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GForce: GPU-Friendly Oblivious and Rapid Neural Network Inference

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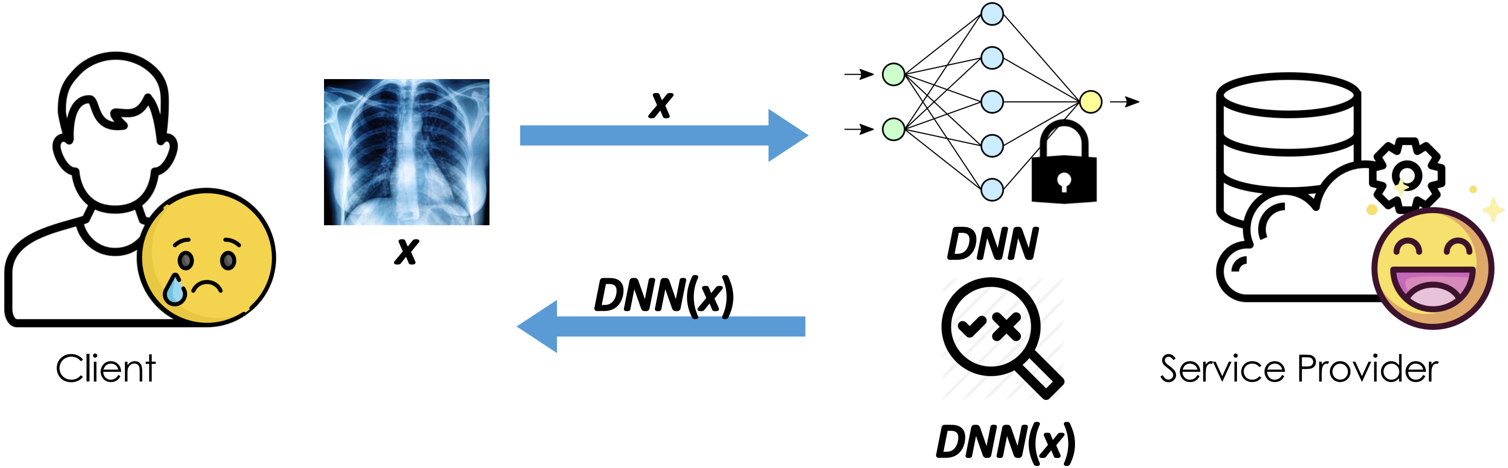
Query Privacy in NN Inference

- Queries in inference can be sensitive
    - Social applications, Medical image analysis, Computer vision, …
- The "natural" way will leak them to the server



x

x

DNN

DNN(x)

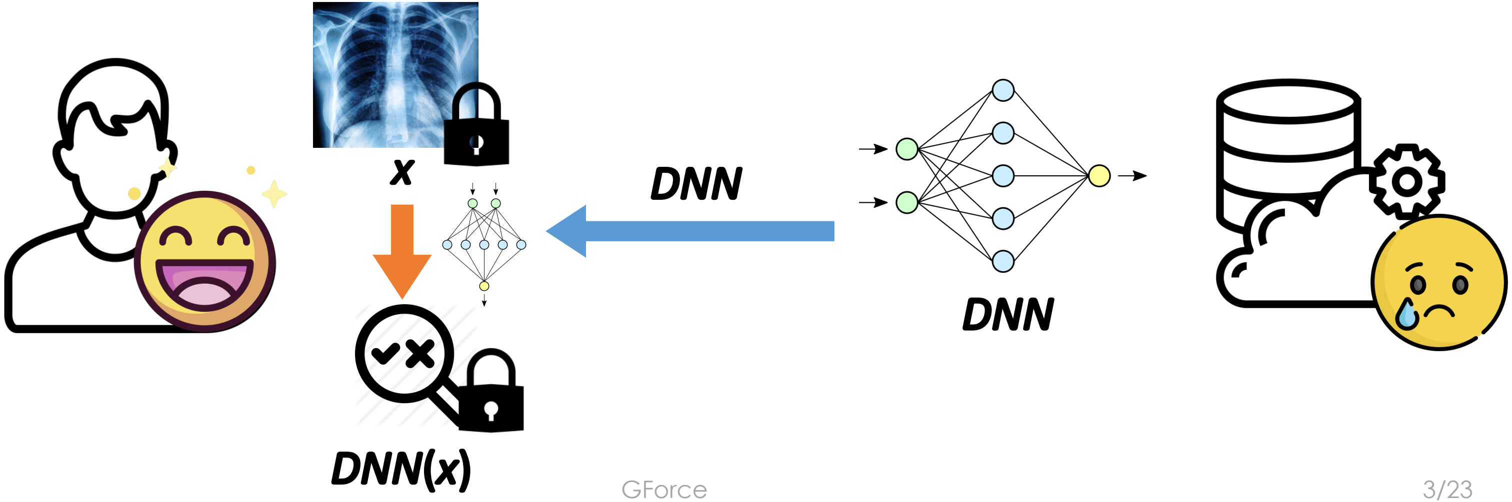
DNN(x)

