AutoPrivacy: Automated Layer-wise Parameter Selection for Secure Neural Network Inference

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Abstract

Hybrid Privacy-Preserving Neural Network (HPPNN) implementing linear layers by Homomorphic Encryption (HE) and nonlinear layers by Garbled Circuit (GC) is one of the most promising secure solutions to emerging Machine Learning as a Service (MLaaS). Unfortunately, a HPPNN suffers from long inference latency, e.g., ∼100 seconds per image, which makes MLaaS unsatisfactory. Because HE-based linear layers of a HPPNN cost 93% inference latency, it is critical to select a set of HE parameters to minimize computational overhead of linear layers. Prior HPPNNs over-pessimistically select huge HE parameters to maintain large noise budgets, since they use the same set of HE parameters for an entire network and ignore the error tolerance capability of a network.

In this paper, for fast and accurate secure neural network inference, we propose an automated layer-wise parameter selector, AutoPrivacy, that leverages deep reinforcement learning to automatically determine a set of HE parameters for each linear layer in a HPPNN. The learning-based HE parameter selection policy outperforms conventional rule-based HE parameter selection policy. Compared to prior HPPNNs, AutoPrivacy-optimized HPPNNs reduce inference latency by 53% ∼ 70% with negligible loss of accuracy.

1 Introduction

Machine Learning as a Service (MLaaS) is an emerging computing paradigm that uses powerful cloud infrastructures to provide machine learning inference services to clients. However, in the setting of MLaaS, cloud servers can arbitrarily access input and output data of clients, thereby introducing privacy risks. Privacy is especially important, when clients upload their sensitive information, e.g., healthcare records and financial data, to cloud servers. Recent works [1, 2, 3, 4, 5] create Hybrid Privacy-Preserving Neural Networks (HPPNNs) to achieve high inference accuracy using a combination of Homomorphic Encryption (HE) and Garbled Circuit (GC). Particularly, DELPHI [5] obtains the state-of-the-art inference latency and accuracy through implementing linear layers by HE, and computing activation layers by GC. However, HPPNNs still suffer from long inference latency. For instance, inferring one single CIFAR-10 image by DELPHI ResNet-32 [5] costs ∼100 seconds and has to exchange 2GB data. Particularly, the HE-based linear layers of DELPHI cost 93% of its inference latency, thereby becoming its performance bottleneck.

The computational overhead of HE-based linear layers in prior HPPNNs is decided by their HE parameters including the plaintext modulus $p$, the ciphertext modulus $q$, and the cyclotomic order (polynomial degree) $n$. HE enables homomorphic additions and multiplications on ciphertexts by manipulating polynomials whose total term number and coefficients are defined by $p$, $q$ and $n$. Each HE operation introduces a small noise. Decrypting a HE output may have errors, if the total noise accumulated along a HE computation path exceeds the noise budget decided by $p$, $q$ and $n$. 
Fully HE adopts bootstrapping operations to eliminate noises, and thus is not sensitive to noise budget. However, to avoid extremely slow bootstrapping operations of fully HE, prior HPPNNs use leveled HE that allows only a limited noise budget. A large noise budget requires large $p$, $q$ and $n$, significantly increasing computational overhead of polynomial additions and multiplications.

Prior HPPNNs over-optimistically assume huge noise budgets using large $p$, $q$ and $n$. First, prior HPPNNs do not consider the error tolerance of neural networks when defining their HE parameters $p$, $q$ and $n$. We found that a HPPNN can tolerate some decryption errors without degrading private inference accuracy. Second, prior HPPNNs assume the same $p$, $q$ and $n$ for all layers. Different layers in a neural network have different architectures, e.g., weight kernel size and output channel number, and thus different error tolerances. Therefore, assuming the same worst case HE parameters for all layers substantially increases computational overheads of a HPPNN. However, defining a set of $p$, $q$ and $n$ for each layer via hand-crafted heuristics is so complicated that even HE and machine learning experts may obtain only sub-optimal results. In this paper, we propose an automated layer-wise HE parameter selection technique, AutoPrivacy, for fast and accurate HPPNN inference.

![Figure 1: The bottleneck analysis, working flow and HE parameter selection of DELPHI.](image)

## 2 Background and Motivation

**Threat Model.** Our threat model is the same as that used by DELPHI \[5\]. AutoPrivacy is designed for the two-party semi-honest setting, where only one of the parties may be corrupted by an adversary. Both parties adhere the security protocol, but try to learn information about private inputs of the other party from messages they receive. AutoPrivacy aims to protect the client’s privacy, but does not prevent the client from learning the architecture of the neural network used by the server \[5\].

