SOTERIA: In Search of Efficient Neural Networks for Private Inference

Anshul Aggarwal, Trevor E. Carlson, Reza Shokri, Shruti Tople
National University of Singapore (NUS), Microsoft Research
{anshul, trevor, reza}@comp.nus.edu.sg, shruti.tople@microsoft.com

Abstract

Confidentiality, performance and acccuracy are desirable properties that are hard to balance in the context of private computation on neural networks. This work presents SOTERIA — a training method to construct model architectures that are *by-design* efficient for private inference. We use neural *architecture search* algorithms with the dual objective of optimizing the accuracy of the model and the overhead of using cryptographic primitives for secure inference. Given the flexibility of modifying a model during training, we find accurate models that are efficient for private computation. We select garbled circuits as our underlying cryptographic primitive, due to their expressiveness and efficiency, but this approach can be extended to hybrid multi-party computation settings.

1 Introduction

We focus on protecting **confidentiality** of inference (prediction) on neural networks in a two-party setting, where the server holds the model and computes inference on client input. We assume the two parties do not trust, nor include any third entity in the protocol. We aim at preserving the confidentiality of the input data and its inference with respect to the server, and the confidentiality of model parameters with respect to the client. We emphasize that *confidentiality* prevents direct information leakage, and is orthogonal to *privacy* (i.e., protecting against inference attacks that infer model parameters [41] or training data [39], by exploiting model predictions).

Existing techniques are based on trusted execution [22, 31], and cryptographic primitives such as homomorphic encryption, garbled circuits, secret sharing [46, 16, 45, 6, 3]. Towards efficient private inference, the dominant approach involves *adapting* cryptographic functions to (an approximation of) a *fixed* model [28, 30, 29, 37, 35, 7, 24, 36]. See Appendix A for an overview of the related work.

Our contributions. Training algorithms for deep learning are inherently flexible with respect to their neural network architecture. This means that different network configurations can achieve similar level of prediction accuracy. We take advantage of this fact and approach the problem of private inference from a novel perspective: instead of modifying cryptographic schemes to support efficient neural network computations, we optimize the training algorithm for producing models which are going to be efficient for cryptographic primitives.

We present SOTERIA — an approach for constructing deep neural networks optimized for performance, accuracy and confidentiality. We use garbled circuits as our main building block to address the *confidentiality* concern in the design of SOTERIA. Garbled circuits are known to be efficient and allow generation of constant depth circuits even for non-linear functions. We show that neural network algorithms can be optimized to efficiently execute garbled circuits without significant accuracy loss. See Appendix B for the discussion on the selection of garbled circuits as our cryptographic primitive, and Appendix C for the discussion on the efficient design of garbled circuits for neural-networks. We design a regularized architecture search algorithm [47, 33, 27] to construct neural networks. SOTERIA selects optimal parameter sparsity and network structure with the objective to guarantee a balance between *performance* on encrypted data/model and model *accuracy*.

34th Conference on Neural Information Processing Systems (NeurIPS 2020), Vancouver, Canada.

2 SOTERIA

We design SOTERIA to automatically learn the model architecture and its connections so as to optimize the cost of private inference in addition to optimizing accuracy. This approach is different than simply fine-tunning or compressing a model, as we aim to include the cost of private computation as part of the objective of *architecture learning* and *parameter learning* of the model. SOTERIA is built on top of two well-established classes of machine learning algorithms: neural architecture search algorithms, and ternary neural network algorithms.

Neural architecture search for efficient private inference. Architecture search algorithms for neural networks are designed to replace the manual design of complex deep models. The objective is to learn a model structure that gives high accuracy when trained on the training set [14, 47, 33, 27]. They automatically construct the model architecture by stacking a number of *cells*. Each cell is a directed acyclic graph, where each node is a neural *operation* (e.g., convolution with different dimensions, maxpool, identity). During the search algorithm, we use stochastic gradient descent to continuously update the scores associated with different candidate operations for each connection in the internal graph of a cell, as to maximize the accuracy of the model on some validation set.

In SOTERIA, we regularize the computation of the connection scores over candidate operations, with factor λ. We penalize each operation proportional to its computation and communication overhead when garbled. Larger values of λ result in models that prefer efficiency of private inference over accuracy. As we balance the trade-off between accuracy and performance, SOTERIA can construct models which *by design* satisfy the requirements of our system.

Ternary (Sparse Binary) Neural Network. To build a system that enables efficient private inference, we also reduce the number of model parameters. One approach is to train a model and then compress the it. However, this might not result in the best construction of the model as far as the model accuracy is concerned. Besides, to be aligned with our approach of *constructing* model architectures, we would prefer to learn model structures which are sparse, and are efficient for garbled circuits. Thus, we learn models with ternary values $(-1, 0, +1)$ [26]. In SOTERIA, we train models with ternary parameters and binary activation functions. This allows us to leverage the benefits for BNNs, as discussed in Appendix C, however on a smaller circuit (due to the model's sparsity). We incorporate TNNs into our regularized architecture search algorithm to find cells containing only ternary convolution and max-pooling layers that operate on binary inputs and ternary parameters.

3 Empirical Evaluation

We evaluate the efficiency of our method in two ways. We show how using ternary neural networks on fixed model architectures, as used in the prior work, can reduce the overhead of secure inference on sparse neural networks (See Appendix E for the results). We also present the performance of SOTERIA architectures, in which model complexity is optimized along with the model accuracy. See Appendix D for the experimental setup and implementation details. Table 2 presents the performance and accuracy of SOTERIA and the prior work.

Cost function for regularized architecture search. Our algorithm searches for the models that are not only accurate but are efficient with respect to the costs of using GC with the model For this, we modify the score value that the DARTS architecture search gives to each operation (e.g., maxpool, or convolution with different dimensions) with a regularized penalty factor proportional to the performance cost of the operation. Table 1a presents the communication and runtime cost of each operation that we use in our algorithm. The penalty factor is computed as the average of the relative communication cost and relative runtime cost of each operation, with respect to the most costly operation (CONV5×5). We use this penalty factor in the experiments.

