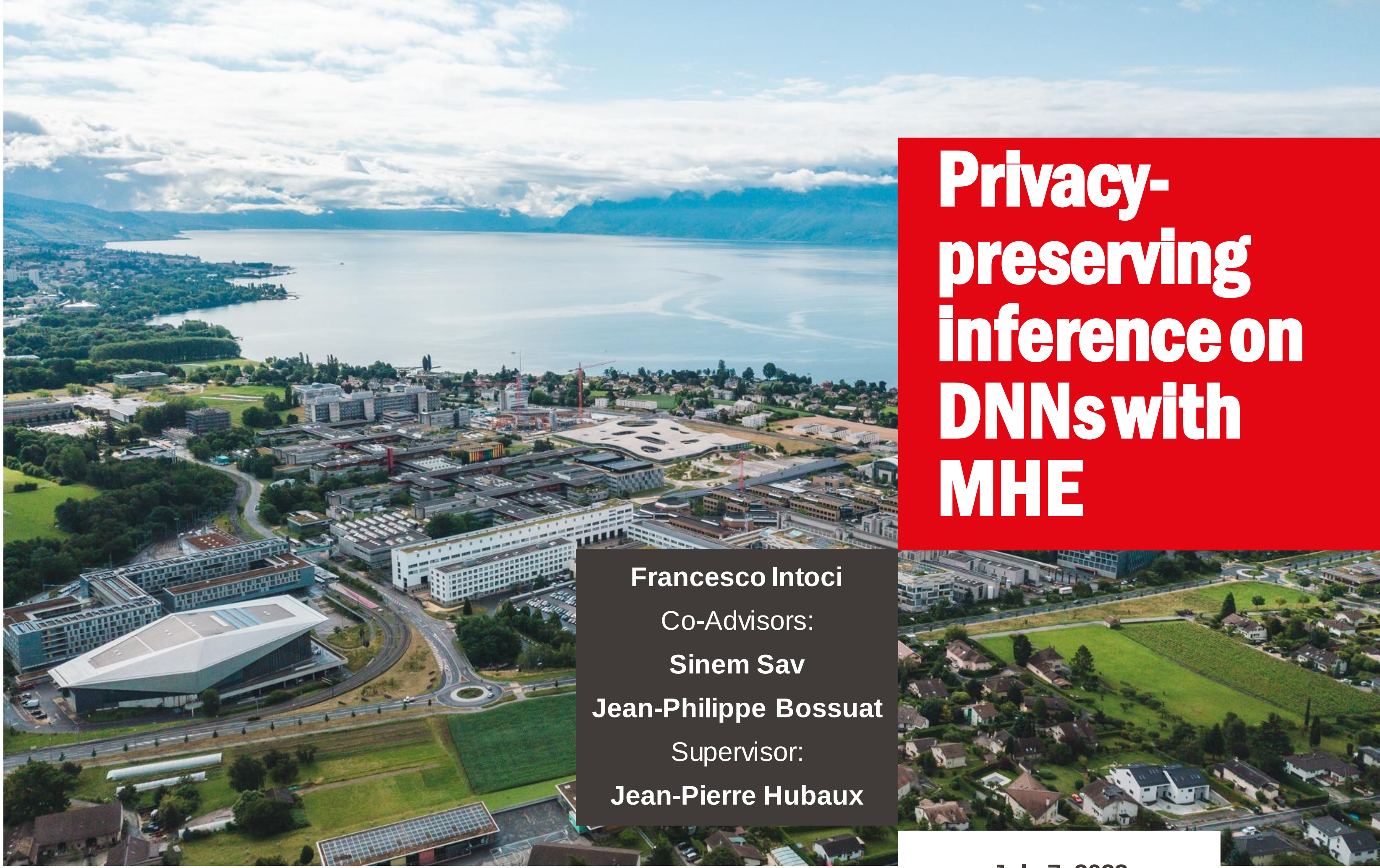

Privacy-preserving inference on DNNs with MHE

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LABORATORY FOR DATA SECURITY

École polytechnique fédérale de Lausanne

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Introduction

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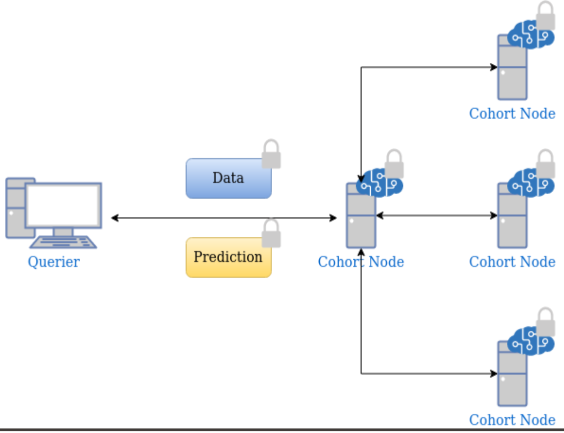
- Enable efficient privacy-preserving inference on Deep Neural Networks
- Different scenarios

Model in plaintext – data encrypted

Model owner offers PaaS

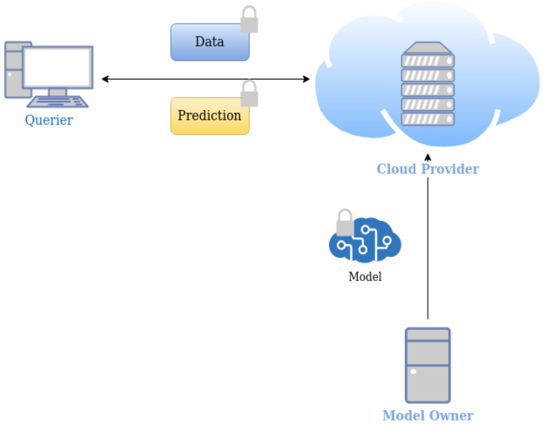
Model encrypted – data encrypted

Model is trained under encryption by a cohort of nodes. Several model holders [1]