Client

Service Provider

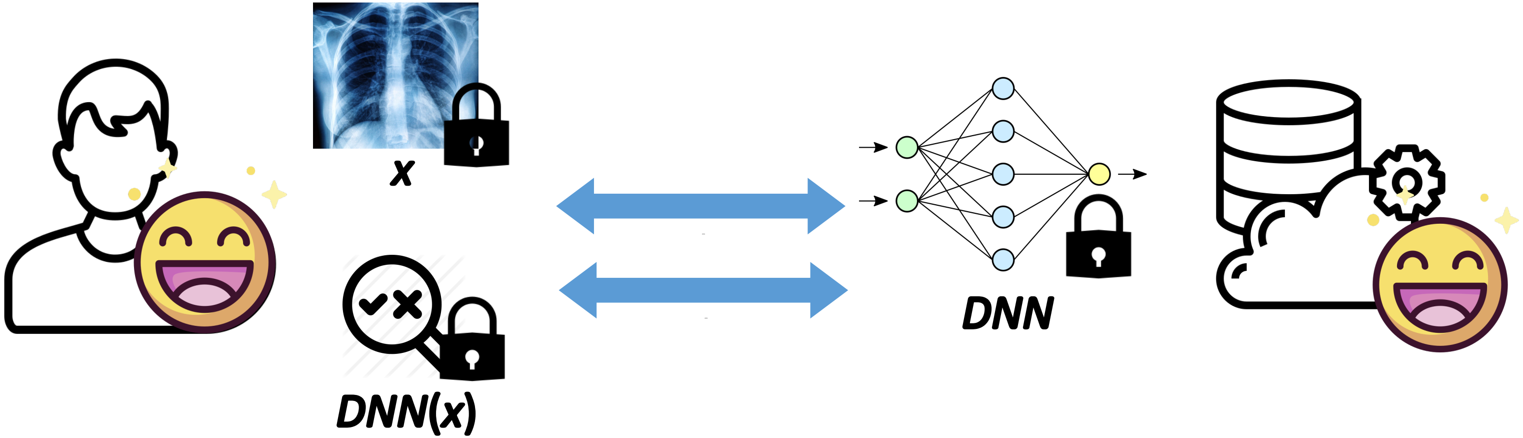
Revealing the model to all clients?

- Local inference well protects the client
  - The model itself is an intellectual property
  - One may reverse-engineer the model to recover training data



Oblivious NN Inference

- The client can learn *DNN(x)* but not *DNN*
- The server cannot learn anything about *x*



GForce

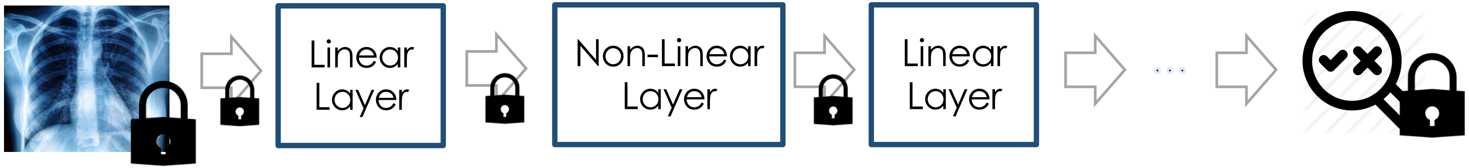
- Oblivious, rapid, and accurate NN Inference

- GForce attains **~73%** in **0.4s** (the *first* for *purely*-crypto solutions)
  - (*e.g.*, no trusted execution environment, no non-colluding server)
  - over CIFAR-100: Image dataset consisting of 100 classes
  - Delphi (prior best [USS20]): **~68%** in **14s** (or ~66% in 2.6s)

- *Spoiler Alert*:
  - I: Make (non-linear) Crypto GPU-friendly
    - "GPU-DGK"
  - II: Tackle the (notorious) issue of Accuracy vs. Bitwidth
    - "SRT" for "SWALP"