Balancing accuracy and inference costs. For the architecture search in SOTERIA, we balance accuracy and inference cost over GC protocol, using a regularization factor λ. With $\lambda = 1$ the importance of the penalty factor is maximum, and $\lambda = 0$ represents the case where we ignore the performance cost. We execute the search process with different values of λ. Figure 1 presents trade-off between test accuracy of the optimal architectures and their inference runtime. Table 1b provides the statistics on the number of model parameters and the model sparsity for different values of λ for the MNIST dataset. As λ increases, cheaper operations, that have fewer trainable parameters are chosen by the search process, which improves the inference runtime at the expense of the model

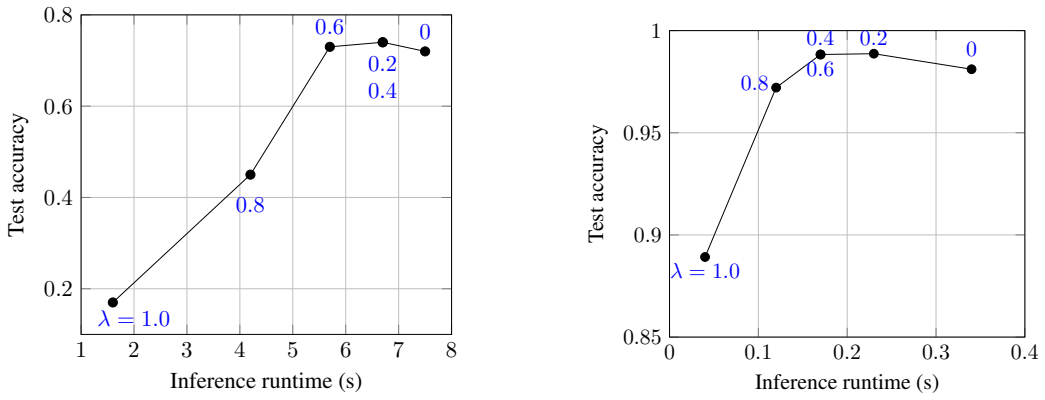
(a) Runtime and communication cost per operation.

Operation	Runtime (ms)	Comm. (KB)	Penalty factor
CONV5 × 5	55.40	7942	1.00
CONV3 × 3	23.10	3190	0.41
MAXPOOL2 × 2	3.23	145	0.04
IDENTITY	0.00	0.00	0.00

(b) Number of parameters, sparsity and test accuracy.

λ	Total no. of Parameters	No. of 0-weights	Sparsity	Accuracy
1.0	133,032	41,212	0.31	0.8892
0.8	729,768	200,540	0.27	0.9721
0.6	2,904,168	1,080,217	0.37	0.9883
0.4	2,904,168	1,080,217	0.37	0.9883
0.2	2,941,032	895,034	0.30	0.9887
0.0	11,466,600	5,116,030	0.45	0.9811

Table 1: (a) Runtime and communication cost of each operation based on their garbled circuit inference. We also calculate the performance penalty factor (which we use in our regularized architecture search algorithm) as the average of the relative costs for each unit w.r.t the most expensive operation. (b) Number of parameters and corresponding sparsity and test accuracy with different levels of λ for SOTERIA architecture search over MNIST dataset with 1 cell architecture having 4 sequential operations. The setting is the same as the one illustrated in Figure 1(b). The scaling factor is 3. For larger λ, the algorithm penalizes large/complex models.



(a) CIFAR10 (b) MNIST

Figure 1: Inference runtime versus test accuracy of a garbled ternary model, constructed with SOTERIAarchitecture search algorithm, for various values of circuit cost regularization λ. We obtain the architecture for a neural network with (a) 3 cells for CIFAR10 dataset, and (b) 1 cell for MNIST dataset. Scaling factor is 3.

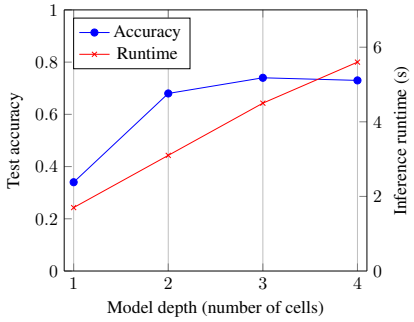


Figure 2: Impact of the model's depth (as the number of cells in the SOTERIA architecture search) on accuracy and inference runtime of garbled model on CIFAR10. Regularization term λ is 0.6. Scaling factor is 3.

accuracy. As we observe, $\lambda = 0.6$ provides a reasonable balance between both accuracy and the inference cost. The search algorithm identifies cheaper operations that collectively result in accuracy equivalent to using expensive operations. It is important to note that selecting λ depends on how much cost or accuracy drop we can tolerate for a given setting. Thus, SOTERIA enables adapting private inference to the specific requirements and limitations of a system.

Finding the optimal depth for the model (number of cells). The number of cells that the final architecture has is a manually-set hyperparameter and defines the depth of the model architecture.

We perform an experiment on the CIFAR10 dataset, using cells with 4 operations in sequence and $\lambda = 0.6$. We run the search process for 100 epochs, and train each resultant architecture for 200 epochs. Figure 2 presents the results of executing the search with different number of cells. It illustrates the model accuracies along with their inference runtime. We observe that for a single cell architecture, the accuracy levels are low, as the network could not process the features required to perform a generalizable classification. The test accuracy peaks for 3-cell architecture, suggesting that it has enough operations to process the required features of the inputs. In parallel, we can see that as the number of cells increases, the runtime also increases.

Comparison with prior work. Table 2 reports the results for SOTERIA trained models that are optimized for both accuracy and efficiency. For the MNIST dataset, we observe that our model with $\lambda = 0$ gives the best model as compared to prior work while balancing the runtime performance (0.034) and accuracy of 0.9811. Increasing $\lambda = 0.6$ increases the accuracy by a small value. Similarly, for CIFAR10 datasets, we observe that a SOTERIA-trained model with $\lambda = 0.6$ gives better accuracy than most of the prior work as compared to the numbers reported in brackets. SOTERIA models provide acceptable runtime performance and communication overhead that outperforms the results from prior work. Our evaluation on MNIST and CIFAR10 datasets confirm that SOTERIA is effective in training models that are customized to perform well for both performance and accuracy.

Table 2: Performance analysis of existing secure schemes for private neural network inference. We compare SOTERIA constructed on fixed model architectures with ternary parameters, as well as optimal architectures constructed by SOTERIA, with the prior work. We provide the descriptions of the model architectures in Appendix F). We use the same scaling factor for SOTERIA and XONN for fixed model architectures (1.75 for m1, 4.0 for m2, 2.0 for m3, 2.0 for m4, 3.0 for m5, 2.0 for m6), and use 3.0 for MNIST (SOTERIA) and CIFAR10 (SOTERIA) for the models constructed by our architecture search algorithm.