Model encrypted – data encrypted

Model owner offloads computation to untrusted cloud provider



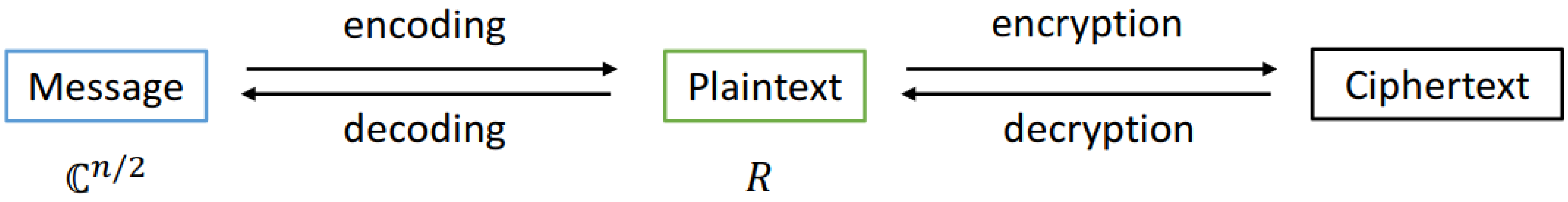
[1] POSEIDON: Privacy-Preserving Federated Neural Network Learning

Challenges

1. How to design an efficient and consistent **data packing** for network evaluation?
2. How to efficiently compute **convolutions on encrypted data** in a layer agnostic way?
3. How to **approximate non linear operations** in the network, and how does this impact the training phase and accuracy of models?
4. How to compute homomorphic **matrix multiplication** in an efficient way?
5. How to handle **data size which does not fit** into one ciphertext?

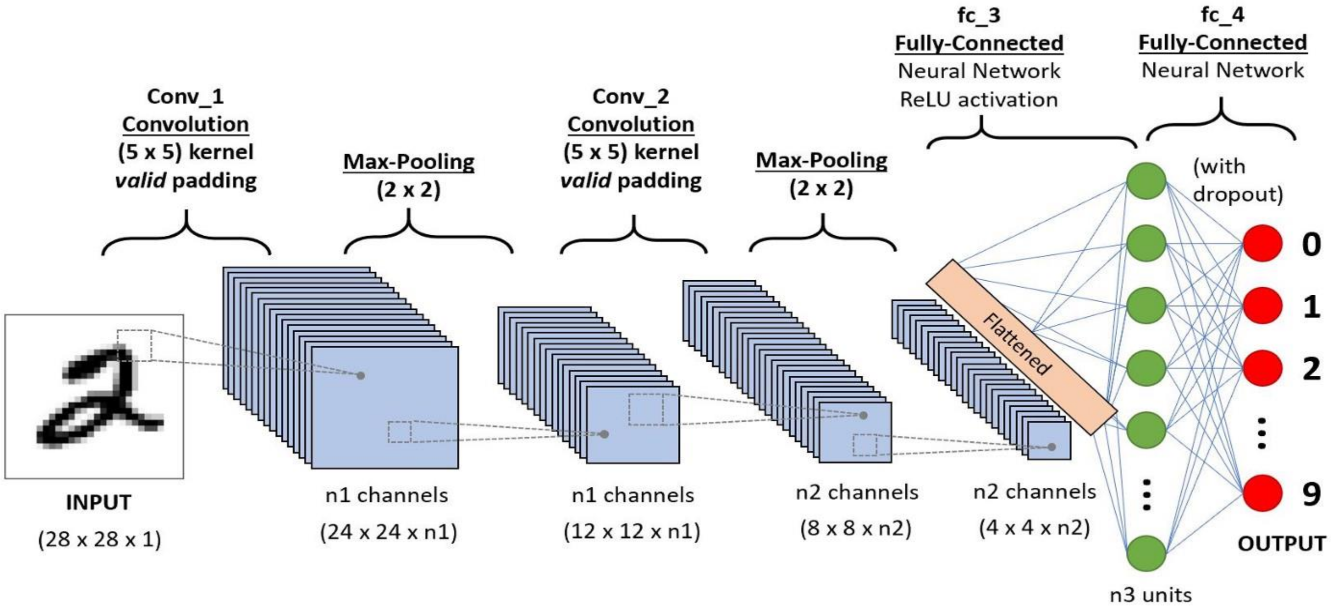
Background – CKKS scheme

- Based on RLWE hardness
- Leveled encryption schemes
- Suited for computation over floating point numbers



From: https://yongsoosong.github.io

Background – Convolutional Neural Network



From: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Challenges

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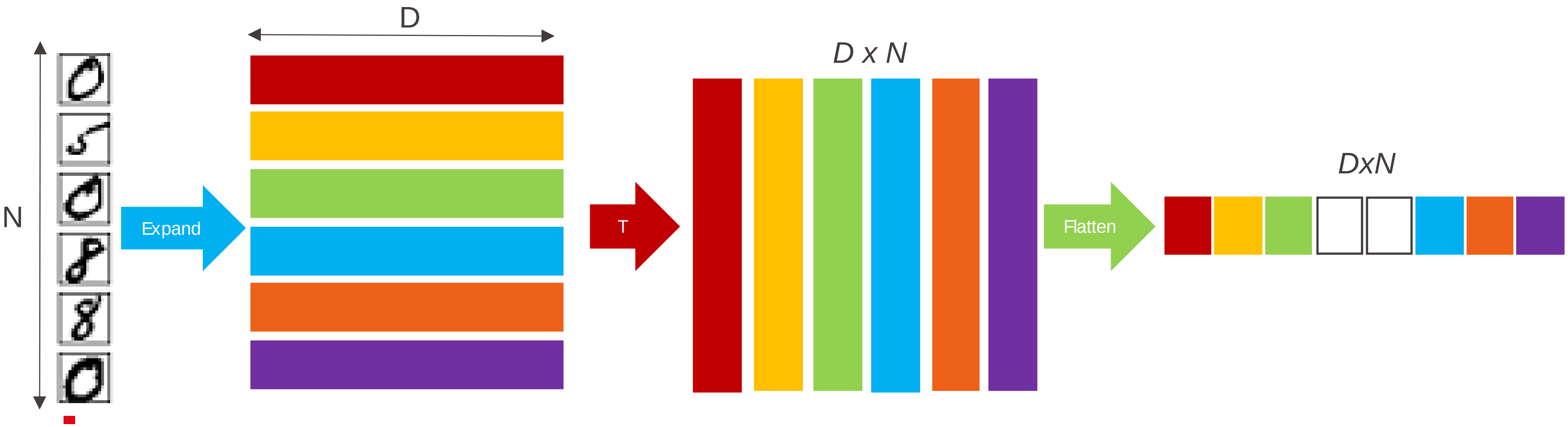
Methods - Data packing

