Fully Homomorphic Encryption FHE.ORG CONFERENCE

AutoFHE: **Auto**mated Adaption of CNNs for Efficient Evaluation over **FHE**

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Michigan State University

Toronto, Canada 2024

Online Slides

Secure deep learning under fully homomorprhic encryption

Deep Learning as a **Service (DLaaS)**

Internet

Deep Learning as a **Service (DLaaS)**

Customer

Internet

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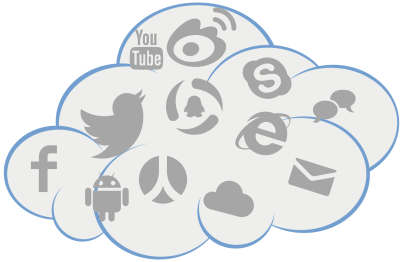
Customer



Cloud

Internet

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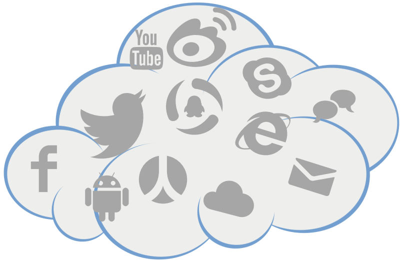

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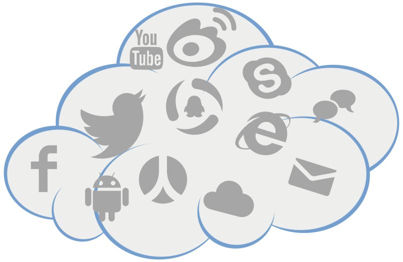

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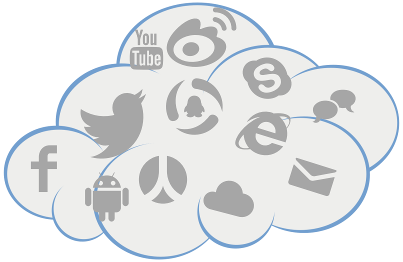

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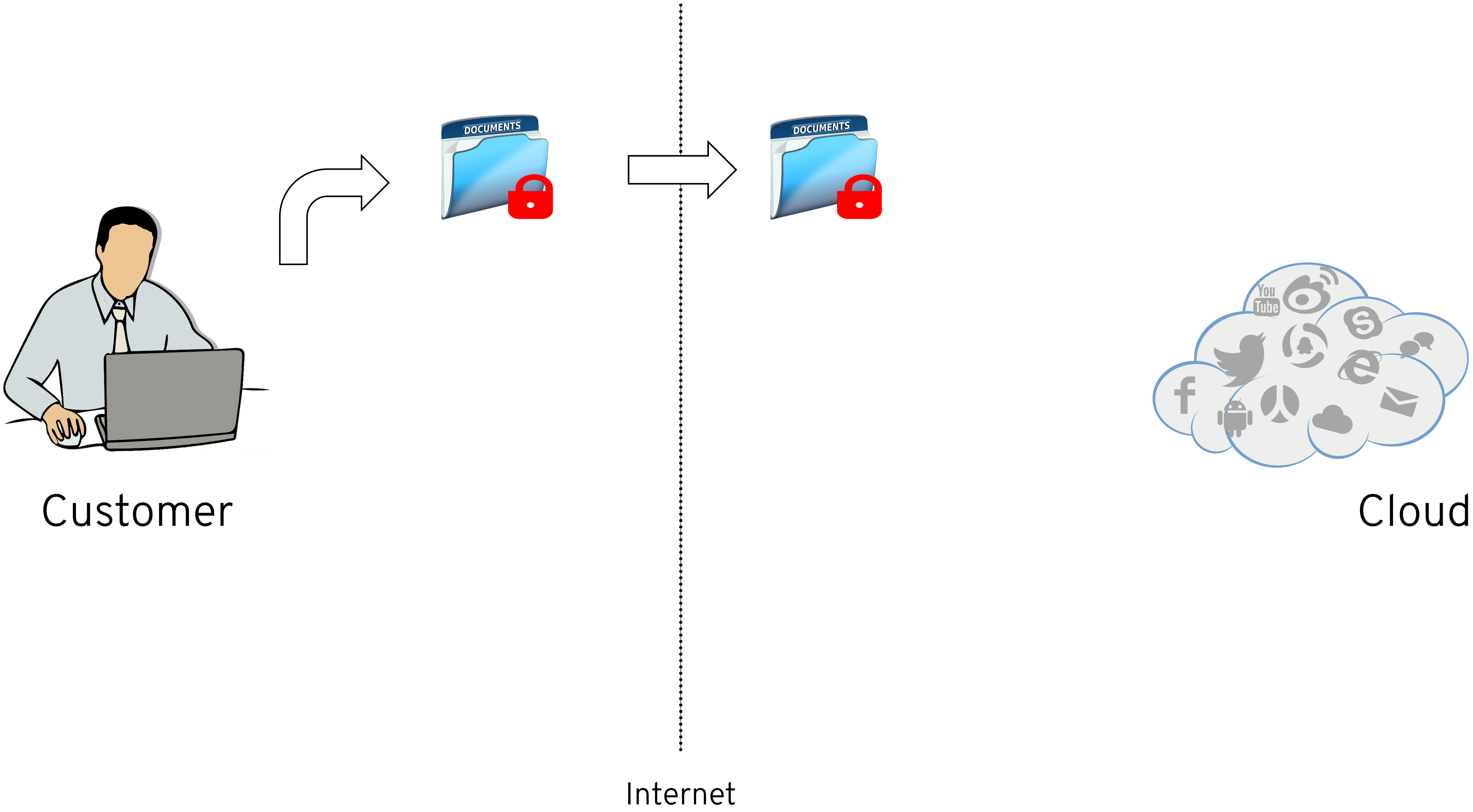

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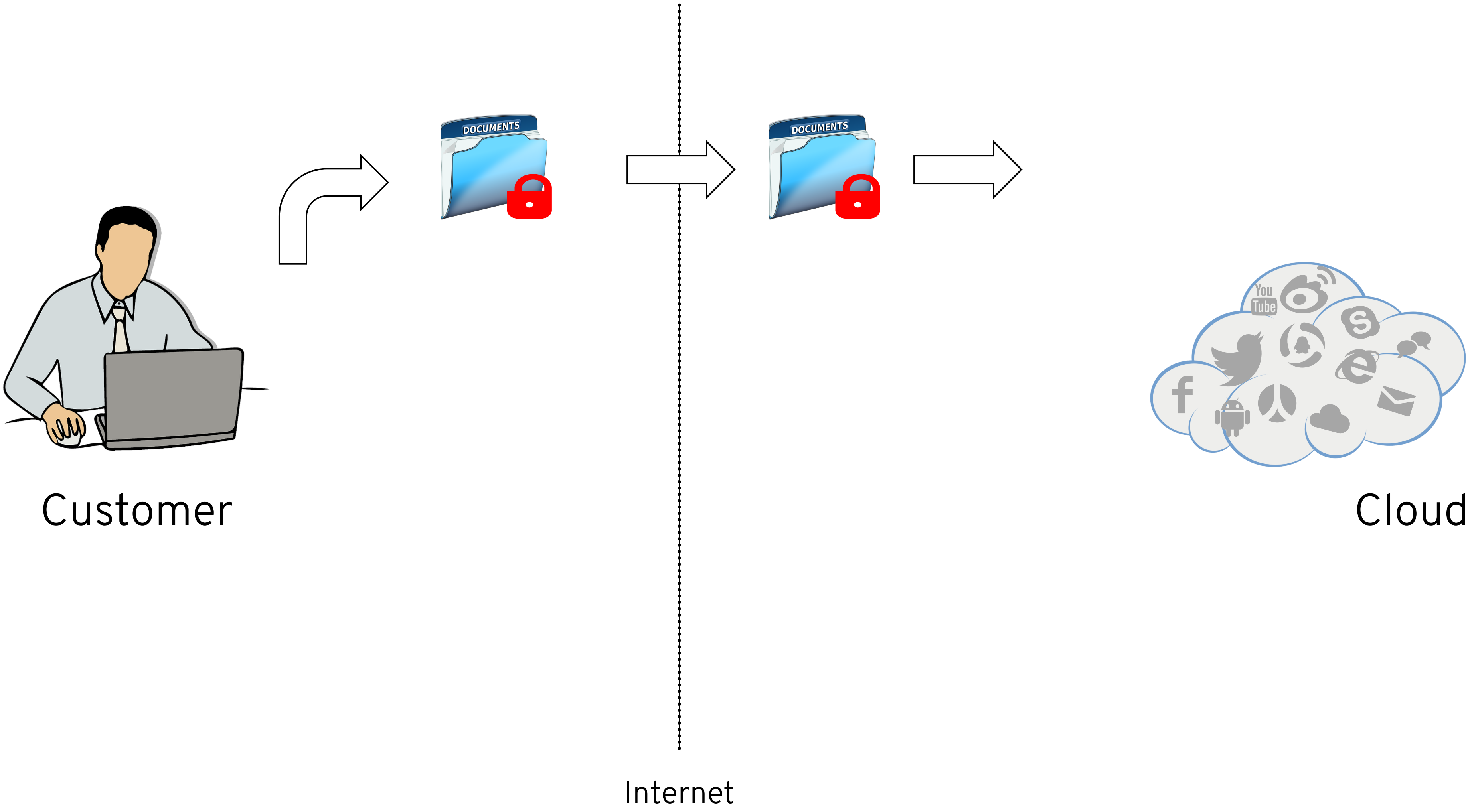

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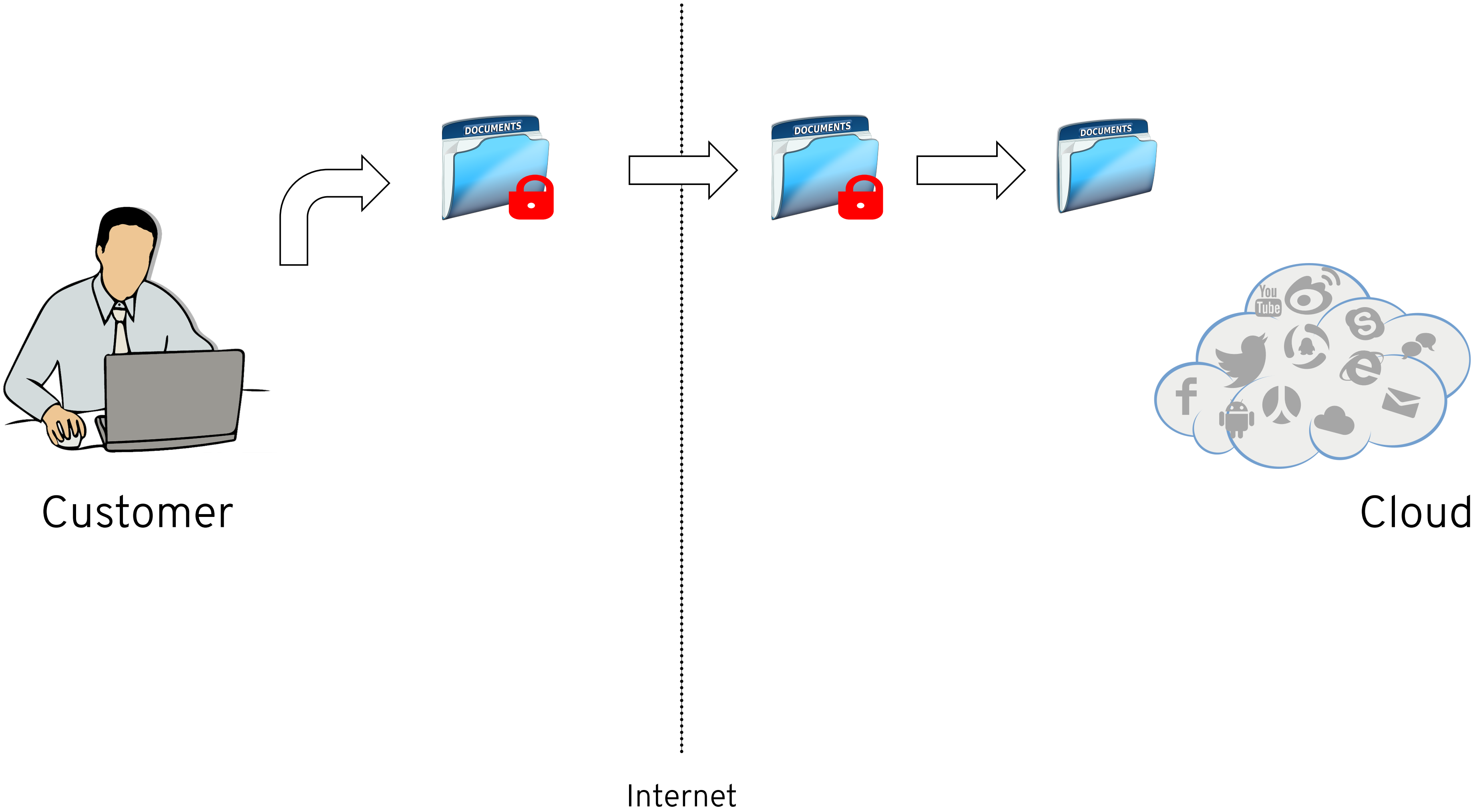

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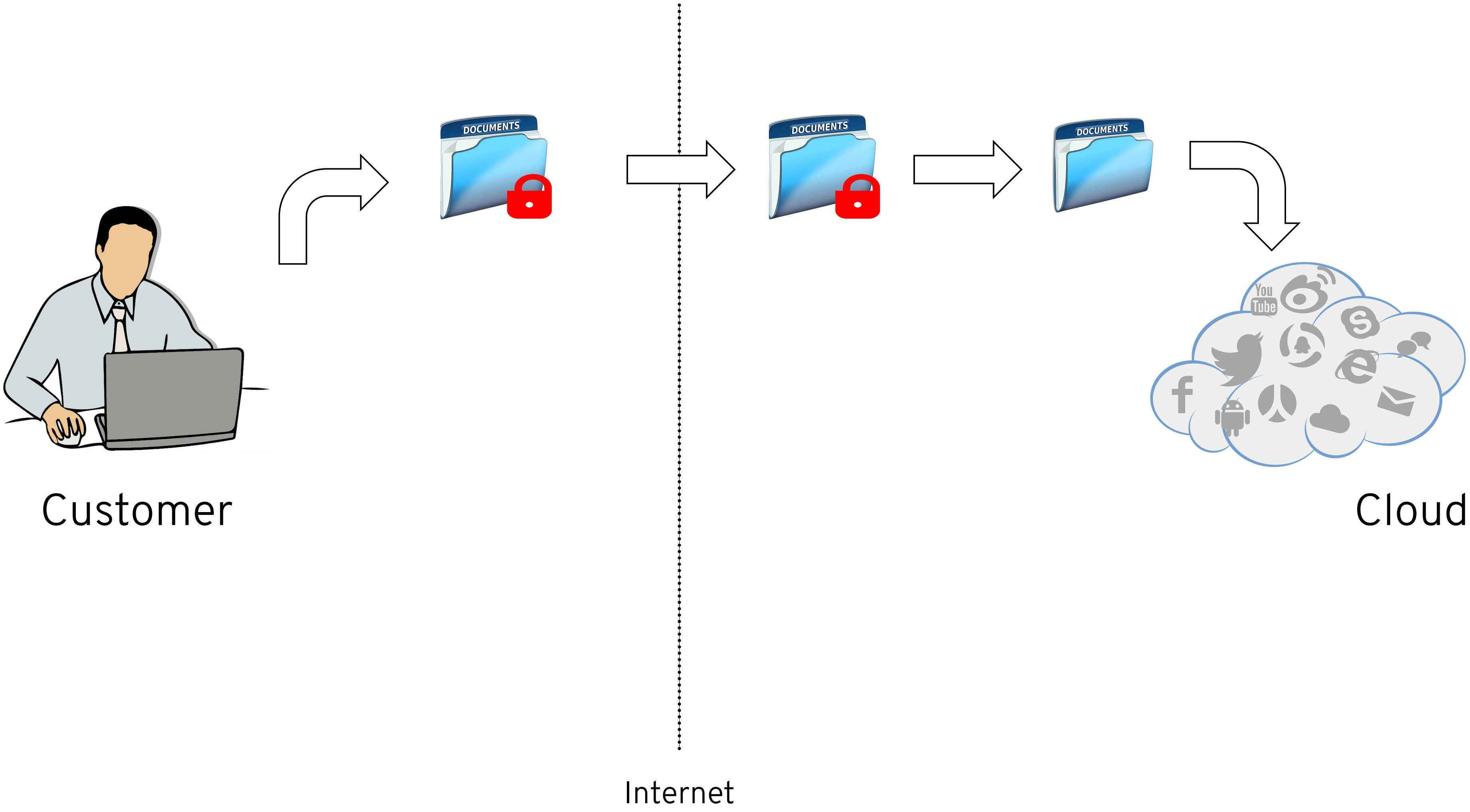

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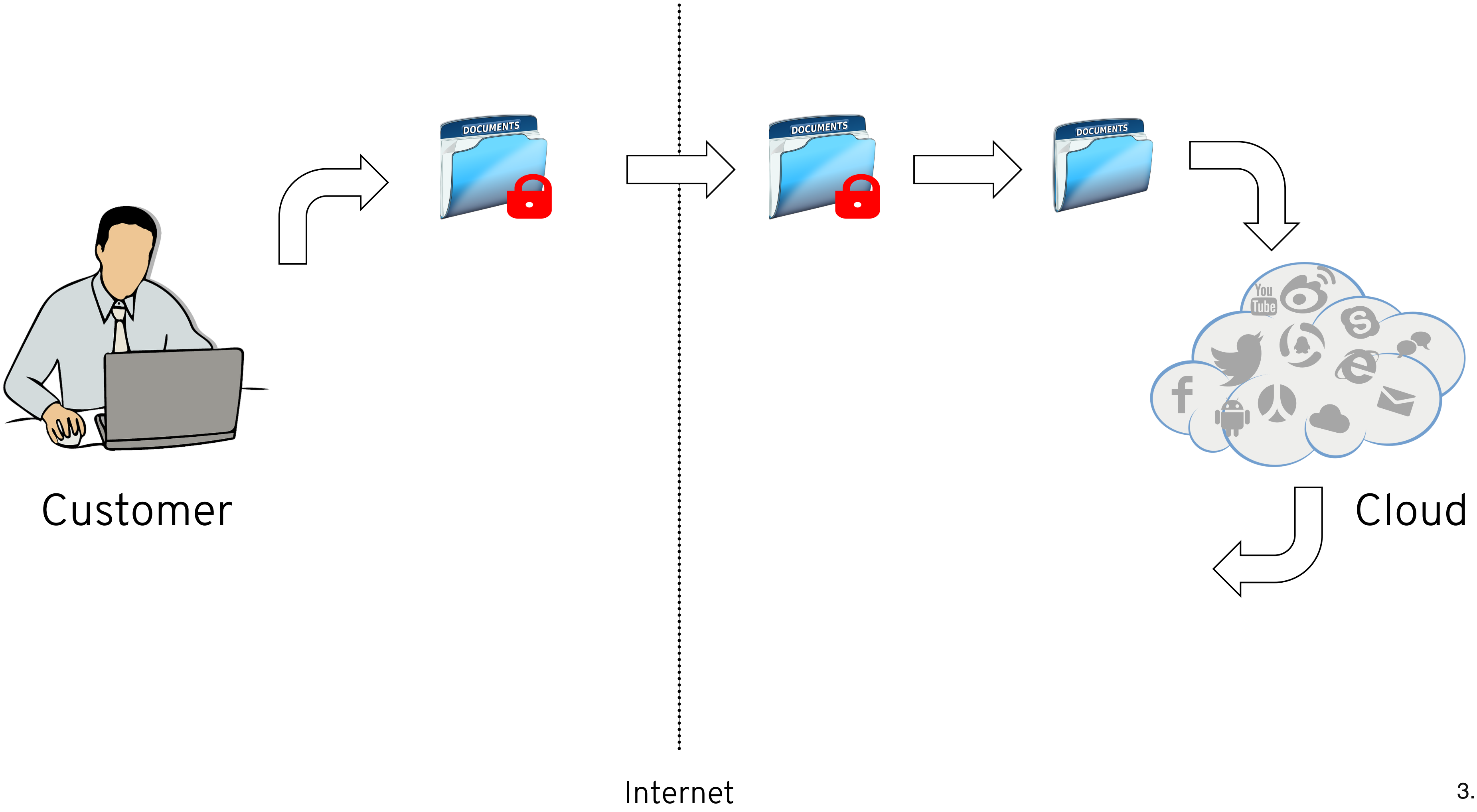