**Privacy-Preserving Neural Network.** Prior HPPNNs \[1,2,3,4\] combine Homomorphic Encryption (HE) and Garbled Circuit (GC) to support privacy-preserving inferences. An HPPNN inference includes a preprocessing stage and an online stage. During the preprocessing stage, a server and a client prepare secret sharing and GC for the online stage. In the online stage, the server and the client compute an inference result. As Figure 1(a) shows, the HE-based linear layers in the preprocessing stage dominate HPPNN inference latency. The security protocol of the preprocessing stage can be summarized as follows.

- **HE-based linear layer.** All linear layers in a HPPNN are implemented by HE that is a cryptosystem supporting homomorphic computations on a ciphertext without decryption. Given a public key $pk$, a secret key $sk$, an encryption function $\epsilon()$, and a decryption function $\sigma()$, $\times$ is an homomorphic operation, if there is another operation $\otimes$ such that $\sigma(\epsilon(x_1, pk) \otimes \epsilon(x_2, pk), sk) = \sigma(\epsilon(x_1 \times x_2, pk), sk)$, where $x_1$ and $x_2$ are plaintexts. Although most HE schemes, e.g., BFV \[6\], can support fast matrix-vector multiplications with SIMD evaluation, HE-based linear layers are still the performance bottleneck of a HPPNN. As Figure 1(a) shows, HE-based linear layers consume 93% of inference latency of the latest HPPNN DELPHI \[3\]. During the preprocessing stage of a linear layer ($L_i$), the client and the server generate two masking vector $r_i$ and $s_i$ respectively for $L_i$, as shown in Figure 1(b). The client encrypts $r_i$ as $[r_i]$, and sends $[r_i]$ to the server, while the server homomorphically computes $[M_i \cdot r_i - s_i]$ and sends it to the client, where $M_i$ indicates the weights and bias of $L_i$. The client decrypts $[M_i \cdot r_i - s_i]$. The server holds $s_i$, so the client and the server hold an additive secret sharing of $M_i \cdot r_i$. Before any HE computation, both the server and the client need to share all HE parameters including $p$, $n$ and $q$. Now the entire HPPNN uses the same set of HE parameters \[1,2,3,4\].

- **GC-based nonlinear layer.** Prior HPPNNs implement nonlinear layers by GC that is a cryptographic protocol enabling the server and the client to jointly compute a nonlinear layer over their private data without learning the other party’s data. In GC, an activation is represented by a Boolean circuit. As Figure 1(c) shows, the server firstly garbles an activation, generates its garbled table
(C_i), and sends it to the client. The client receives C_i by Oblivious Transfer (OT) [3]. In the online stage, the client evaluates C_i to produce an activation result.

- Beaver’s-Triples-based activations. The latest HPPNN DELPHI [5] also adopts Beaver’s Triples (BT) to implement quadratic approximations of the activation function to further reduce computing overhead of GC-based nonlinear layers. To maintain the same inference accuracy, DELPHI uses both GC- and BT-based activations in its nonlinear layers.

Compared to GC-only-based neural networks, e.g., DeepSecure [7], and HE-only-based neural networks, e.g., CryptoNets [8], SHE [9], and Lota [10], HPPNs [5] decrease inference latency by \( \sim 100\times \) and improve inference accuracy by \( \sim 1\% \sim 4\% \).

The BFV Cryptosystem and Its HE Parameters. By following DELPHI [5], we adopt BFV [11] to implement HE operations in a hybrid privacy-preserving network. We use \([r]\) to indicate a ciphertext holding a plaintext vector \(r\), where \(r \in \mathbb{Z}_p^n\) with plaintext modulus \(p\) and cyclotomic order \(n\). In BFV, due to its packing technique, a ciphertext \([r]\) is a set of two polynomials in a quotient ring \(R^2_q\) with ciphertext modulus \(q\). For the encryption of a packed polynomial \(m\) containing the elements in \(r\), a BFV ciphertext is structured as a vector of two polynomials \((c_0, c_1) \in \mathbb{R}^2_q\).

\[
c_0 = -a \\
c_1 = a \cdot s + \frac{q}{p} m + c_0
\]

where \(a\) is a uniformly sampled polynomial, while \(s\) and \(c_0\) are polynomials whose coefficients drawn from \(\mathcal{X}\), where \(\sigma\) is the standard deviation. The decryption simply computes \(\frac{p}{q}(c_0 s + c_1) = m + \frac{p}{q} c_0\). When \(\frac{p}{q} \gg c_0, c_0\) can be rounded off. As Figure 1(d) exhibits, the larger \(q\) is, the more likely \(c_0\) can be rounded off, the more accurate the BFV cryptosystem is. For each set of \(p, q, n,\) and \(\sigma\), the LWE-Estimator [12] can estimate the HE security level \(\lambda\) based on the BFV standard. The larger \(q\) and \(n\) are, the more secure a BFV-based cryptosystem is. To guarantee the correctness and execution efficiency of BFV, the HE parameters have to follow the 5 rules [5]: ı) \(n\) is a power of two; 2) \(q \equiv 1 \mod n\); 3) \(p \equiv 1 \mod n\); 4) \([q \mod p] = \gamma\) \(\approx 1\); and 5) \(q\) is pseudo-Mersenne.