- Querier holds batch of *N* images:
  - Pre-processing tasks (normalization,padding, etc...)
  - Images are represented as vectors of size *D* (feature number)
  - The *NxD* matrix is transposed
  - The *NxD* matrix is row-flattened
- Benefits:
  - Very simple
  - Fully compatible with matrix multiplication approach



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Methods - Convolutional layer «linearization»

- Transform the convolutional layer into a sparse layer and use matrix multiplication (Toeplitz matrix representation)

- Example: transformation of a filter operating on a 3x3 matrix with stride 1

$$\begin{bmatrix} k_1 & k_2 \\ k_3 & k_4 \end{bmatrix} = \begin{bmatrix} k_1 & k_2 & 0 & k_3 & k_4 & 0 & 0 & 0 & 0 \\ 0 & k_1 & k_2 & 0 & k_3 & k_4 & 0 & 0 & 0 \\ 0 & 0 & 0 & k_1 & k_2 & 0 & k_3 & k_4 & 0 \\ 0 & 0 & 0 & 0 & k_1 & k_2 & 0 & k_3 & k_4 \end{bmatrix}$$

Methods - Convolutional layer «linearization» cont'd

- Generalized for *f* kernels of KxK size, with *M* input channels

$$\begin{bmatrix} \langle m(k_{1,ch1}) | \dots | m(k_{1,chM}) \rangle \\ \langle m(k_{2,ch1}) | \dots | m(k_{2,chM}) \rangle \\ \langle m(k_{f,ch1}) | \dots | m(k_{f,chM}) \rangle \end{bmatrix}$$

- Benefits:
  - Can represent any convolution
  - Self-consistent for subsequent convolutional or linear layers

Challenges

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Methods - Non linear operations in network

- Approximate non-linear activation functions with polynomials using Minimax approximation
  - Polynomial activations introduced new challenges in training phase:
    - Weight explosion
    - Slow convergence
    - Partially solved with fine-tuned weight initialization and learning rate
  - Polynomial activations might introduce errors during encrypted inference with respect to the original function:
    - For each layer, record the interval of intermediate results and approximate the function only on the interval
      - Lower degree of approximation needed
      - Higher accuracy
- Average Pooling and Sum Pooling in place of Max Pooling

Challenges

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Methods - Matrix Multiplication

- Input matrix is transposed and row-flattened (same as data packing)
- Weight matrix in diagonal form
- Element wise multiplications, rotations and additions

$$\begin{bmatrix} a_{00} a_{01} a_{02} \\ a_{10} a_{11} a_{12} \\ a_{20} a_{21} a_{22} \end{bmatrix} \times \begin{bmatrix} w_{00} w_{01} w_{02} \\ w_{10} w_{11} w_{12} \\ w_{20} w_{21} w_{22} \end{bmatrix} = \begin{bmatrix} b_{00} b_{01} b_{02} \\ b_{10} b_{11} b_{12} \\ b_{20} b_{21} b_{22} \end{bmatrix}$$

Transpose and row-flatten

$$\begin{aligned} & [w_{00} w_{00} w_{00} w_{11} w_{11} w_{11} w_{22} w_{22} w_{22}] \odot \boxed{[a_{00} a_{10} a_{20} a_{01} a_{11} a_{21} a_{02} a_{12} a_{22}]} \\ + & [w_{10} w_{10} w_{10} w_{21} w_{21} w_{21} w_{02} w_{02} w_{02}] \odot [a_{01} a_{11} a_{21} a_{02} a_{12} a_{22} a_{00} a_{10} a_{20}] \\ + & [w_{20} w_{20} w_{20} w_{01} w_{01} w_{01} w_{12} w_{12} w_{12}] \odot [a_{02} a_{12} a_{22} a_{00} a_{10} a_{20} a_{01} a_{11} a_{21}] \\ = & \boxed{[b_{00} b_{10} b_{20} b_{01} b_{11} b_{21} b_{02} b_{12} b_{22}]} \end{aligned}$$

Same format

$$\sum_{j=0}^{d-1} \mathrm{Diag}_j(W) \odot \mathrm{Rotate}_{dj}(\mathrm{Flatten}(A^T)) \rightarrow O(d) \text{ rotations}$$

- Benefits:
  - Linear complexity
  - Fully compatible with data packing
  - Easily Parallelizable