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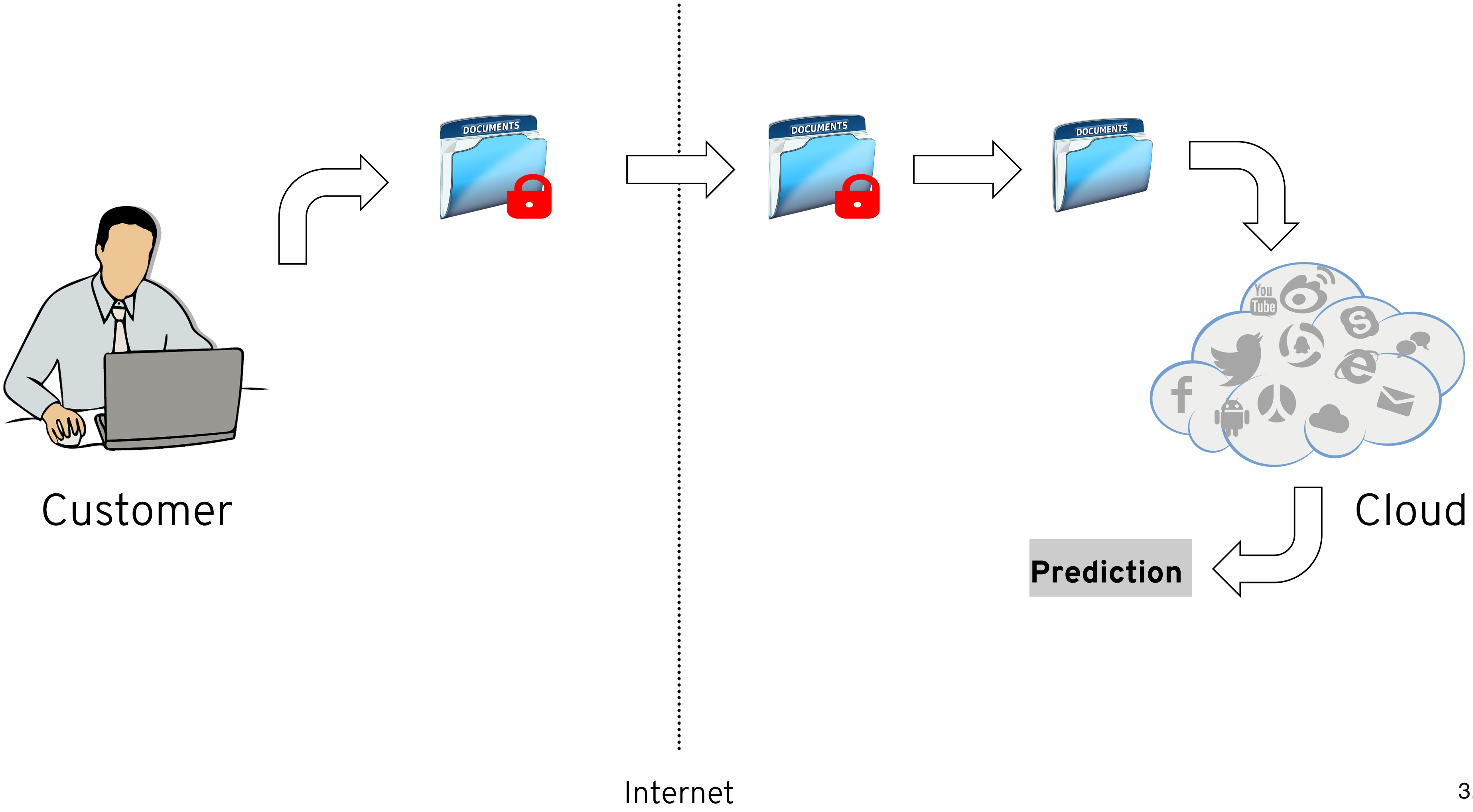

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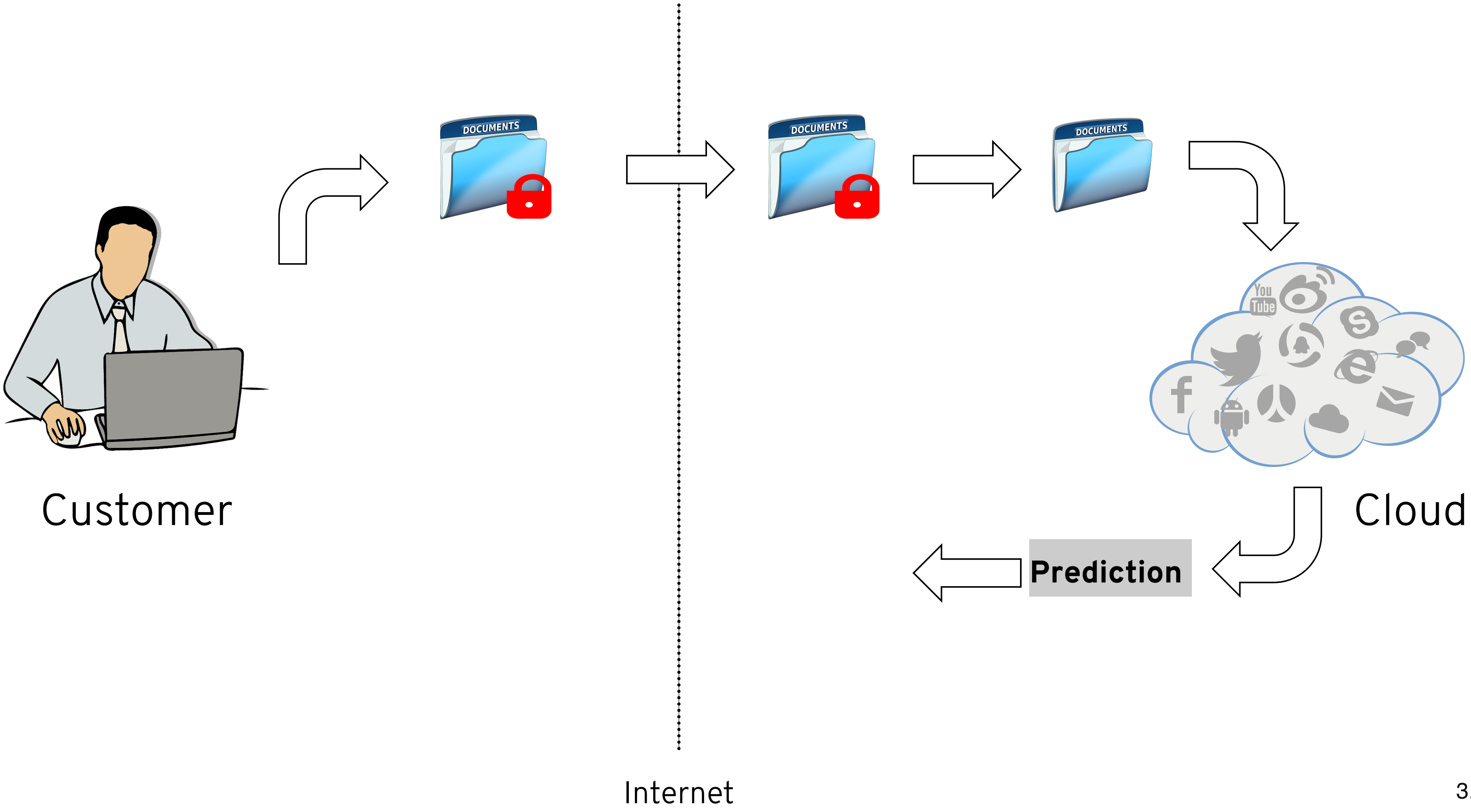

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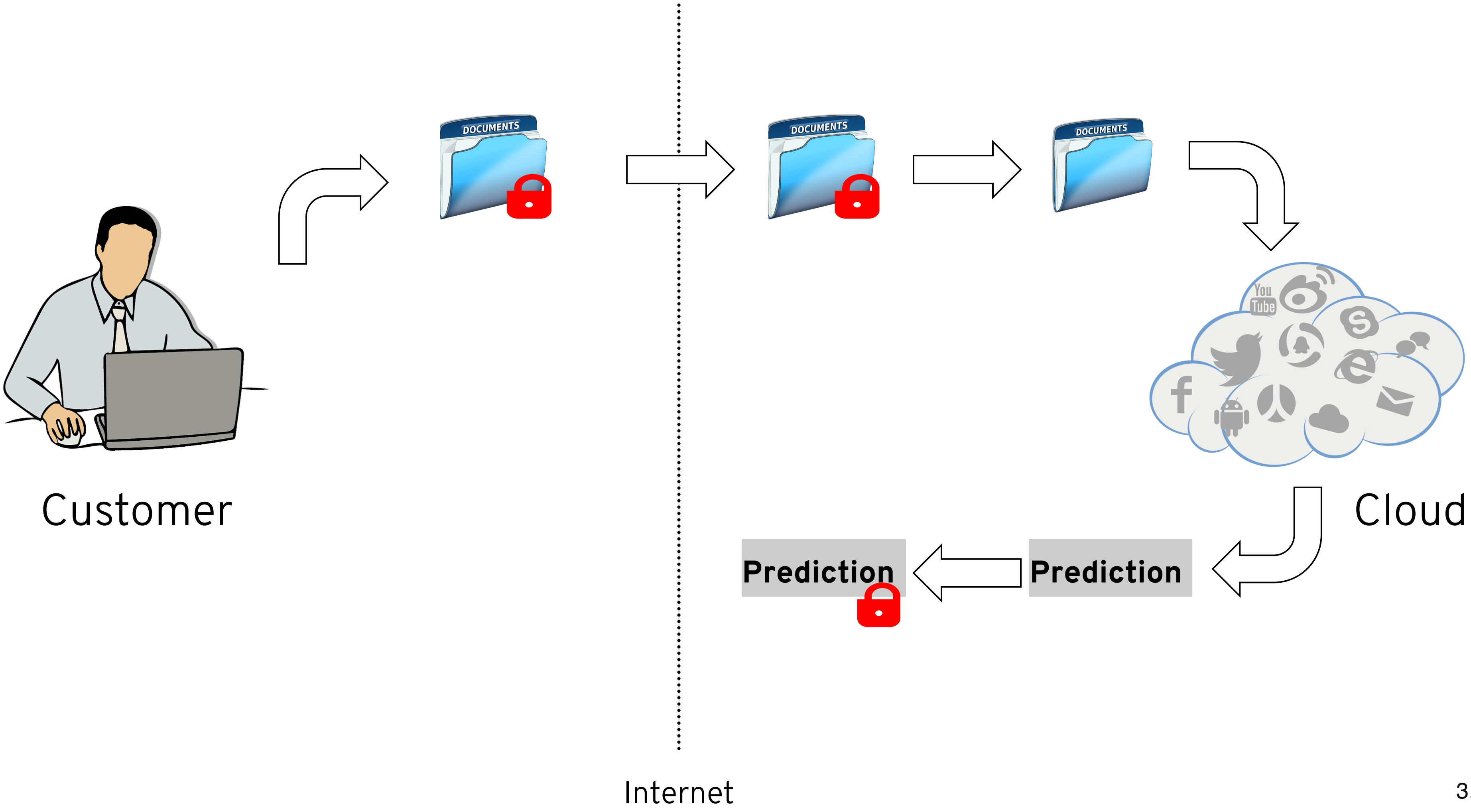

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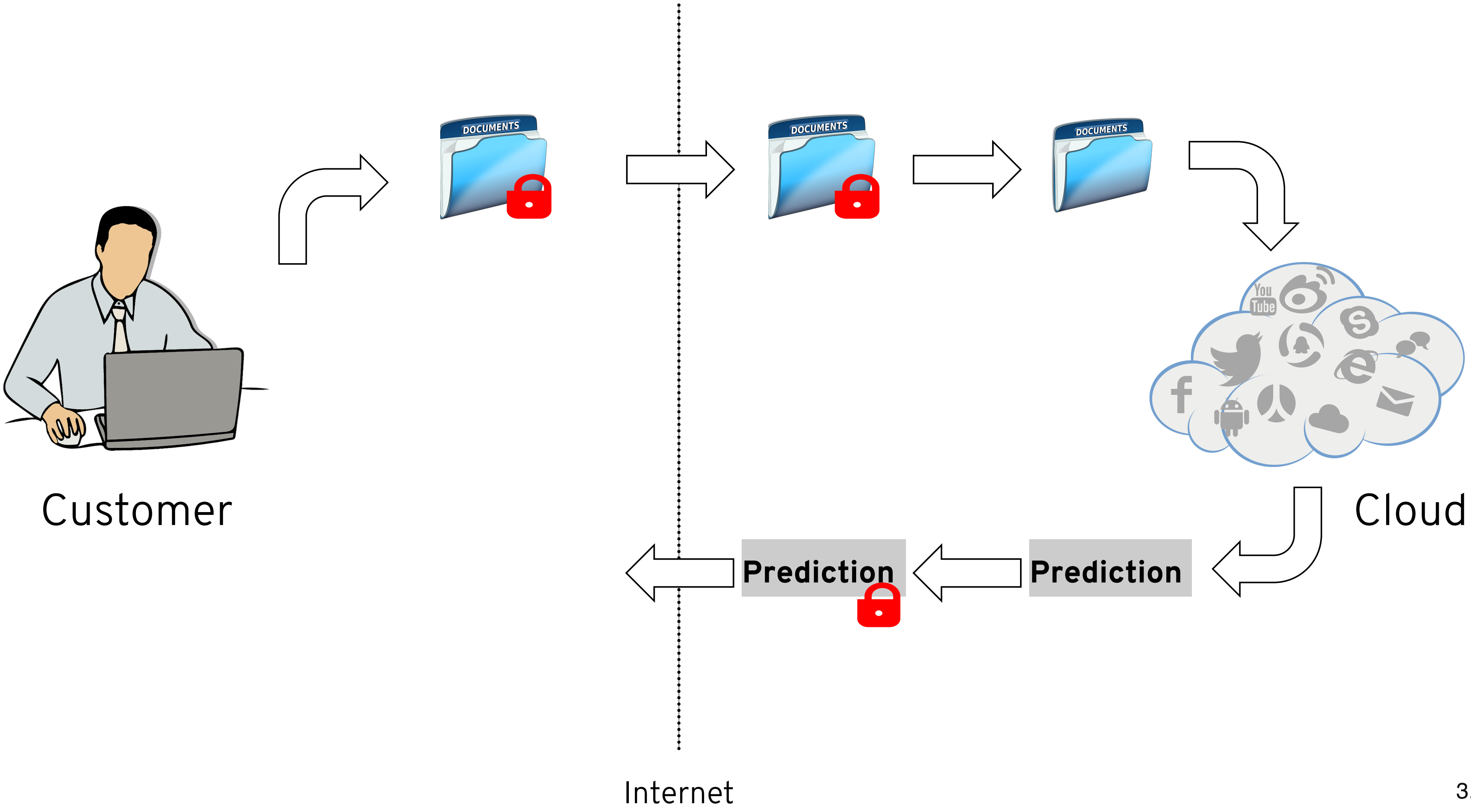

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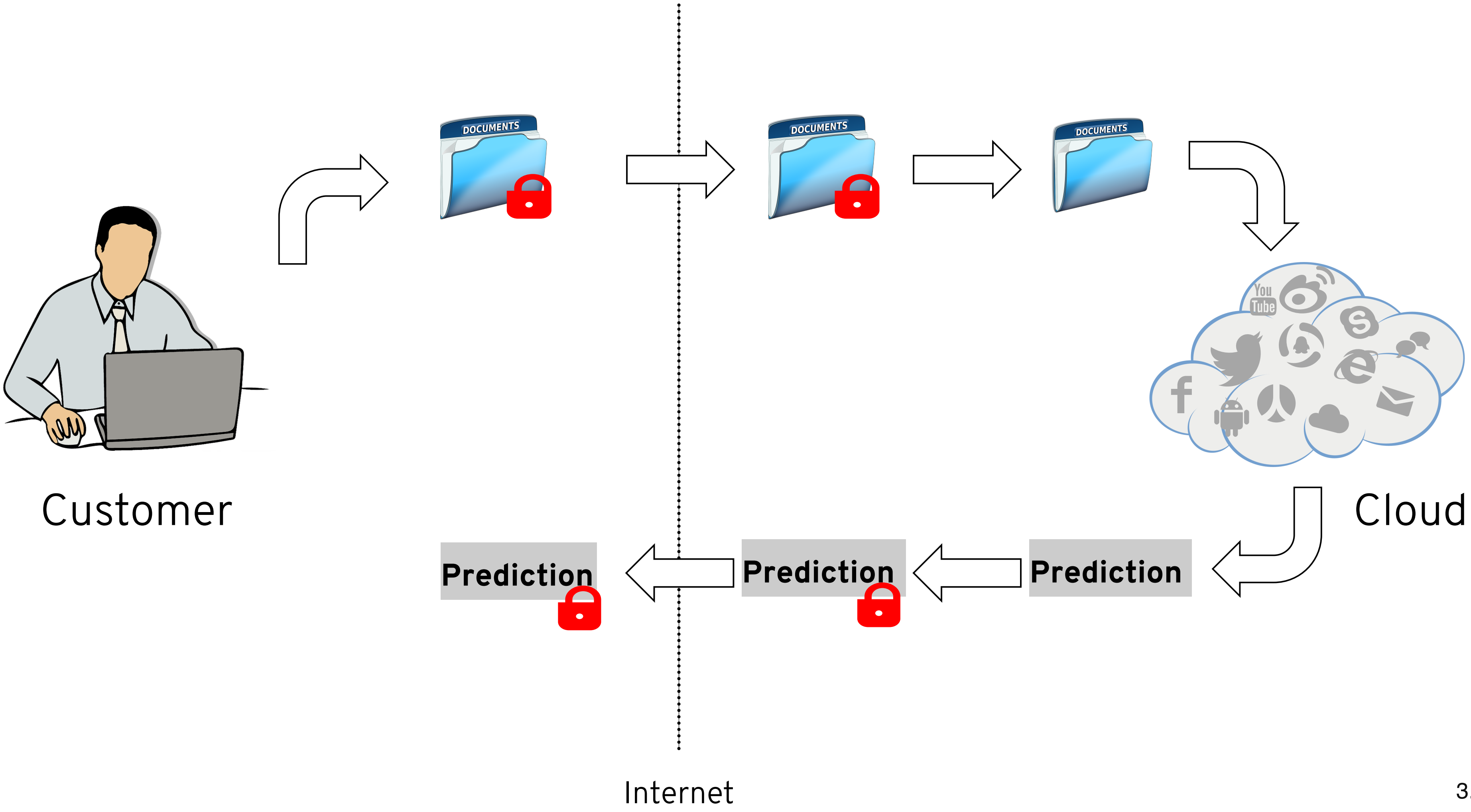

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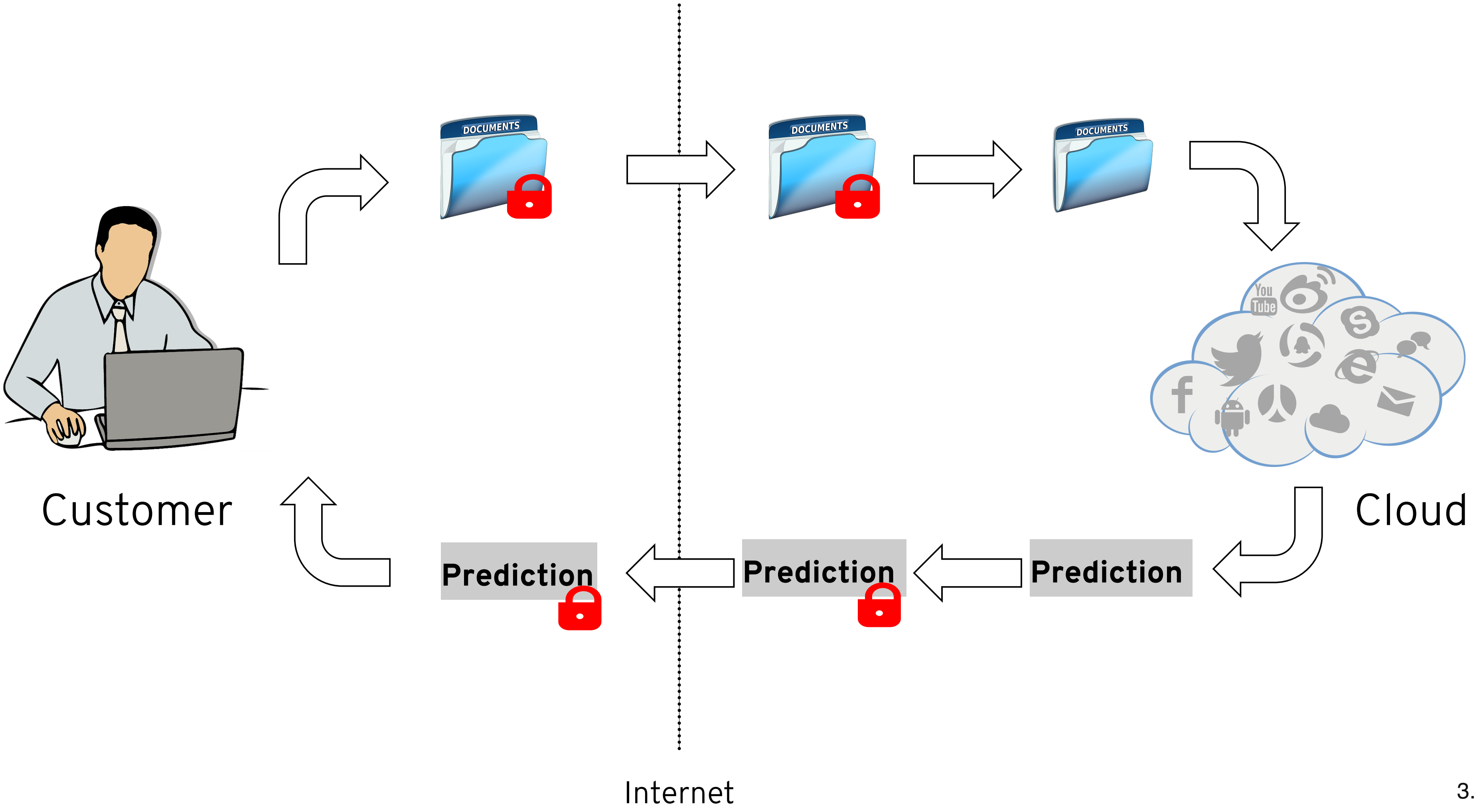

