PrivateSNN: Privacy-Preserving Spiking Neural Networks

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Abstract
How can we bring both privacy and energy-efficiency to a neural system? In this paper, we propose PrivateSNN, which aims to build low-power Spiking Neural Networks (SNNs) from a pre-trained ANN model without leaking sensitive information contained in a dataset. Here, we tackle two types of leakage problems: 1) Data leakage is caused when the networks access real training data during an ANN-SNN conversion process. 2) Class leakage is caused when class-related features can be reconstructed from network parameters. In order to address the data leakage issue, we generate synthetic images from the pre-trained ANNs and convert ANNs to SNNs using the generated images. However, converted SNNs remain vulnerable to class leakage since the weight parameters have the same (or scaled) value with respect to ANN parameters. Therefore, we encrypt SNN weights by training SNNs with a temporal spike-based learning rule. Updating weight parameters with temporal data makes SNNs difficult to be interpreted in the spatial domain. We observe that the encrypted PrivateSNN eliminates data and class leakage issues with a slight performance drop (less than ∼2%) and significant energy-efficiency gain (about 55×) compared to the standard ANN. We conduct extensive experiments on various datasets including CIFAR10, CIFAR100, and TinyImageNet, highlighting the importance of privacy-preserving SNN training.

Introduction
Neuromorphic computing has gained considerable attention as an energy-efficient alternative to conventional Artificial Neural Networks (ANNs) (He et al. 2016; Simonyan and Zisserman 2015; Goodfellow et al. 2014; Girshick 2015). Spiking Neural Networks (SNNs) process binary spikes through time like the human brain, and have been shown to yield 1-2 orders of magnitude energy efficiency over ANNs on emerging neuromorphic hardware (Roy, Jaiswal, and Panda 2019; Furber et al. 2014; Akopyan et al. 2015; Davies et al. 2018). Due to the energy advantages and neuroscientific interest, SNNs have made great strides on various applications such as image recognition (Lee, Delbruck, and Pfeiffer 2016; Kim and Panda 2020; Diehl and Cook 2015), optimization (Fang et al. 2019; Frady et al. 2020), object detection (Kim et al. 2019), and visualization (Kim and Panda 2021). Going forward, SNNs offer a huge potential for power constrained edge applications.

Among various SNN training algorithms, ANN-SNN conversion is well-established and achieves high performance on complex datasets. Here, pre-trained ANNs are converted to SNNs using weight or threshold balancing in order to replace Rectified Linear Unit (ReLU) activation with a spiking Leaky-Integrate-and-Fire (LIF) activation (Sengupta et al. 2019; Han et al. 2020; Diehl et al. 2015; Rueckauer et al. 2017). Existing conversion algorithms are based on the assumption that the model can access the entire training data. Specifically, training samples are passed through a network and maximum activation value is used to calculate the layer-wise threshold or weight scaling constant. However, this may not always be feasible. Enterprises would not allow proprietary information to be shared publicly with other companies and individuals. Importantly, the training set may contain sensitive information, such as biometrics. Overall, such concerns motivates a line of research on privacy-preserving algorithms (Kundu et al. 2020; Nayak et al. 2019; Li et al. 2020; Haroush et al. 2020; Liang, Hu, and Feng 2020). We refer to this problem as data leakage (Fig. 1(a)).

In addition, we tackle the class leakage problem after deployment (i.e., inference), as shown in Fig. 1(b). It is a well-known fact that one can obtain a representative class image from model parameters by using simple gradient back-propagation (see Fig. 2) (Mopuri, Uppala, and Babu 2018; Yosinski et al. 2015). From a security perspective, reveal-
We propose PrivateSNN. We tackle two leakage problems (Algorithm 1. (CIFAR10: automobile, bird, and dog; Tiny-ImageNet: goldfish, bullfrog, and goose). The right image is generated using Algorithm 1.