BFV batching. To support single instruction multiple data (SIMD), BFV [11] adopts Chinese Remainder Theorem (CRT) to pack \(g\) plaintexts into one polynomial \(m\) using a composite plaintext modulus \(p = \prod_{i=0}^{g-1} p_i\), where \(p_0, \ldots, p_{g-1}\) are primes. In this way, \(p\) can be large enough to accommodate the maximum intermediate result during a HPPNN inference. The CRT offers an isomorphism between \(\mathbb{Z}_t\) and \(\prod_{i=0}^{g-1} \mathbb{Z}_{t_i}\):

\[
\text{CRT : } \mathbb{Z}_{t_0} \times \ldots \times \mathbb{Z}_{t_{g-1}} \to \mathbb{Z}_t \quad m = (r_0, \ldots, r_{g-1}) \mapsto r
\]

where \(r_i \in \mathbb{Z}_{t_i}\) and \(r \in \mathbb{Z}_t\). The inverse CRT (ICRT) is:

\[
\text{ICRT : } \mathbb{Z}_t \to \mathbb{Z}_{t_0} \times \ldots \times \mathbb{Z}_{t_{g-1}} \quad r \mapsto m = (r_0, \ldots, r_{g-1})
\]

where for any \(r \in \mathbb{Z}_t\), we have \(\text{CRT}(\text{ICRT}(r)) = r\). During decryption, we need to compute \(m + \frac{p}{q} c_0\) and use ICRT to decompose \(m\) to obtain unpacked plaintexts. If \(c_0\) cannot be rounded off during decryption, it will be decomposed into each unpacked plaintexts.

![Figure 2: AutoPrivacy](image)

(a) network-wise selection (b) layer-wise selection

**HE Parameter Selection.** Prior HPPNs [11,5,5,3,4] decide their HE parameters using the flow shown in Figure 2. For an entire neural network, prior HPPNs first choose the cyclotomic order \(n\) that is a power of two and typically \(\geq 10^{10}\), and then select a prime \(p \geq M\), where \(M\) is the maximum plaintext value of the neural network model (i.e., weights and biases). Prior HPPNs must guarantee \(p \equiv 1 \mod n\), otherwise they increase \(p\). By the LWE-Estimator [12], based on \(n, p,\) a standard deviation \(\sigma\) of noise and a security level value \(\lambda\) (e.g., 128-bit), prior HPPNs computes the maximum value \((q_{\text{max}})\) of \(q\). According to the network architecture, prior HPPNs obtains
| HPPNN | plaintext modulus \(\log(p)\) | cyclotomic order \(\log(q)\) | ciphertext modulus \(\log(q)\) | standard deviation \(\sigma\) | security level \(\lambda\) | decryption error \(\%\) |
|-------|----------------|-----------------|-----------------|----------------|----------------|----------------|
| DELPHI [5] | 22 | 13 | 180 | 3.2 | > 128 | > 2\(^{-40}\) |
| DARL [4] | 14 | 13 | 165 | 3.2 | > 128 | > 2\(^{-40}\) |

Table 1: The HE parameters of prior HPPNNs.

the minimal value \((q_{\min})\) of \(q\) that can make the HE error failure rate < 2\(^{-40}\) [4]. From \(q_{\min}\) to \(q_{\max}\), prior NPPNNs choose the smallest \(q\) that can meet the other rules of HE parameters. A recent compiler [13] implements the procedure of HE parameter selection shown in Figure 4(a) for a neural network. To provide circuit privacy, prior HPPNNs [5] have to implement noise flooding [5] by tripling \(\log_2(q)\) and quadrupling \(n\). The HE parameters of recent HPPNNs are shown in Table 1.

**HE Execution Efficiency.** The latency of HE-based linear layers of a HPPNN is decided by its HE parameters, i.e., \(n\) and \(q\). Inputs of a HPPNN are encrypted into polynomials consisting of \(n\) terms. Homomorphic multiplications during a HPPNN inference are performed through polynomial multiplications, where the coefficient of each term has a modulus of \(q\). BFV [11] adopts Number-Theoretic Transform (NTT) [14] with modular reduction to accelerate polynomial multiplications. The time complexity of a NTT-based polynomial multiplication is \(O(n \log n)\). Because \(q\) can be larger than 64-bit, recent BFV implementations use Residue Number System (RNS) [6] to decompose large \(q\) into vectors of smaller integers. A smaller \(q\) greatly accelerates HE operations. As Figure 3 \(2 \times n\) and \(1.5 \times \log(q)\) increases the latency of a HE multiplication by 3.2x.