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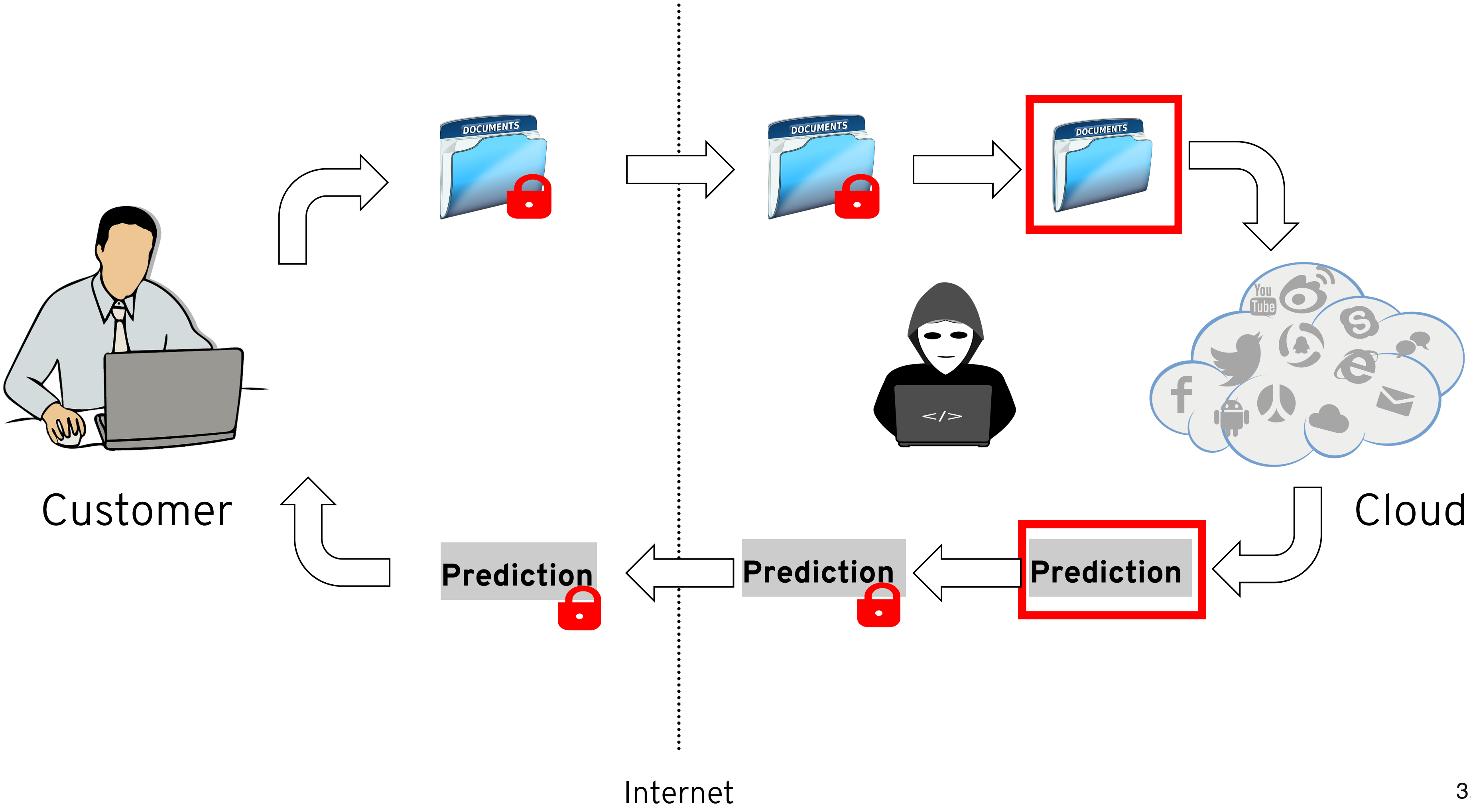

Secure DLaaS under **Fully Homomorphic Encryption (FHE)**

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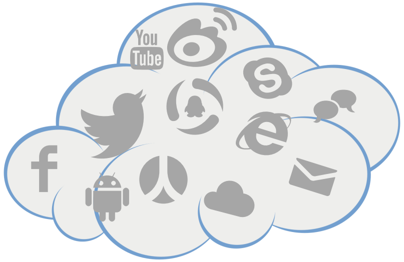

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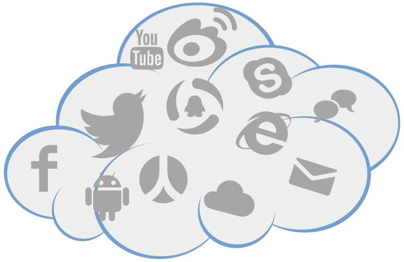

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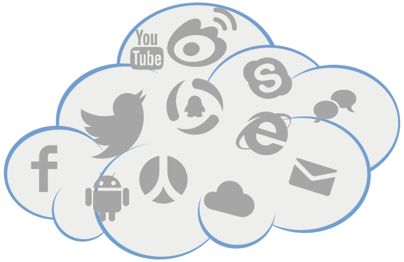

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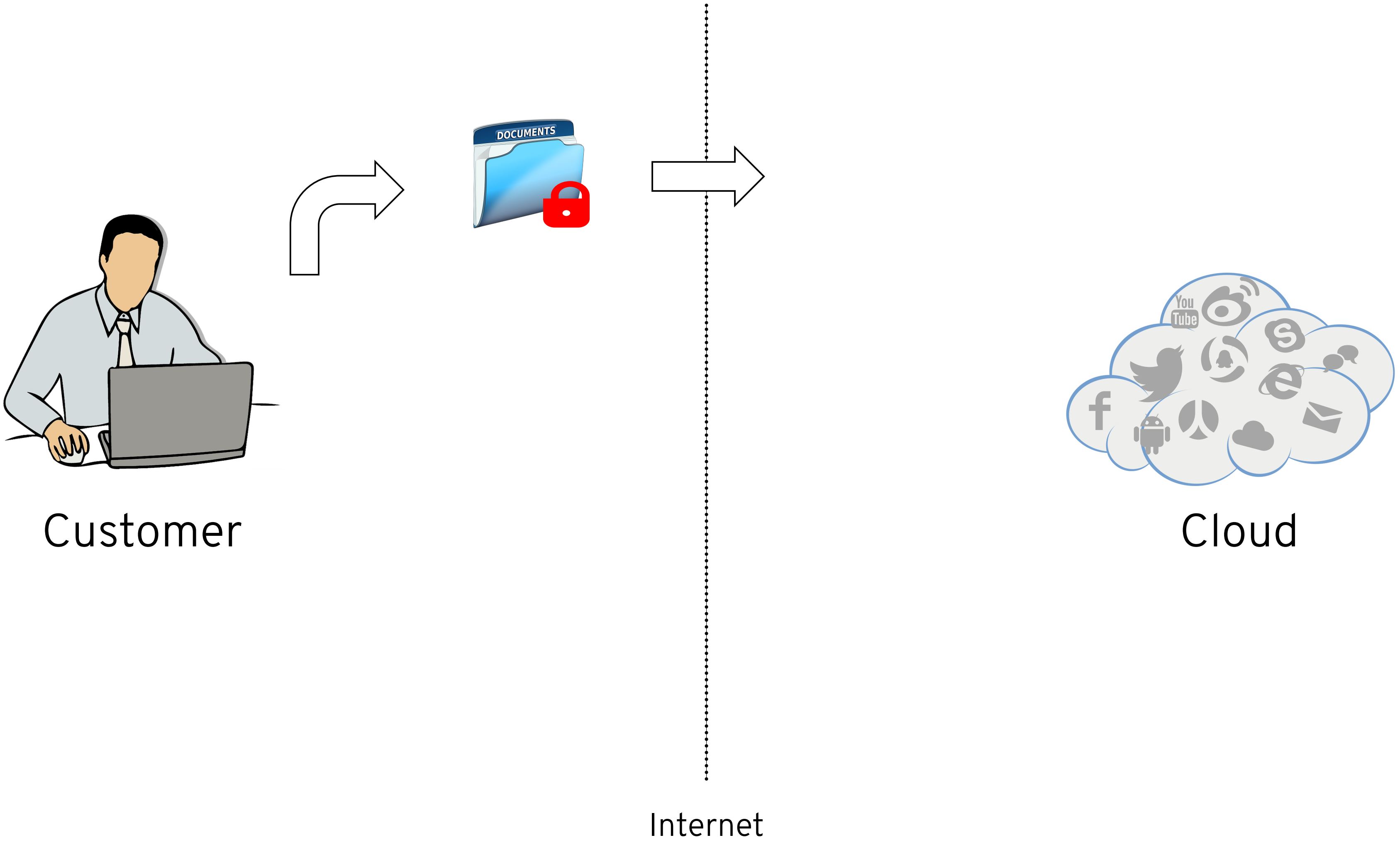

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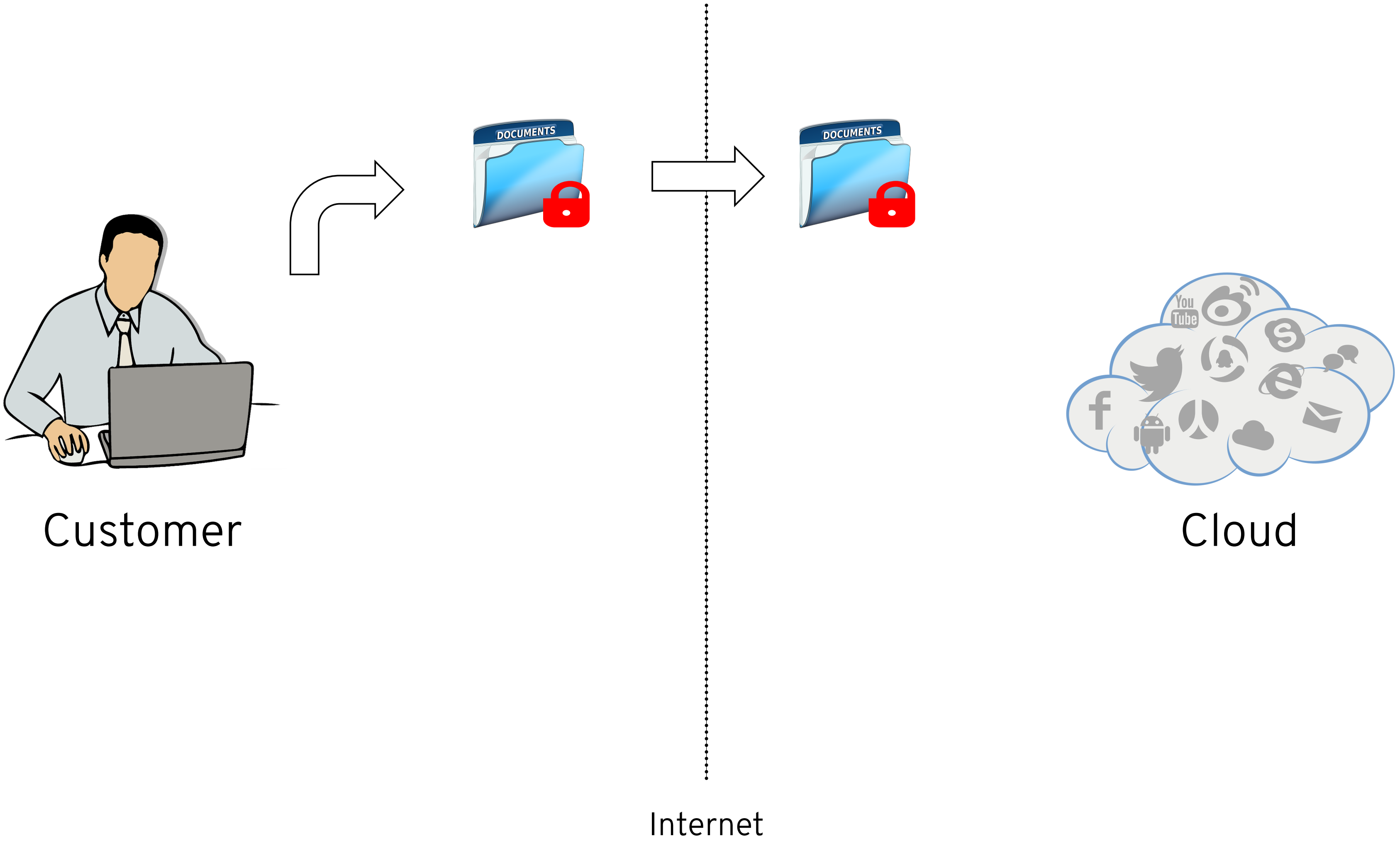

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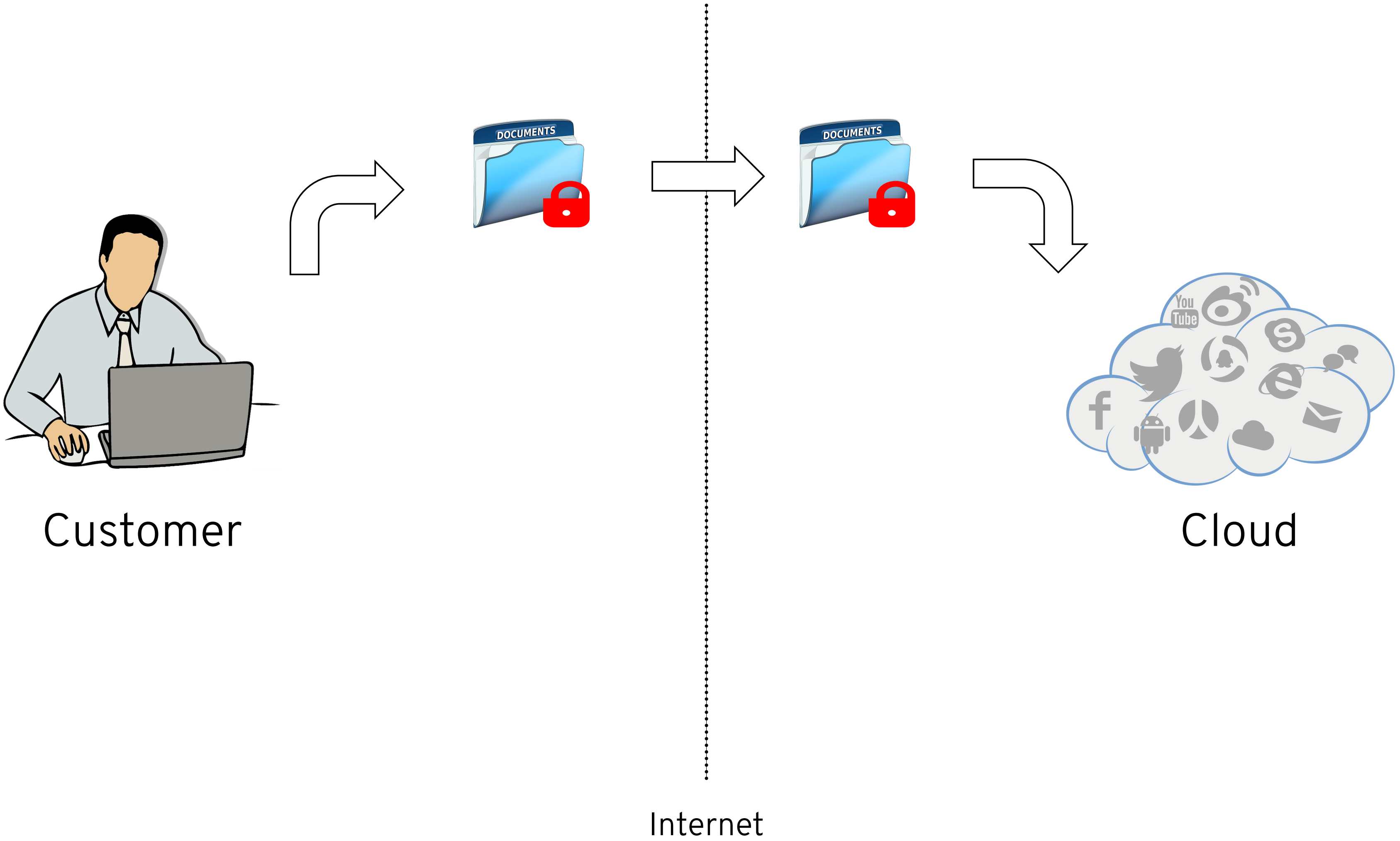

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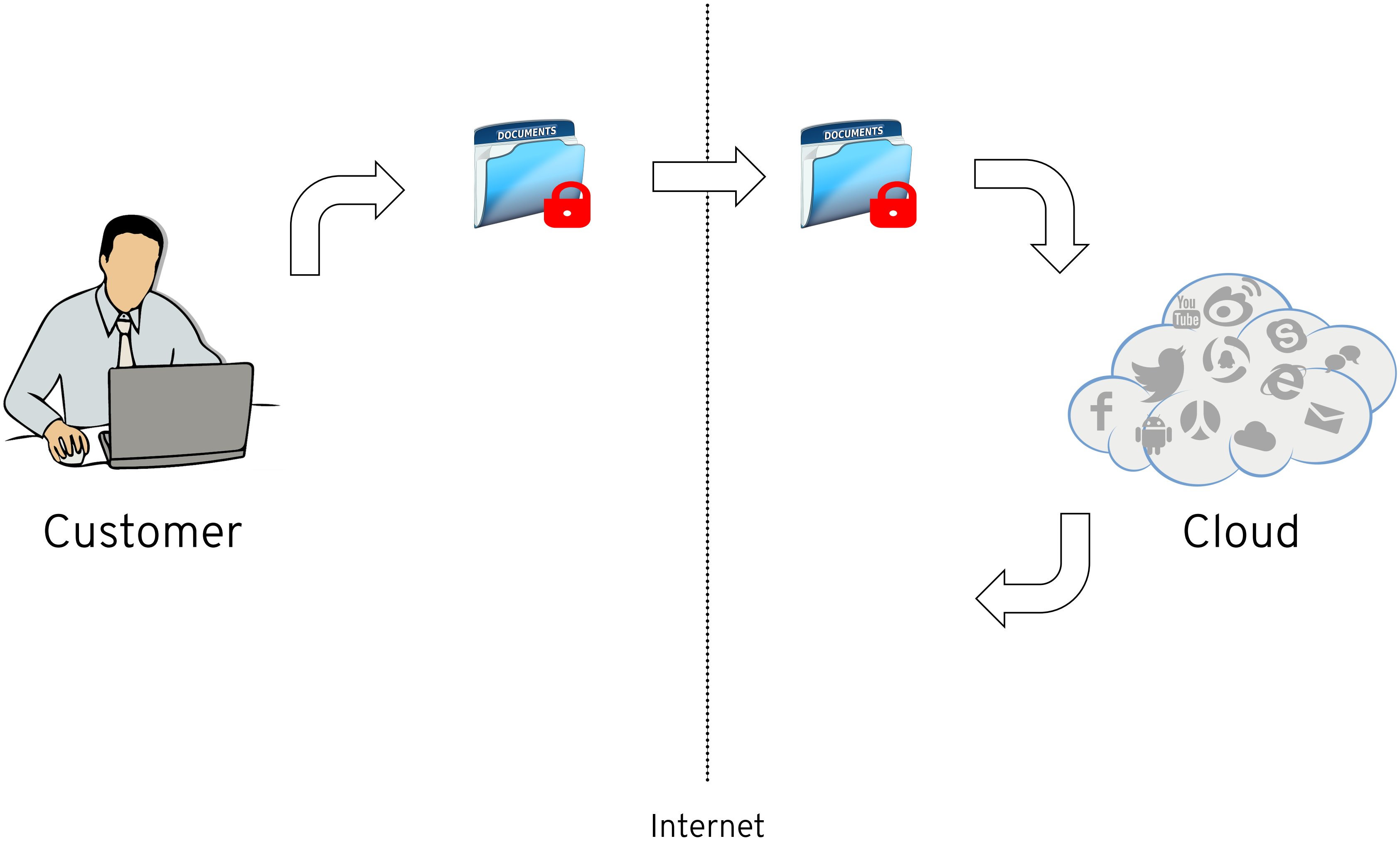