Matrix Multiplication – cont'd

- Optimized version for $O\left(\frac{d}{2}\right)$
- Half the (intermediate) size of the matrices by packing real values in complex form
- Later remove the imaginary part with 1 addition and 1 rotation

$$\begin{pmatrix} a_{1,1} & \dots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \dots & a_{n,m} \end{pmatrix} \times \begin{pmatrix} b_{1,1} & \dots & b_{1,h} \\ \vdots & \ddots & \vdots \\ b_{m,1} & \dots & b_{m,h} \end{pmatrix} \rightarrow \begin{pmatrix} a_{1,1} - ia_{1,2} & \dots & a_{1,m-1} - ia_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} - ia_{n,2} & \dots & a_{n,m-1} - ia_{n,m} \end{pmatrix} \times \begin{pmatrix} b_{1,1} + ib_{2,1} & \dots & b_{1,m} + ib_{2,m} \\ \vdots & \ddots & \vdots \\ b_{n-1,1} + ib_{n,1} & \dots & b_{n-1,m-1} + ib_{n,m} \end{pmatrix}$$

Challenges

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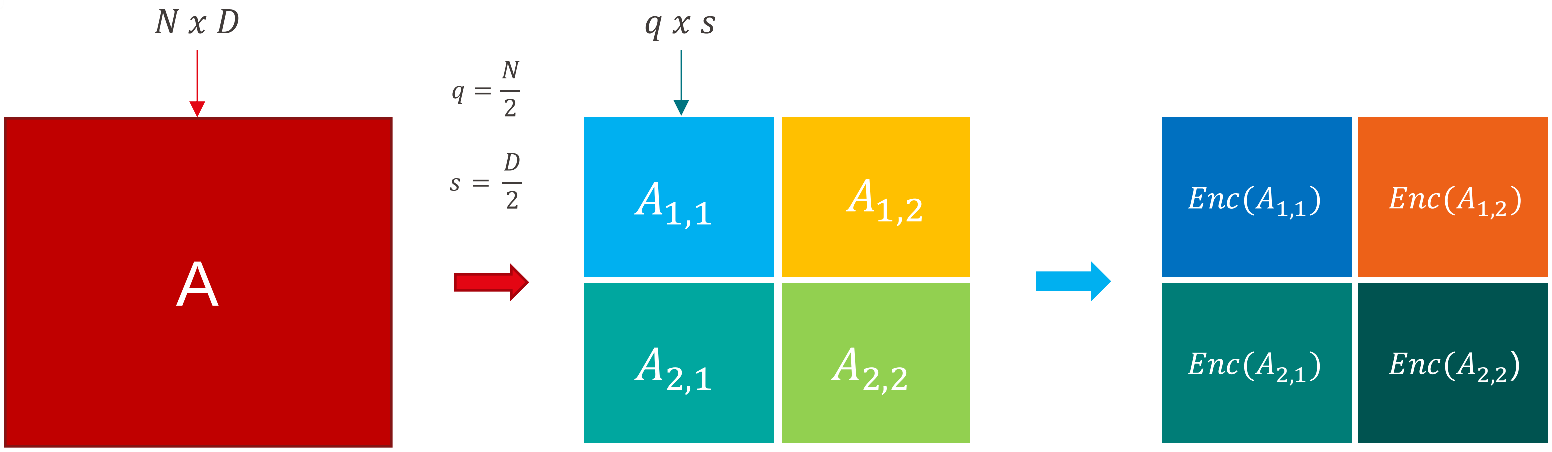
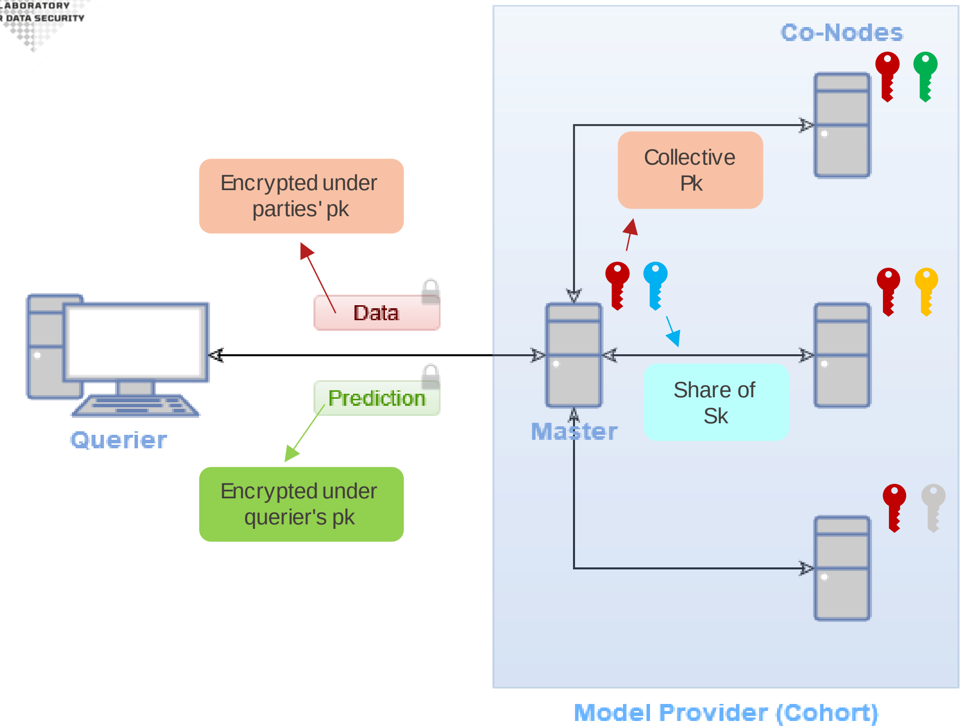
Methods – Block Matrix Arithmetics



- Each block (sub-matrix) is encrypted/encoded indipendently
- Operations can be carried out on each block using block matrix arithmetics

- Benefits:
  - Smaller ciphertexts/plaintexts
  - Easily parallelizable
  - Flexible: block splits can be adjusted to maximize latency or throughput