**Drawbacks of Prior HE Parameter Selection Policies.** We find prior HPPNNs over-optimistically choose huge values of \(n\) and \(q\), resulting in unnecessarily long privacy-preserving inference latency. First, prior HPPNNs ignore their error tolerance capability, i.e., a NPPNN encrypted with smaller \(n\) and \(q\) producing a higher decryption error rate may still achieve the same inference accuracy but uses much shorter inference latency. Second, different layers of a HPPNN have distinctive architectures, and thus can tolerate different amounts of decryption errors. So a HPPNN should select \(n\) and \(q\) for each layer to shorten its inference latency. Choosing \(n\) and \(q\) for each layer does not expose more information to the client, since prior HPPNNs [1, 2, 5, 3, 4] cannot protect the architecture of the network from being known by the client.

**Neural Architecture Search.** Deep reinforcement learning (DRL) [15, 16], genetic algorithm [17], and Bayesian optimization [18] are widely used to automatically search a network architecture improving inference accuracy and latency. DRL-found network architectures without privacy-preserving awareness can outperform human-designed and rule-based results [15, 16]. However, naively applying DRL on HPPNN architecture search [19] cannot effectively optimize privacy-preserving inference accuracy and latency, because conventional neural architecture search explores the design space of layer number, weight kernel size and model quantization bitwidth, but not HE parameters. Particularly, \(n\) and \(q\) are not sensitive to changes of weight kernel size, as shown in Figure 4(a). In Figure 4(b) \(n\) and \(q\) are not sensitive to model quantization bitwidth either, particularly when model quantization bitwidth is < 16. Although smaller weight and bias bitwidth reduces \(p\), \(p\) has to follow the 5 rules, and thus cannot be reduced in a highly quantized model.

**DRL-based Layer-wise HE Parameter Search.** On the contrary, if the HE decryption error rate is moderately enlarged, as Figure 4(c) shows, \(q\) can be obviously reduced. In this paper, as Figure 4(b)
shows, we propose a DDPG agent [20]. AutoPrivacy, to predict a HE decryption error rate for each layer of a HPPNN to reduce \( n \) and \( q \), without sacrificing its accuracy, so that a HPPNN inference can be accelerated. As Figure 4(d) shows, prior HPPNNs [1,2,3,4] (net) has to select a 180-bit \( q \) to guarantee a \( > 2^{-40} \) HE decryption error rate for the whole network without considering the error tolerance capability of a neural network. Recent DARL [4] (net-L) finds the upper bounds of HE matrix multiplications, so it can use smaller \( q \) but still achieve a \( 2^{-40} \) HE decryption error rate. However, DARL does not take the error tolerance capability of a neural network into its consideration, nor selects a set of \( n \) and \( q \) for each layer. AutoPrivacy (layer) can choose and minimize \( n \) and \( q \) for each HPPNN layer by considering its error tolerance capability. As a result, AutoPrivacy greatly decreases HPPNN inference latency without degrading its HE security level or inference accuracy.

The search space of predicting a decryption error rate for each layer of a HPPNN is so huge that even HE and machine learning experts may obtain only sub-optimal results. There are totally \((D \times S)^N_L\), e.g., \( D = 20 \); \( S \) is the number of possible HE parameter sets, e.g., \( S \approx 5 \); and \( N_L \) is the layer number of a HPPNN, e.g., \( N_L = 8 \).

3 AutoPrivacy

For each layer in a HPPNN, our goal is to precisely find out the maximal decryption error rate that can be tolerated by the layer without degrading HE security level (128-bit) or inference accuracy. The HE parameter selection procedure obtains smaller \( q \) and \( n \) with a higher decryption error rate as its input to shorten HPPNN inference latency. We first quantize the HPPNN with 8-bit [21] to minimize \( p \). Further decreasing the bitwidth of a HPPNN only decreases its accuracy, but cannot further reduce \( p \) due to the 5 rules of HE parameter selection. We formulate the layer-wise decryption error rate prediction task as a DRL problem.

3.1 Automated Layer-wise Decryption Error Rate Prediction

As Figure 5 shows, AutoPrivacy leverages a DDPG agent [20] for efficient search over action space. We introduce the detailed setting of DDPG framework.

1 State Space. AutoPrivacy considers only linear layers, and thus processes a HPPNN inference layer by layer. For each linear layer \( i \) (\( L_i \)), the state of \( O_i \) is represented by \( O_i = (i, c_{in}, c_{out}, x_w, x_h, k_h, s_h, p_i, q_i, n_i, a_{i-1}) \), where \( i \) is the layer index; \( c_{in} \) indicates the number of input channels; \( c_{out} \) means the number of output channels; \( x_w \) is the input width; \( x_h \) is the input height; \( k_h \) denotes the kernel size; \( s_h \) is the stride size; \( p_i \) is the plaintext modulus; \( q_i \) means the ciphertext modulus; \( n_i \) is the polynomial degree; and \( a_{i-1} \) is the action in the last time step. If \( L_i \) is fully-connected layer, \( O_i = (i, c_{in}, c_{out}, x_w, x_h, k_h = 1, s_h = 0, p_i, q_i, n_i, a_{i-1}) \). We normalize each metric in the \( O_i \) vector into \([0, 1]\) to make them in the same scale.