Model	**Secure Scheme**	**Runtime (s)**			**Communication (MB)**	**Test Accuracy**
		Offline	**Online**	**Total**		
MNIST (m1)	SecureML [30]	4.7	0.18	4.88	–[d]	0.931
	MiniONN [28]	0.9	0.14	1.04	15.8	0.976
	EzPC [7]	–	–[c]	0.7	76	0.976
	Gazelle [24]	0	0.03	0.03	0.5	0.976
	XONN [35]	–	–[c]	0.13[b]	4.29	0.976[a] (0.9591)
	SOTERIA (TNN)	0.04	0.03	0.07	3.72	0.9642
MNIST (m2)	DeepSecure [37]	7.69	1.98	9.67	791	0.9895
	MiniONN	0.88	0.4	1.28	47.6	0.9895
	EzPC	–	–[c]	0.6	70	0.990
	Gazelle	0.15	0.05	0.20	8.0	0.990
	XONN	–	–[c]	0.16[b]	38.28	0.9864[a] (0.9718)
	SOTERIA (TNN)	0.08	0.06	0.14	30.68	0.9733
MNIST (m3)	MiniONN	3.58	5.74	9.32	657.5	0.990
	EzPC	–	–[c]	5.1	501	0.990
	Gazelle	0.48	0.33	0.81	70	0.990
	XONN	–	–[c]	0.15[b]	32.13	0.990[a] (0.9672)
	SOTERIA (TNN)	0.08	0.07	0.15	26.04	0.9740
MNIST (SOTERIA)	SOTERIA ($\lambda = 0.6$)	0.09	0.08	0.17	36.24	0.9883
	SOTERIA ($\lambda = 0$)	0.016	0.018	0.034	95.18	0.9811
CIFAR10 (m4)	XONN	–	–[c]	15.07[b]	4980	0.80[a] (0.7197)
	SOTERIA (TNN)	8.56	6.14	14.70	936.1	0.7314
CIFAR10 (m5)	MiniONN	472	72	544	9272	0.8161
	EzPC	–	–[c]	265.6	40683	0.8161
	Gazelle	9.34	3.56	12.9	1236	0.8161
	Delphi[e]	45	1	46	200	0.85
	XONN	–	–[c]	5.79[b]	2599	0.8185[a] (0.7266)
	SOTERIA (TNN)	3.48	2.95	6.43	461.3	0.7252
CIFAR10 (m6)	XONN	–	–[c]	16.09[b]	5320	0.83[a] (0.7341)
	SOTERIA (TNN)	9.01	6.63	15.64	982.7	0.7396
CIFAR10 (SOTERIA)	SOTERIA ($\lambda = 0.6$)	3.69	3.26	6.95	497.6	0.7384
	SOTERIA ($\lambda = 0$)	4.01	3.53	7.54	561.2	0.7211

[a]We could not reproduce the test accuracies for XONN. We report the results that we obtained on the same model architectures with the same setting in the respective paper in parenthesis. [b]XONN's runtime reported by the authors is measured on a high-performance Intel processor, which is faster than the one used by all other methods. [c]Breakdown of runtime cost into offline and online runtime is not reported by the authors. [d]Communication cost is not reported by the authors. [e]The runtime, communication cost and test accuracy are estimates from the graphs reported by the authors.

Reproducibility

The code for our work is available at https://github.com/privacytrustlab/soteria_private_nn_inference.

References

[1] Pytorch 1.3. https://pytorch.org/.

[2] Synopsys design compiler, version L-2016.03-SP5-2. https://www.synopsys.com/implementation-and-signoff/rtl-synthesis-test/dc-ultra.html.

[3] Donald Beaver. Efficient multiparty protocols using circuit randomization. In Joan Feigenbaum, editor, *Advances in Cryptology — CRYPTO '91*, pages 420–432, Berlin, Heidelberg, 1992. Springer Berlin Heidelberg.

[4] Raphael Bost, Raluca Ada Popa, Stephen Tu, and Shafi Goldwasser. Machine learning classification over encrypted data. Cryptology ePrint Archive, Report 2014/331, 2014. https://eprint.iacr.org/2014/331.

[5] Florian Bourse, Michele Minelli, Matthias Minihold, and Pascal Paillier. Fast homomorphic evaluation of deep discretized neural networks. Cryptology ePrint Archive, Report 2017/1114, 2017. https://eprint.iacr.org/2017/1114.

[6] Zvika Brakerski, Craig Gentry, and Vinod Vaikuntanathan. Fully homomorphic encryption without bootstrapping. Cryptology ePrint Archive, Report 2011/277, 2011. https://eprint.iacr.org/2011/277.

[7] Nishanth Chandran, Divya Gupta, Aseem Rastogi, Rahul Sharma, and Shardul Tripathi. EzPC: Programmable, efficient, and scalable secure two-party computation for machine learning. In *IEEE European Symposium on Security and Privacy*, February 2019.

[8] Henry Corrigan-Gibbs and Dan Boneh. Prio: Private, robust, and scalable computation of aggregate statistics. In *14th USENIX Symposium on Networked Systems Design and Implementation (NSDI 17)*, pages 259–282, Boston, MA, March 2017. USENIX Association.

[9] I. Damgard, V. Pastro, N.P. Smart, and S. Zakarias. Multiparty computation from somewhat homomorphic encryption. Cryptology ePrint Archive, Report 2011/535, 2011. https://eprint.iacr.org/2011/535.

[10] Ivan Damgard, Marcel Keller, Enrique Larraia, Valerio Pastro, Peter Scholl, and Nigel P. Smart. Practical covertly secure mpc for dishonest majority – or: Breaking the spdz limits. Cryptology ePrint Archive, Report 2012/642, 2012. https://eprint.iacr.org/2012/642.

[11] Daniel Demmler, Thomas Schneider, and Michael Zohner. ABY - A framework for efficient mixed-protocol secure two-party computation. In *22nd Annual Network and Distributed System Security Symposium, NDSS 2015, San Diego, California, USA, February 8-11, 2015*. The Internet Society, 2015.

[12] Nathan Dowlin, Ran Gilad-Bachrach, Kim Laine, Kristin Lauter, Michael Naehrig, and John Wernsing. CryptoNets: Applying neural networks to encrypted data with high throughput and accuracy. In *Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48*, ICML'16, pages 201–210. JMLR.org, 2016.

[13] Taher ElGamal. A public key cryptosystem and a signature scheme based on discrete logarithms. In George Robert Blakley and David Chaum, editors, *Advances in Cryptology*, pages 10–18, Berlin, Heidelberg, 1985. Springer Berlin Heidelberg.

[14] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. Neural architecture search: A survey, 2018.

[15] Craig Gentry. *A Fully Homomorphic Encryption Scheme*. PhD thesis, Stanford, CA, USA, 2009. AAI3382729, Advisor: D. Boneh.

[16] Craig Gentry. Fully homomorphic encryption using ideal lattices. In *Proceedings of the Forty-First Annual ACM Symposium on Theory of Computing*, STOC '09, page 169–178, New York, NY, USA, 2009. Association for Computing Machinery.

[17] O. Goldreich, S. Micali, and A. Wigderson. How to Play ANY Mental Game. In *Proceedings of the Nineteenth Annual ACM Symposium on Theory of Computing*, STOC '87, pages 218–229, New York, NY, USA, 1987. ACM.

[18] Thore Graepel, Kristin Lauter, and Michael Naehrig. ML Confidential: Machine learning on encrypted data. Cryptology ePrint Archive, Report 2012/323, 2012. `https://eprint.iacr.org/2012/323`.

[19] Ehsan Hesamifard, Hassan Takabi, and Mehdi Ghasemi. CryptoDL: Deep neural networks over encrypted data, 2017.

[20] Ehsan Hesamifard, Hassan Takabi, Mehdi Ghasemi, and Catherine Jones. Privacy-preserving machine learning in cloud. In *Proceedings of the 2017 on Cloud Computing Security Workshop*, CCSW '17, page 39–43, New York, NY, USA, 2017. Association for Computing Machinery.