Training samples. (iv) We conduct extensive experiments on various datasets including CIFAR10, CIFAR100, and Tiny-ImageNet and demonstrate the advantages of PrivateSNN for privacy and energy-efficiency.

In summary, our key contributions are as follows: (i) So far, in SNN literature, there is no discussion about the privacy issue of ANN-SNN conversion. For the first time, we showcase the privacy issues and also propose ways to tackle them. (ii) We address the class leakage problem in ANN domain since previous ANN or SNN approaches have not addressed the class leakage issue. To clarify the objective of our work, in Table 1, we compare the position of our work with privacy preserving approaches in ANN domain (Haroush et al. 2020; Nayak et al. 2019). Most prior ANN works generate synthetic data from a pre-trained model and then train a model for a target task, while our approach for addressing data leakage is similar to previous privacy-preserving approaches in ANN domain. Our approach for addressing data leakage is similar to previous privacy-preserving approaches in ANN domain. Our approach for addressing data leakage is similar to previous privacy-preserving approaches in ANN domain. Our approach for addressing data leakage is similar to previous privacy-preserving approaches in ANN domain.
The Vulnerability of ANN-SNN Conversion

In this section, we present the ANN-SNN conversion algorithm and show the two possible leakage problems.

ANN-SNN Conversion

Our model is based on LIF neuron. We formulate the membrane potential $u^t_i$ of a single neuron $i$ as:

$$u^t_i = \lambda u^{t-1}_i + \sum_j w_{ij} o^t_j,$$

where, $\lambda$ is a leak factor, $w_{ij}$ is a the weight of the connection between pre-synaptic neuron $j$ and post-synaptic neuron $i$. If the membrane potential $u^t_i$ exceeds a firing threshold $\theta$, the neuron $i$ generates spikes $o^t_i$, which can be formulated as:

$$o^t_i = \begin{cases} 1, & \text{if } u^t_i > \theta, \\ 0, & \text{otherwise}. \end{cases}$$

After the neuron fires, we perform a soft reset, where the membrane potential value $u^t_i$ is lowered by the threshold $\theta$.

We use the method described by (Sengupta et al. 2019) for implementing the ANN-SNN conversion. They normalize the weights or the firing threshold ($\theta$ in Eq. 2) to take into account the actual SNN operation in the conversion process. The overall algorithm for the conversion method is detailed in Supplementary D. First, we copy the weight parameters of a pre-trained ANN to an SNN. Then, for every layer, we compute the maximum activation across all time-steps and set the firing threshold to the maximum activation value. The conversion process starts from the first layer and sequentially goes through deeper layers. Note that we do not use batch normalization (Ioffe and Szegedy 2015) since all input spikes have zero mean values. Also, following the previous works (Han et al. 2020; Sengupta et al. 2019; Diehl et al. 2015), we use Dropout (Srivasstava et al. 2014) for both ANNs and SNNs.

Two Types of Leakage Problems

Data Leakage from Public Datasets: The entire training data is required to convert ANNs to SNNs (see Supplementary D). However, due to privacy issues, we might not be able to access the training samples. Even techniques such as, quantization, model compression, distillation, and domain adaptation have been shown to use synthetically generated data to deploy the final model to preserve privacy (Kundra et al. 2020; Kim, Cho, and Hong 2020; Nayak et al. 2019; Li et al. 2020; Haroush et al. 2020; Liang, Hu, and Feng 2020). Therefore, there is a need to develop a data-free conversion algorithm in the neuromorphic domain.

Class Leakage from Reconverting SNNs to ANNs: In addition to data leakage, class information, e.g., pattern and shape of the object, also can be targeted by the attacker. Algorithm 1 presents a simple way to obtain class representative information from an ANN model. First, we initialize the input tensor with uniform random distribution. After that, we use an iterative optimization strategy where input noise is updated to maximize the pre-softmax logit $y_c$ of target class $c$. For every blur period $f_{blur}$, we smooth the image with Gaussian blur kernel since gradient at input layer has a high frequency (Yosinski et al. 2015). Fig. 2 shows examples of class representative images generated from a pre-trained model.