2 Action Space. AutoPrivacy use HE decryption error rate as action \( a_i \) for linear layers. We use a continuous action space to determine HE decryption error rate, since compared to a discrete action space, the continuous action space maintain the relative order, e.g., \( 2^{-30} \) is more aggressive than \( 2^{-40} \). For \( L_i \), we take the continuous action \( a_i \in [0, 1] \), and round it into the discrete HE decryption error rate (DER) \( DER_i = 2^{-\text{round}(D_i + a_i \times (D_i - D_i)))} \), where \( 2^{-D_i} \) and \( 2^{-D_i} \) denote the maximal and minimal HE decryption error rate. In this paper, we set \( D_i = 5 \) and \( D_i = 15 \). We input the predicted HE decryption error rate to the procedure of HE parameter selection shown in Figure [2]b) to get \( p, q, \) and \( n \). To consider a constraint on inference latency, we can limit the action space.

• Latency Constraint on Action Space. Some privacy-persevering applications have a limited budget on inference latency. We aim to find the HE parameter policy with the best accuracy under a latency constraint. We make our agent to meet a given latency budget by limiting its action

![](image)

Figure 5: AutoPrivacy.
We performed extensive experiments to show the consistent effectiveness of AutoPrivacy to minimize HPPNN inference latency with trivial loss of accuracy.

### 4 Experimental Methodology

#### Inference Latency Estimation

To avoid high HPPNN inference overhead, we profile and record the latencies of polynomial multiplications and additions with various values of $n$ and $q$. From the network topology, we extract key operation information such as the number of homomorphic SIMD multiplications, the number of homomorphic slot rotations, and the number of SIMD additions. By the latency and number of each type of operations, we can fast calculate the approximate latency of a HPPNN inference.

#### Reward

Since a latency constraint can be imposed by limiting the action space, we define our reward $R$ to be related to only inference accuracy, i.e., $R = -err$, where $err$ is HPPNN inference error rate. We estimate the inference accuracy of a HPPNN as follows. Performing millions of HPPNN inferences on encrypted data is extremely computationally expensive. After AutoPrivacy generates HE parameters for all layers of a HPPNN, instead, we adopt the HE decryption error simulation infrastructure in [4] to estimate the HPPNN inference accuracy. We did not observe any accuracy loss on a HPPNN until the decryption error rate degrades to $2^{-7}$. In most cases, we perform brute-force Monte-Carlo runs are required. However, to simulate a $2^{-15}$ decryption error rate, at least $2^{30}$ brute-force Monte-Carlo runs are required. To reduce simulation overhead, we adopt Sigma-Scaled Sampling [22] to study high dimensional Gaussian random variables. A HE-based linear layer with the initial noise vector $e$ can be abstracted as a function $f(e)$. Its decryption error rate is the probability of the decryption error $||e||$ being greater than the noise budget $\eta$, generated by HE parameter $p$ and $q$. The decryption error rate can be calculated as $P_e = \int_{-\infty}^{+\infty} f(e)de$, where $I(e) = 1$ if and only if $||e|| > \eta$, and $I(e) = 0$ otherwise. Sigma-Scaled Sampling reduces error simulation time by sampling from a different density function $g$, where $g$ is the same as $f$ but scales the sigma of $e$ by a constant $s$. Because $P_g$ offers a much larger probability, we can use less brute-force Monte-Carlo to obtain an accurate $P_g$. By scaling factors and model fittings, we can run at most 10 million $P_g$s and convert these values back to $P_e$. We record $||e||s$ resulting in decryption errors and decompose them by ICRT. We use 50% of the ICRT-decomposed results to retrain the HPPNN by adding them to the output of each linear layer in the forward propagation. And then, we use the other 50% of the ICRT-decomposed results to obtain its inference accuracy.

#### Agent

AutoPrivacy uses a DDPG agent [20], which is an off-policy actor-critic algorithm for continuous control. In the environment, one step means that the DDPG agent makes an action to decide the decryption error rate for a specific linear layer, while one episode is composed of multiple steps, where the DRL agent chooses actions to all layers. The environment generates a reward $R_t$ and next state $O_{t+1}$. We use a variant form of the Bellman’s Equation, where each transition in an episode is defined as $T_i = (O_i, a_i, R_i, O_{i+1})$. During the exploration, $Q$-function is computed as $Q_i = R_i + \gamma \times Q(O_{i+1}, \mu(O_{i+1})|\theta^Q)$, where $\mu()$ is the output of the actor; $Q()$ is the output of the critic; $\theta^Q$ is the parameters of the critic network; and $\gamma$ is the discount factor. The loss function can be approximated by $L = \frac{1}{N_s} \sum_{i=1}^{N_s} (Q_i - Q(O_i, \mu(O_i)|\theta^Q))^2$, where $N_s$ is the number of steps in this episode. We present implementation details of the agent as follows.

