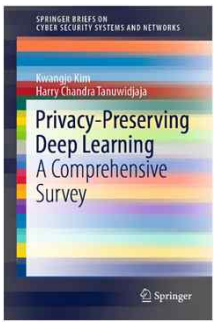
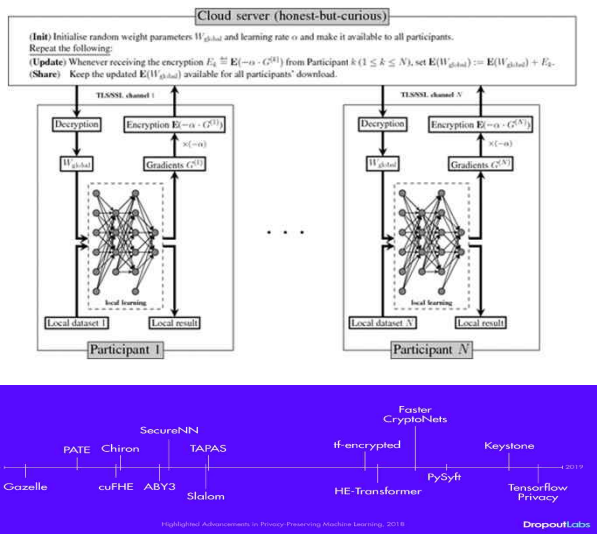
Part II: Survey on Deep Learning Techniques for Privacy-Preserving



Kwangjo Kim, Harry Chandra Tanuwidjaja, "Privacy-preserving Deep Learning – A Comprehensive Survey", ISBN 978-981-16-3763-6, 2021, Springer

Background



Contents of my book

This monograph aims to give a survey on the state-of-the-art of Privacy-Preserving Deep Learning (PPDL), which is considered to be one of emerging technologies by combining classical privacy preserving and cryptographic protocols with deep learning in a systematic way.

Google and Microsoft announced a big investment in PPDL in the early 2019, followed by the announcement of "Private Join and Compute", an open source PPDL tools that based on Secure Multi Party Computation (Secure MPC) and Homomorphic Encryption (HE) on June 2019 by Google. One of main issues in PPDL is about its applicability, e.g., to understand the gap between the theory and practice exists. In order to solve this, there are many advances relying on the classical privacy-preserving method (HE, secure MPC, differential privacy, secure enclaves and its hybrid) and together with deep learning. The basic architecture of PPDL is to build a cloud framework that enables collaborative learning while keeping the training data on the client device. After the model is fully trained, the privacy during the sensitive data exchange or storage must be strictly preserved and the overall framework must be feasible for the real applications.

This monograph plans to provide the fundamental understandings for privacy-preserving and deep learning, followed by comprehensive overview of the state-of-the-art of PPDL methods, suggesting the pros-and-cons of each method, and introducing the recent advances of the federated learning and split learning-based PPDL called as Privacy-Preserving Federated Learning (PPFL). In addition, this monograph gives a guideline to general people and students, and practitioners who are interested to know about PPDL and also helping early stage researcher who wants to explore PPDL area. We hope that the early stage researchers can grasp the basic theory of PPDL, understand the pros and cons of current PPDL and PPFL methods, addressing the gap between theory and practice in the most recent approach, so that they can propose their own method later.

Daejeon, Republic of Korea
March 2021

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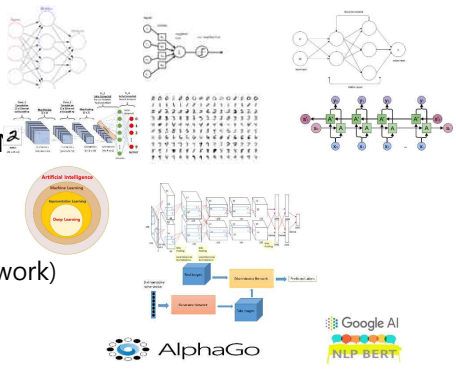
Harry Chandra Tanuwidjaja