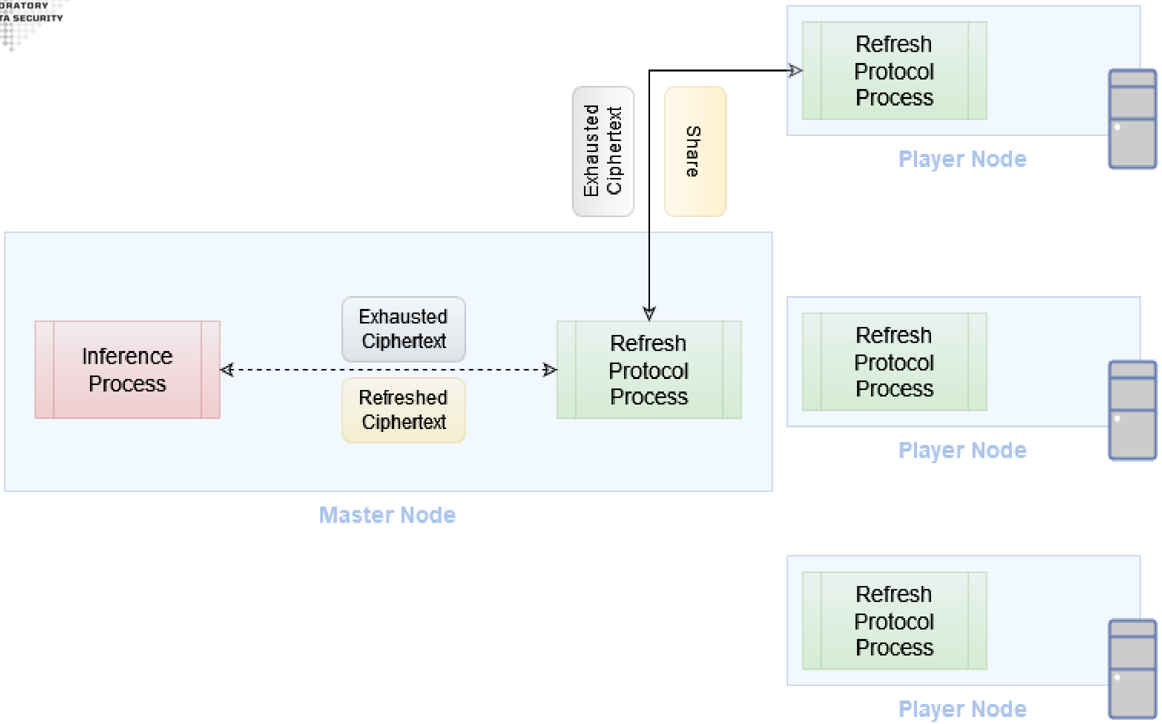
Methods – Distributed protocols for MHE



- Assumption: model is trained encrypted by a cohort of nodes.
- Very efficient: 1 Round Protocols!
- Reference: Mouchet et al.[2]

- [2] Multiparty Homomorphic Encryption from Ring-Learning-With-Errors

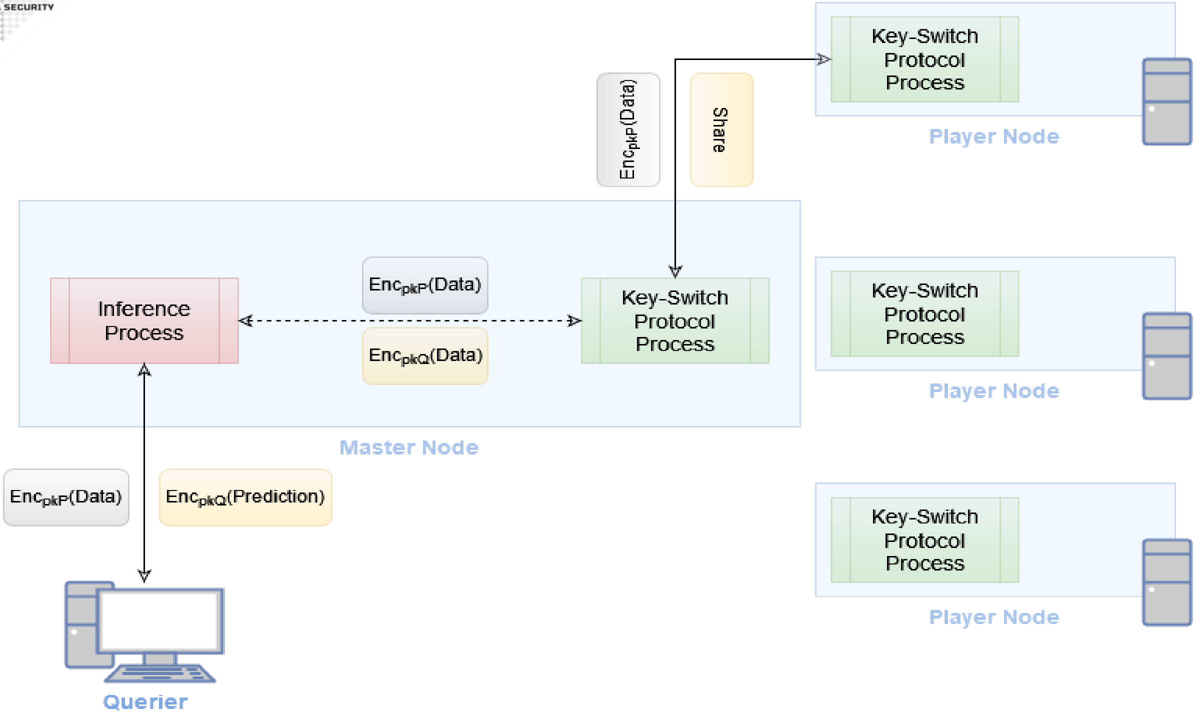
Methods – Distributed protocols for MHE - Refresh



- Distributed Bootstrapping generates a freshly encrypted ciphertext from a "low-level" ciphertext