[21] Itay Hubara, Matthieu Courbariaux, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Binarized neural networks. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 4107–4115. Curran Associates, Inc., 2016.

[22] Tyler Hunt, Congzheng Song, Reza Shokri, Vitaly Shmatikov, and Emmett Witchel. Chiron: Privacy-preserving machine learning as a service. *arXiv preprint arXiv:1803.05961*, 2018.

[23] Tyler Hunt, Zhiting Zhu, Yuanzhong Xu, Simon Peter, and Emmett Witchel. Ryoan: A distributed sandbox for untrusted computation on secret data. *ACM Trans. Comput. Syst.*, 35(4), December 2018.

[24] Chiraag Juvekar, Vinod Vaikuntanathan, and Anantha Chandrakasan. GAZELLE: A Low Latency Framework for Secure Neural Network Inference. In *Proceedings of the 27th USENIX Conference on Security Symposium*, SEC'18, pages 1651–1668, Berkeley, CA, USA, 2018. USENIX Association.

[25] Vladimir Kolesnikov and Thomas Schneider. Improved garbled circuit: Free xor gates and applications. In *International Colloquium on Automata, Languages, and Programming*, pages 486–498. Springer, 2008.

[26] Fengfu Li, Bo Zhang, and Bin Liu. Ternary weight networks. *arXiv preprint arXiv:1605.04711*, 2016.

[27] Hanxiao Liu, Karen Simonyan, and Yiming Yang. DARTS: Differentiable architecture search. In *International Conference on Learning Representations*, 2019.

[28] Jian Liu, Mika Juuti, Yao Lu, and N. Asokan. Oblivious neural network predictions via MiniONN transformations. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, CCS '17, pages 619–631, New York, NY, USA, 2017. ACM.

[29] Pratyush Mishra, Ryan Lehmkuhl, Akshayaram Srinivasan, Wenting Zheng, and Raluca Ada Popa. Delphi: A cryptographic inference service for neural networks. Cryptology ePrint Archive, Report 2020/050, 2020. `https://eprint.iacr.org/2020/050`.

[30] P. Mohassel and Y. Zhang. SecureML: A system for scalable privacy-preserving machine learning. In *2017 IEEE Symposium on Security and Privacy (SP)*, pages 19–38, May 2017.

[31] Olga Ohrimenko, Felix Schuster, Cédric Fournet, Aastha Mehta, Sebastian Nowozin, Kapil Vaswani, and Manuel Costa. Oblivious multi-party machine learning on trusted processors. In *USENIX Security Symposium*, 2016.

[32] Pascal Paillier. Public-key cryptosystems based on composite degree residuosity classes. In Jacques Stern, editor, *Advances in Cryptology — EUROCRYPT '99*, pages 223–238, Berlin, Heidelberg, 1999. Springer Berlin Heidelberg.

[33] Hieu Pham, Melody Guan, Barret Zoph, Quoc Le, and Jeff Dean. Efficient neural architecture search via parameters sharing. In Jennifer Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pages 4095–4104, Stockholmsmässan, Stockholm Sweden, 10–15 Jul 2018. PMLR.

[34] Michael O. Rabin. How to exchange secrets with oblivious transfer. Technical Report TR-81, Aiken Computation Lab, Harvard University, 1981.

[35] M. Sadegh Riazi, Mohammad Samragh, Hao Chen, Kim Laine, Kristin Lauter, and Farinaz Koushanfar. XONN: XNOR-based oblivious deep neural network inference. In *28th USENIX Security Symposium (USENIX Security 19)*, pages 1501–1518, Santa Clara, CA, August 2019. USENIX Association.

[36] M. Sadegh Riazi, Christian Weinert, Oleksandr Tkachenko, Ebrahim M. Songhori, Thomas Schneider, and Farinaz Koushanfar. Chameleon: A Hybrid Secure Computation Framework for Machine Learning Applications. In *Proceedings of the 2018 on Asia Conference on Computer and Communications Security*, ASIACCS '18, pages 707–721, New York, NY, USA, 2018. ACM.

[37] B. D. Rouhani, M. S. Riazi, and F. Koushanfar. DeepSecure: Scalable provably-secure deep learning. In *2018 55th ACM/ESDA/IEEE Design Automation Conference (DAC)*, June 2018.

[38] Adi Shamir. How to share a secret. *Commun. ACM*, 22(11):612–613, Nov 1979.

[39] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *Security and Privacy (SP), 2017 IEEE Symposium on*, 2017.

[40] E. M. Songhori, S. U. Hussain, A. Sadeghi, T. Schneider, and F. Koushanfar. TinyGarble: Highly Compressed and Scalable Sequential Garbled Circuits. In *2015 IEEE Symposium on Security and Privacy*, pages 411–428, May 2015.

[41] Florian Tramèr, Fan Zhang, Ari Juels, Michael K Reiter, and Thomas Ristenpart. Stealing machine learning models via prediction APIs. In *USENIX Security*, 2016.

[42] Florian Tramèr and Dan Boneh. Slalom: Fast, verifiable and private execution of neural networks in trusted hardware, 2018.

[43] Marten van Dijk, Craig Gentry, Shai Halevi, and Vinod Vaikuntanathan. Fully homomorphic encryption over the integers. In Henri Gilbert, editor, *Advances in Cryptology – EUROCRYPT 2010*, pages 24–43, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg.

[44] Pengtao Xie, Misha Bilenko, Tom Finley, Ran Gilad-Bachrach, Kristin E. Lauter, and Michael Naehrig. Crypto-Nets: Neural networks over encrypted data. *CoRR*, abs/1412.6181, 2014.

[45] Andrew C. Yao. Protocols for secure computations. In *Proceedings of the 23rd Annual Symposium on Foundations of Computer Science*, SFCS '82, page 160–164, USA, 1982. IEEE Computer Society.

[46] Andrew C. Yao. How to generate and exchange secrets. In *27th Annual Symposium on Foundations of Computer Science (SCFS 1986)*, pages 162–167, Oct 1986.

[47] Barret Zoph and Quoc V. Le. Neural architecture search with reinforcement learning. *CoRR*, abs/1611.01578, 2016.

A Related Work

Several prior work targets the problem techniques for secure machine learning, or build up on existing techniques by trying to optimize bottlenecks.

Homomorphic Encryption. In CryptoNets [12][44], the authors modify the neural network operation by using square function as an activation and average pool instead of maxpool to reduce the non-linear functions to low degree polynomial to control the noise. Similar approaches of using homomorphic encryption on data and optimizing the machine learning operations to limit the noise have been explored extensively [5, 18, 4]. Hesamifard et al. [20] explore using homomorphic encrypted data for training the neural networks. CryptoDL [19] explores various activation functions with low polynomial degree that can work well with homomorphic encrypted data and proposed an activation using the derivative of ReLU function. However, using homomorphic encryption adds to an additional computational overhead and most of the non-linear activations cannot be effectively computed which results in a degradation of the deep learning systems.