History of Deep Learning : Ideas and Milestone

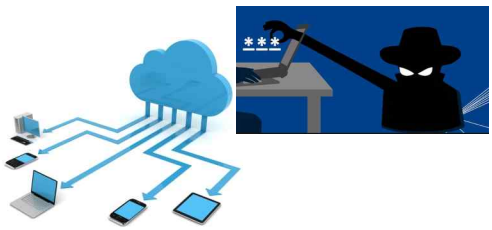
- 1943: Neural networks
- 1957: Perceptron
- 1974-86: Backpropagation, RBM, RNN
- 1889-98: CNN, MNIST, Bidirectional RNN
- 2006: Deep Learning
- 2009: Image Net
- 2012: AlexNet, Dropout
- 2014: GAN (Generative Adversarial Network)
- 2014: DeepFace
- 2016: AlphaGo
- 2018: AlphaZero, Capsule Networks
- 2018 : BERT(Bidirectional Encoder Representations from Transformers) by Google



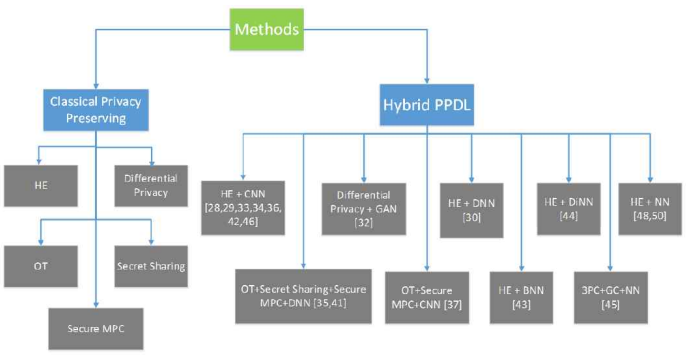
https://deeplearning.mit.edu

Why we need Privacy-Preserving Deep Learning?

- Advances of **machine learning**
- Users (Data Owner) submit data to the trustful cloud server who want to get useful statics of users
- Data **privacy** during **training**
- Solution?
  - **Privacy Preserving Deep Learning (PPDL)**



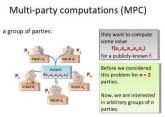
Our Classification

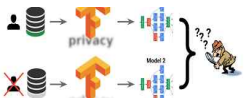


Acronym	Definition
PP	Privacy Preserving
DL	Deep Learning
HE	Homomorphic Encryption
OT	Oblivious Transfer
MPC	Multi Party Computing
CNN	Convolutional Neural Network
DNN	Deep Neural Network
BNN	Binary Neural Network

Classical Privacy-Preserving Technology

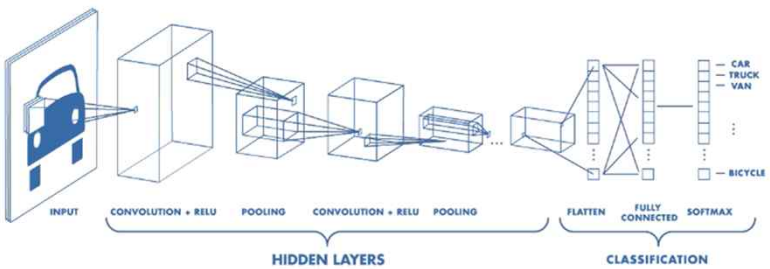
- Homomorphic Encryption
  - Support **operations** on encrypted data without private key
  - **Not directly applicable** to DL
- Secure Multi-party Computation
  - Joint computation of f( ), keeping each input to be **secret**
- Differential Privacy
  - Keeping privacy before and after PP
  - Release statistics **without revealing data**





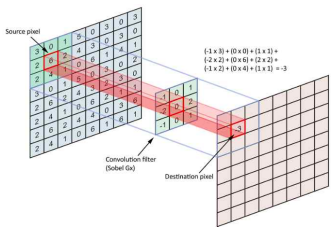
Deep Learning in Privacy-Preserving Technology(2/2)