However, this technique is based on the assumption that we can compute the exact gradient for all layers. It is difficult to compute gradient value of SNNs due to the non-differentiable nature of LIF neuron (Eq. 1 and Eq. 2). Therefore, in order to generate proper class representation, the attacker should reconvert SNNs to ANNs. The re-conversion process depends on the type of conversion technique; weight scaling or threshold scaling. There are several conversion algorithms (Rueckauer et al. 2017; Diehl et al. 2015) that scale weight parameters of each layer. In such cases, the attacker cannot directly recover original ANN weights. However, each layer is scaled by a constant value, therefore the original ANN weights might be recovered by searching several combinations of layer-wise scaling factors. Recent state-of-the-art conversion algorithms (Sengupta et al. 2019; Han et al. 2020; Han and Roy 2020) use threshold scaling, i.e., change the thresholds while maintaining the weight parameters to obtain high performance. In our experiments, we use threshold scaling for ANN-SNN conversion and then, explore the class leakage issues. In this case, the original ANN can be reconverted by simply changing LIF neuron to ReLU neuron. With the reconverted ANN, the attacker can simply reconstruct class representation by backpropagation as shown in Algorithm 1. Overall, a non-linear weight encryption technique is required to make SNNs robust to class leakage.

Methodology

This section presents a detailed methodology for PrivateSNN. We first propose a data-free conversion method from a pre-trained ANN. Then, we describe how a temporal spike-based learning rule can encrypt weight parameters in SNNs. Fig. 4 illustrates the overall approach.

Data-Free Conversion for Data Leakage

Data Generation from a Pre-trained ANN: Without accessing real data, we generate synthetic images from a pre-trained ANN. Conversion performance relies on the maximum activation value of features, therefore synthetic images have to carefully reflect underlying data distribution from the pre-trained ANN. Nayak et al. (2019) take into account the relationship between classes in order to generate data, resulting in better performance on a distillation task. Following this pioneering work, we generate synthetic images based on class
relationships from the weights of the last fully-connected layer. Specifically, we can define a weight vector \( w_c \) between the penultimate layer and the class logit \( c \) in the last layer. Then, we calculate the class similarity score between class \( i \) and \( j \):

\[
s_{ij} = \frac{w_i^T w_j}{\|w_i\|_2 \|w_j\|_2}
\]

Then, we sample a soft label based on Dirichlet distribution where a concentration parameter \( \alpha_c \) is a class similarity vector of class \( c \). For each class \( c \), the class similarity vector consists of class similarity between class \( c \) and other classes. For example, for class 1 of CIFAR10 dataset, the concentration parameter is \( \alpha_1 = [s_{10}, s_{11}, s_{12}, ..., s_{19}] \). For a sampled soft label from Dirichlet distribution, we optimize input \( x \) initialized with uniform random distribution. We collect the same number of samples for each class and exploit this synthetic dataset for conversion. The overall procedure for data-free conversion is shown in Algorithm 2 [Step1].

**ANN-SNN Conversion with synthetic images:** By generating synthetic images, we do not have to access the original dataset. Instead, we find the threshold of each layer from the maximum activation of synthetic images (see ANN-SNN Conversion algorithm in Supplementary D). Interestingly, we observe that converted SNNs with synthetic images almost recover the performance of the original ANN. This means that conversion process is feasible with inherent data distribution from a trained model. However, SNNs are still vulnerable to class leakage. If the attacker gets access to the weights of the SNN, they can easily recover the original ANN by simply changing the LIF neuron to ReLU. Therefore, we encrypt the converted SNN using the temporal spike-based learning rule (will be described in the next subsection). Note, we use a relatively small number of time-steps (e.g., 100 ~ 150) for conversion. This is because short time-steps reduces training time and memory for post-conversion training. Also, short latency can bring more energy efficiency at inference. We observe that encryption training recovers the performance loss caused by using small number of time-steps for conversion.

