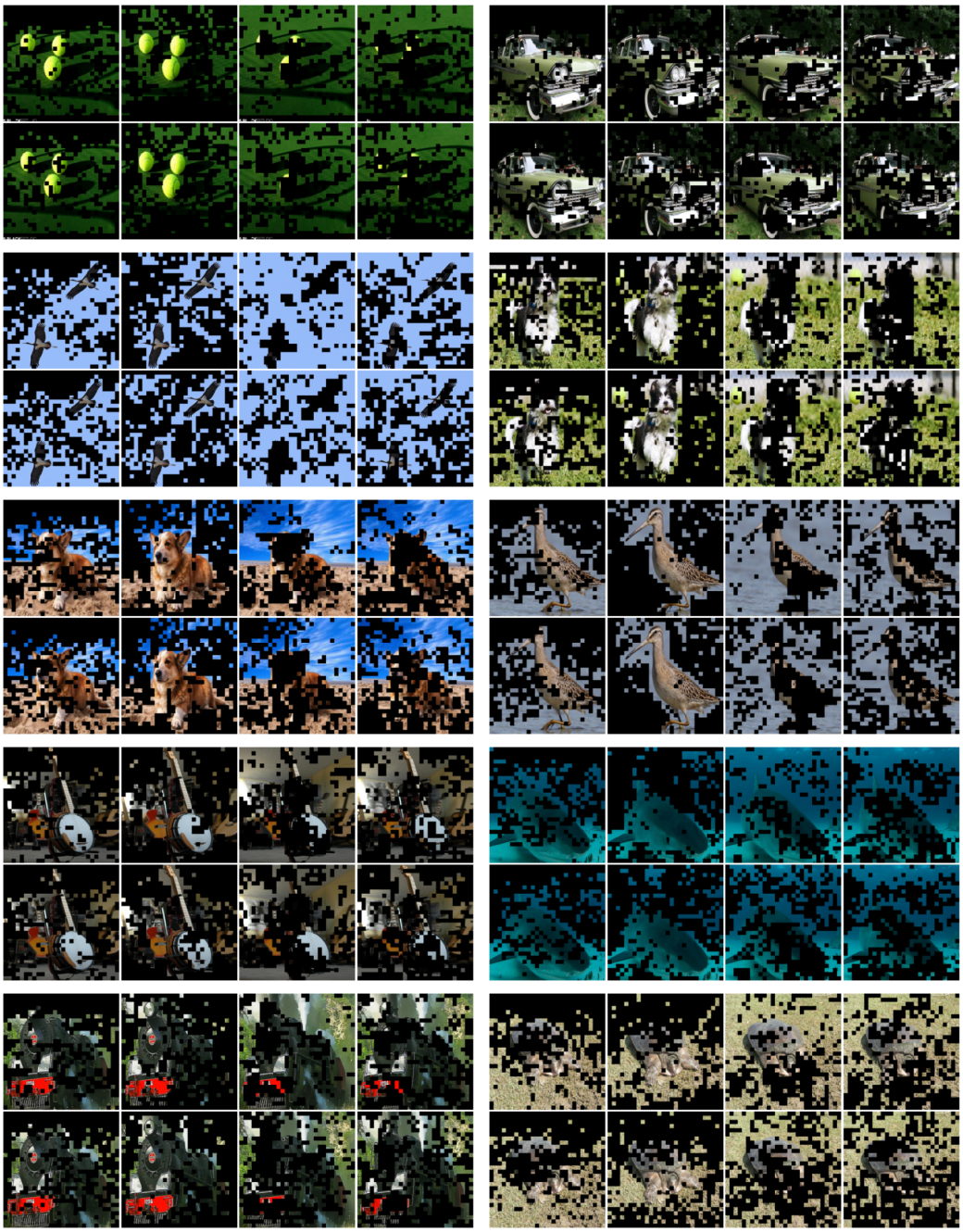

Figure 9: More visualization samples of routers as masks.

https://doi.org/10.52202/079017-0322

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes] , [No] , or [NA] .
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes] " is generally preferable to "[No] ", it is perfectly acceptable to answer "[No] " provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No] " or "[NA] " is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading "NeurIPS paper checklist"**,
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers**.

1. **Claims**

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

   Answer: [Yes]

   Justification: Please see abstract.

   Guidelines:

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

2. **Limitations**

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

   Answer: [Yes]

   Justification: Please see Section 5.

Guidelines:

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

3. **Theory Assumptions and Proofs**

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

   Answer: [NA]

   Justification: The work does not involve proof of theory.

   Guidelines:

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

4. **Experimental Result Reproducibility**

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

   Answer:[Yes]

   Justification: We detail all the techniques for reproducing the results of our work in Section. 4 and Appendix. C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.

https://doi.org/10.52202/079017-0322

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

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

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

   Answer: [Yes]

   Justification: Please see the codes in the supplementary material.

   Guidelines:

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

- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental Setting/Details**

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

   Answer: [Yes]

   Justification: Please see Appendix. C.

   Guidelines:

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

7. **Experiment Statistical Significance**

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

   Answer: [No]

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
   - The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
   - The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
   - The assumptions made should be given (e.g., Normally distributed errors).
   - It should be clear whether the error bar is the standard deviation or the standard error of the mean.
   - It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
   - For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
   - If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments Compute Resources**

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

   Answer: [Yes]

   Justification: Please see Appendix C.2.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.

https://doi.org/10.52202/079017-0322

- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code Of Ethics**

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

   Answer: [Yes]

   Justification: Our work conforms with the NeurIPS Code of Ethics.

   Guidelines:

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

10. **Broader Impacts**

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

    Answer: [NA]

    Justification: Our work does not involve social impact.

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
    - The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
    - The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
    - If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

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

    Answer: [NA]

    Justification: Our work does not release data or models with a high risk of misuse.

    Guidelines:

    - The answer NA means that the paper poses no such risks.

- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

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

    Answer: [Yes]

    Justification: We describe in Section C.1.

    Guidelines:

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

13. **New Assets**

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

    Answer: [NA]

    Justification: Our work does not introduce new assets.

    Guidelines:

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

14. **Crowdsourcing and Research with Human Subjects**

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

    Answer: [NA]

    Justification: Our work does not involve crowdsourcing experiments and research with human subjects.

https://doi.org/10.52202/079017-0322

Guidelines:

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

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

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

    Answer: [NA]

    Justification: Our work does not study participants.

    Guidelines:

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