- Convolutional Neural Network (CNN)



Deep Learning Layers(1/5)

- Convolutional Layer
  - Apply a convolution operation to the input, **passing the result** to the next layer.
  - **Dot product** operation
  - Can be used **directly** in HE

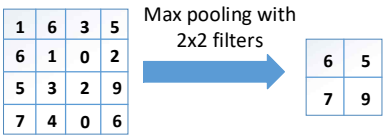


Deep Learning Layers(2/5)

- Activation Layer
  - **Non-linear** function that applies mathematical process on the output of convolutional layer.
  - Activation function: ReLU, Sigmoid, Tanh
  - Non-linear -> **high complexity**

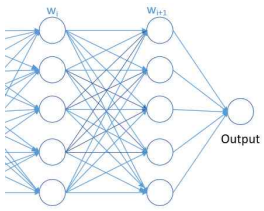
Deep Learning Layers(3/5)

- Pooling Layer
  - A sampling layer, whose purpose is to reduce the size of data
  - **Cannot** use max pooling in HE
  - Solution? **Average pooling**



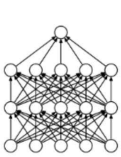
Deep Learning Layers(4/5)

- Fully Connected Layer
  - **Each** neuron in this layer is **connected** to neuron in previous layer
  - The connection represents the **weight of the feature** like a complete graph
  - **Dot product** function
  - Can be **used directly** in HE

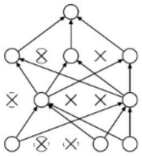


Deep Learning Layers(5/5)

- Dropout Layer
  - **Reduce overfitting**, act as regularizer
  - Not using all neurons
  - **Drops** some neurons **randomly**



Standard neural network



Neural Network after applying dropout

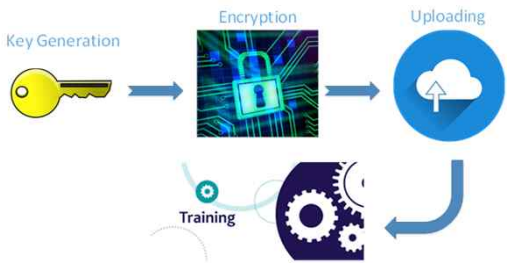
X-based Hybrid PPDL

- HE-based Hybrid PPDL
- Secure MPC-based Hybrid PPDL
- Differential Privacy-based Hybrid PPDL

HE-based Hybrid PPDL

HE-based Hybrid PPDL(1/10)

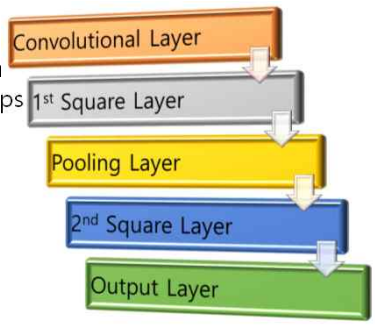
- ML Confidential: Machine Learning on Encrypted Data
  - **Polynomial approximation** as activation function
  - Cloud based scenario
  - Homomorphic encryption
  - Data is transferred to server
  - Cloud server do training process



T. Graepel, K. Lauter, and M. Naehrig, "ML confidential: Machine learning on encrypted data," International Conference on Information Security and Cryptology, pp. 1-21, 2012.

HE-based Hybrid PPDL(2/10)

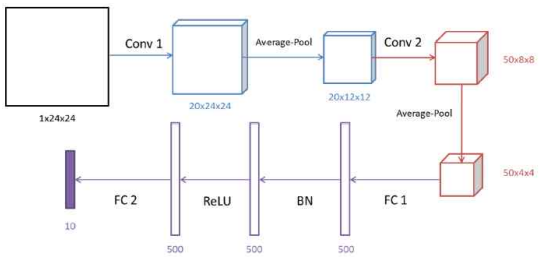
- Cryptonets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy
  - Protect data exchange in cloud service
  - Apply CNN to homomorphically encrypted data
  - **Weakness**: error rate increase and accuracy drops
    - When?
    - If the number of non linear layer is big



R. Gilad-Bachrach, N. Dowlin, K. Laine, K. Lauter, M. Naehrig, and J. Wernsing, "Cryptonets: Applying neural networks to encrypted data with high throughput and accuracy," In ternational Conference on Machine Learning, pp. 201-210, 2016.