**Class Encryption with Spike-based Training**

The key idea here is that training SNNs with temporal data representation makes class information difficult to be interpreted in the spatial domain.

**Encoding static images with rate coding:** In order to map static images to temporal signals, we use rate coding (or Poisson coding). Given the time window, rate coding generates spikes where the number of spikes is proportional to the pixel intensity. For time-step \( t \), we generate a random number for each pixel \( i,j \) with normal distribution ranging between \([I_{min}, I_{max}]\), where \( I_{min}, I_{max} \) correspond to the minimum and maximum possible pixel intensity. After that, for each pixel location, we compare the pixel intensity with the generated random number. If the random number is greater than the pixel intensity, the Poisson spike generator outputs a spike with amplitude 1. Otherwise, the Poisson spike generator does not yield any spikes. Overall, rate coding enables static images to span the temporal axis without huge information loss.

**Training SNNs with spike-based learning:** Given input
spikes, we train converted SNNs based on gradient optimization. Intermediate LIF neurons accumulate pre-synaptic spikes and generate output spikes (Eq. 1 and Eq. 2). Spike information is passed through all layers and stacked or accumulated at the output layer (i.e., prediction layer) This enables the accumulated temporal spikes to be represented as probability distribution after the softmax function. From the accumulated membrane potential, we can define the cross-entropy loss for SNNs as:

$$L_{CE} = - \sum_i y_i \log \left( \frac{e^{u^T_i}}{\sum_{k=1}^C e^{u^T_k}} \right),$$  \hspace{1cm} (4)

where, $y$ and $T$ stand for the ground-truth label and the total number of time-steps, respectively.

**On-device distillation:** One important thing we have to consider is the computational cost for post-conversion training. This is crucial to a limited-resource environment such as a mobile device with battery constraints. Also, SNNs require multiple feed-forward steps per one image, and thus are more energy-consuming compared to ANN training. In order to reduce the training cost, we can reduce the number of synthetic training samples. However, with a small number of training samples, the networks easily overfit, resulting in performance degradation. To address this issue, we distill knowledge from ANNs to SNNs. Yuan et al. (2019) recently discovered the connection between knowledge distillation and label smoothing, which supports distillation improves the generalization power of the model. Thus, it is intuitive that if we use knowledge distillation during the spike-based training of the converted SNN, then the model is likely to show better generalization to small number of data samples. Therefore, the total loss function becomes the combination of cross-entropy loss and distillation loss:

$$L = (1-m)L_{CE} + mL_{KD}(A(X, \tau), S(X, \tau)).$$  \hspace{1cm} (5)

Here, $A(\cdot)$ and $S(\cdot)$ represent ANN and SNN models, respectively. Also, $\tau$ denotes distillation temperature, and $m$ is the balancing coefficient between two losses. Note that $L_{KD}$ is knowledge distillation loss (Hinton, Vinyals, and Dean 2015). The training samples $X$ used in this stage are a subset of the synthetically generated data used during conversion.

Based on Eq. 5, we compute the gradients of each layer. Here, we use spatio-temporal back-propagation (STBP), which accumulates the gradients over all time-steps (Wu et al. 2018; Neftci et al. 2019). We can formulate the gradients at the layer $l$ by chain rule as:

$$\frac{\partial L}{\partial W_l} = \sum_i \left( \frac{\partial L}{\partial o^t_l} \frac{\partial o^t_l}{\partial u^t_{l-1}} + \frac{\partial L}{\partial u^t_{l+1}} \frac{\partial u^t_{l+1}}{\partial u^t_l} \right) \frac{\partial u^t_l}{\partial W_l},$$  \hspace{1cm} (6)