Secure Multiparty Computation. Secure multiparty computation requires a very low computation overhead but requires extensive communication between the parties. It has been used for several machine learning operations. DeepSecure [37] only uses GC to compute all the operations in the neural network. They rely on pre-processing of the data by reducing the dimensions to improve the performance and is implemented on the TinyGarble [40] library. Chameleon [36] uses a combination of arithmetic sharing, garbled circuit and boolean sharing to compute the neural networks for secure inference. They rely on third party server to perform computation in the offline phase resulting in better performance than the previous work. XONN [35] leverages Binary Neural Networks with GC. Binarization dramatically reduces the inference latency for the network compared to other frameworks that utilize full-precision weights and inputs, as it converts matrix multiplications into simple XNOR-popcounts. They use TinyGarble library as well to implement the Boolean circuits for GC. Prio [8] uses a secret sharing [38] based protocol to compute aggregate statistics over private data from multiple sources. They deploy a secret-shared non-interactive zero-knowledge proof mechanism to verify whether data sent by clients is well-formed, and then decode summed encodings of clients' data to generate aggregate statistic. They extend the application of Prio to foundational machine learning techniques such as least squares regression.

Hybrid Schemes. A judicious combination of homomorphic encryption and multiparty computation protocol have shown to give some additional benefits in terms of runtime and communication costs. Gazelle [24] uses lattice based Packed Additive homomorphic encryption to compute dot product and convolution but relies on garbled circuits for implementing non-linear operations like Maxpool and ReLU. They reduce the overall bandwidth by packing ciphertexts and re-encryption to refresh the noise budget. Delphi [29] builds upon this work and uses Architecture Search to select optimal replacement positions for expensive ReLU activation function with a quadratic approximation with minimal loss in accuracy. MiniONN [28] pre-computes multiplication triplets using homomorphic encryption for GMW protocol followed by SPDZ [9, 10] protocol. The multiplication triplets are exchanged securely using additive homomorphic encryption like Paillier or DGK. SecureML [30] uses garbled circuits and additive homomorphic encryption to speed up some NN operations. However, the conversion costs between of homomorphic encryption and Yao's garbled circuits is expensive and the performance of homomorphic encryption scales poorly with increasing security parameter [11]. Hence, we rely on only garbled circuit protocol to efficiently compute neural network operations during inference with low communication bandwidth, low computation complexity and low memory footprint using binary neural networks while maintaining the accuracy. Most of the previous work have relied heavily on optimizing the complex cryptographic operations to work well with the neural networks. We show that it is possible to optimize the neural network to get an efficient privacy preserving neural network architectures.

Trusted Computing. Some research uses trusted processors where they assume that the underlying hardware is trustworthy and outsource all the machine learning computations to the trusted hardware. Chiron [22] is a training system for privacy-preserving machine learning as a service which conceals the training data from the operator. It uses Intel Software Guard Extensions (SGX) and runs the standard ML training in an enclave and confines it in a Ryoan sandbox [23] to prevent it from leaking the training data outside the enclave. Ohrimenko et al. [31] propose a solution for secure

multiparty ML by using trusted Intel SGX-enabled processors and used oblivious protocols between client and server where the input and outputs are blinded. However, the memory of enclaves is limited and it is difficult to process memory and computationally intensive operations like matrix multiplication in the enclaves with paralellism. To address this, Slalom [42] provides a methodology to outsource the matrix multiplication to a faster untrusted processor and verify the computation.

B Selecting the Cryptographic Primitive

In designing SOTERIA, we make several design choices with the goal of achieving efficiency. The most important among them is the selection of the underlying cryptographic primitive to ensure privacy of data. Several cryptographic primitives such as partially homomorphic encryption schemes (PHE) and fully homomorphic encryption schemes (FHE), Goldreich-Micali-Widgerson protocol (GMW), arithmetic secret sharing (SS), and Yao's garbled circuit (GC) have been proposed to enable two-party secure computation. Each of these primitives perform differently with respect to the factors such as efficiency, functionality, required resources and so on. PHE schemes allow either addition or multiplication operations but not both on encrypted data [32, 13]. In contrast, FHE schemes enable both addition and multiplication on encrypted data [16, 15, 43, 6] but incur huge performance overhead. SS involves distributing the secret shares among non-trusting parties such that any operation can be computed on encrypted data without revealing the individual inputs of each party [3]. GMW [17] and GC [45] allow designing boolean circuits and evaluating them between a client and a server. The differences between these schemes might make it difficult to decide which primitive is the best fit for designing a privacy-preserving system for a particular application. Therefore, we first outline the desirable properties specifically for private neural network inference and then compare these primitives with respect to these properties (see Table 3). We select a cryptographic scheme that satisfies all our requirements.

	PHE	FHE	SS	GMW	GC
Expressiveness	×	✓	✓	✓	✓
Efficiency	✓	×	✓	✓	✓
Communication (One time setup)	✓	✓	×	×	✓

Table 3: Properties of secure computation cryptographic primitives: Partially and fully homomorphic encryption schemes (PHE, FHE), Goldreich-Micali-Widgerson protocol (GMW), arithmetic secret sharing (SS), and Yao's garbled circuit (GC).

Expressiveness. This property ensures that the cryptographic primitive supports encrypted computation for a variety of operations. With the goal to enable private computation for neural networks, we examine the type of computations required in deep learning algorithms. Neural network algorithms are composed of linear and non-linear operations. Linear operations include computation required in the execution of fully-connected and convolution layers. Non-linear operations include activation functions such as Tanh, Sigmoid and ReLU. The research in deep learning is at its peak with a plethora of new models being proposed by the community to improve the accuracy of various tasks. Hence, we desire that the underlying primitive should be expressive with respect to any new operations used in the future as well. PHE schemes offer limited operations (either addition or multiplication) on encrypted data. This limits their usage in applications that demand expressive functionalities such as neural network algorithms. Alternative approaches such as FHE, SS, GMW and GC protocols allow arbitrary operations.

Computation Efficiency. Efficiency is one of the key factors while designing a client-server application such as a neural network inference service on the cloud. FHE techniques have shown to incur orders of magnitude overhead for computation of higher-degree polynmials or non-linear functions. Existing approaches using FHE schemes have restricted its use to compute only linear functions. However, most of the neural network architectures such as CNNs have each linear layer followed by a non-linear layer. To handle non-linear operations, previous solutions either approximate them to linear functions or switch to cryptographic primitives that support non-linearlity [12, 30, 24, 29]. Approximation of non-linear functions such as ReLU highly impacts the accuracy of the model. Switching between schemes introduces additional computation cost which is directly proportional to the network size. In comparison to FHE, research has shown that SS, GMW and GC schemes provide constructions with reasonable computation overhead for both linear and non-linear operations.