HE-based Hybrid PPDL(3/10)

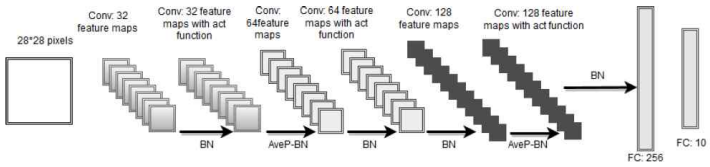
- Privacy-Preserving on Deep Neural Network
  - Cloud service environment
  - Combining HE with CNN
  - **Solve Cryptonets problem**
  - Polynomial approximation
  - Batch normalization layer



H. Chabanne, A. de Wargny, J. Milgram, C. Morel, and E. Prou, "Privacy-preserving classification on deep neura l network," IACR Cryptology ePrint Archive, p. 35, 2017.

HE-based Hybrid PPDL(4/10)

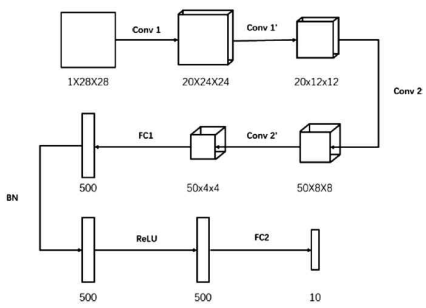
- CryptoDL: Deep Neural Networks Over Encrypted Data
  - Modified CNN for encrypted data with HE
  - **Approximation technique**:
    - Taylor series (Acc 40%)
    - Chebysev polynomial (Acc 70%)
    - Derivative of activation function **(Acc 99.52%)**



E. Hesamifard, H. Takabi, and M. Ghasemi, "Cryptodl: Deep neural networks over encrypted data," arXiv preprint, vol. 1711.051 89, 2017.

HE-based Hybrid PPDL(5/10)

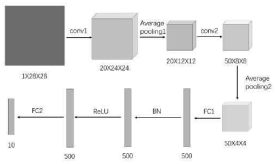
- Privacy-Preserving All Convolutional Net Based on Homomorphic Encryption
  - PP technique on CNN by using HE
  - Adding **batch normalization layer**
  - **Polynomial approximation**
  - Convolution layer with **increased stride**

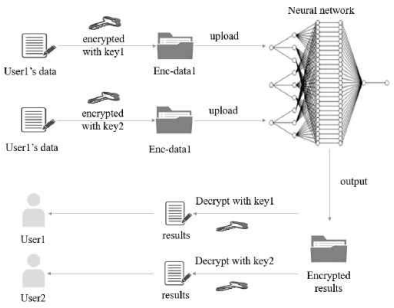


W. Liu, F. Pan, X. A.Wang, Y. Cao, and D. Tang, "Privacy-preserving all convolutional net based on homomorphic encryption," International Conference on Network-Based Information Systems, pp. 752-762, 2018.

HE-based Hybrid PPDL(6/10)

- Distributed Privacy-Preserving Multi-Key Fully Homomorphic Encryption
  - Substituting ReLU function with low degree polynomial
  - Using batch normalization layer
  - Max pooling -> **average pooling**
  - Beneficial for classifying **large scale distributed data**

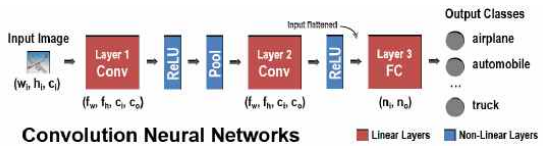




H. Xue, Z. Huang, H. Lian, W. Qiu, J. Guo, S. Wang, and Z. Gong, "Distributed large scale privacy-preserving deep mining," IEEE Third International Conference on Data Science in Cyberspace, pp. 418-422, 2018.