- **Implementation.** The DDPG agent consists of an actor network and a critic network. They share the same network architecture with 3 hidden layers: 400 units, 300 units and 1 unit. For the actor network, we add an additional sigmoid function to normalize the output into range of $[0, 1]$. The DDPG agent is trained with fixed learning rates, i.e., $10^{-4}$ for the actor network and $10^{-3}$ for the critic network. The replay buffer size of AutoPrivacy is 2000. During exploration, the DDPG agent adds a random noise to each action. The standard deviation of Gaussian action noise is initially set to 0.5. After each episode, the noise is decayed exponentially with a decay rate of 0.99.

- **Finetuning.** During exploration, we finetune the HPPNN model with generated decryption errors for one epoch to recover the accuracy. We randomly select 2 categories from CIFAR-10 (10 categories from CIFAR-100) to accelerate the HPPNN model finetuning during exploration. After exploration, we generate decryption errors based on the best HE parameter selection policy and finetune it on the full dataset.
Hardware configuration. We ran HPPNN inferences and measured the latency of each type of operations on an Intel Xeon E7-4850 CPU with 1T DRAM. We assume the same network LAN setting as DELPHI [5]. We implemented and trained AutoPrivacy on a Nvidia GTX1080-Ti GPU.

HE and GC setting. We implemented HE-based linear layers of HPPNNs by Microsoft SEAL library [5], and GC-based nonlinear layers of HPPNNs through swanky library [23]. Because we quantized all network models with 8-bit, we fix the plaintext modulus $\rho$ as 14 [4]. To evaluate the security level of a set of HE parameters, we relied on LWE-Estimator [12]. The same as DELPHI [5] and DARL [4], all HE parameters we studied satisfy the > 128-bit security level. To estimate inference accuracy, we use the original HE parameters $n$ and $q$. On the contrary, we use $4 \times n$ and $3 \times \log(q)$ to enable noise flooding and evaluate inference latency.

Dataset and model. Our experiments are performed on the CIFAR-10/100 dataset. We studied a series of neural network architectures including a 7-layer CNN network used by [5] (7CN), ResNet-32 [24] (RESNET), and MobileNet-V2 [25] (MOBNET). 7CN consists of 5 convolutional layers with $3 \times 3$ kernel size and 64 output channels, and 2 convolutional layers with $3 \times 3$ kernel size and 64/16 output channels. MOBNET consists of pointwise and depthwise convolution layers, each of which is a pointwise-depthwise-pointwise block. Only 7CN is trained and tested on CIFAR-10, while experiments of RESNET and MOBNET are performed on CIFAR-100.

| Network | Scheme | Latency (s)  | Communication (GB) | accuracy (%) |
|---------|--------|--------------|--------------------|--------------|
|         | $t_{pre}$ | $t_{on}$ | $t_{total}$ | $m_{pre}$ | $m_{on}$ | $m_{total}$ |
| 7CN     | DELPHI  | 41.0        | 0.8       | 41.8        | 0.12 | 0.01 | 0.13 | 81.63 |
|         | DARL    | 28.7        | 0.42      | 29.12       | 0.11 | 0.01 | 0.12 | 81.63 |
|         | AutoPrivacy | 10.24    | 0.31      | 19.55       | 0.09 | 0.01 | 0.1 | 81.5 |
| RESNET  | DELPHI  | 90.0        | 6.4       | 96.4        | 1.94 | 0.04 | 1.98 | 76.78 |
|         | DARL    | 56.7        | 3.83      | 60.53       | 1.77 | 0.04 | 1.74 | 76.78 |
|         | AutoPrivacy | 27.0     | 1.36      | **28.56**   | 1.07 | 0.03 | 1.1 | 76.78 |
| MOBNET  | DELPHI  | 17.4        | 1.74      | 19.14       | 0.24 | 0.01 | 0.25 | 68.08 |
|         | DARL    | 11.2        | 1.23      | 12.45       | 0.25 | 0.01 | 0.24 | 68.08 |
|         | AutoPrivacy | 6.2      | 0.72      | **6.92**    | 0.19 | 0.01 | 0.2 | 68.05 |

Table 2: The execution time, communication overhead and inference accuracy comparison ($t_{pre}$ is the preprocessing latency; $t_{on}$ indicates the online latency; $t_{total}$ is the total HPPNN inference latency; $m_{pre}$ is the preprocessing communication overhead; $m_{on}$ means the online communication overhead; and $m_{total}$ is the total inference communication overhead).