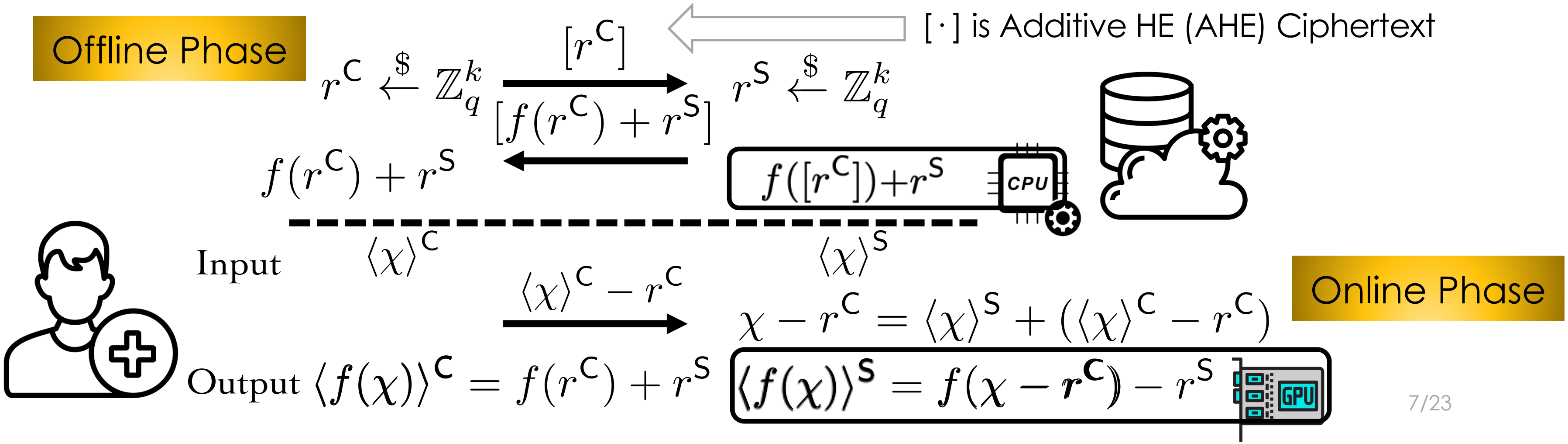
Basic: Dividing a NN

- Treat linear layers and non-linear layers *differently*
  - non-linear: *e.g.*, ReLU, Maxpool
  - linear: *e.g.*, Convolution, Matrix Multiplication



Secure On-/Offline Share Comp.

- To compute a linear function *f*: $f(x) = f(x-r) + f(r)$
  - Offline pre-compute $f(r)$ with (slow) *Homomorphic Encryption* (HE)
  - Online compute $f(x-r)$ in GPU in a batch of *k* (100× faster than CPU)
  - $(x-r, r)$ are like Additive *Secret Share* (SS) of *x*: $\langle x\rangle^{S} + \langle x\rangle^{C} = x \pmod{q}$



Offline Phase

[·] is Additive HE (AHE) Ciphertext

$r^{C} \xleftarrow{\$} \mathbb{Z}_q^k \xrightarrow{[r^{C}]} r^{S} \xleftarrow{\$} \mathbb{Z}_q^k$

$f(r^{C}) + r^{S} \xleftarrow{[f(r^{C}) + r^{S}]} \boxed{f([r^{C}])+r^{S}}$

Input $\langle\chi\rangle^{C}$ $\langle\chi\rangle^{S}$

$\xrightarrow{\langle\chi\rangle^{C} - r^{C}}$ $\chi - r^{C} = \langle\chi\rangle^{S} + (\langle\chi\rangle^{C} - r^{C})$

Online Phase

Output $\langle f(\chi)\rangle^{C} = f(r^{C}) + r^{S}$ $\boxed{\langle f(\chi)\rangle^{S} = f(\chi - r^{C}) - r^{S}}$

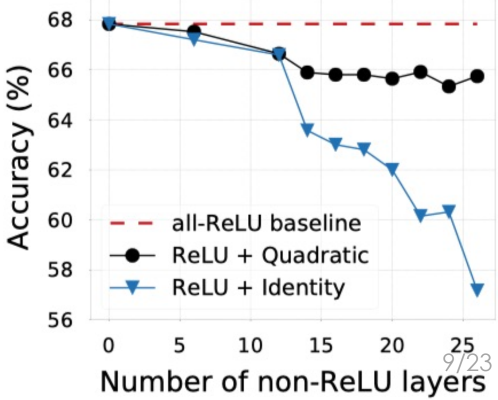
Linear Layers by SOS

- *Secure On-/Offline Share Comp.* (SOS) suits linear layers
  - e.g., used by the prior art Delphi [USS20]
- Operation of a linear layer: $y = W \otimes x$
  - y: output; x: inputs; W: weight (e.g., kernel in a conv. layer)
- The linear layers can be treated as a linear function f_W
  - $f_W(x) = W \otimes x$
  - apply SOS to f_W
- Can we call SOS for non-linear layers?