Here, $O^t_l$ and $U^t_l$ are output spikes and membrane potential at time-step $t$ for layer $l$, respectively. For the output layer, we get the derivative of the loss $L$ with respect to the membrane potential $u^T_1$ at final time-step $T$:

$$\frac{\partial L}{\partial u^T_1} = e^{u^T_1} \sum_{k=1}^C e^{u^T_k} - y_i.$$  \hspace{1cm} (7)

This derivative function is continuous and differentiable for all possible membrane potential values. On the other hand, LIF neurons in hidden layers generate spike output only if the membrane potential $u^T_l$ exceeds the firing threshold, leading to non-differentiability. To deal with this problem, we introduce an approximate gradient:

$$\frac{\partial o^t_l}{\partial u^t_1} = \max\{0, 1 - \frac{|u^t_1 - \theta|}{\theta}\}. \hspace{1cm} (8)$$

Overall, we update the network parameters at the layer $l$ based on the gradient value (Eq. 6) as $W_l = W_l - \eta \Delta W_l$. The procedure for spike-based training for encrypting the model is detailed in Algorithm 2 [Step2].

**Attack Scenarios for Class Leakage**

In this section, we present two possible attack scenarios on class leakage. Since we do not access the original training data, the data leakage problem is addressed. Therefore, here we only discuss the class leakage problem.

**Attack scenario 1 (Reconverting SNN to ANN):** As discussed earlier, the attacker might copy the weights of SNN and recover the original ANN. By using the re-converted ANN, the attacker optimizes the input noise based on Algorithm 1. Without post-conversion encryption training, the attacker simply reconstructs class representation by backpropagation. However, if we use spike-based training, the weight of SNN is fully encrypted in the spatial domain.

**Attack scenario 2 (Directly generate class representation from SNN):** The attacker might directly backpropagate gradients in SNN architecture and reconstruct class representation. Thus, this is the SNN version of Algorithm 1. The technical problem here is that LIF neurons and Poisson spike generation process are non-differentiable. To address this issue, we use approximated gradient functions (Eq. 8) for LIF neurons. Also, in order to convert the gradient in the temporal domain to the spatial domain, we accumulate gradient at the first convolution layer. After that, we deconvolve the accumulated gradients with weights of the first layer. These deconvolved gradients have a similar value with original gradients of images before the Poisson spike generator, which has been validated in previous work (Sharmin et al. 2020). Thus, we can get a gradient $\delta x$ converted into spatial domain, and the input noise is updated with gradient $\delta x$ scaled by $\zeta$. Algorithm 3 illustrates the overall optimization process. However, this attack does not show meaningful features due to the discrepancy between real gradients and approximated gradients. This supports that SNN model itself is robust to gradient-based security attacks (Roy, Jaiswal, and Panda 2019; Sharmin et al. 2020). We show the qualitative results for Attack 1, 2 scenarios in Fig. 6.

**Experiments**

**Experimental Setting**

We evaluate our PrivateSNN on three public datasets (i.e., CIFAR-10, CIFAR-100, Tiny-ImageNet). CIFAR-10 (Krizhevsky, Hinton et al. 2009) consists of 60,000 images (50,000 for training / 10,000 for testing) with 10 categories. All images are RGB color images whose size are $32 \times 32$. 
Algorithm 3: Directly generate class representation from SNNs (Attack scenario 2)

**Input:** target class (c); max iteration (N); scaling factor (ζ); SNN model (SNN); spike time-step (T)

**Output:** class representative image x

1. \(x \leftarrow U(0, 1)\)  \(\triangleright\) Initialize input
2. \(W_1 \leftarrow \text{SNN}.conv1.weight\)  \(\triangleright\) First convolution weight
3. \(G = 0\)  \(\triangleright\) Accumulated gradient at the first conv layer
4. for \(n \leftarrow 1 \text{ to } N\) do
5. \(t \leftarrow 1 \text{ to } T\) do
6. \(y \leftarrow \text{SNN}(x_t)\)
7. \(G = \frac{1}{T} \frac{\partial y}{\partial x_{conv1}}\)  \(\triangleright\) Accumulate gradients in layer 1
8. end for
9. \(\delta x \leftarrow \text{Deconvolution}(W_1, G)\)  \(\triangleright\) Deconvolution
10. \(x \leftarrow x + \zeta \delta x\)
11. end for