HE-based Hybrid PPDL(7/10)

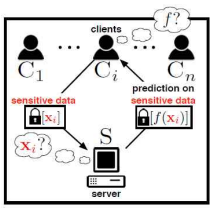
- Gazelle: A Low Latency Framework for Secure Neural Network Inference
  - Able to switch protocol between HE and GC in PaaS scenario.
  - Structure: two convolutional layers, two ReLU layers, one pooling layer, and one fully connected layer.
  - Hide the weight, bias, and stride size in the convolutional layer.
  - Limit the number of classification queries from client to prevent linkage attack.



C. Juvekar, V. Vaikuntanathan, and A. Chandrakasan, "GAZELLE: A Low Latency Framework for Secure Neural Network Inference." 27th USENIX Security Symposium , pp. 1651-1669, 2018.

HE-based Hybrid PPDL(8/10)

- Tapas
  - Accelerate parallel computation using encrypted data in PaaS environment.
  - Current problem: large amount of processing time needed.
  - Main contribution:
    - New algorithm to speed up binary computation in Binary Neural Network (BNN).
  - Their technique can be parallelized by evaluating gates at the same Level for three representations at the same time -> **time improved drastically**



A. Sanyal, M.J. Kusner, A. Gascn, and V. Kanade, "TAPAS: Tricks to Accelerate (Encrypted) Prediction as a Service." arXiv preprint, arXiv:1806.03461, 2018.

HE-based Hybrid PPDL(9/10)

- FHE DiNN
  - Reduce complexity problem in HE+NN
  - Deeper network, more complexity
  - Use bootstrapping -> linear complexity of NN
  - How to do it?
    - Discretize the weight, bias value, and the domain of activation function.
    - Using sign activation function to limit the growth of signal in the range of [-1,1]

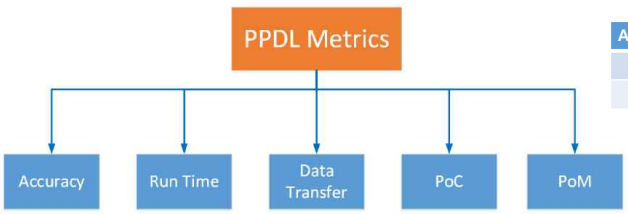
F. Bourse, M. Minelli, M. Minihold, and P. Paillier, "Fast Homomorphic Evaluation of Deep Discretized Neural Networks," Springer, Cham, 2018

HE-based Hybrid PPDL(10/10)

- E2DM
  - PPDL framework that performs matrix operations on HE system
  - Encrypts a matrix homomorphically, then do arithmetic operations on it.
  - Reduce complexity of matrix multiplication
    - O(d) complexity for dot product between two d x d matrices
    - instead of $O(d^2)$ complexity.
  - Leverage CNN with one convolutional layer, two fully connected layers, and a square activation function.

X. Jiang, M. Kim, K. Lauter, and Y. Song, "Secure Outsourced Matrix Computation and Application to Neural Networks," in Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, pp. 1209-1222, ACM, 2018.

Metrics for Comparison



Acronym	Definition
PoC	Privacy of Client
PoM	Privacy of Model

- Accuracy: % of **correct prediction** made by used PPDL
- Run time: the total **time of encryption**, sending data from client to server, and classification process.
- Data transfer: the **amount of data** transferred from client to server.
- PoC: **neither the server or any other party knows** about **client** data.
- PoM: **neither the client or any other party knows** about the classification **model** used in server.