GPU for Non-Linear Layers?

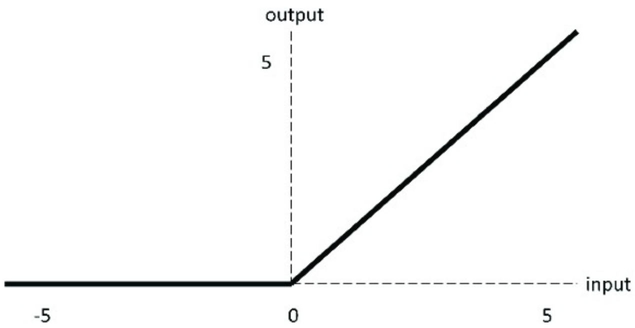
- Non-linear layers need slow *garbled circuit* (GC)
- Delphi replaces some ReLU by quadratic *approximation*
  - Computing x^2 is fast with additive SS and Beaver’s trick

- Problem 1: Approximation ➔ Worse Accuracy
- Problem 2: Maxpool is still using *slow* GC
  - Maxpool: another popular non-linear layer



I: GPU for Non-Linear Layers!

- *Comparison* $(x \leq y)$ is a fundamental operation
  - $\mathrm{ReLU}(x) = \mathrm{Max}(x, 0)$
  - $\mathrm{Maxpool}(\{x\}_{0..3}) = \mathrm{Max}(x_0, x_1, x_2, x_3)$
    - *e.g.*, for a pooling window of size 4
  - $\mathrm{Max}(x, y) = (x \leq y) \cdot (y-x) + x$



ReLU(*x*)

2	2	7	3
9	4	6	1
8	5	2	4
3	1	2	6

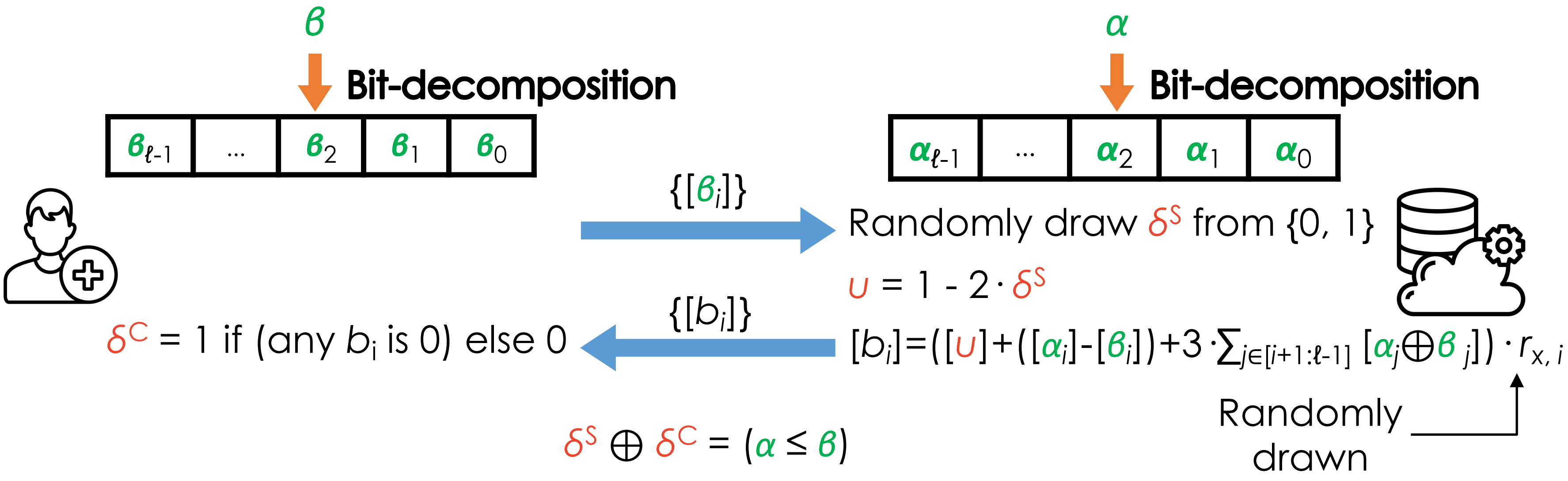
Filter: (2 × 2)
Stride: (2, 2)