**CIFAR-100** has the same configuration as CIFAR-10, except it contains images from 100 categories. **Tiny-ImageNet** is the modified subset of the original ImageNet dataset. Here, there are 200 different classes of ImageNet dataset (Deng et al. 2009), with 100,000 training and 10,000 validation images. The resolution of the images is 64×64 pixels.

Our implementation is based on Pytorch (Paszke et al. 2017). For conversion, we apply threshold scaling technique as proposed in (Han et al. 2020). For post-conversion training, we use Adam with base learning rate 1e-4. Here, we use 5000, 10,000, 100,000 synthetic samples for training SNNs on CIFAR10, CIFAR100, and TinyImageNet, respectively. We use step-wise learning rate scheduling with a decay factor of 10 at 50% and 70% of the total number of epochs. We set the total number of epochs to 20 for all datasets. For on-device distillation, we set \(m\) and \(\tau\) to 0.7 and 20 in Eq. 5, respectively. For class representation, we set \(f_{blur}\) and \(\eta\) in Algorithm 1 to 4 and 6, respectively. For attack scenario 2 in Algorithm 3, we set \(\zeta\) to 0.01. All detailed experimental setup and hyperparameters are described in Supplementary B. Note that our objective is to showcase the advantages of PrivateSNN for tackling data and class leakage.

**Performance Comparison**

Before we present the experimental results, we define the terms used in our method: **Data-free Conversion (DC)**, **Class Encryption Training (CET)**, and **On-device Distillation (OD)**. We call our final method as **PrivateSNN**, thus, **PrivateSNN = DC + CET + OD**.

Surprisingly, we find that **PrivateSNN** encrypts the networks without significant performance loss. Table 2 shows the performance of reference ANN (i.e., VGG16) and previous conversion methods which uses training data. Here, we use Sengupta et al. (2019); Han et al. (2020); Zambrano et al. (2019) as representative state-of-the-art conversion methods for comparison. The results show that our **PrivateSNN** can be designed without a huge performance drop across all datasets. This implies that synthetic samples generated from the ANN model contain enough information for a successful conversion and post-processing.

In Table 3, we conduct ablation studies on each component (i.e., DC, CET, and OD) of our method. Here, we present the robustness of model on data leakage and class leakage and compare the number of training samples, and classification accuracy. With DC, the SNN model can address data leakage, however, it is still vulnerable to class leakage. Adding CET on DC resolves class leakage with performance improvement. However, an insufficient number of training samples cannot achieve near state-of-the-art performance. Finally, using OD helps the networks to improve the performance with a limited number of samples.

**Analysis on Data-free Conversion**

In Fig. 5(a), we measure the data-free conversion performance with respect to the number of time-steps in the conversion process. The results show that the data-free SNN conversion model can almost recover the original ANN performance with large number of time-steps (i.e., \( \geq 500\)). But, we use a small number of time-steps (i.e., \( \leq 200\)) to perform the conversion and then, perform CET in the low time-step regime. Here, we only show CIFAR10 results. The CIFAR100, and TinyImageNet results are shown in Supplementary E. Specifically, **PrivateSNN** is trained with time-step 150, 200, and 200 for CIFAR10, CIFAR100, and TinyImageNet. This is because smaller time-steps bring more energy-efficiency during both training and inference. Also, we observe that encryption training with distillation recovers the accuracy even though SNNs are converted in a low time-step regime (Table 3).