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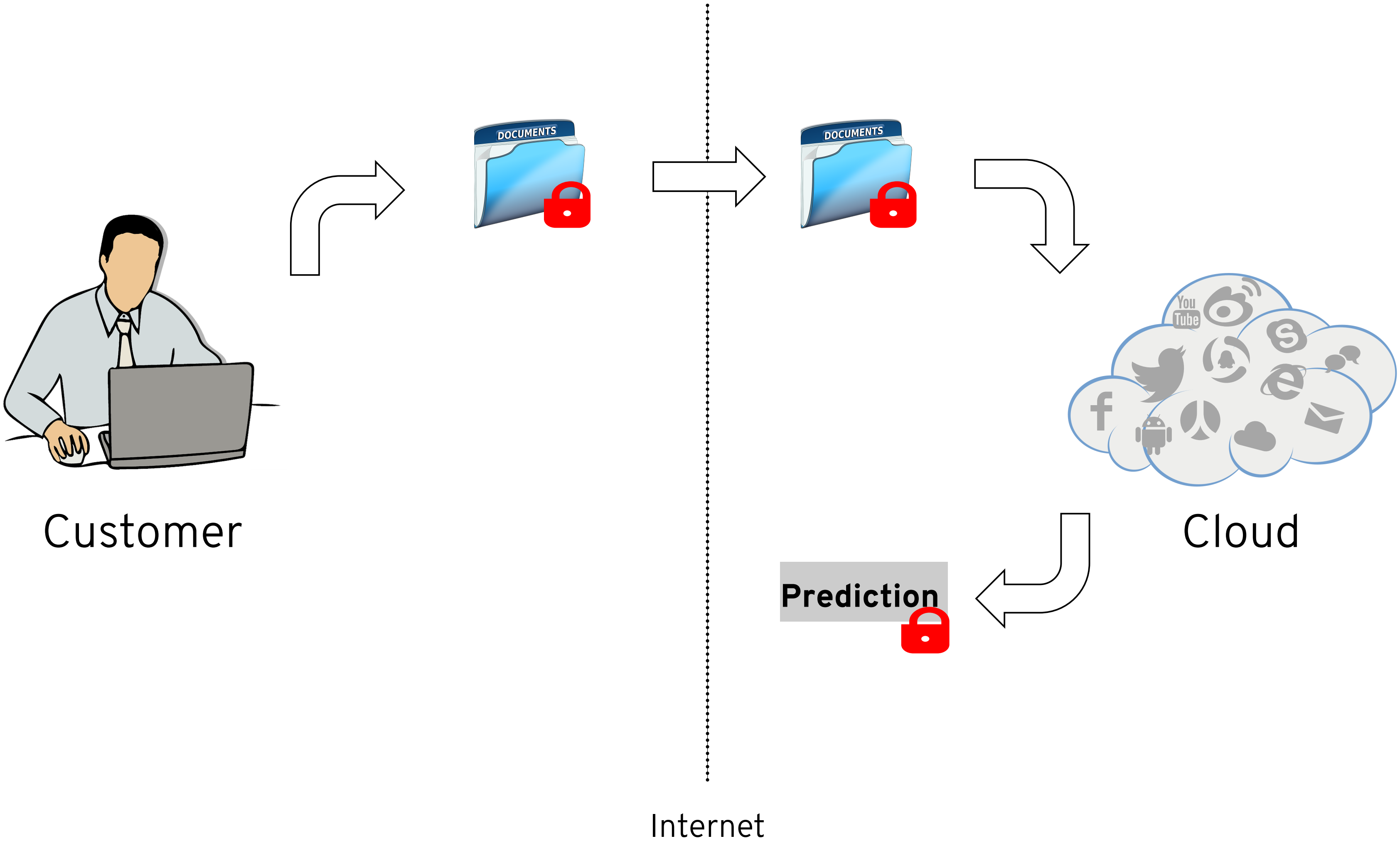

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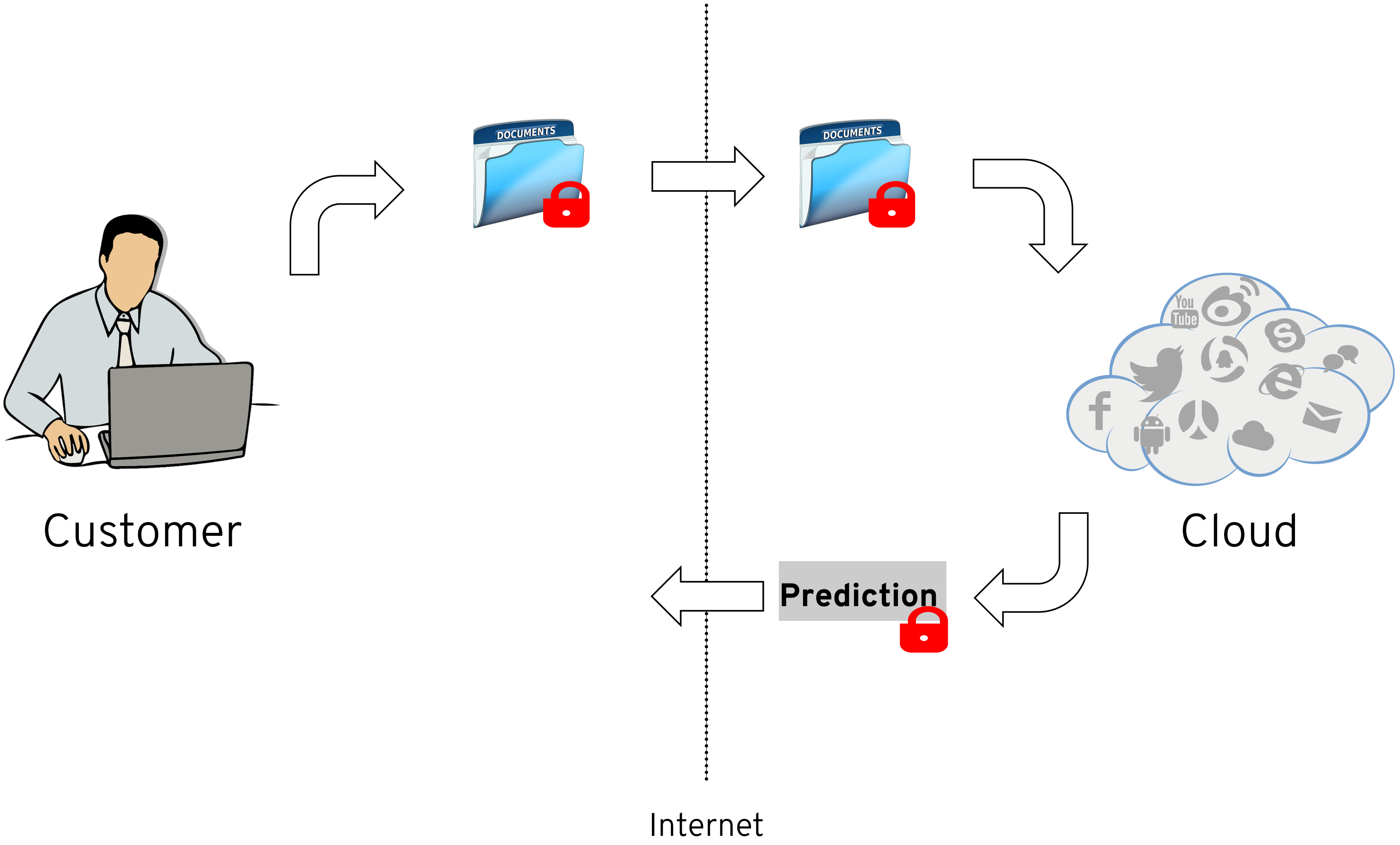

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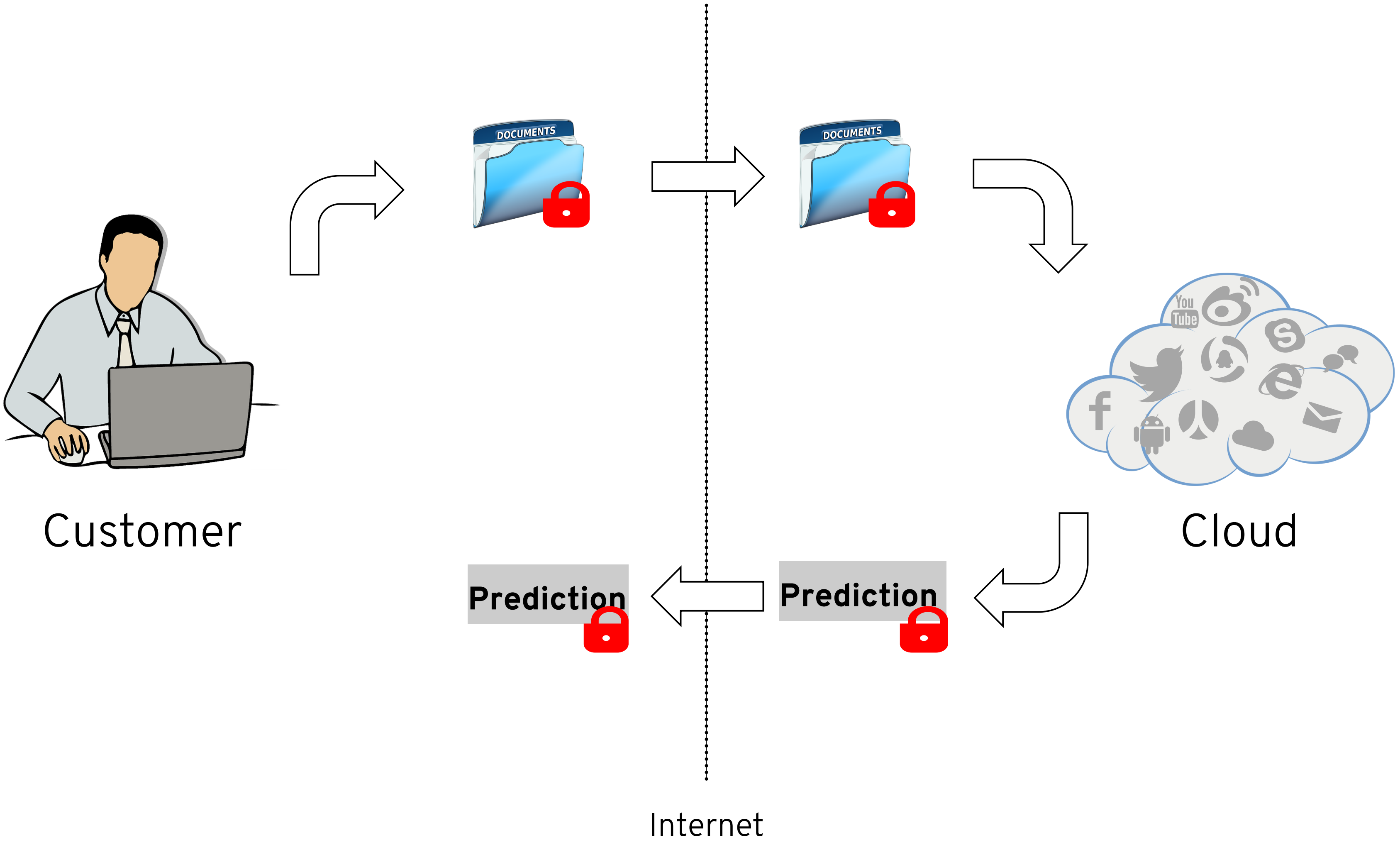

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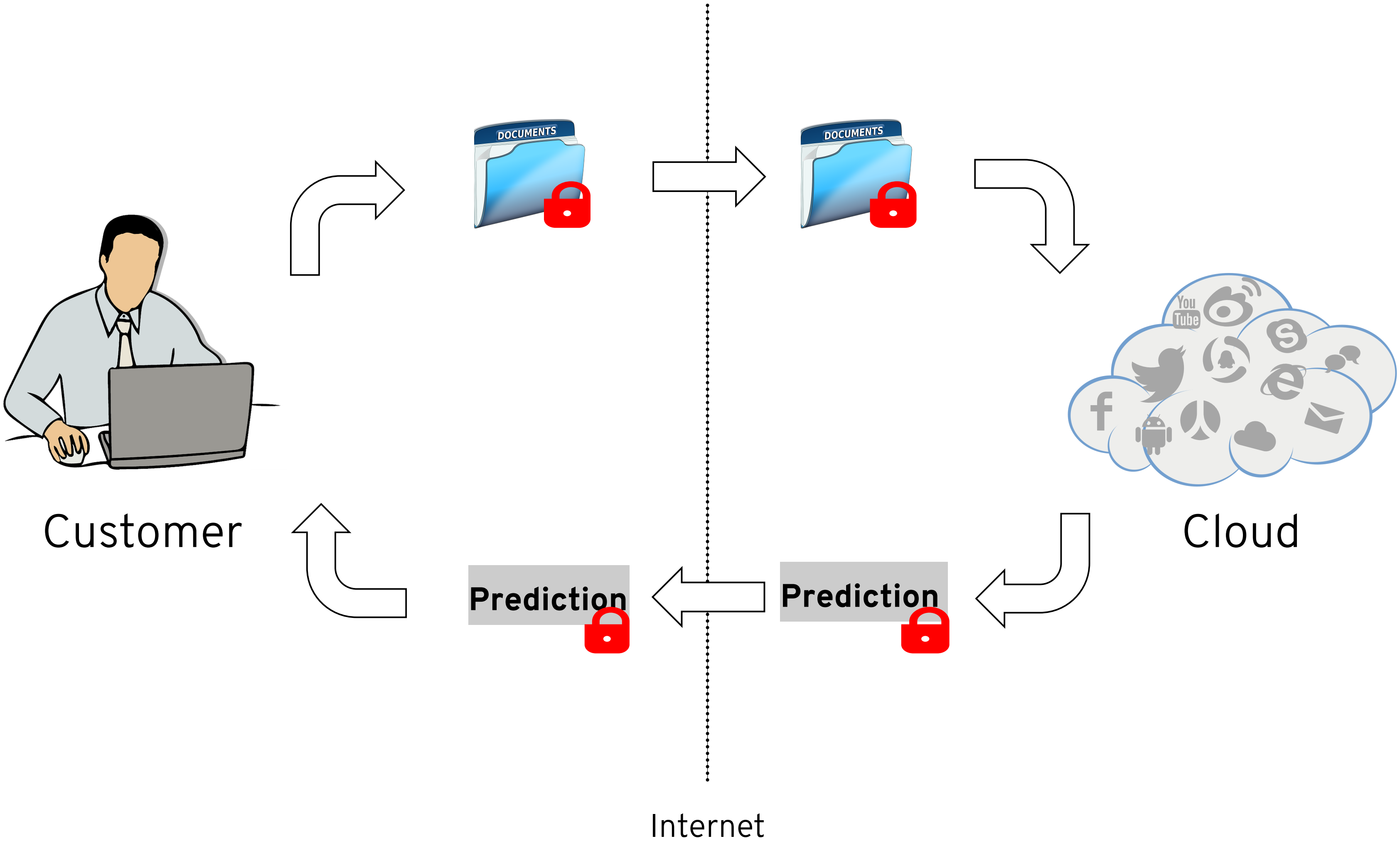

From **Secure Computation** to **Secure Deep Learning**

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1

Initiative: privacy homomorphisms, 1978

From **Secure Computation** to **Secure Deep Learning**

2

Craig's Blueprint uses
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Approximate Arithmetic under leveled homomorphic encryption: CKKS (HEAAN), ASIACRYPT 2017

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AutoFHE: Automated Adaption of CNNs for Efficient Evaluation over **FHE**, USENIX 2024

Convolutional Neural Networks (CNNs)

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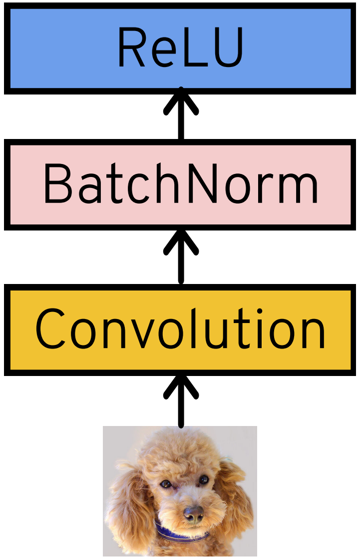
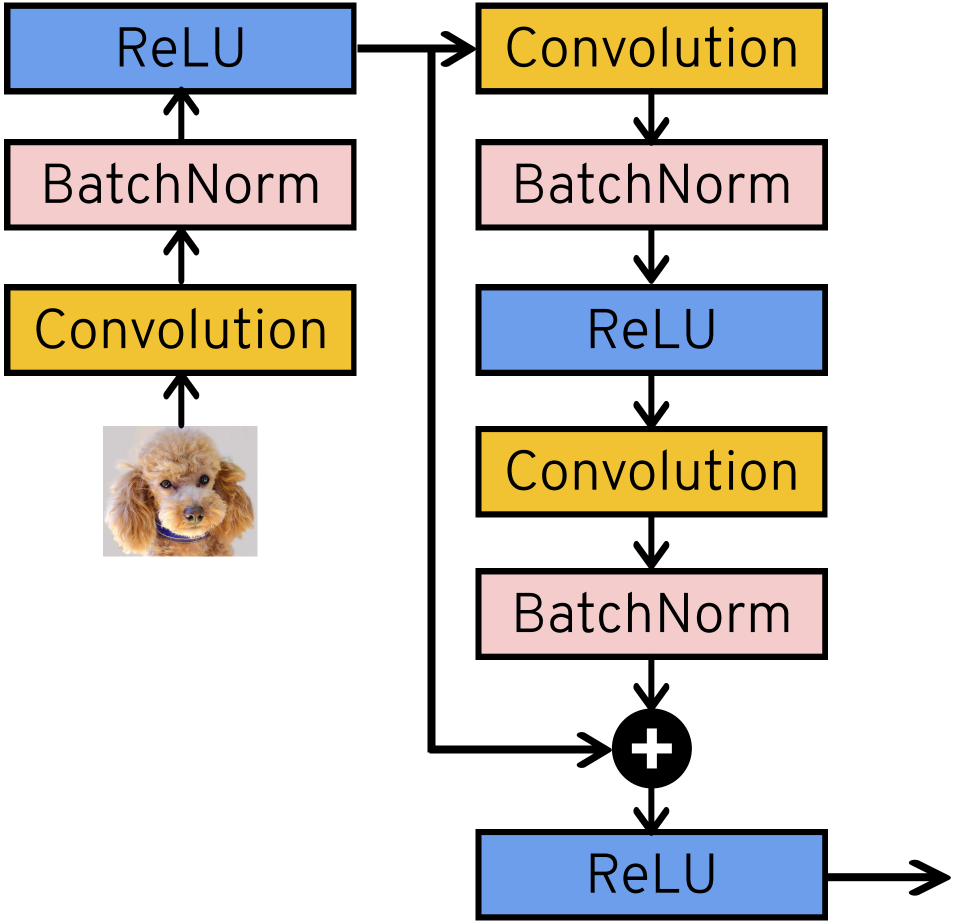


Convolutional Neural Networks (CNNs)