- [2] Multiparty Homomorphic Encryption from Ring-Learning-With-Errors

Methods – Distributed protocols for MHE – Collective Key Switch



- Collective Key Switch Protocol is invoked to generate an encryption of the result under querier's public key

- [2] Multiparty Homomorphic Encryption from Ring-Learning-With-Errors

Experimental setup

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- Hardware specifications:
  - 2x Intel Xeon E5-2680 2.5 GHz (48 threads)
  - 16 GB RAM DDR4
- Parameters for CKKS scheme:

Set	LogN (bits)	LogQP (bits)	Levels	Scale (bits)
CryptoNets	14	329	7	30
NN20	15	874	18	35
NN50	15	629	11	35
NN50-light	14	436	10	31
NN-Central-Btp	15	768	13	25

Experiment 1 - CryptoNets

- We benchmarked our framework on the Microsoft CryptoNets[3] model
  - Training and inference on MNIST dataset
  - Scenario is “model in clear – data encrypted”

Model	Batching	Batch	Latency(s)	Throughput(im/s)
CryptoNets	Y	4096	250	16.54
Faster Cryptonets [5]	N	1	39.1	0.02
LoLa [4]	N	1	2.2	0.5
MiniONN [6]	N	1	1.28	0.78
Ours	Y	83	10.5	7.9

[3] CryptoNets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy
[4] Low Latency Privacy Preserving Inference
[5] Faster CryptoNets: Leveraging Sparsity for Real-World Encrypted Inference
[6] Oblivious Neural Network Predictions via MiniONN transformations

Experiment 2 – ZAMA NN

- We further tested our framework on deeper and more complex networks, using the models proposed by ZAMA[8]
  - Training and inference on MNIST dataset
  - Model is encrypted
  - Two models tested → 20 and 50 layers
  - Two bootstrapping approaches → centralized and distributed

[8] Programmable Bootstrapping Enables Efficient Homomorphic Inference of Deep Neural Networks

Experiment 2 – ZAMA NN – 20 layers

Setting	Batch	Latency (s)	Throughput (im/s)	Communication (MB/cipher)
1PC	292	639.6	0.45	-
MPC-5	292	365	0.85	21
MPC-10	292	417	0.70	21
Baseline-PC	1	115.52	0.008	-
Baseline-AWS	1	17.96	0.055	-

[4] Programmable Bootstrapping Enables Efficient Homomorphic Inference of Deep Neural Networks

Experiment 2 – ZAMA NN – 50 layers

Parameters with smaller ring size!

Setting	Batch	Latency (s)	Throughput (im/s)	Communication (MB/cipher)
1PC	292	1343	0.21	-
MPC-3	292	811	0.36	21
MPC-5	146	759	0.19	21
MPC-10	146	1007	0.14	21
Baseline-PC	1	233.55	0.004	-
Baseline-AWS	1	37.69	0.026	-

[4] Programmable Bootstrapping Enables Efficient Homomorphic Inference of Deep Neural Networks

EPFL

Final Remarks

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- Results are promising...
  - CKKS allows for data packing and SIMD operations for high throughput
- ...but optimization is hard!
  - Finding optimal data packing approach is crucial for performance
    - Data packing and block matrices splitting greatly influence latency and throughput
  - Dealing with non-linearities is complex
    - Introducing polynomial activations during training might cause slow or no convergence
    - Polynomial approximations must be fine-tuned (tradeoff between accuracy – efficiency)
  - <u>CKKS parametrization is hard!</u>
    - A bad choice for the parameters of the scheme might completely disrupt performance and accuracy!

EPFL

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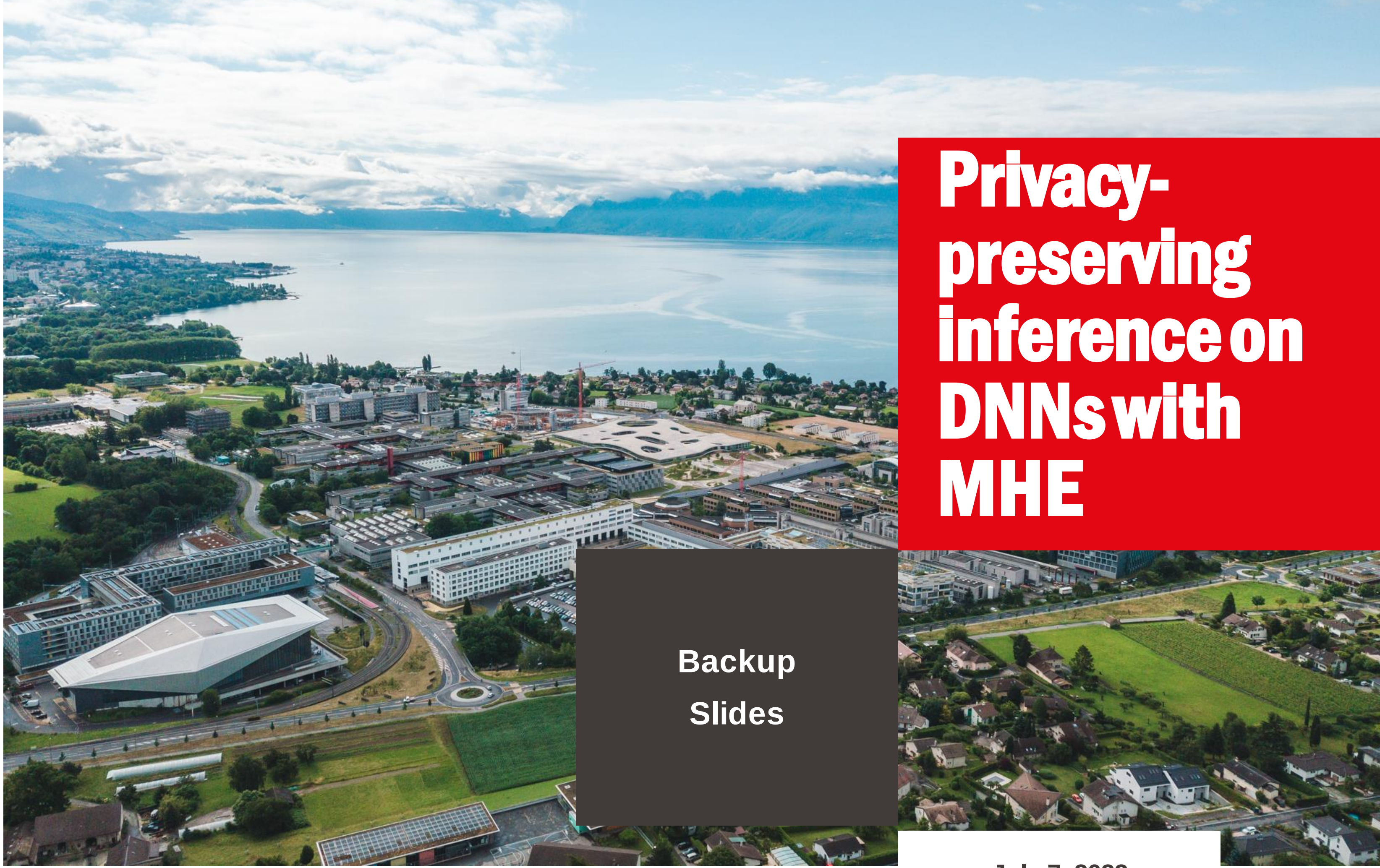
Privacy-preserving inference on DNNs with MHE