5 Results and Analysis

Overall Performance. The execution time, communication overhead, and inference accuracy comparison between prior HPPNNs and AutoPrivacy-optimized HPPNNs are shown in Table 2. Compared to DELPHI, our AutoPrivacy-optimized counterparts reduce inference latency by $53\% \sim 70\%$, decrease ciphertext size by $20\% \sim 43\%$, and maintain trivial inference accuracy loss ($0.1\%$). Particularly, AutoPrivacy reduces offline inference latency of RESNET by $70\%$, and online inference latency $75\%$. If a client infer multiple images, only the first one costs 28.56 seconds. It takes only 1.56 seconds for each of the following images to be tested by a heavyweight RESNET. 7CNET, ResNet-32, and MobileNet-V2 RESNET and MOBNET consists of pointwise and depthwise convolution layers, each of which is a pointwise-depthwise-pointwise block. Only 7CN is trained and tested on CIFAR-10, while experiments of RESNET and MOBNET are performed on CIFAR-100.

HP Parameter Selection. We report the details of HE parameter selection of RESNET and MOBNET inferring on the CIFAR-100 dataset in Figure [a] and (b) receptively. For CIFAR-100, besides the first convolutional layer and the last fully-connected layer, RESNET applies a stack of $6M$ layers with $3 \times 3$ convolutions on the feature maps of sizes of $\{32, 16, 8\}$ respectively on $32 \times 32$ images, where $M$ is an odd integer. $2M$ layers for each feature map size form a residual block. As Figure [a] shows, AutoPrivacy automatically observes the boundary of each residual block of RESNET. Inside each residual block, AutoPrivacy identifies the 2nd and 6th layers can work with smaller $q$ and $n$, since they have less influence to inference accuracy. On the contrary, the 4th and 8th layers in a
residual block have to use larger $q$ and $n$, because they own larger weight in deciding inference accuracy. For MOBNET, AutoPrivacy automatically finds the difference between depth-wise and point-wise convolutions. Depth-wise convolution layers have less accumulations thereby reducing the number of HE rotation operations that greatly increase the noises in packed ciphertexts. Therefore, AutoPrivacy assigns smaller $n$ and $q$ to depth-wise convolution layers without sacrificing inference accuracy. In contrast, point-wise convolution layers have $1 \times 1$ convolutions and tens to hundreds of output channels requiring a great number of accumulations. Point-wise convolution layers have to invoke many HE rotation operations in ciphertexts, and thus increase HE noise in ciphertexts. To tolerate larger HE noise, AutoPrivacy has to select larger $n$ and $q$ to provide larger noise budgets in point-wise convolution layers without human guidance.

### Table 3: The comparison between NASS and AutoPrivacy.

| Name     | Network Architecture | Quantization (bits) | Latency (seconds) | Communication (GB) | Accuracy (%) | Search time (hours) |
|----------|----------------------|---------------------|-------------------|--------------------|--------------|---------------------|
| NASS [19] | 5 CONV. + 1 FC        | 4–16                | 20.1              | 0.978              | 84.6         | 60                  |
| AutoPrivacy | MOBNET               | 14                  | 6.13              | 0.2                | 91.4         | 8                   |

**Comparison against NASS.** A recent work, NASS [19], automatically builds a privacy-preserving neural network architecture by a deep reinforcement learning agent. However, instead of HE parameters, NASS automatically searches neural network architectures and quantization bitwidths for each linear and nonlinear layer. As a result, its search space size is too large to be efficiently and effectively explored. Table 3 highlights the comparison of results achieved by NASS and AutoPrivacy searching for the CIFAR-10 dataset. NASS finds a network architecture with five convolutional layers and one fully-connected layers on the CIFAR-10 dataset. It also quantizes each linear and nonlinear layers with $4 \sim 16$ bits. On the contrary, we train a MOBNET on the CIFAR-10 dataset and quantize the model with 14-bit. Compared to the NASS-found network, MOBNET optimized by AutoPrivacy improves inference latency by 69.5%, communication overhead by 79%, and inference accuracy by 8%. The search of AutoPrivacy takes only 8 hours, but the search time of NASS is $>60$ hours. This is because each time NASS has to train a neural network from scratch, then quantize it, and finally retrain it, once it selects a topology for the HPPNN. The design space is too large for its deep reinforcement learning agent. In contrast, we argue that the emerging compact network architectures like MOBNET can maximize inference accuracy with less parameters. We can use a pre-decided network architecture, quantize it with the same bitwidth, and rely on AutoPrivacy to automatically choose HP parameters for each linear layer of the fixed architecture. Compared to the network architecture and quantization bitwidth, choosing appropriate HP parameters for linear layers of the fixed network more effectively reduces inference latency.

### 6 Conclusion

In this paper, we propose, AutoPrivacy, an automated layer-wise HE parameter selector to optimize for fast and accurate privacy-preserving neural network inferences on encrypted data. AutoPrivacy uses deep reinforcement learning to automatically find a set of HE parameters for each linear layer in a HPPNN without sacrificing the 128-bit security level. Compared to prior HPPNNs, AutoPrivacy-optimized HPPNNs reduce inference latency by 53% $\sim 70\%$ with negligible accuracy loss.
References

[1] P. Mohassel and Y. Zhang. SecureML: A System for Scalable Privacy-Preserving Machine Learning. In *IEEE Symposium on Security and Privacy*, 2017.