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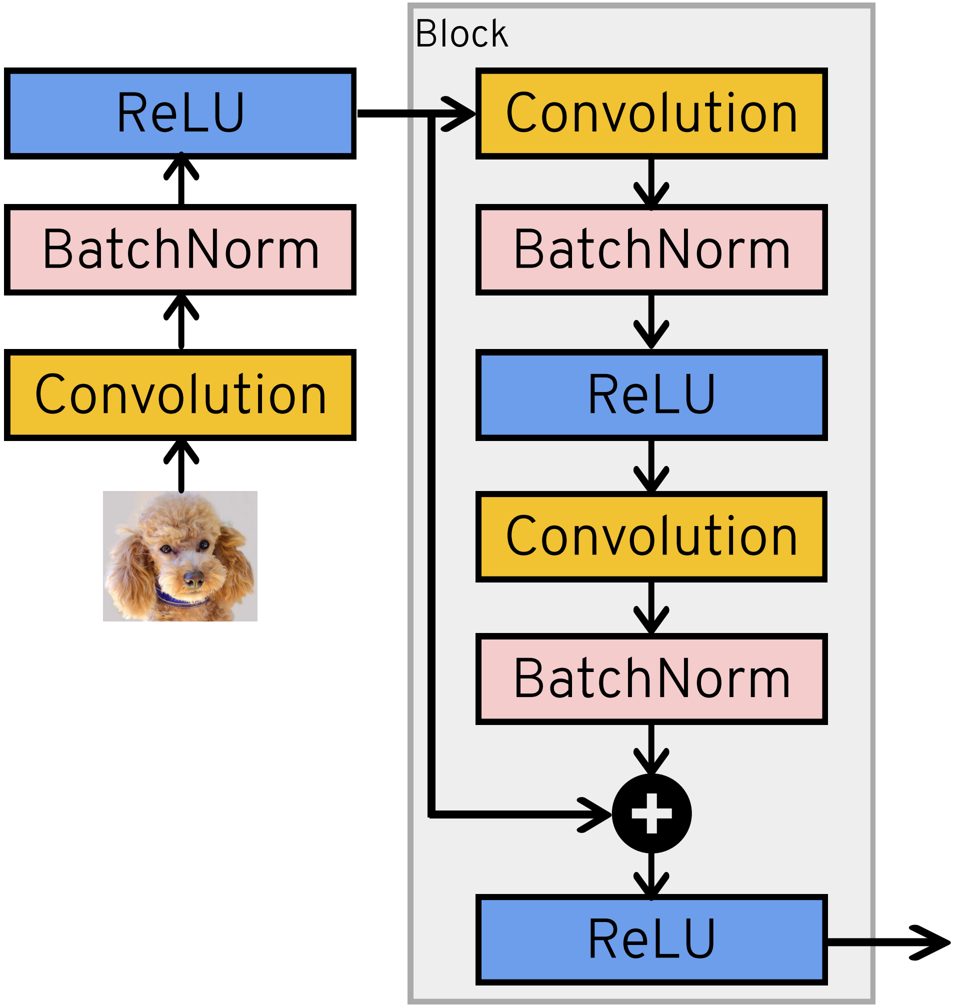

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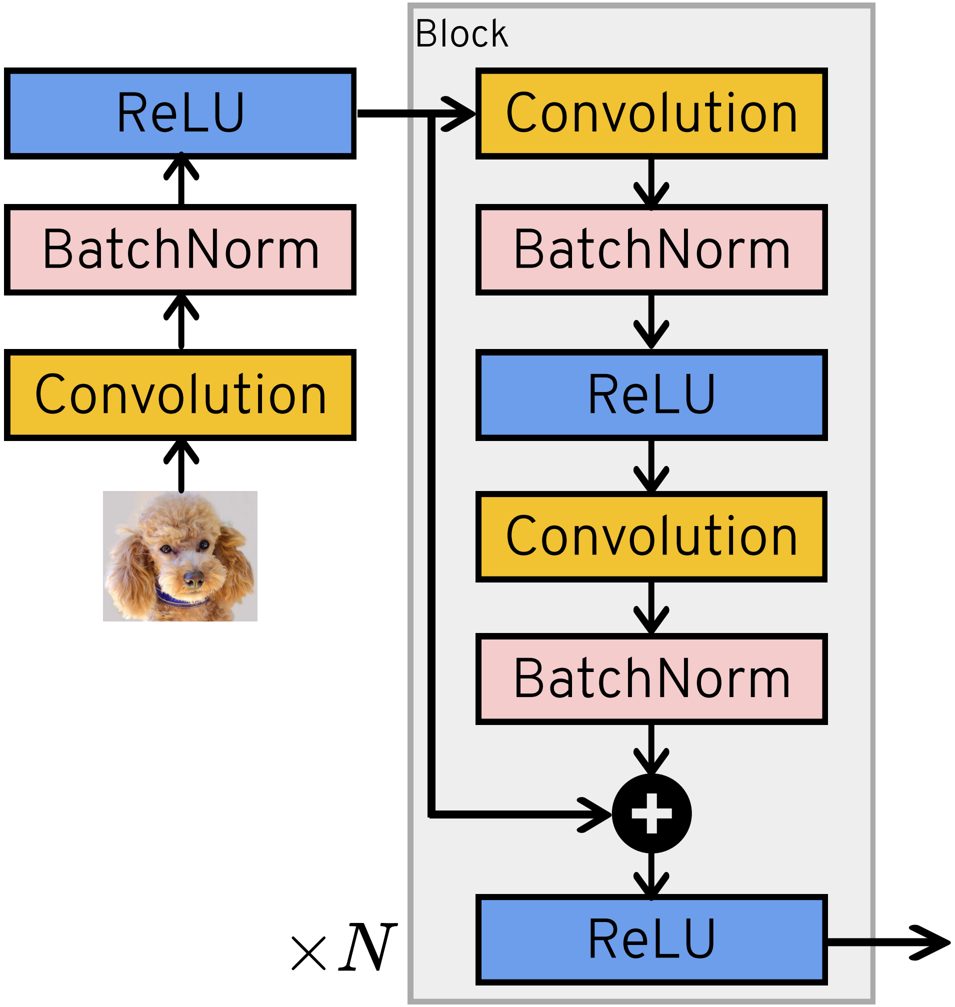

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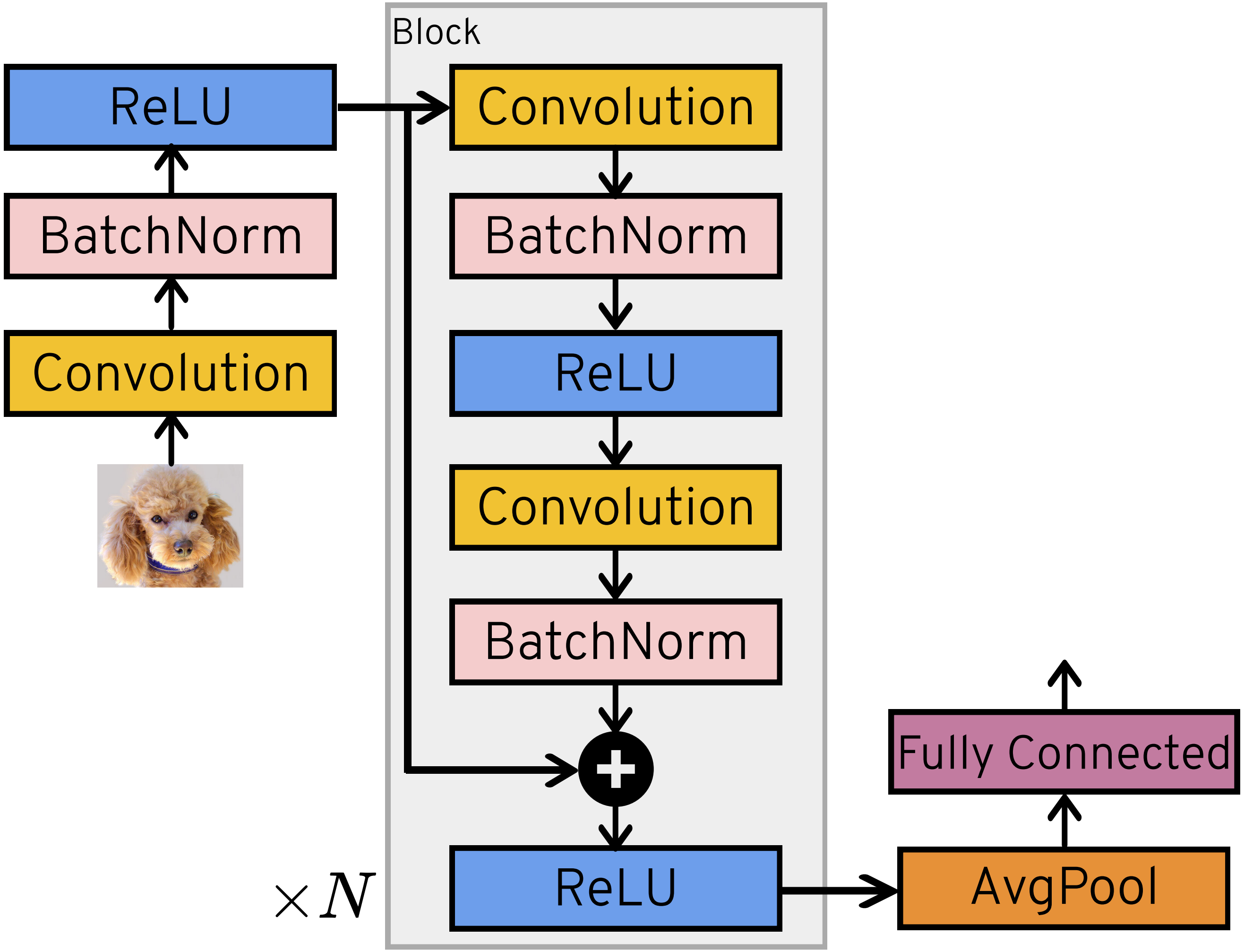

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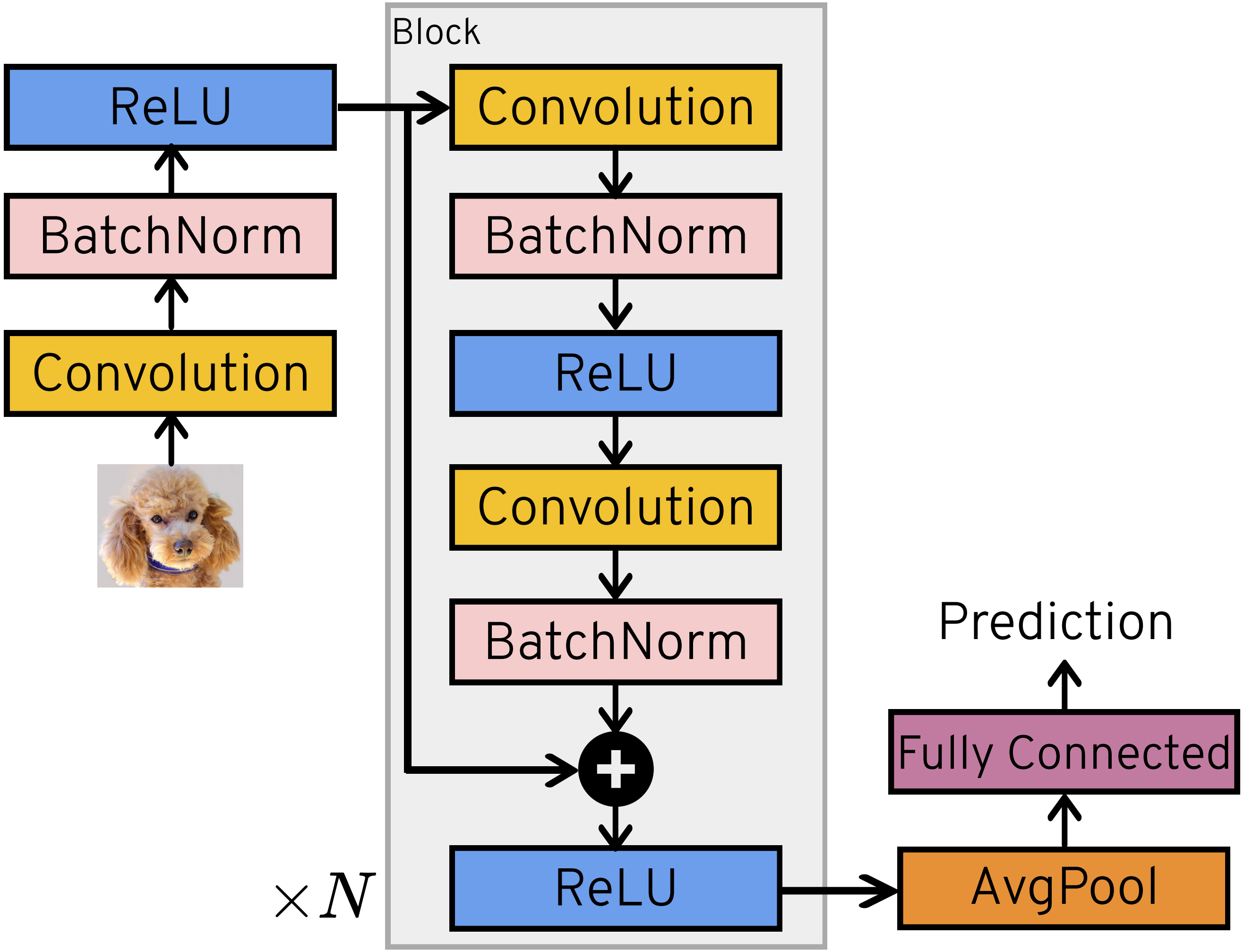
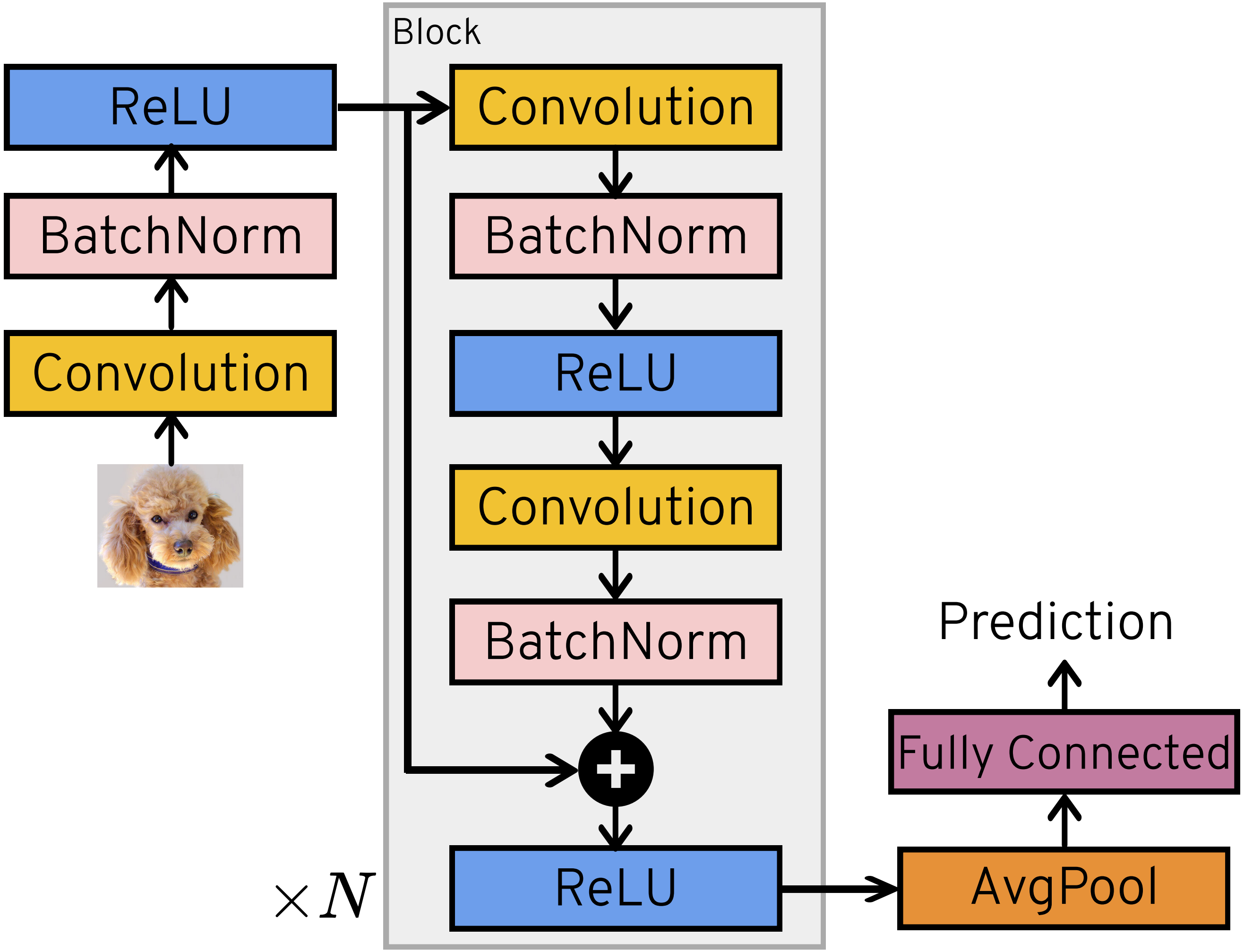


CNNs under **Homomorphic Encryption (HE)**



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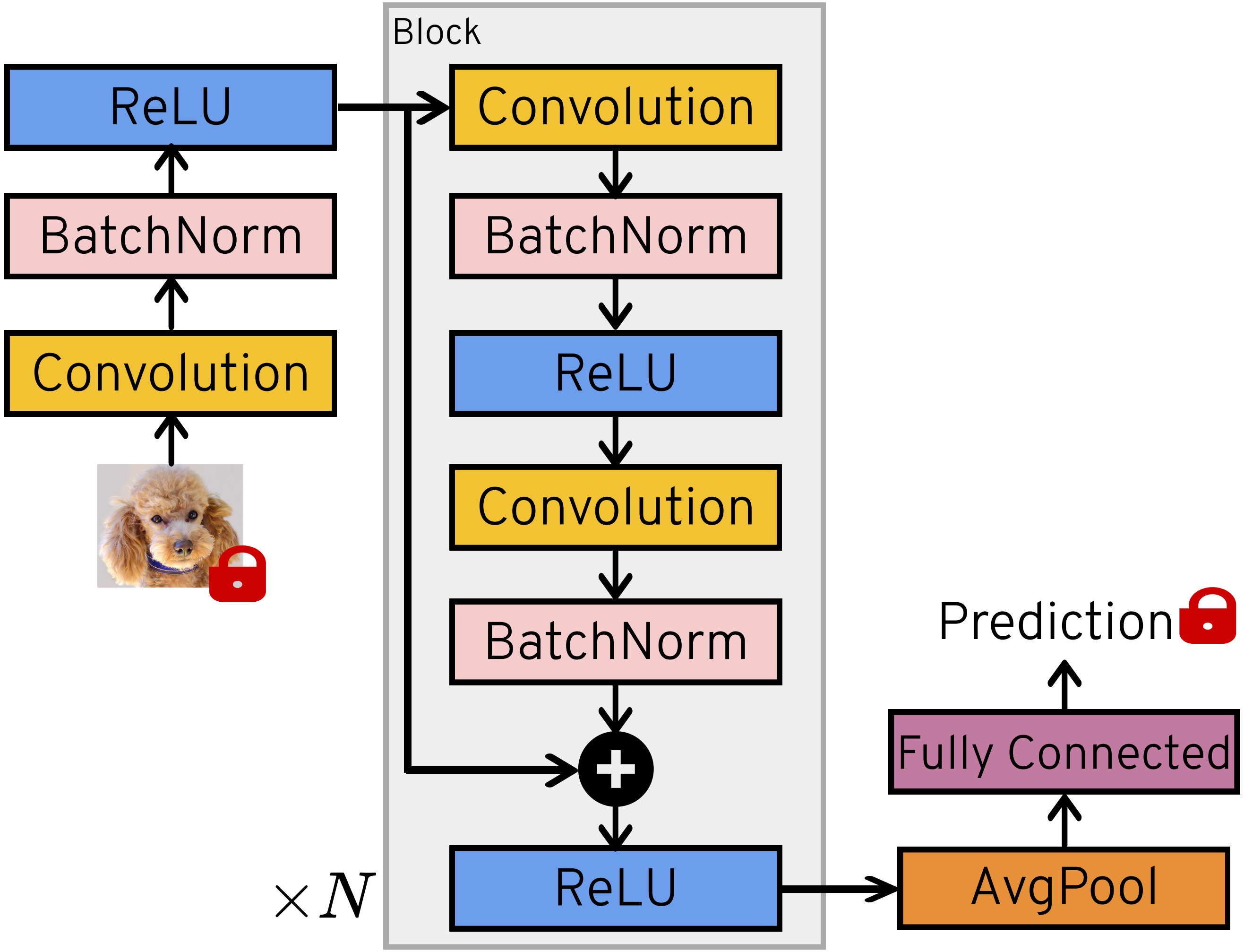
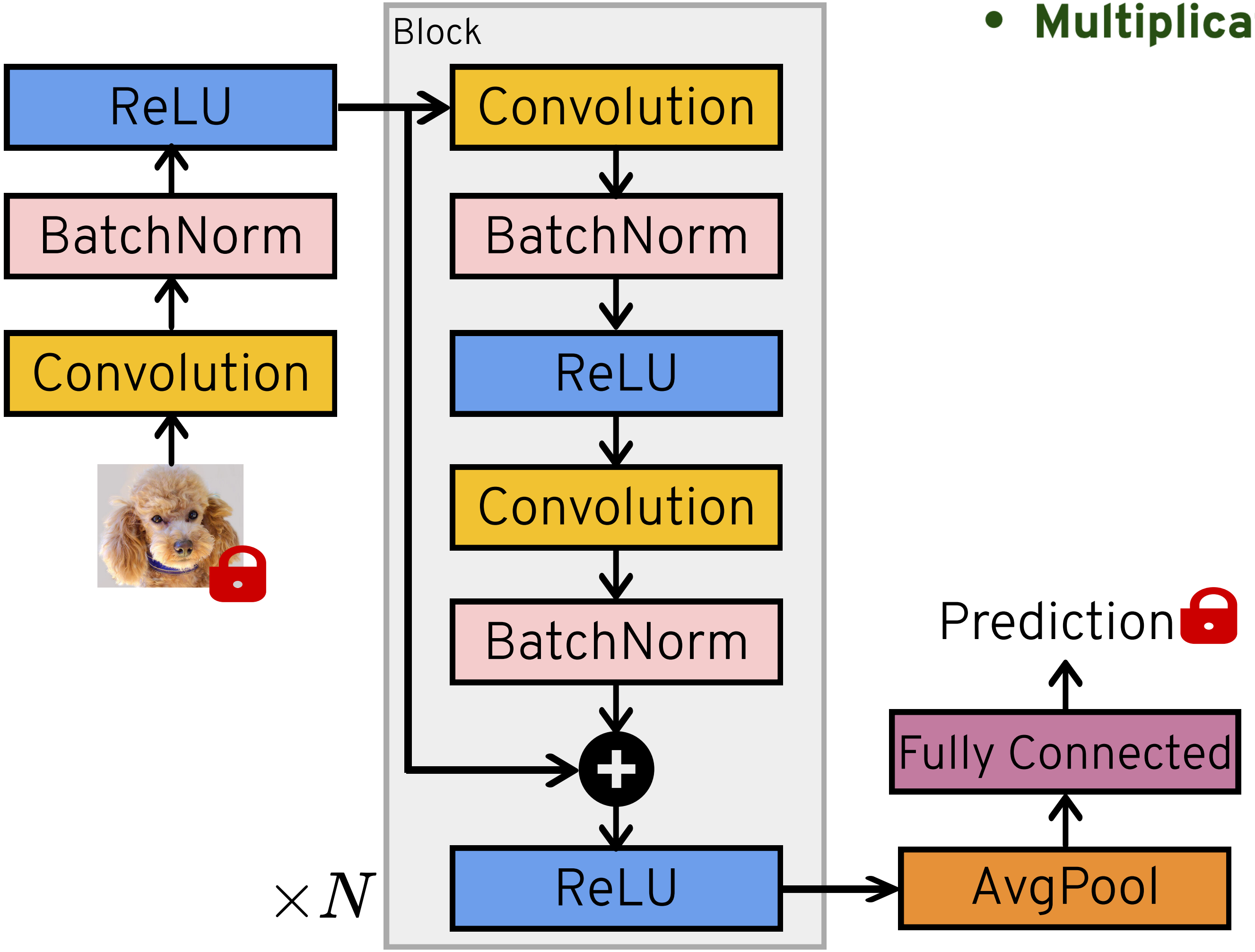