Communication Overhead. The communication costs incurred for private computation contribute to the decision of selecting our cryptographic primitive, as the network should not become a bottleneck in the execution of the private machine learning as a service. We expect the client and server to interact only once during the setup phase and at the end of the execution to receive the output. We aim to remain backward compatible to the existing cloud service setting where the client does not need to be online at all time between the request and response. In contradiction to this property, the GMW scheme requires communication rounds proportional to the depth of the circuit. To evaluate every layer with an AND gate, the client and server have to exchange secrets among them forcing the client to be online throughout the execution. Similarly, construction of non-linear bitwise functions with arithmetic secret shares require communication rounds logarithmic to the number of bits in the input. This makes the use of these schemes almost infeasible in the cloud setting that have a high-latency network. Unlike these primitives, Yao's garbled circuits combined with recent optimizations require an exchange of data only once at the beginning of the protocol.

We select GC as our underlying cryptographic primitive in SOTERIA as it satisfies all the desired properties for a designing private inference for cloud service applications.

C Garbled Circuit for Efficient Neural-Networks

We investigate the problem of performing private inference on neural networks. Let W be the model parameters stored on the server, x be the client's input, y be the expected output and f is the inference function to be computed. Given this, we want to compute $f(x;\theta) \rightarrow y$. We aim for the following main goals:

- *Confidentiality:* The solution should preserve confidentiality of the model parameters θ from the users and that of x and y from the server. We assume an honest-but-curious threat model.
- *Accuracy:* The drop in accuracy of the privately computed inference function should be negligible as compared to the accuracy of the model on plaintext data.
- *Performance:* The private computation should demonstrate acceptable performance (runtime and communication) overhead.

Garbled circuits. GC protocol allows construction of any function as a boolean circuit with a one time setup cost of data exchange [46]. In our setting, the client is the *garbler* and the server is the *evaluator*. In the setup phase, the client first transforms the function into a boolean circuit with two-input gates. The function (model architecture) and the circuit are known to both the parties, but its parameters and input are private. The client then garbles the circuit. This process involves creating a garbled computation table (GCT), which is an encrypted version of the truth table for the boolean circuit. The entries for this table are randomly permuted, so that the order does not leak information. The client then shares the garbled circuit and its encrypted inputs to the circuit (binary values representing x) with the server. In the next phase, the parties perform an oblivious transfer (OT) protocol [34], so the server obtains the encryption of its inputs to the circuit (binary values representing W), without leaking information about its parameters to the client. Then, the server evaluates the circuit, and obtains the output value which is encrypted. The server transfers the output to the client which can match the encrypted values to their plaintext and obtain $f(x;\theta)$.

Performance. In GC, the communication and computation overhead is directly dependent on the number of AND, OR gates in the boolean circuit. Prior research has proposed several techniques that make it free for the GC to execute XOR, XNOR and NOT gates [25]. Given this prior work, the communication overhead of the GC protocol for a given circuit is proportional to its security parameter and the number of non-XOR gates in the circuit. The total runtime for evaluating a circuit is the sum of the time required during the **online** (evaluation) and **offline** (garbling and oblivious transfer) computation.

Efficient neural networks. In SOTERIA, we leverage the above-mentioned properties of GC to design an optimized neural network algorithm. Neural network algorithms are shown to be flexible with respect to their architectures i.e., multiple models with different configuration can achieve a similar level of accuracy. We take advantage of this observation and propose designing neural

network **architectures** that help optimize the performance of executing inference with garbled circuits. The number of gates in a circuit corresponding to a neural network depends on its activation functions and the size of its parameter vector.

Neural networks have shown to exhibit relatively high accuracy for various tasks even with low precision parameters. **Binary neural networks** [21] are designed with the lowest possible size for each parameter, i.e., one bit to represent $\{-1, +1\}$ values. Using BNNs naturally aligns with our selected cryptographic primitive because each wire in garbled circuits represents 1 bit value (representing -1 in the model with 0 in the circuit). Binarizing the model parameters further allows us to heavily use the free XOR, XNOR and NOT gates in garbled circuits, thus minimizing the computation and communication overhead of private inference. This has recently been shown in the performance evaluation of garbled circuits on binary neural networks [35].

In neural networks, **linear functions** such as those used in the convolutional or fully connected layers form an important part of the network. These functions involve dot product vector multiplications. Instead of using multiplications, this can be computed very efficiently using XNOR-popcount: $\mathbf{x} \cdot \mathbf{w} = 2 \times \text{bitcount}(\text{xnor}(\mathbf{x}, \mathbf{w})) - N$, where $N = |\mathbf{x}|$. In binary neural networks, the output of activation functions is also binary. But, the output of XNOR-popcount is not a binary number, thus, according to BNN algorithms one would need to compare it with 0; positive numbers will be converted to 1 and negative numbers will be converted to 0.

We can compute some **non-linear functions** such as maxpool very efficiently in BNNs. Max-pooling is a simple operation which returns the maximum value from a vector, which in the case of neural networks is usually a one-dimensional representation of a 2D max-pooling window. In binary neural networks, maxpool need to simply return 1 if there is a 1 in the vector. This is achieved by a logical OR-operation over the elements of the vector.

To achieve a learning capacity for binary neural networks similar to full-precision models, we would need to scale up the the number of model parameters. We can increase the number of kernels in a convolution layer and the number of nodes in a fully connected layer, by a given **scaling factor**. This technique has been used in the prior work [35], and enables learning more accurate models, however at the cost of increasing the number of computations in the network.

D Implementation and Experiments

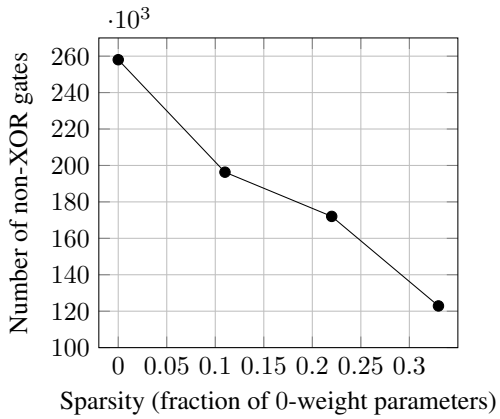
D.1 Experimental Setup

We evaluate our work on MNIST and CIFAR10 image classification datasets, as they have been extensively used in the literature to evaluate the performance of cryptographically secure neural network schemes. We run our experiments on an AWS c5.2xlarge instance, running Ubuntu 18.04 LTS on an Intel Xeon 8124M at 3.0 GHz. We use PyTorch 1.3 [1], a python-based deep learning framework to implement our architecture search algorithm and train the ternary models. We use Synopsys Design Compiler [2], version L-2016.03-SP5-2, to synthesize SystemVerilog code into the gate-level netlist. Our synthesis runs the TinyGarble gate library infrastructure[1]. We compute the number of non-XOR gates in the generated boolean circuit netlist as a measure of its complexity. We measure the exact performance of SOTERIA as its runtime during the offline and online phases of the protocol, and its communication cost. We present the experimental setup of prior work and SOTERIA, including their CPU specification and link to available software codes, in Table 7 in Appendix G. We also present the details of all neural network architectures which we evaluate in this paper in Table 6 in Appendix F.