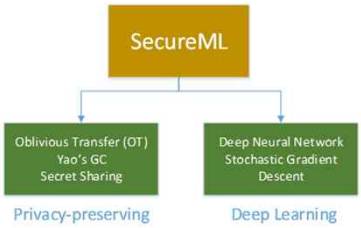
Comparison of HE-based PPDL

Scenario	Proposed Schemes	DL Technique	Accuracy (%)	Run Time (s)	Data Transfer (Mbytes)	PoC	PoM
Cloud Service	ML Confidential [30]	DNN	Bad (95.00)	Bad (255.7)	-	Yes	No
	Cryptonets [33]	CNN	Good (98.95)	Bad (697)	Bad (595.5)	Yes	No
	PP on DNN [34]	CNN	Good (99.30)	-	-	Yes	No
	E2DM [46]	CNN	Good (98.10)	Good (28.59)	Good (17.48)	Yes	Yes
Image Recognition	CryptoDL [28]	CNN	Good (99.52)	Bad (320)	Bad (336.7)	Yes	No
	PP All Convolutional Net [29]	CNN	Good (98.97)	Bad (477.6)	Bad (361.6)	Yes	No
Content Sharing	Distributed PP Multi-Key FHE [38]	CNN	Good (99.73)	-	-	Yes	No
PaaS	Gazelle [42]	CNN	-	Good (0.03)	Good (0.5)	Yes	Yes
	Tapas [43]	BNN	Good (98.60)	Good (147)	-	Yes	Yes
	FHE-DNN [44]	DiNN	Bad (96.35)	Good (1.64)	-	Yes	Yes

Secure MPC-based Hybrid PPDL

MPC-based Hybrid PPDL(1/4)

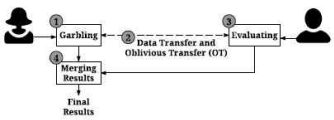
- SecureML: A System for Scalable Privacy-Preserving Machine Learning
  - Based on **OT, Yao's GC, and secret sharing**
  - The sender of message remains oblivious
    - whether the receiver has got the message or not
  - **Linear regression and logistic regression**
  - Optimum value of regression?
    - Stochastic Gradient Descent (SGD)

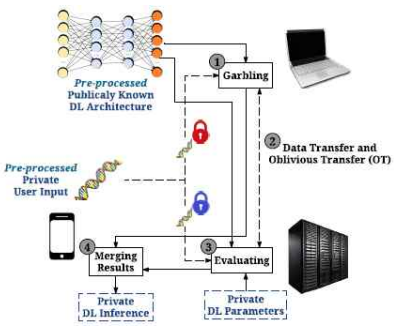


P. Mohassel and Y. Zhang, ₩Secureml: A system for scalable privacy-preserving machine learning," pp. 19-38, 2017.

MPC-based Hybrid PPDL(2/4)

- Deepsecure: Scalable Provably-Secure Deep Learning
  - Use **OT and Yao's GC** protocol with CNN
  - Collaboration between client and server
  - **Weakness**: limited number of instance processed
  - Only able to classify one instance during each round





B. Rouhani, M. Riazi, and F. Koushanfar, "Deepsecure: Scalable provably-secure deep learning," 55th ACM/ESDA/IEEE Design Automation Conference, pp . 1-6, 2018.

MPC-based Hybrid PPDL(3/4)

- MiniONN
  - PP framework that transforms a NN into an oblivious NN.
  - Two kind of transformations:
    - piecewise linear activation function
    - oblivious transformation for smooth activation function
  - Supports all activation functions that have:
    - monotonic range
    - piecewise polynomial, or
    - can be approximated into polynomial function.

J. Liu, M. Juuti, Y. Lu, and N. Asokan, "Oblivious Neural Network Predictions via MiniONN Transformations," in Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, pp. 619-631, ACM, 2017.

MPC-based Hybrid PPDL(4/4)

- ABY3
  - PPDL framework based on three-party computation
  - Can switch between arithmetic, binary, and Yao's 3PC
  - Use binary sharing on three-party Garbled Circuit
  - Arithmetic sharing when training linear regression model
  - Outperform MiniONN by four order of magnitude faster

P. Mohassel and P. Rindal, "ABY 3: a Mixed Protocol Framework for Machine Learning," in Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, pp. 35-52. ACM, 2018.