9	7
8	6

Maxpool(*x*)

Recap: DGK Protocol

- DGK uses AHE for Comparison
- Each input α or β and get an additive SS of $(\alpha \leq \beta)$



Randomly draw δ^S from {0, 1}

$u = 1 - 2 \cdot \delta^S$

$[b_i]=([u]+([\alpha_i]-[\beta_i])+3 \cdot \sum_{j\in[i+1:\ell-1]} [\alpha_j \oplus \beta_j]) \cdot r_{x,i}$

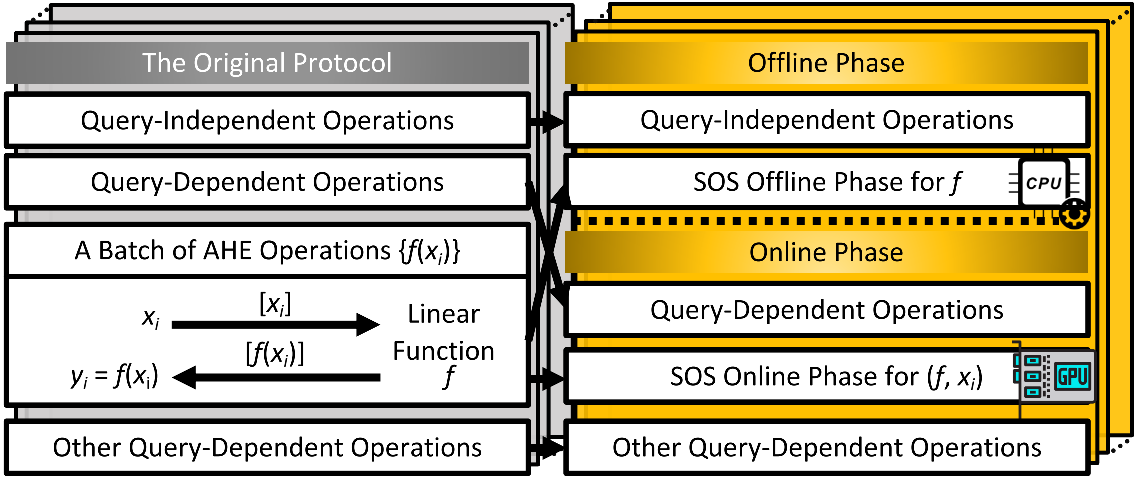
Randomly drawn

$\delta^C = 1$ if (any b_i is 0) else 0

$\delta^S \oplus \delta^C = (\alpha \leq \beta)$

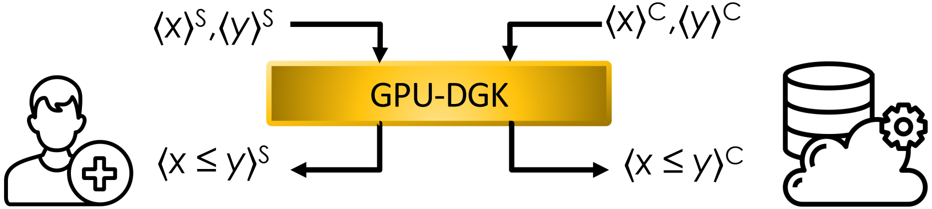
AHE-to-SOS

- Observation: SOS is appliable to many AHE Protocols
- Non-linear “becomes” linear!
- Batch many instances to fully utilize GPU in online phase



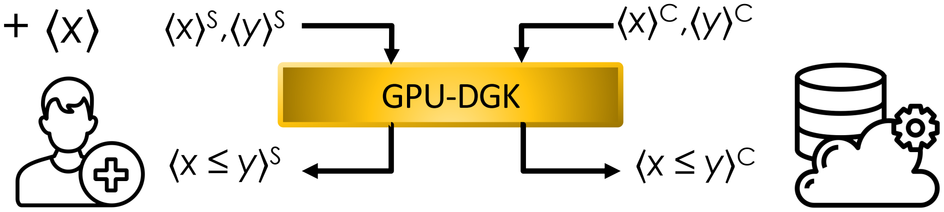
GPU-DGK = AHE-to-SOS + DGK

- Transform the core AHE steps into linear functions
  - $dgk_{i, u, \alpha, r}(\beta) = (u + \alpha_i - \beta_i + 3 \cdot xor_{i, \alpha}(\beta)) \cdot r_{x, i}$ (*xor*() defined in the paper)
  - *i* is the bit position, *u* and *r* are server's randomness
  - but α, β is the ***online*** input of the server/client
- Server can't know/precompute $dgk_{\alpha}()$ in the offline phase
- We devise a trick to "let the server know" α offline
- by deriving β from α and the actual online inputs x and y
  - (More detail in our paper)