CNNs under **Homomorphic Encryption (HE)**

- **Multiplication**



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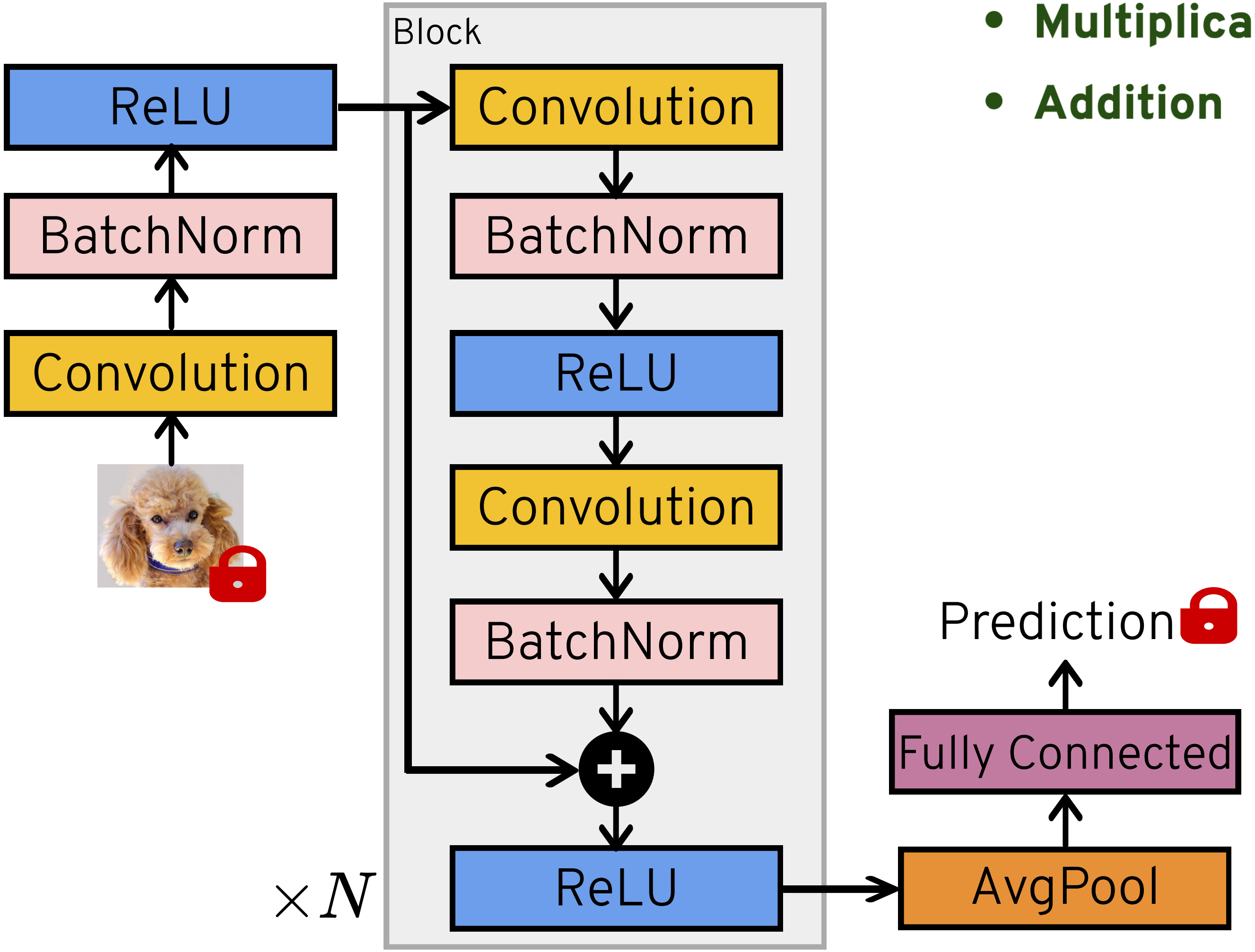
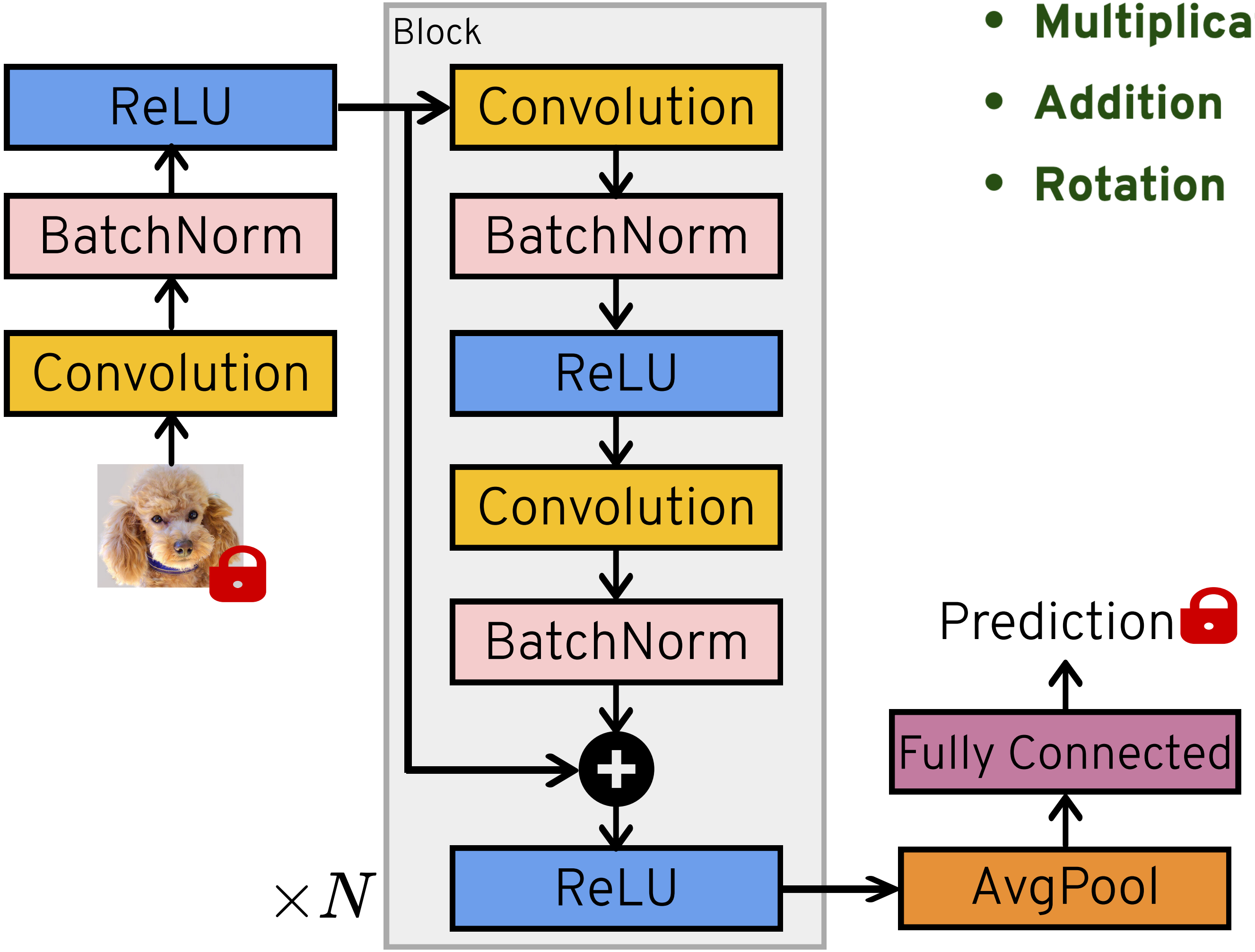


- **Multiplication**
- **Addition**

CNNs under **Homomorphic Encryption (HE)**



- **Multiplication**
- **Addition**
- **Rotation**

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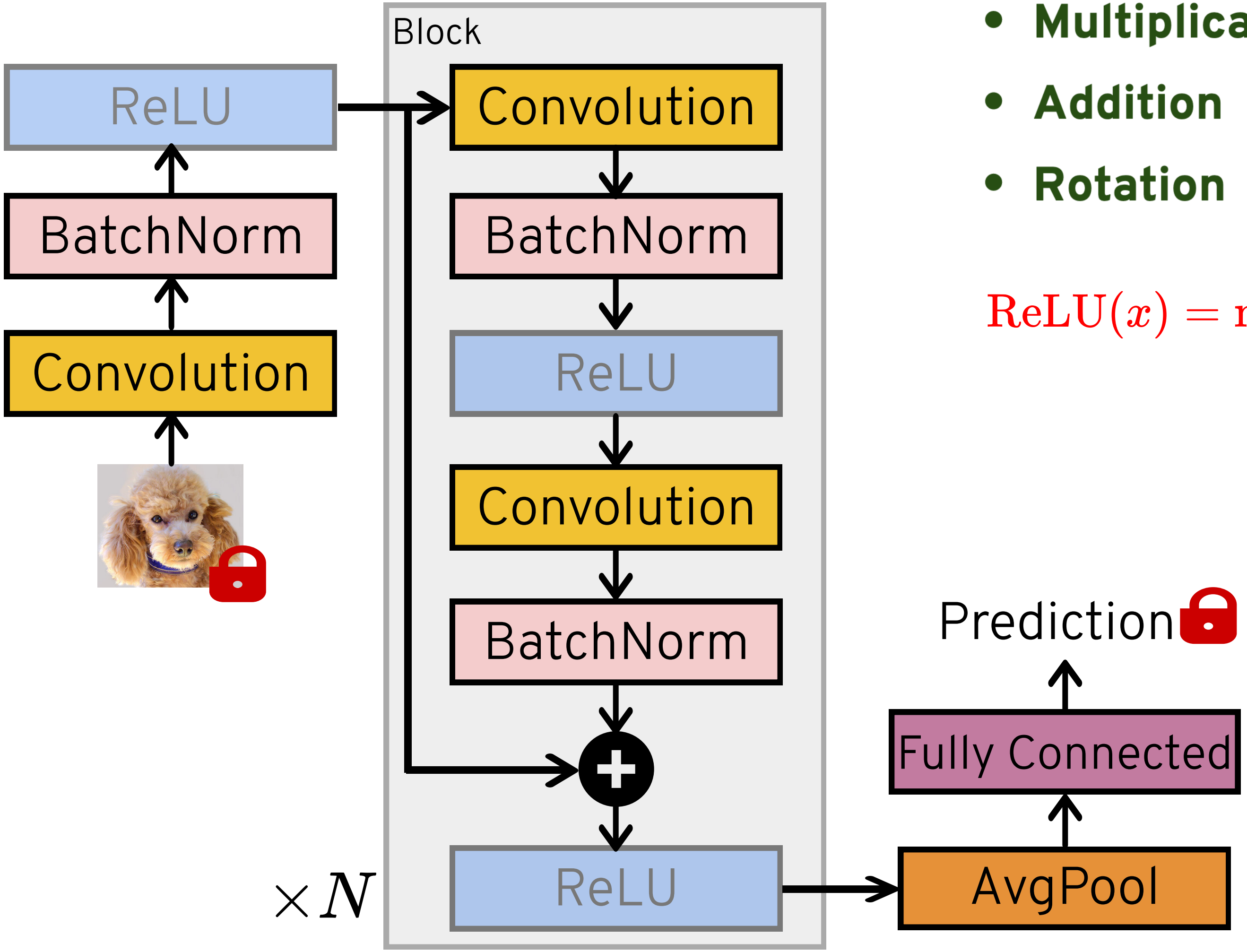

- **Multiplication**
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$$\mathrm{ReLU}(x) = \max(x, 0)$$

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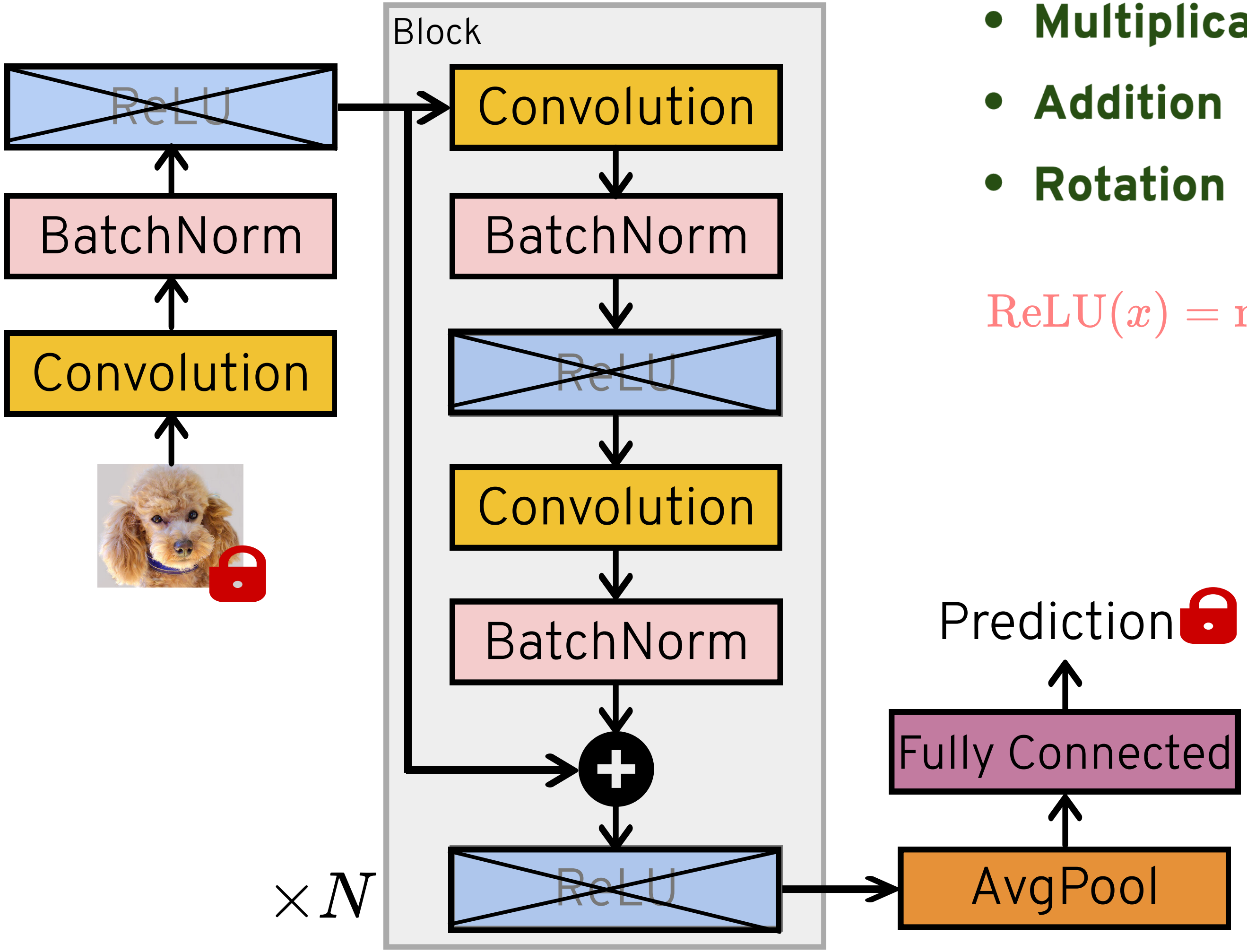

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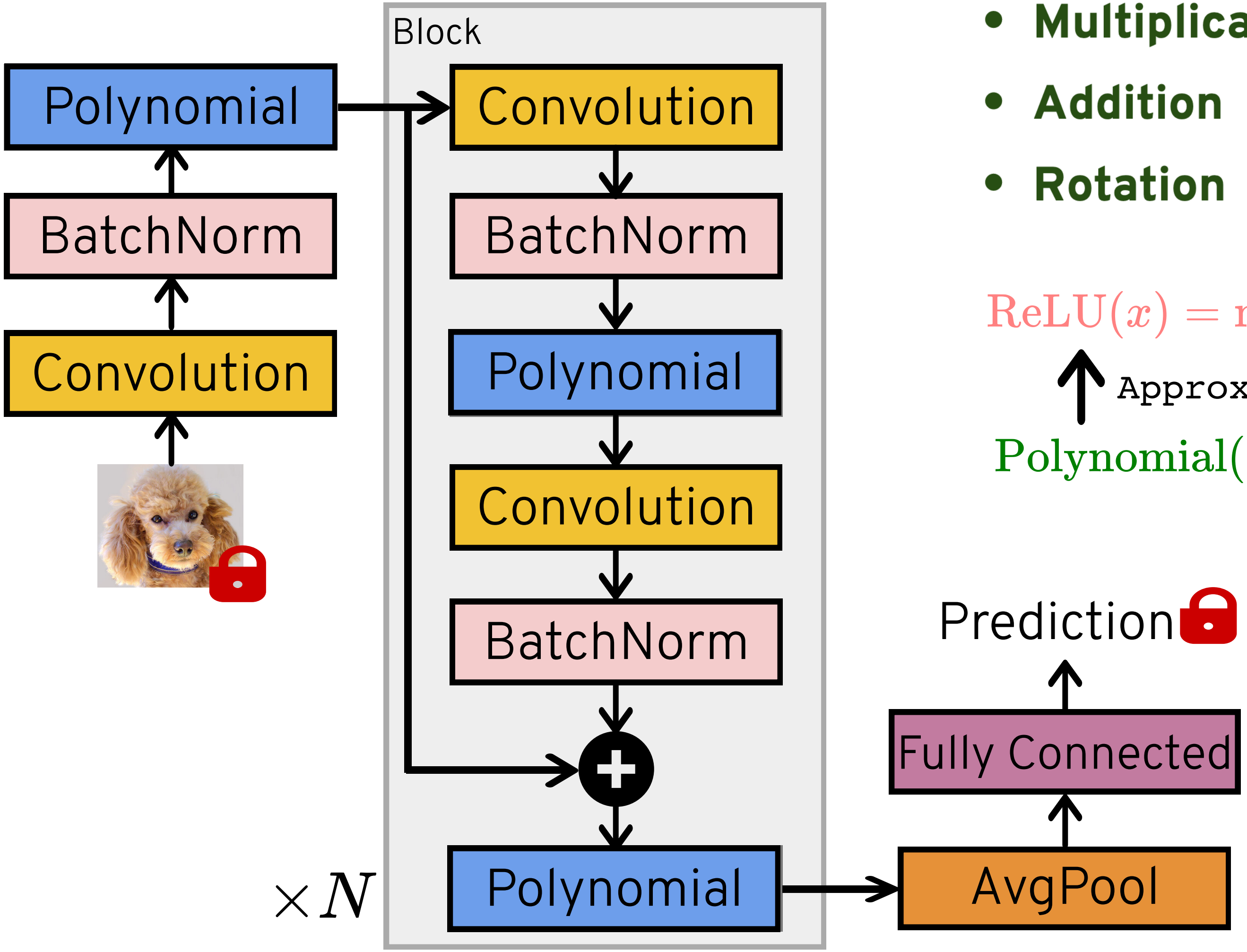