**Effect of Distillation in Encryption Training**

After converting ANNs to SNNs, we train the networks with synthetic images. In order to figure out how many samples are required for post training, we show the performance with respect to the number of synthetic samples in Fig. 5(b). Note, data-free conversion at 150 time-steps achieves 82.8 % accuracy (black dotted line in the figure). The results show that encryption training (without distillation) degrades the perfor-
with temporal spike-based learning rule, Attack1 does not with (w/) and without (w/o) class encryption training (CET).

(The results from CIFAR10, and TinyImageNet are shown To validate the robustness of PrivateSNN Table 4: FIDs between test set and generated images from re-generated images provide the original data-like feature. Thus, a lower FID score means that features in a feature space (see Supplementary C for more detailed explanation). Thus, distillation is an effective regularization method for spike-based learning with a small number of synthetic images.

**Robustness on Class Leakage Problem**

To validate the robustness of PrivateSNN against Attack scenario 1 and Attack scenario 2 (two most likely class leakage scenarios), we synthesize the class representation of SNNs with (w/) and without (w/o) class encryption training (CET). Fig. 6 shows 8 examples of generated images from CIFAR10 (The results from CIFAR100, and TinyImageNet are shown in Supplementary H). We visualize images from five configurations: original images, Attack1 w/o CET, Attack1 w/ CET, Attack2 w/o CET, and Attack2 w/ CET. We observe that SNNs without CET (i.e., simply, data free converted SNNs) are vulnerable to Attack1, showing important features of original classes (see Fig. 6(b)). On the other hand, with temporal spike-based learning rule, Attack1 does not discover any meaningful information as shown in Fig. 6(c). For Attack2 (Fig. 6(d) and Fig. 6(e)), synthetic images show noisy results due to discrepancy between real gradients and approximated gradients. This comes from the intrinsic nature of SNNs, therefore SNNs are robust to Attack2 even without encryption. Overall, PrivateSNN is an effective solution to class leakage problem.

We quantify the security of the model by measuring how much generated images represent similar features with that of original images. To this end, we use Frechet inception distance (FID) metric (Heusel et al. 2017) that is widely used in GAN evaluation (Miyato and Koyama 2018; Miyato et al. 2018). The FID score compares the statistics of embedded features in a feature space (see Supplementary C for more detailed explanation). Thus, a lower FID score means that the generated images provide the original data-like feature.

In Table 4, the SNN model without encryption training on attack scenario 1 achieves a much lower FID score (i.e., 354.8) compared to others, which supports our visualization results.

**Energy-efficiency of PrivateSNN**

For the sake of complete analysis, we calculate the inference energy of PrivateSNN and compare with ANN and other conversion methods. Note that, we use the same energy estimation model as (Panda, Aketi, and Roy 2020), which is rather a rough estimate that considers only Multiply and Accumulate (MAC) operations and neglects memory and peripheral circuit energy. We calculate the energy based on spike rate (i.e., the average number of spikes across time) of all layers (see Supplementary F for details). In Table 5, we compare the energy efficiency between VGG16, standard conversion (Sengupta et al. 2019; Han et al. 2020), and our method. The results show that PrivateSNN is more efficient than both ANN as well as a standard converted SNN. This implies our approach of DC + CET + OD lowers the overall spike rate which makes PrivateSNN more energy-efficient.

**Conclusion**

For the first time, we expose the vulnerability of converted SNNs to data and class leakage. We propose PrivateSNN that comprises of data-free conversion followed by weight encryption with spike-based training on synthetic data to tackle the privacy issues. We further optimize the training process with distillation that enables stable encryption training with very few training samples. So far, the discussion around SNNs has more or less been limited to energy-efficiency. This work sets precedence on the vulnerabilities unique to the SNN domain and also showcases the benefits of energy-inefficient temporal spike-based learning for encryption. We hope this fosters future work around security and privacy in SNNs. One limitation of data-free conversion is that the conversion performance is reduced with the overfitted networks which are likely to generate biased data representation. We discuss such limitation in Supplementary.
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