Backup Slides

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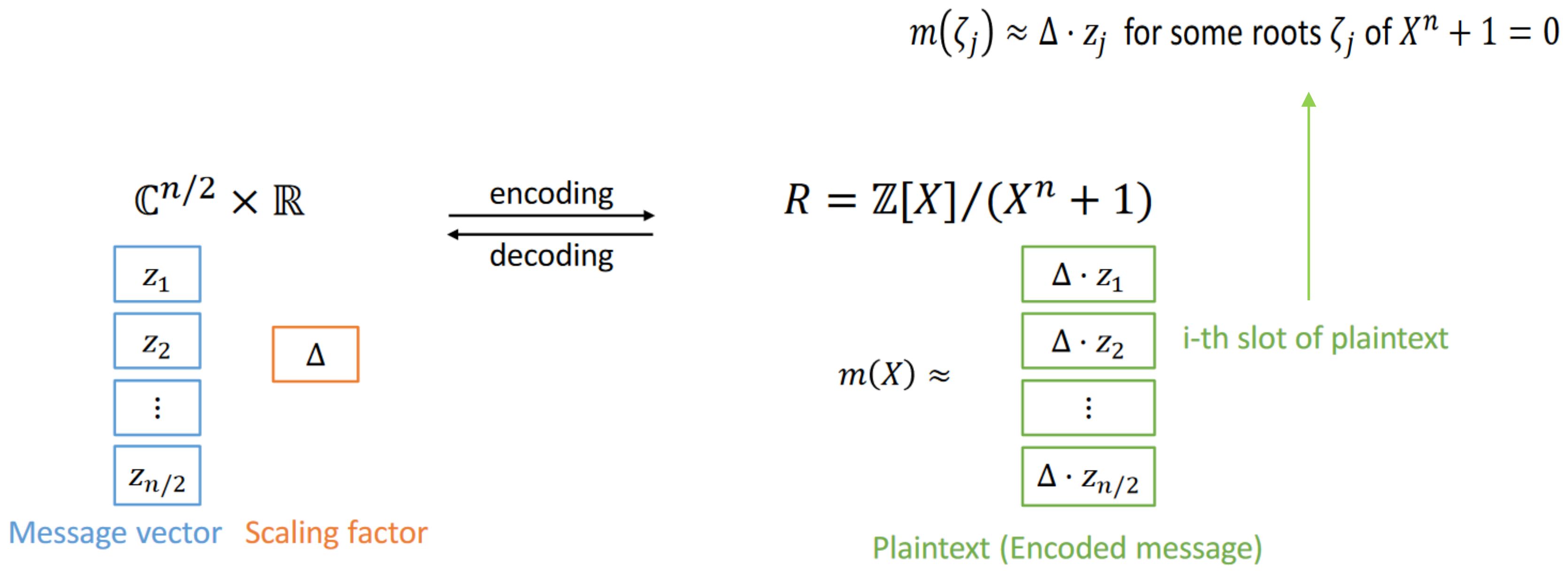
Background – CKKS scheme – Encoding & Decoding