GPU-DGK for Non-Linear Layers

- $\langle \mathrm{Max}(x, y)\rangle = \langle x \leq y\rangle \cdot (\langle y\rangle - \langle x\rangle) + \langle x\rangle$
  - Notation: $\langle x\rangle = \{\langle x\rangle^S, \langle x\rangle^C\}$
  - $\mathrm{Max}(x, y) = (x \leq y) \cdot (y-x) + x$
- Max ➔ ReLU and Maxpool
- Better (Online) Performance w/o (GC) approx.!



non-approximate garble circuit approach ([USS18])

Framework	ReLU	Speedup	Maxpool	Speedup
Gazelle	1754.00ms	-	2950.00ms	-
GForce	65.15ms	**27×**	99.02ms	**34**×

Number of input elements = 2^{17}

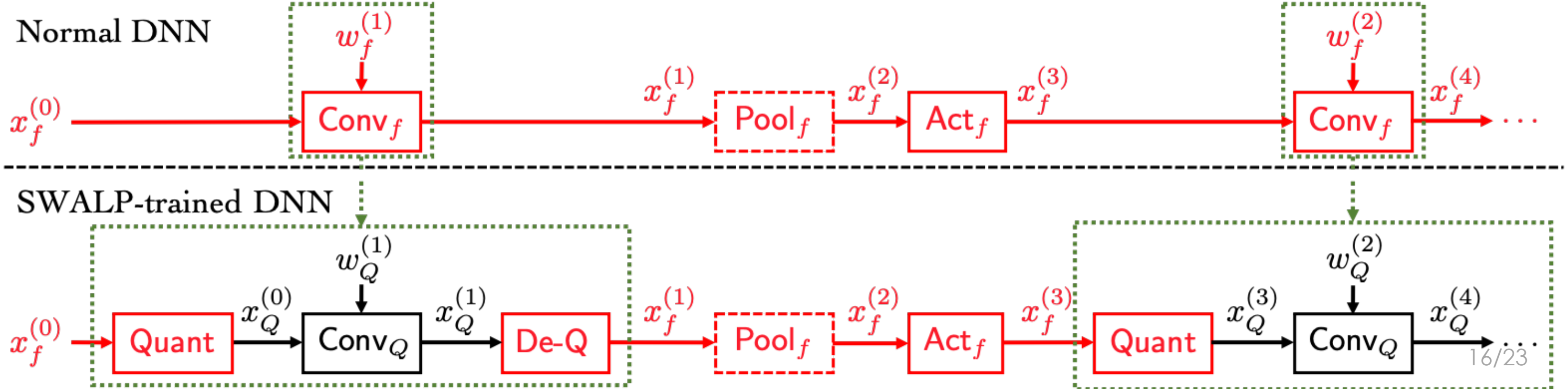
II: Accuracy vs. Bitwidth

- AHE/Additive SS: Operating in $\mathbf{Z}_q$ (integers)
  - Parameters are mostly floating points, w/ *highly dynamic* ranges
    - from 2^{-127} to 2^{127}
  - Need *high-bitwidth* integers to simulate floating points
    - may need integers with 255(=127 + 127 +1) bitwidth

- Small $\mathbf{Z}_q$ (low bitwidth) ➔ Worse Accuracy
  - Error in conversion between floating points and integers
- Large $\mathbf{Z}_q$ (high bitwidth) ➔ Worse Performance
  - GC: *larger* circuit
  - DGK: *more* “bit comparison”: $[b_i]=[a_i]+([x_i]-[y_i])+3\sum_{j\in[i+1:\ell-1]}[x_j\oplus y_j]$
  - GPU has *limited bitwidth* for efficient computation over integers

(De-)Quantizing Linear Layers

- Quantize the NN using SWALP [ICML19]
  - **S**tochastic **W**eight **A**veraging in **L**ow-**P**recision Training
  - almost as good as floating
- Quant(): find maximum ➔ scale up/down ➔ round to int.
- De-Q(): scale up/down



Issues in adopting SWALP

- How to find the maximum (securely and efficiently)?
- How to represent floating points after dequantization?