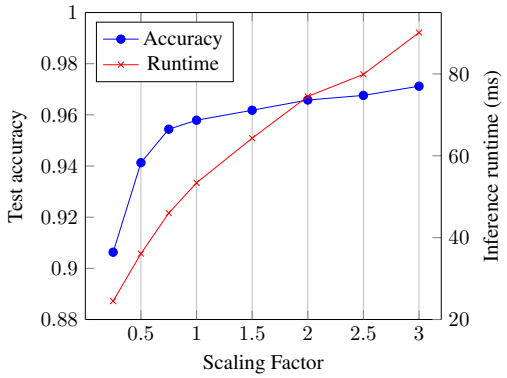
D.2 Implementation

To handle conversion of the model into a digital circuit supported by TinyGarble, we first build a representation of the model and parameters in SystemVerilog, and then synthesize and optimize our circuit (using Synopsys Design Compiler) to use circuit elements supported by TinyGarble. In this first step, we designed a collection of parameterized components (notably dot product, and maxpool) to use as building blocks our architecture search algorithm. Each component is flexibly designed to

[1]We use TinyGarble with 21ecca7cb75b33fd7508771fd35f03657dd44e5e gitid on `https://github.com/esonghori/TinyGarble` master branch.



(a) Sparsity of a model versus its circuit complexity.



(b) Test accuracy versus inference runtime.

Figure 3: (a) We measure sparsity as the fraction of model parameters with 0 weight. We quantify circuit complexity as the number of non-XOR gates. The numbers are computed on a ternary neural network with a 3×3 convolution operation with 4 kernels and a $32 \times 32 \times 3$ input. For this experiment, we assign 0 weights to a random set of parameters, to get different levels of sparsity and corresponding number of non-XOR gates. (b) Test accuracy versus inference runtime for a ternary neural network trained on a fixed MNIST (m1) architecture, in various scale. See Appendix F for description of the model.

efficiently accept arbitrary size input and output, and is composed to form the complete model. In a general setting, hardware-level code is typically straight-forward to generate. However, to enable TNNs with SOTERIA, we have to dynamically define the sparsity of the modules depending on the result of model training and architecture search. Along with the parameter data, we define the sparsity information which is used during `generate` phases in SystemVerilog to build the sparse network in hardware (taking advantage of the 0-valued parameters of the model).

E Performance of Garbled Circuits on Ternary Neural Networks

We perform two experiments to illustrate the benefit of the sparsity (fraction of parameters with weight 0) of ternary models. Further, we analyze the effect of the scale of the network in the tradeoff between model accuracy and performance of private inference.

Sparsity. Figure 3a shows the number of non-XOR gates for a toy example: a 4-kernel 3×3 convolution operation taking input of size $32 \times 32 \times 3$ with padding sized 1 ternary neural network. We randomly set a fraction of parameters to zero to manually control the sparsity of the model. A BNN model is equivalent to the case where the sparsity is 0. We observe that as the sparsity increases the number of non-XOR gates decrease with almost the same factor. This can result in reducing both the communication overhead and the inference runtime, as we will see in training large models.

Note that while training a TNN, we cannot control the sparsity of the network. In Table 5, we show the result of training binary and ternary models on MNIST dataset, model architecture m3. The table reports the GC costs of the components of the network for both BNNs and TNNs. We can observe that the ternary model has a significant sparsity (about 0.3). This results in constructing smaller circuits for the model, which reduces the inference cost of using GC protocol over ternary neural networks. This is reflected in the smaller number of non-XOR gates in the ternary circuits constructed on convolution and fully connected operations. The costs for maxpool operation will remain the same, as it does not have any learnable parameter.

Scale. As discussed in Section C, we need to scale the network operations to achieve a higher capacity for binary and ternary models and obtain better accuracies. Figure 3b demonstrates the impact of scale of the network on accuracy of the model and its GC runtime for private inference. Although inference time increases linearly with the scaling factor, accuracy improves upto a certain extent with scaling (scaling factor of 1) and then becomes almost constant. This denotes that we can select a sweet spot for scaling factor thereby optimizing for both accuracy and performance.

Table 5: Performance of inference on garbled circuit models with binary versus ternary parameters. We show the independent offline and online runtimes, communication costs and number of non-XOR gates for three different types of operations. The operations are taken from MNIST (m3) network, trained in both binary (BNN) and ternary (TNN) configurations using a scaling factor of 1.

Operation Type	Size	Runtime (ms)						Communication (KB)		Number of non-XOR gates		TNN Sparsity
		Offline		Online		Total						
		BNN	TNN	BNN	TNN	BNN	TNN	BNN	TNN	BNN	TNN	
Convolution	Input: $12 \times 12 \times 16$ Padding: 0 Window: 5×5 Kernels: 16	39.16	28.27	52.87	38.17	92.03	66.43	2,572	1,876	589,824	425,558	0.27
Maxpool	Input: $8 \times 8 \times 16$ Window: 2×2	0.35		0.57		0.92		34		768		N.A.
Fully Connected	Input: 100 Nodes: 10	0.49	0.34	0.83	0.60	1.32	0.94	68	47	3150	2246	0.35

Table 4 shows how scaling factor affects the number of parameters in the network. As the scaling factor in TNNs increases, the accuracy increases. However, with diminishing returns after a certain limit. The inference cost of the circuit also increases, as is evident from the growth of runtime with change in scaling factor. Note that the sparsity is about 0.24 for scaling factor 3 for the ternary neural network, which means that the effective size of the model (hence its performance cost) remains comparable to a binary neural network (without any scaling), albiet with better accuracy. As a reference, the test accuracy of a BNN model with the same architecture is 0.9514.

Table 4: Number of parameters and corresponding sparsity and trained model test accuracy for MNIST (m1) architecture with various levels of scaling factor. The table reports the statistics of the experiment in Figure 3b.

Scaling Factor	Total no. of Parameters	No. of 0-weights	Sparsity	Accuracy
0.25	26,432	5,946	0.22	0.9063
0.50	54,912	13,058	0.24	0.9413
0.75	85,440	18,703	0.22	0.9544
1.00	118,016	25,317	0.21	0.9579
1.50	189,312	43,428	0.23	0.9618
2.00	268,800	58,040	0.22	0.9658
2.50	356,480	83,451	0.23	0.9676
3.00	452,352	107,343	0.24	0.9712

Comparison with prior work. We present the outcome of basic SOTERIA on *fixed* model architectures which are used in the literature, thus only discussing the effect of sparsity of ternary neural networks on the tradeoff between accuracy and performance costs (shown in Table 2). We use three different architectures for each of the two datasets, which have been used in existing work. m1-3 are used with the MNIST dataset, while m4-6 are used with the CIFAR10 dataset. See Appendix F for the descriptions of model architectures. We use the same scaling factors for our networks as used by [35], which is the only other comparable work with quantized (binary) weights and inputs, for a fair comparison. We observe that for MNIST datasets, the basic TNN SOTERIA models (m1-m3) provide better runtime and communication performance on average than prior work with maximum drop in accuracy of only 0.016 (for model m3). This shows that SOTERIA is useful in designing custom models that provide optimal performance guarantees while retaining high prediction accuracy. For CIFAR10 datasets, we observe that for models used in prior work (m4 to m6), our basic TNN models exhibit a slightly higher drop in accuracy of 0.8, but provide a computation and communication gain, on average, as compared to prior work. Overall, our results show that SOTERIA provides a flexible approach of training private models given the constraint on performance and accuracy of the model.