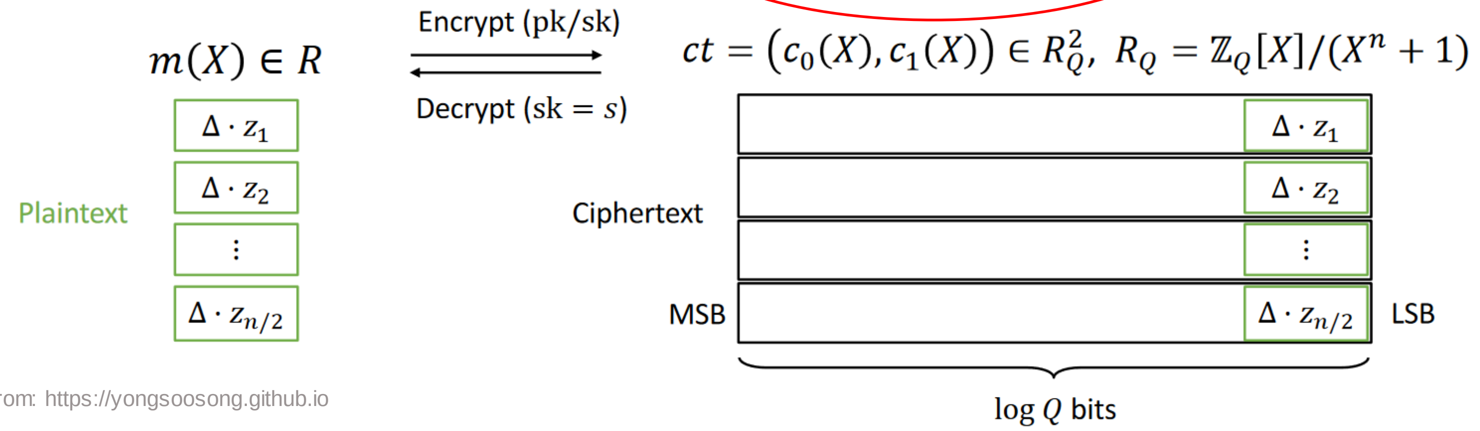
From: https://yongsoosong.github.io

Background – CKKS scheme – Encryption & Decryption

Modulus Chain

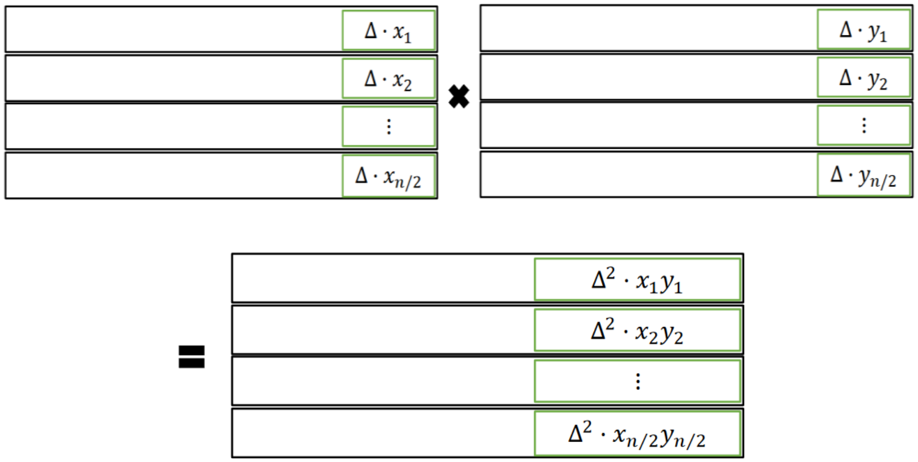
Ring structure $R_q = \mathbb{Z}_q[x]/(x^n + 1)$.

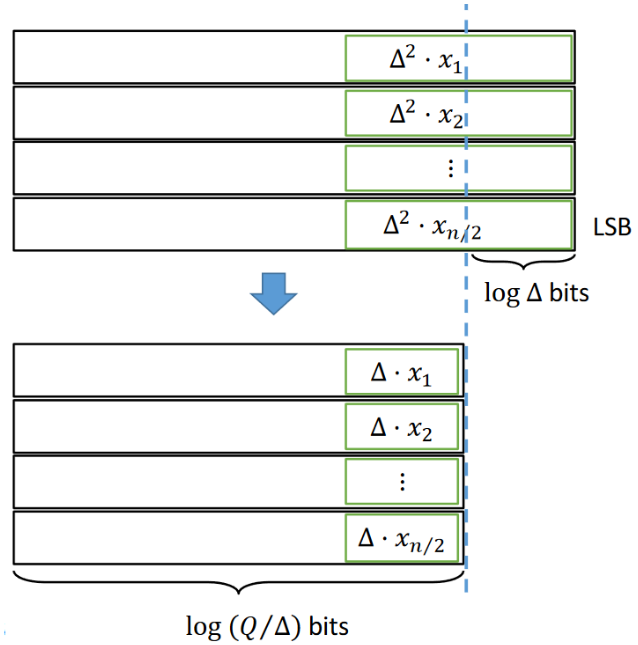
Residue Number System (RNS) : $\mathbb{Z}_q \cong \mathbb{Z}_{p_1} \times \mathbb{Z}_{p_2} \times \cdots \times \mathbb{Z}_{p_L}$.



From: https://yongsoosong.github.io

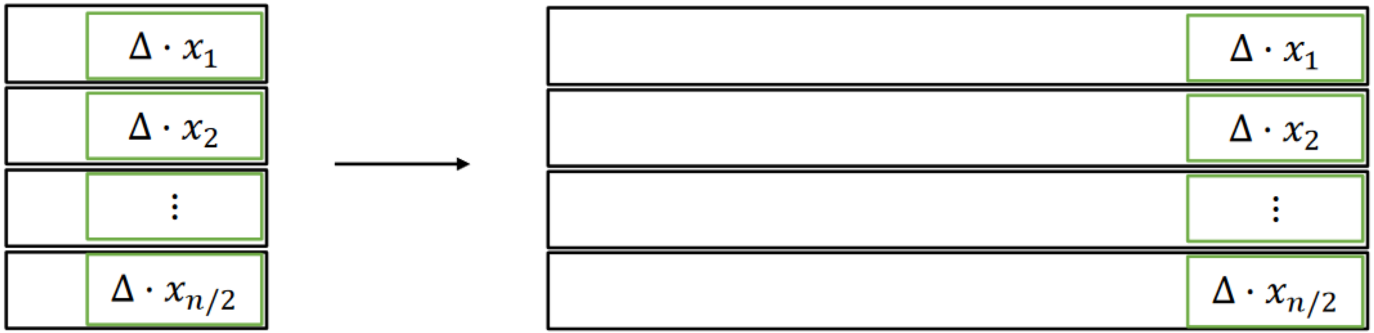
Background – CKKS scheme – Multiplication & Rescaling





From: https://yongsoosong.github.io

Background – CKKS scheme – Bootstrapping



Level l_0

Level $l_0 < l \leq L$

From: https://yongsoosong.github.io