- How to scale down?
  - Naive division over additive SS *ruins* low-bitwidth NNs
- How to do rounding?
- Experiments over VGG-16 shows:

Dataset	Rounding w/ Proper Scale Down	Naive Division
CIFAR-10	**93.22%**	10.06%
CIFAR-100	**72.83%**	1.03%

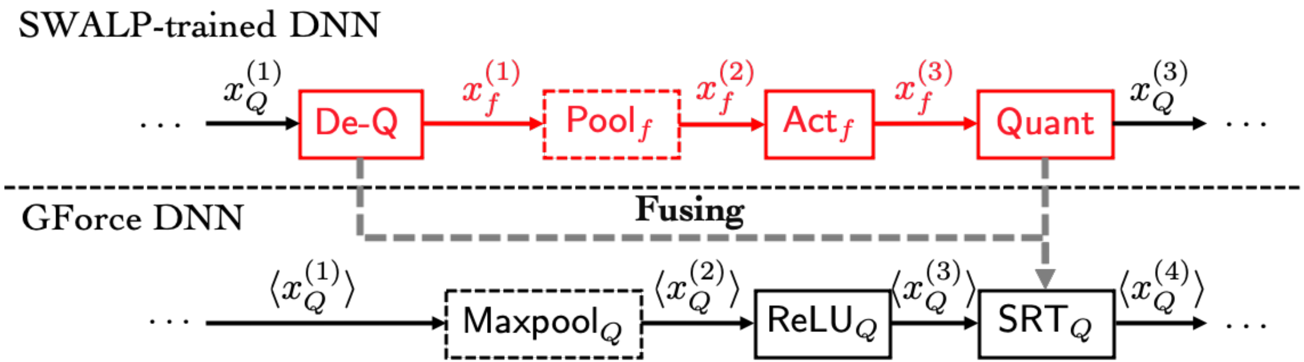
Precomputation & Fusing

- Finding the Maximum: Precompute using training data

- Fusing (De)quantization into just a *division*!
  - De-Q o ReLU o Maxpool o Quant
    = (ReLU o Maxpool) / **d**
  - *d* is computed with the precomputed maximum
  - No floating points now

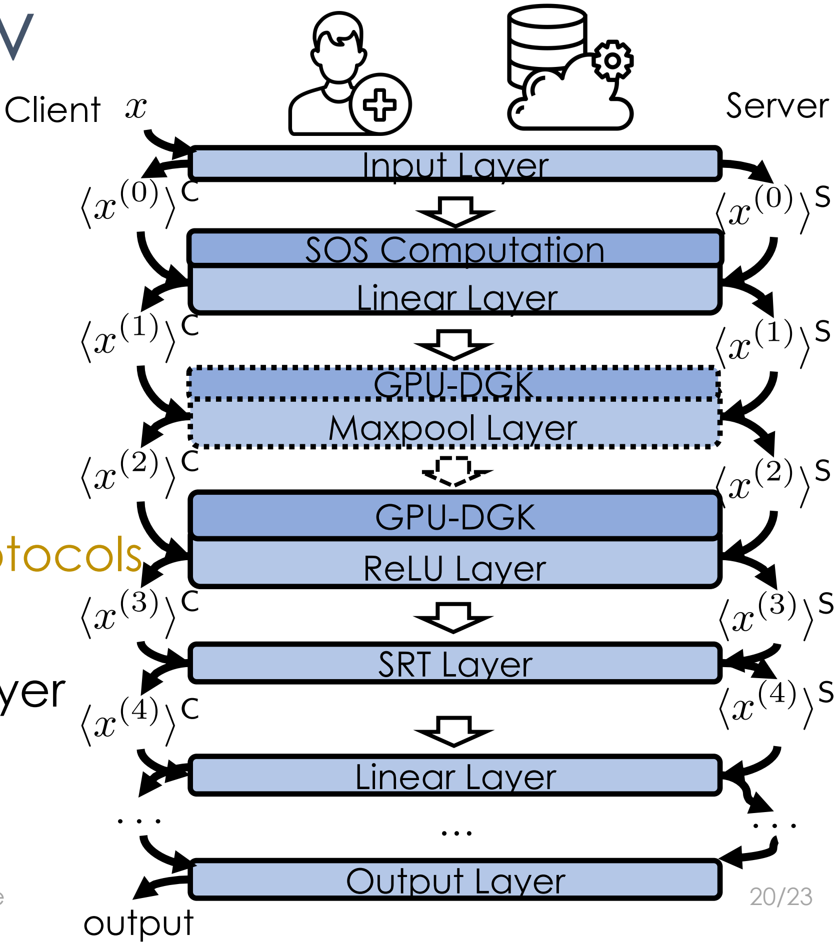
Stochastic **R**ounding **T**runcation

- We form a new *SRT layer* (also utilizing AHE-to-SOS) that
- performs stochastic rounding
- corrects the error in naive division/truncation (“for free”)
    - (More detail in our paper)