- **Multiplication**
- **Addition**
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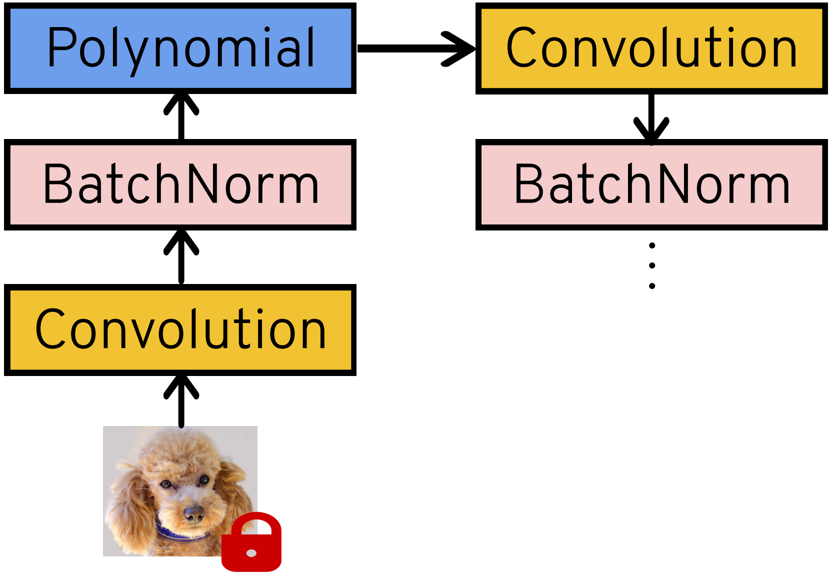
$$\mathrm{ReLU}(x) = \max(x, 0)$$

Approximate

$$\mathrm{Polynomial}(x) = \sum_i a_i x^i$$

Deep CNNs under **Fully Homomorphic Encryption (FHE)**



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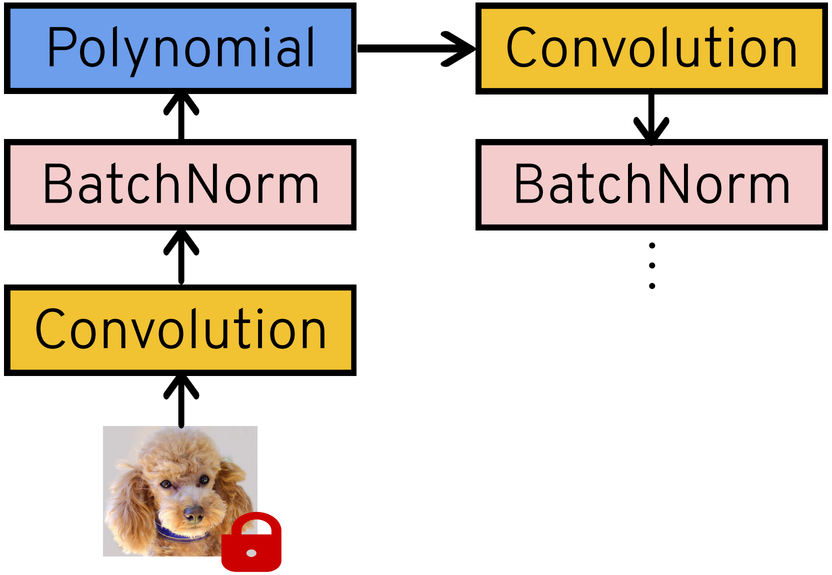

Level:
number of multiplications
allowed to evaluate

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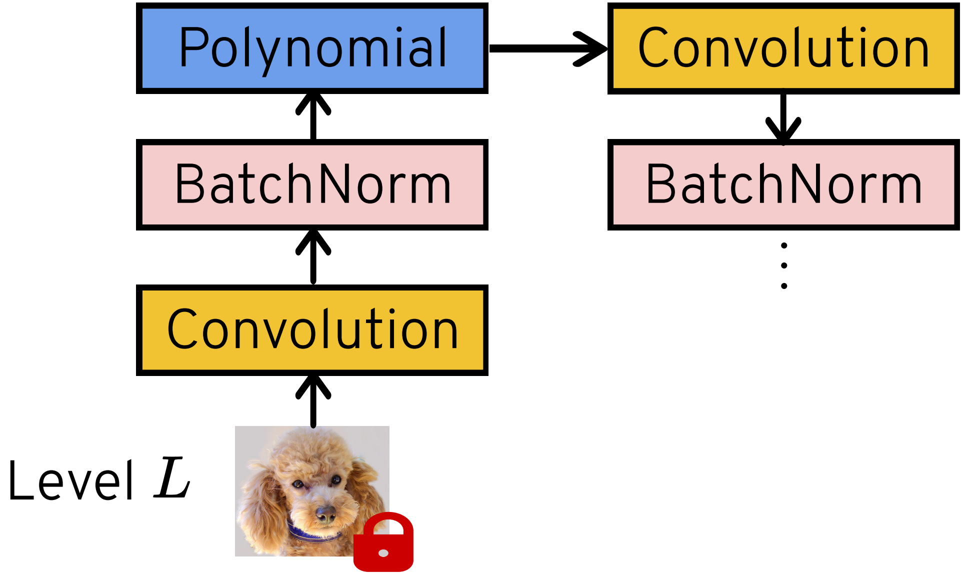


```
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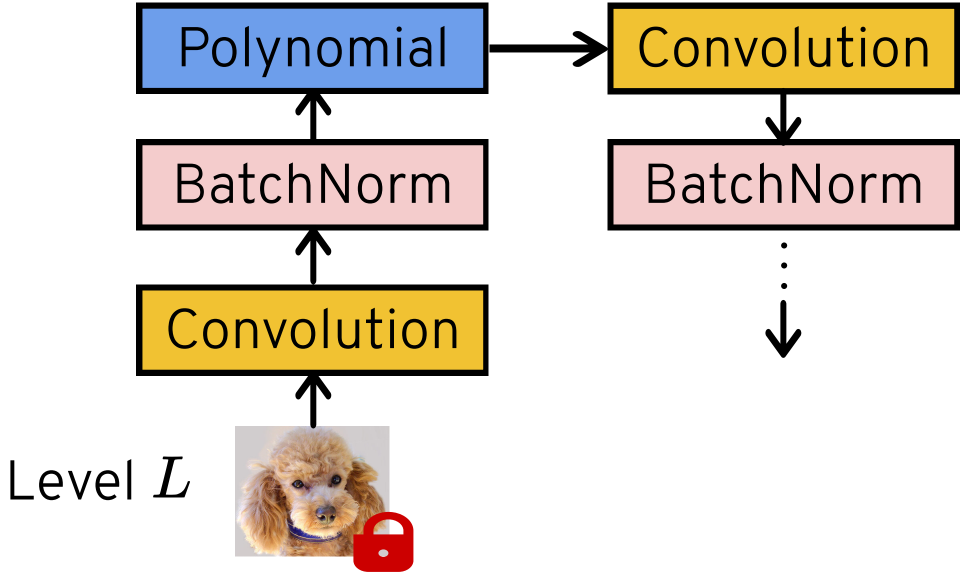


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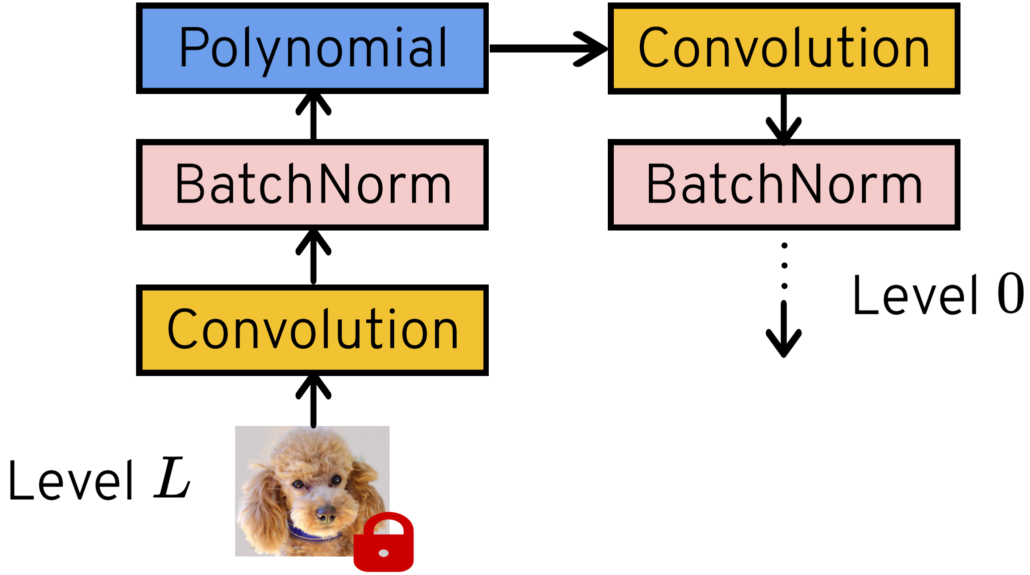


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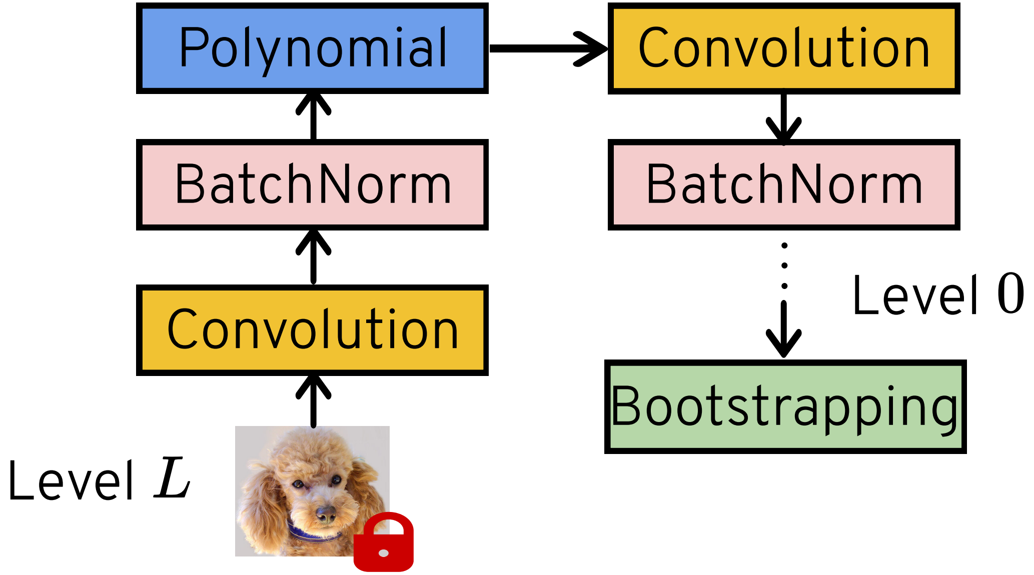


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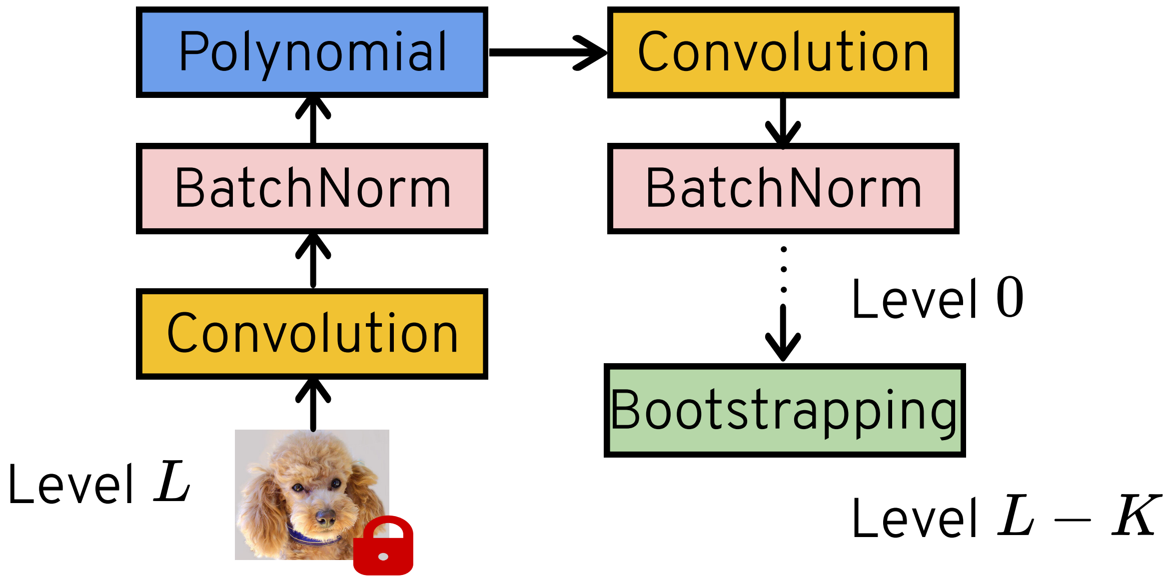

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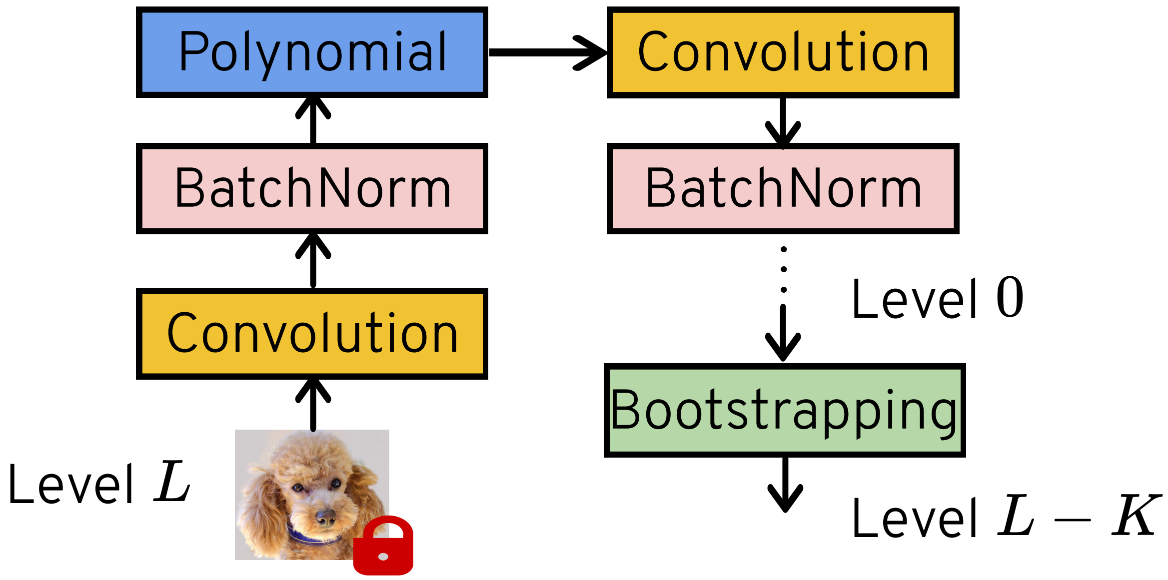


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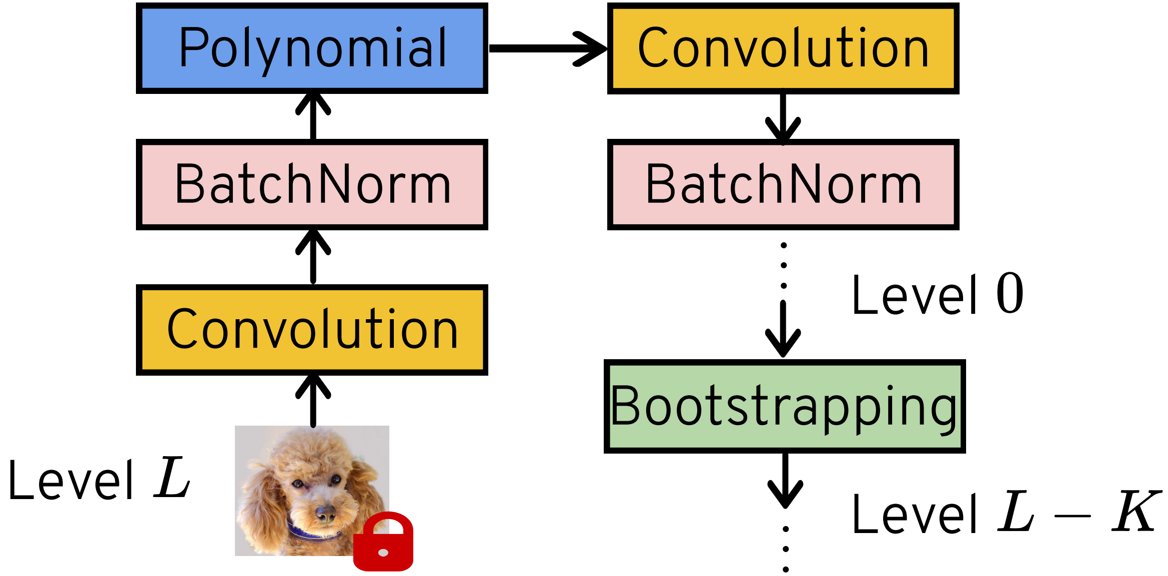


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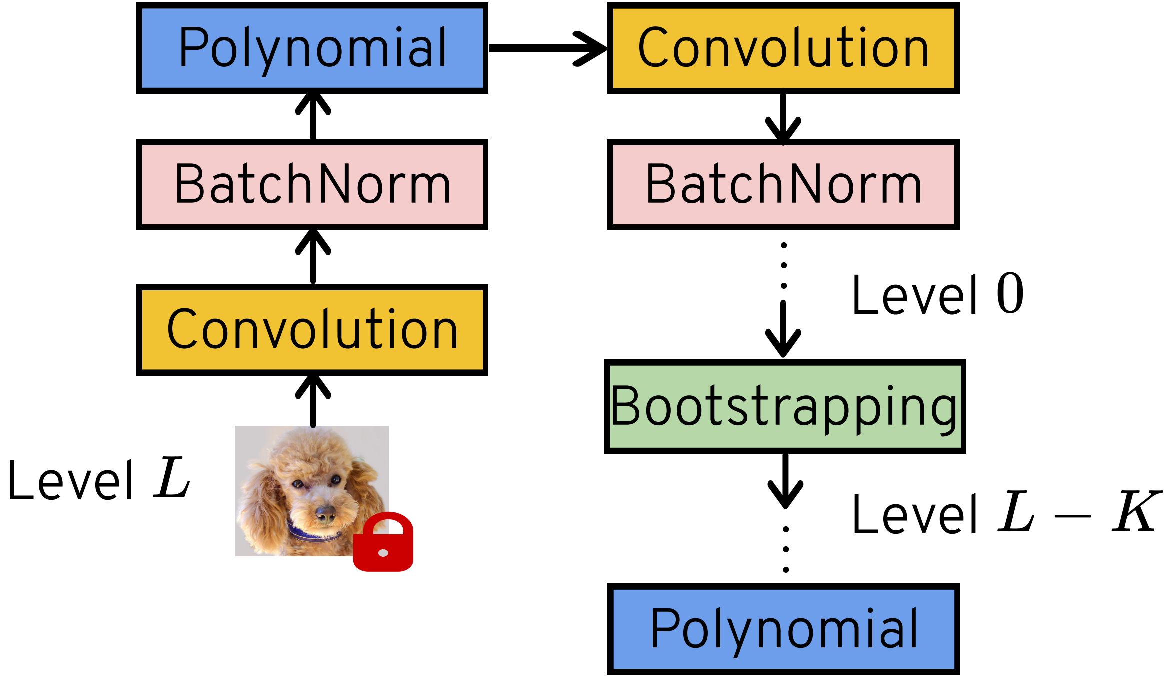


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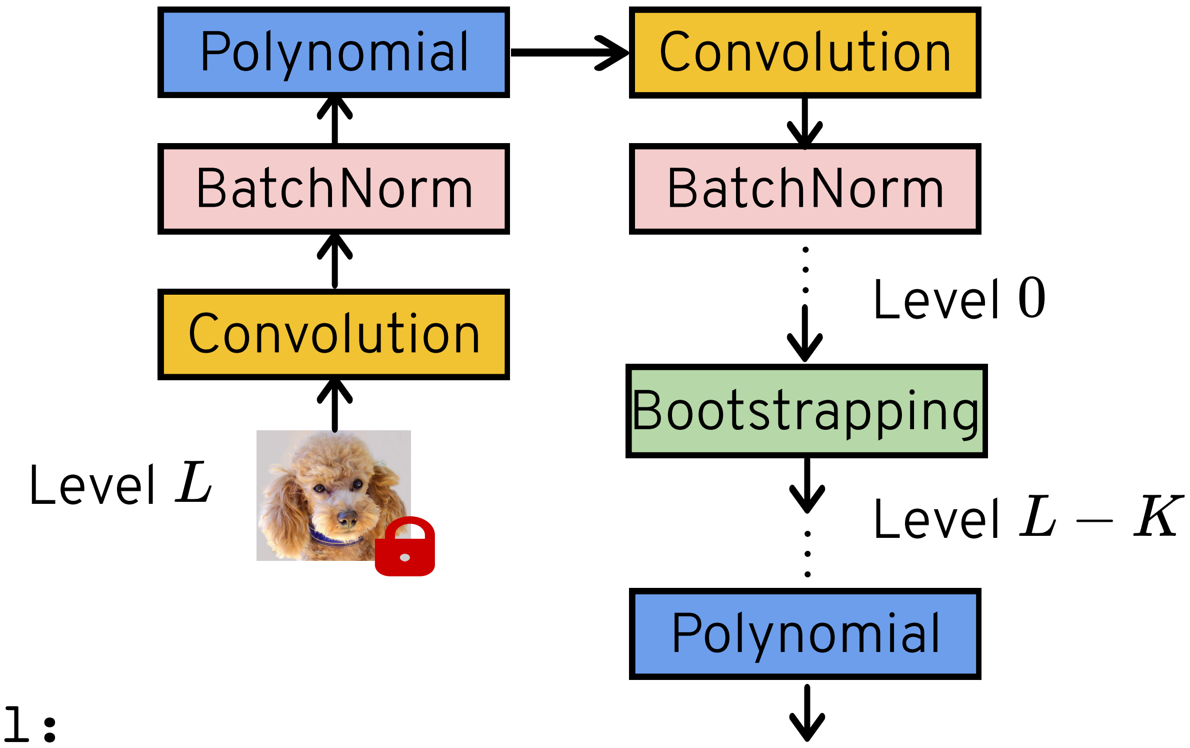

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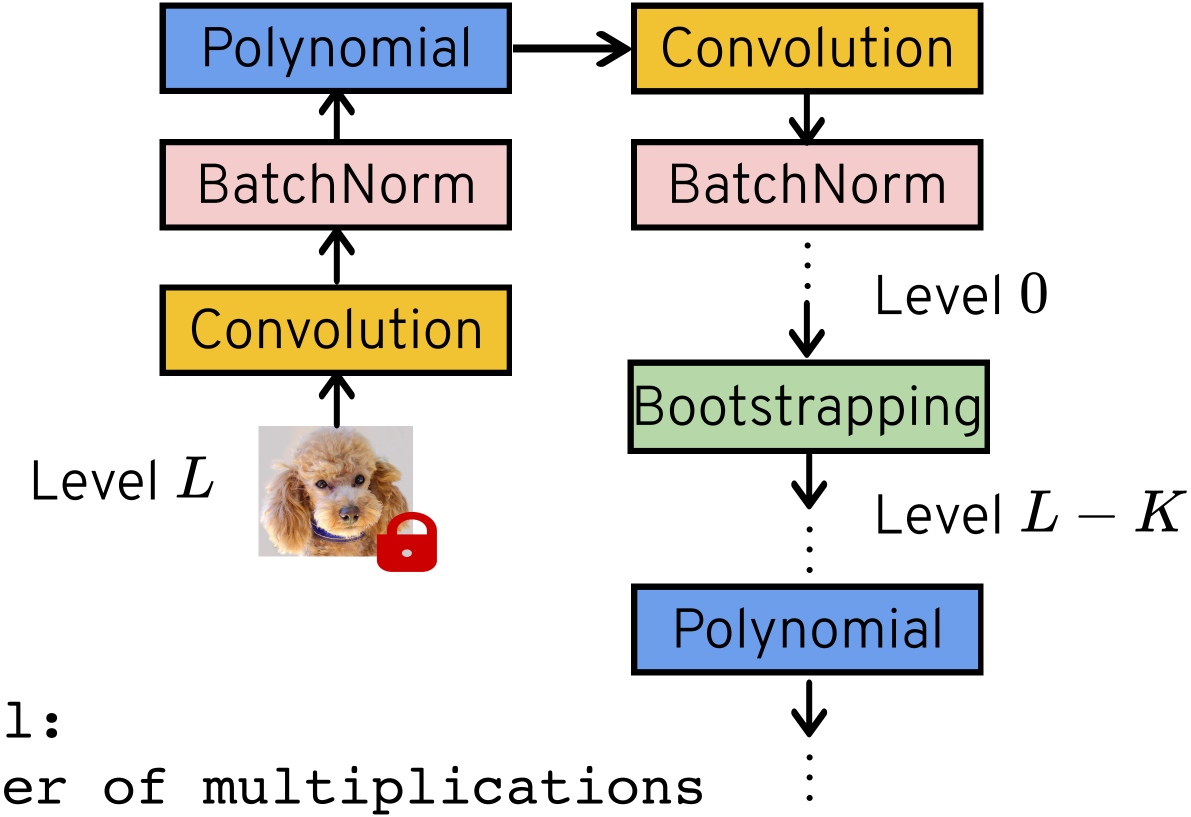


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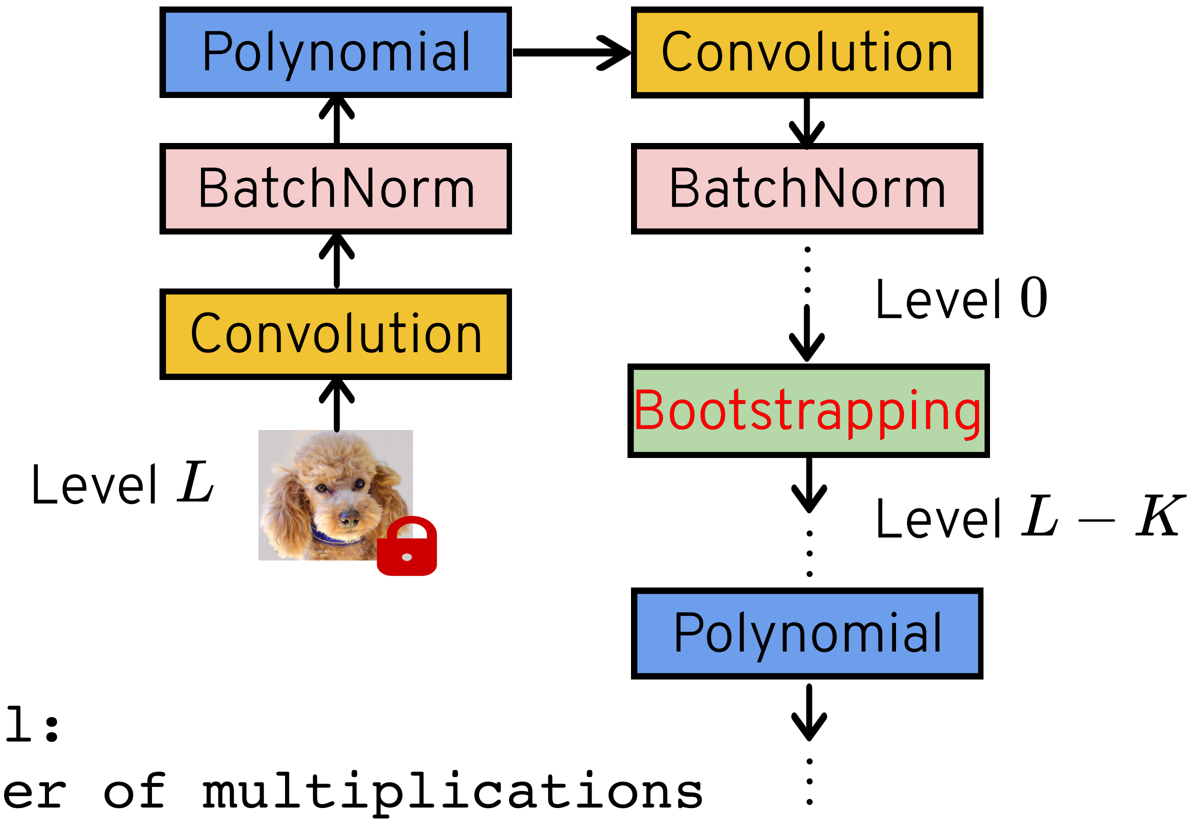


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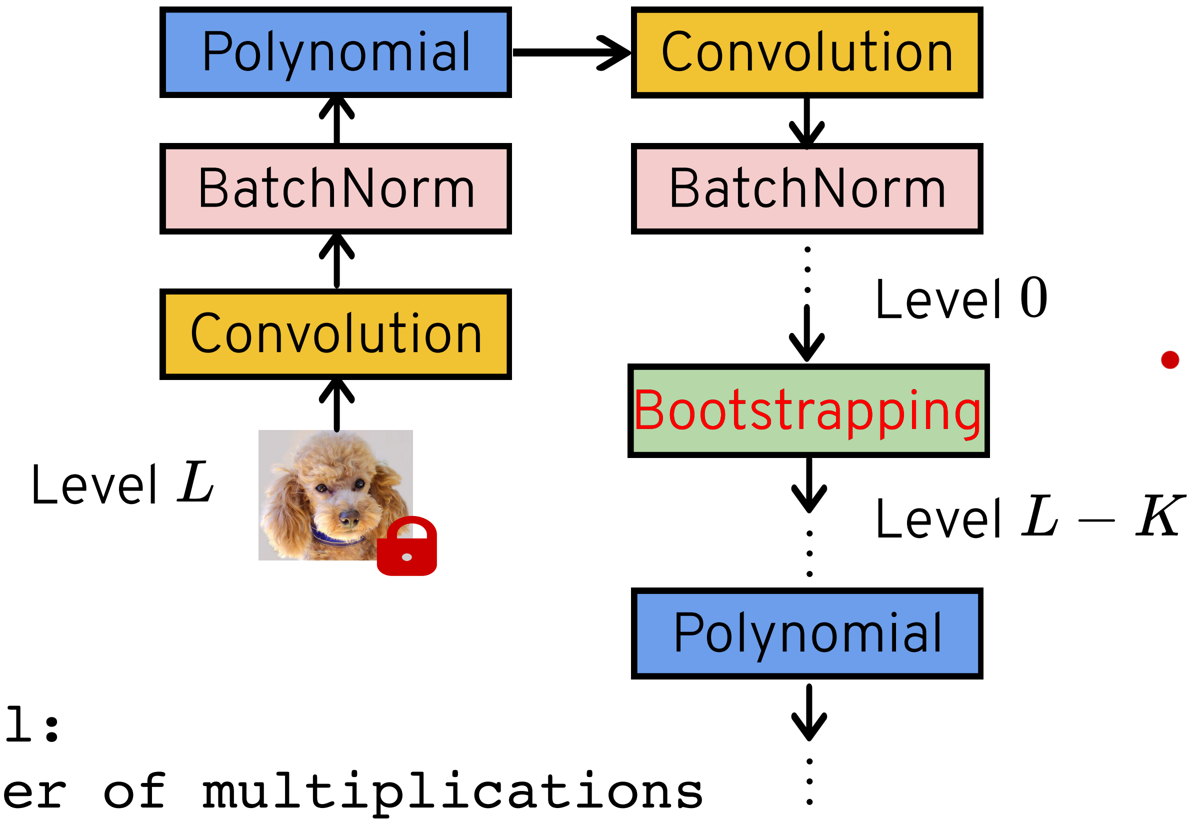

- **High Latency**

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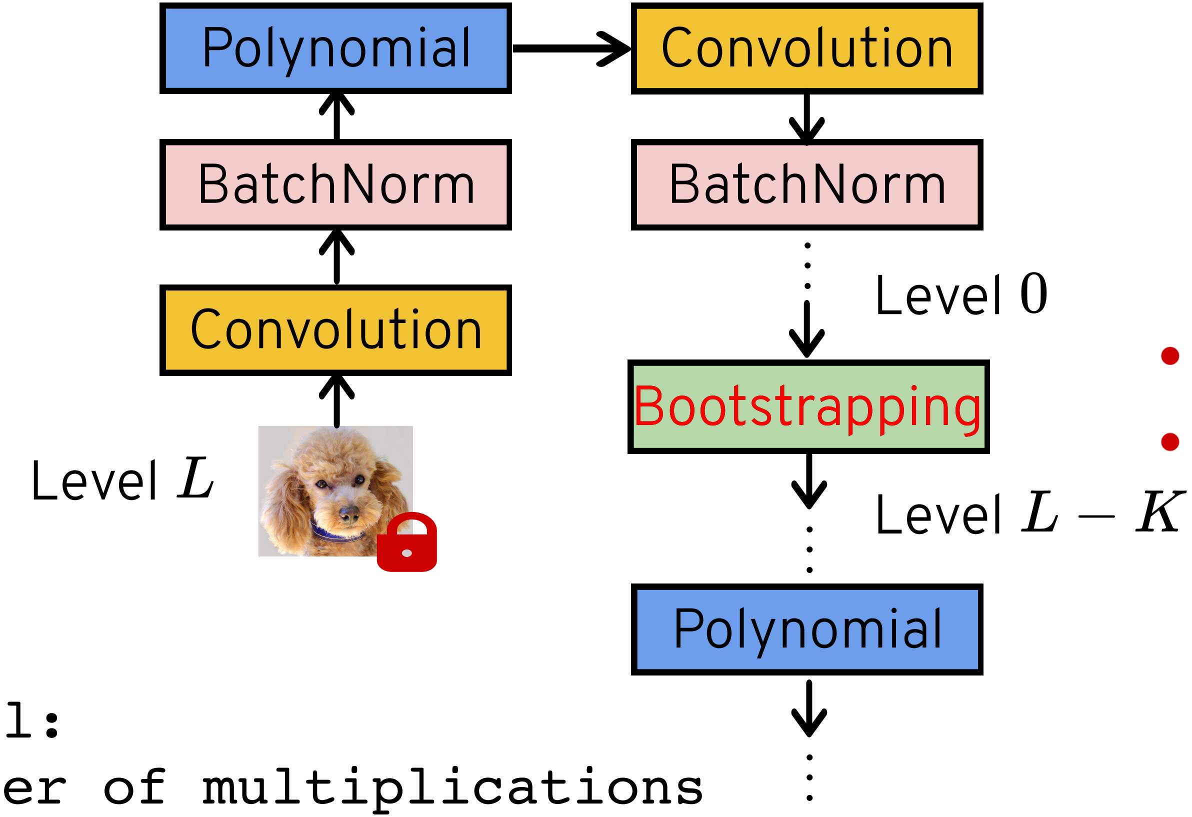

- **High Latency**
- **High Memory Footprint**