F Specifications of the Model Architectures

Table 6: Model architectures used in our experiments. Models m1-6 are used in the prior work on MNIST and CIFAR10 datasets, and we constructed the SOTERIA models using our regularized architecture search algorithm.

	Type	Kernels/ Nodes
	MNIST (m1)	
1	FC	128
2	FC	128
3	FC	10
	MNIST (m2)	
1	CONV 5×5	5
2	FC	100
3	FC	10
	MNIST (m3)	
1	CONV 5×5	16
2	MAXPOOL 2×2	-
3	CONV 5×5	16
4	MAXPOOL 2×2	-
5	FC	100
6	FC	10
	CIFAR10 (m4)	
1	CONV 3×3	64
2	CONV 3×3	64
3	MAXPOOL 2×2	-
4	CONV 3×3	64
5	CONV 3×3	64
6	MAXPOOL 2×2	-
7	CONV 3×3	64
8	CONV 1×1	64
9	CONV 1×1	16
10	FC	10

	Type	Kernels/ Nodes
	CIFAR10 (m5)	
1	CONV 3×3	16
2	CONV 3×3	16
3	CONV 3×3	16
4	MAXPOOL 2×2	-
5	CONV 3×3	32
6	CONV 3×3	32
7	CONV 3×3	32
8	MAXPOOL 2×2	-
9	CONV 3×3	48
10	CONV 3×3	48
11	CONV 3×3	64
12	MAXPOOL 2×2	-
13	FC	10
	CIFAR10 (m6)	
1	CONV 3×3	16
2	CONV 3×3	32
3	CONV 3×3	32
4	MAXPOOL 2×2	-
5	CONV 3×3	48
6	CONV 3×3	64
7	CONV 3×3	80
8	MAXPOOL 2×2	-
9	CONV 3×3	96
10	CONV 3×3	96
11	CONV 3×3	128
12	MAXPOOL 2×2	-
13	FC	10

	Type	Kernels/ Nodes
	CIFAR10 (SOTERIA) $\lambda = 0$, No. of cells = 3, No. of operations per cell = 4	
1	CONV 5×5	16
2	MAXPOOL 2×2	-
3	CONV 5×5	16
4	CONV 5×5	16
5	CONV 5×5	32
6	MAXPOOL 2×2	-
7	CONV 5×5	32
8	CONV 5×5	32
9	CONV 5×5	64
10	MAXPOOL 2×2	-
11	CONV 5×5	64
12	CONV 5×5	64
13	FC	10
	MNIST (SOTERIA) $\lambda = 0$, No. of cells = 1, No. of operations per cell = 4	
1	CONV 5×5	16
2	CONV 5×5	16
3	CONV 5×5	16
4	CONV 5×5	16
5	FC	100
6	FC	10

	Type	Kernels/ Nodes
	CIFAR10 (SOTERIA) $\lambda = 0.6$, No. of cells = 3, No. of operations per cell = 4	
1	CONV 3×3	16
2	CONV 3×3	16
3	CONV 3×3	16
4	MAXPOOL 2×2	-
5	CONV 3×3	32
6	CONV 3×3	32
7	CONV 3×3	32
8	MAXPOOL 2×2	-
9	CONV 3×3	64
10	CONV 3×3	64
11	CONV 3×3	64
12	MAXPOOL 2×2	-
13	FC	10
	MNIST (SOTERIA) $\lambda = 0.6$, No. of cells = 1, No. of operations per cell = 4	
1	CONV 3×3	16
2	CONV 3×3	16
3	MAXPOOL 2×2	-
4	CONV 5×5	16
5	FC	100
6	FC	10

G Details for Experimental Evaluation for Prior Work

Table 7: Overview of the existing private inference methods, including the cryptographic schemes used, precision of neural networks supported, number of parties involved, evaluation setup configuration and availability of code.

Prior Work	Cryptographic Scheme	Model Precision	Parties	Performance Evaluation Setup			Code
				CPU	CPU Mark (Single Thread)[f]	Relative CPU Mark	
MiniONN [28]	Additively HE, GC	Full	2	Server: Intel Core i5 4 × 3.30 GHz cores Client: Intel Core i5 4 × 3.20 GHz cores	1,686-2,300	0.61-0.83	Available[a]
EzPC [7]	GC, Additive SS	Full	2	Intel Xeon E5-2673 v3 2.40GHz	1,723	0.62	Available[b]
DeepSecure [37]	GC	16-bit fixed-point	2	Intel Core i7-2600 3.40GHz	1,737	0.63	–
SecureML [30]	Linear HE, GC	Full	2	AWS c4.8xlarge (Intel Xeon E5-2666 v3 2.90 GHz)	1,918	0.69	–
Gazelle [24]	Additively HE, GC	Full	2	AWS c4.xlarge (Intel Xeon E5-2666 v3 2.90GHz)	1,918	0.69	–
Delphi [29]	Additively HE, GC	Full	2	AWS c5.2xlarge (Intel Xeon 8000 series 3.0 GHz)	2,082	0.75	Available[c]
SOTERIA	GC	Ternary	2	AWS c5.2xlarge (Intel Xeon 8124M 3.0 GHz)	2,082	0.75	Available[d]
Chameleon [36]	GC, GMW, Additive SS	Full	3[e]	Intel Core i7-4790 3.60GHz	2,266	0.82	–
XONN [35]	GC	Binary	2	Intel Core i7-7700k 4.5GHz	2,777	1.0	–

[a] MiniONN: `https://github.com/SSGAalto/minionn`
[b] EzPC: `https://github.com/mpc-msri/EzPC`
[c] Delphi: `https://github.com/mc2-project/delphi`
[d] SOTERIA: `https://github.com/privacytrustlab/soteria_private_nn_inference`
[e] Chameleon only uses the third party in pre-processing stage.
[f] CPU mark: The configurations are listed with their the single-threaded CPU Mark scores as reported by `cpubenchmark.net/singleThread.html`. These single-thread benchmarks test processors on a variety of tasks, from floating point operations, string sorting and data compression (`https://www.cpubenchmark.net/cpu_test_info.html`) to provide an estimate of the capabilities of a processor. As microarchitectural optimizations vary from processor to processor, frequency alone cannot be used as a performance metric. The absolute scores and relative scores (compared to the highest scoring CPU in the table) for CPUs used in evaluation of related work are reported.