End-to-End Workflow

- Setup:
  - Training a NN with SWALP
  - Precompute $\{d_i\}$ for SRT Layers
- Inference:
  - Offline computation with AHE
  - Online: Run our *GPU-friendly* protocols
  - We make *all* layers GPU-friendly
  - They jointly run them layer-by-layer



Client x

Server

Input Layer

$\langle x^{(0)} \rangle^C$ $\langle x^{(0)} \rangle^S$

SOS Computation

Linear Layer

$\langle x^{(1)} \rangle^C$ $\langle x^{(1)} \rangle^S$

GPU-DGK

Maxpool Layer

$\langle x^{(2)} \rangle^C$ $\langle x^{(2)} \rangle^S$

GPU-DGK

ReLU Layer

$\langle x^{(3)} \rangle^C$ $\langle x^{(3)} \rangle^S$

SRT Layer

$\langle x^{(4)} \rangle^C$ $\langle x^{(4)} \rangle^S$

Linear Layer

$\cdots$

Output Layer

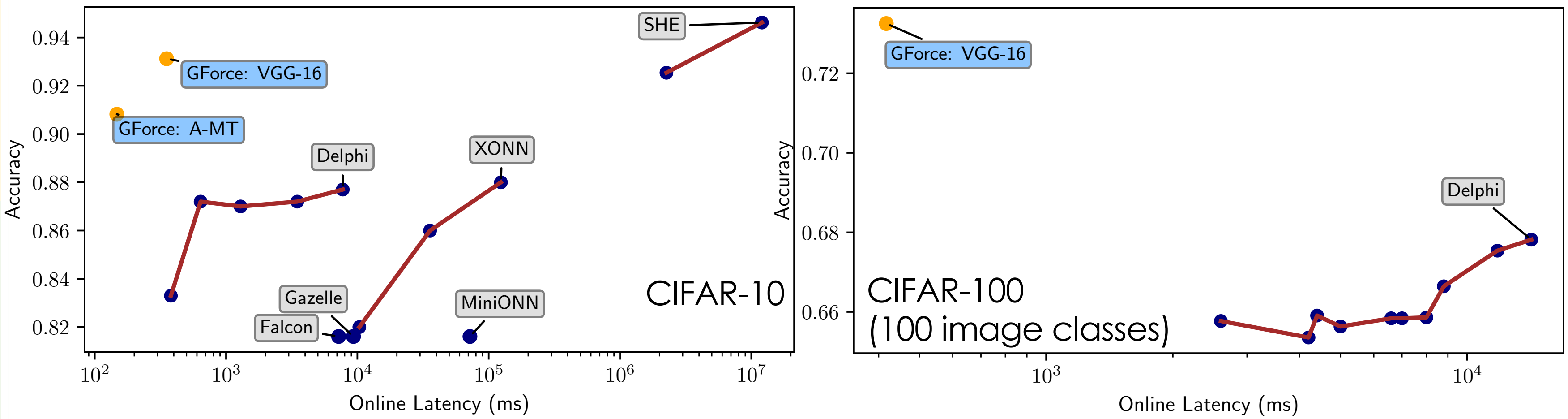
output

Security Analysis

- GForce assumes *semi-honest* client and server
- The client learns
  - *DNN*(x), the query result
- The server learns
  - $\{M_i\}$, the weight (and bias) in linear layers
- Common knowledge/leakage:
  - *DNN* architecture
  - $\{d_i\}$ in SRT Layers (~4 bits for each layer)

Overall Accuracy and Latency

- Shortest (Online) Latency: (CIFAR-10/100: 150/350ms)
- Highest Accuracy in CIFAR-100 (73% vs. 68% of Delphi)



GPU: Nvidia V100 16GB
CPU: Intel Xeon (Skylake) CPUs at 2GHz

Network: Google Cloud (8Gbps & <5ms latency)

Final Remarks

- Utilizing GPU for the *entire* model
- Further applications:
  - Integrating with Delphi
  - Oblivious Decision-Tree Inference (vs. *SS*-based? [NDSS21])
- Code: github.com/Lucieno/gforce-public
  - `SEAL` w/ noise flooding (for AHE) and `PyTorch` (for GPU & NN)
- Also see our GPU-friendly work for training [AAAI21]
  - **G**PU-**O**utsourcing **T**rusted **E**xecution of **N**eural Network Training
- Contact: `{luciengkl, sherman}@ie.cuhk.edu.hk`