[2] Jian Liu, Mika Juuti, Yao Lu, and N. Asokan. Oblivious neural network predictions via minionn transformations. In *ACM SIGSAC Conference on Computer and Communications Security*, pages 619–631, 2017.

[3] Chiraag Juvekar et al. GAZELLE: A Low Latency Framework for Secure Neural Network Inference. In *USENIX Security Symposium*, 2018.

[4] Song Bian, Masayuki Hiromoto, and Takashi Sato. Darl: Dynamic parameter adjustment for lwe-based secure inference. In *IEEE/ACM Design, Automation & Test in Europe Conference & Exhibition*, 2019.

[5] Pratyush Mishra, Ryan Lehmkuhl, Akshayaram Srinivasan, Wenting Zheng, and Raluca Ada Popa. Delphi: A cryptographic inference service for neural networks. In *USENIX Security*, 2020.

[6] Microsoft SEAL (release 3.2). [https://github.com/Microsoft/SEAL](https://github.com/Microsoft/SEAL), February 2019. Microsoft Research, Redmond, WA.

[7] Bita Darvish Rouhani et al. DeepSecure: Scalable Provably-Secure Deep Learning. In *ACM/IEEE Design Automation Conference*, 2018.

[8] Nathan Dowlin et al. CryptoNets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy. In *International Conference on Machine Learning*, 2016.

[9] Qian Lou and Lei Jiang. She: A fast and accurate deep neural network for encrypted data. In *Advances in Neural Information Processing Systems 32*, pages 10035–10043. Curran Associates, Inc., 2019.

[10] Alon Brutzkus et al. Low Latency Privacy Preserving Inference. In *International Conference on Machine Learning*, 2019.

[11] Zvika Brakerski. Fully homomorphic encryption without modulus switching from classical gapsvp. In *Advances in Cryptology – CRYPTO 2012*, pages 868–886. Springer Berlin Heidelberg, 2012.

[12] Martin R. Albrecht, Rachel Player, and Sam Scott. On the concrete hardness of learning with errors. Cryptology ePrint Archive, Report 2015/046, 2015. [https://eprint.iacr.org/2015/046](https://eprint.iacr.org/2015/046).

[13] Roshan Dathathri, Olli Saarikivi, Hao Chen, Kim Laine, Kristin Lauter, Saeed Maleki, Madanlal Musuvathi, and Todd Mytkowicz. Chet: An optimizing compiler for fully-homomorphic neural-network inferencing. In *ACM SIGPLAN Conference on Programming Language Design and Implementation*, page 142–156, 2019.

[14] Gregor Seiler. Faster AVX2 optimized NTT multiplication for ring-lwe lattice cryptography. *IACR Cryptol. ePrint Arch.*, 2018:39, 2018.

[15] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V. Le. Learning transferable architectures for scalable image recognition. *CoRR*, abs/1707.07012, 2017.

[16] Qian Lou, Feng Guo, Minje Kim, Lantao Liu, and Lei Jiang. Autoq: Automated kernel-wise neural network quantization. In *International Conference on Learning Representations*, 2020.

[17] Masanori Suganuma, Shinichi Shirakawa, and Tomoharu Nagao. A genetic programming approach to designing convolutional neural network architectures. In *ACM Genetic and Evolutionary Computation Conference*, pages 497–504, 2017.

[18] Kirthevasan Kandasamy, Willie Neiswanger, Jeff Schneider, Barnabás Póczos, and Eric Xing. Neural architecture search with bayesian optimisation and optimal transport. *CoRR*, abs/1802.07191, 2018.

[19] Song Bian, Weiwen Jiang, Qing Lu, Yiyu Shi, and Takashi Sato. Nass: Optimizing secure inference via neural architecture search. In *European Conference on Artificial Intelligence*, 2020.

[20] Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. In *International Conference on Learning Representations*, 2018.
[21] Edward Chou, Josh Beal, Daniel Levy, Serena Yeung, Albert Haque, and Li Fei-Fei. Faster cryptonets: Leveraging sparsity for real-world encrypted inference. *CoRR*, abs/1811.09953, 2018.

[22] Shupeng Sun, Xin Li, Hongzhou Liu, Kangsheng Luo, and Ben Gu. Fast statistical analysis of rare circuit failure events via scaled-sigma sampling for high-dimensional variation space. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 34(7):1096–1109, 2015.

[23] Brent Carmer, Alex J. Malozemoff, and Marc Rosen. swanky: A suite of rust libraries for secure multi-party computation. [https://github.com/GaloisInc/swanky](https://github.com/GaloisInc/swanky) 2019.

[24] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 770–778, 2016.

[25] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2018.