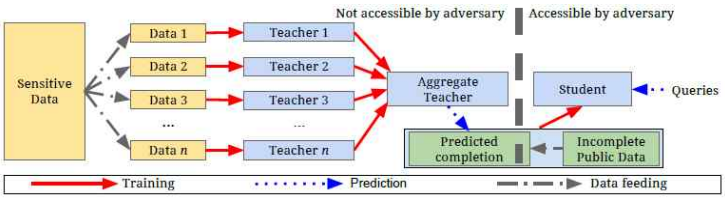
Comparison of MPC-based PPDL

Scenario	Proposed Schemes	DL Technique	Accuracy (%)	Run Time (s)	Data Transfer (Mbytes)	PoC	PoM
Cloud Service	DeepSecure [39]	CNN	Good (98.95)	Bad (10,649)	Bad (722,000)	No	Yes
Image Recognition	SecureML [35]	DNN	Bad (93.40)	-	-	No	Yes
PaaS	MiniONN [41]	NN	Good (98.95)	Good (1.04)	Good (47.60)	No	Yes
	ABY3 [45]	NN	Bad (94.00)	Good (0.01)	Good (5.20)	No	Yes

Differential Privacy(DP)-based PPDL

DP-based Hybrid PPDL

- Private Aggregation of Teacher Ensembles(PATE)
  - **Teacher phase and student phase**
  - Possible failure that reveals some part of training data



M. Abadi, U. Erlingsson, and I. Goodfellow, "On the protection of private information in machine learning systems: Two recent approaches," Com puter Security Foundations Symposium, pp. 1-6, 2017.

Comparison-All

- E2DM gives the best performance:
  - High accuracy
  - Fast run time
  - Small data transfer

- PoC
- PoM

Proposed Schemes	DL Technique	Accuracy (%)	Run Time (s)	Data Transfer (Mbytes)	PoC	PoM
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ABY3 [45]	NN	Bad (94.00)	Good (0.01)	Good (5.20)	No	Yes

Proposed Schemes	DL Technique	Accuracy (%)	Run Time (s)	Data Transfer (Mbytes)	PoC	PoM
ML Confidential [30]	DNN	Bad (95.00)	Bad (255.7)	-	Yes	No
Cryptonets [33]	CNN	Good (98.95)	Bad (697)	Bad (595.5)	Yes	No
PP on DNN [34]	CNN	Good (99.30)	-	-	Yes	No
E2DM [46]	CNN	Good (98.10)	Good (28.59)	Good (17.48)	Yes	Yes
CryptoDL [28]	CNN	Good (99.52)	Bad (320)	Bad (336.7)	Yes	No
PP All Convolutional Net [29]	CNN	Good (98.97)	Bad (477.6)	Bad (361.6)	Yes	No
Distributed PP Multi-Key FHE [38]	CNN	Good (99.73)	-	-	Yes	No
Gazelle [42]	CNN	-	Good (0.03)	Good (0.5)	Yes	Yes
Tapas [43]	BNN	Good (98.60)	Good (147)	-	Yes	Yes
FHE-DNN [44]	DiNN	Bad (96.35)	Good (1.64)	-	Yes	Yes

Further Challenges

- Further Work
  - Achieving more than 99% accuracy with good PoC and PoM
- Lots of Challenges still remain
  - No one-solution for all PP application
  - Federated Learning is emerging
  - GAN (Generative Adversarial Network)
- Other AI for X
  - AI for Cryptography
  - AI for Authentication and Privacy
  - Security of AI
- https://conferenceservice.jp/www/ai-sig-sec/ and more

For details, refer to Dr.Harry Chandra Tanuwidjaja's Thesis entitled "*Deep Abstraction for Android Malware Detection and Recent Development on Privacy-Preserving Deep Learning*", 2021, KAIST
https://caislab.kaist.ac.kr/publication/thesis_files/2021/HRPHD.pdf

Q&A

THANK YOU!