```
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```

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

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- Security Requirement

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- Security Requirement
- Inference Latency

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

- Security Requirement
- Inference Latency
- Prediction Accuracy

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Cryptographic Parameters

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

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Cryptographic Parameters

Cyclotomic polynomial degree N

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

- Security Requirement
- Inference Latency
- Prediction Accuracy

Cryptographic Parameters

Cyclotomic polynomial degree	N
Level	L

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

- Security Requirement
- Inference Latency
- Prediction Accuracy

Cryptographic Parameters

Cyclotomic polynomial degree	N
Level	L
Modulus	$Q_\ell = \prod_{i=0}^{\ell} q_\ell, 0 \leq \ell \leq L$

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

- Security Requirement
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Cryptographic Parameters

Cyclotomic polynomial degree	N
Level	L
Modulus	$Q_\ell = \prod_{i=0}^{\ell} q_\ell, 0 \le \ell \le L$
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Deep CNNs under **Fully Homomorphic Encryption (FHE)**

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Cryptographic Parameters

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Level	L
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Bootstrapping depth	K
Hamming weight	h

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Polynomial CNNS

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Polynomial CNNS

Conv, BN, pooling, FC layers: packing

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Conv, BN, pooling, FC layers: packing

Polynomials: degree -> depth

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Polynomial CNNS

Conv, BN, pooling, FC layers: packing

Polynomials: degree -> depth

Number of layers: ResNet20, ResNet32

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

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- Prediction Accuracy

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Polynomial CNNS

Conv, BN, pooling, FC layers: packing

Polynomials: degree -> depth

Number of layers: ResNet20, ResNet32

Input image resolution

Deep CNNs under **Fully Homomorphic Encryption (FHE)**

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Polynomial CNNS

Conv, BN, pooling, FC layers: packing

Polynomials: degree -> depth

Number of layers: ResNet20, ResNet32

Input image resolution

Channels/kernels

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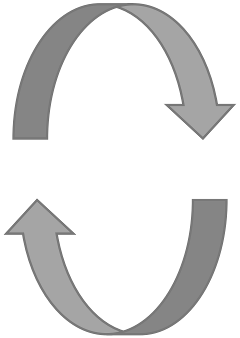


Polynomial CNNS

Conv, BN, pooling, FC layers: packing

Polynomials: degree -> depth

Number of layers: ResNet20, ResNet32

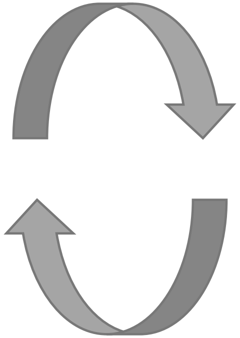
Input image resolution

Channels/kernels

Hand-crafted Design of **Polynomial** for **CNNs** under **FHE**

Cryptographic Parameters

$$N, L, Q_\ell = \prod_{i=0}^{\ell} q_\ell (0 \leq \ell \leq L), K, h$$



Polynomial CNNS

`Polynomials: degree -> depth`

Hand-crafted Design of **Polynomial** for **CNNs** under **FHE**

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Polynomial CNNS

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Polynomial CNNS

`Polynomials: degree -> depth`

MPCNN [1]:

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MPCNN [1]:

Level 2

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Convolution

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Level 2 Level 0

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Polynomials: degree -> depth

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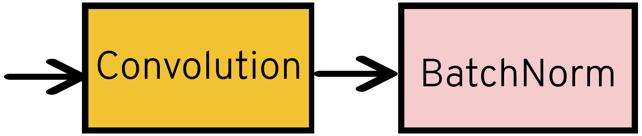

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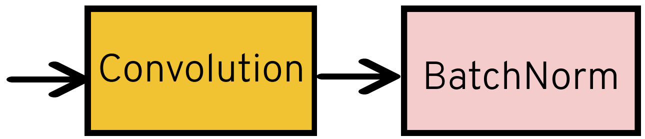

Level 2 Level 0 Level 0

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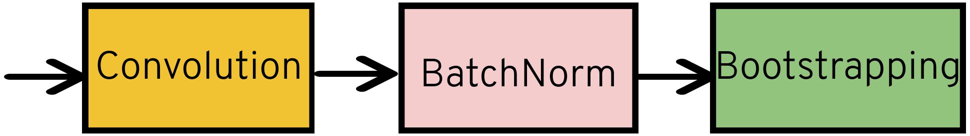

Level 2 Level 0 Level 0

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Polynomials: degree -> depth

MPCNN [1]:

→ Convolution → BatchNorm → Bootstrapping

Level 2 Level 0 Level 0 Level 16

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Polynomial CNNS

`Polynomials: degree -> depth`

MPCNN [1]:

→ Convolution → BatchNorm → Bootstrapping → High-degree Polynomial →

Level 2 Level 0 Level 0 Level 16

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Polynomial CNNS

Polynomials: degree -> depth

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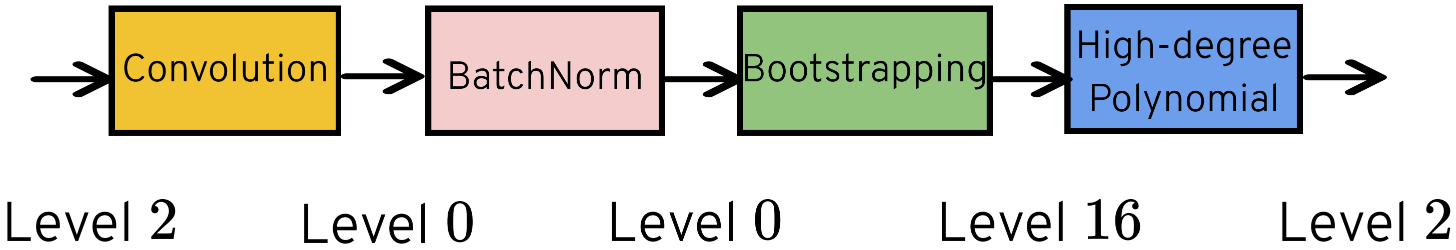

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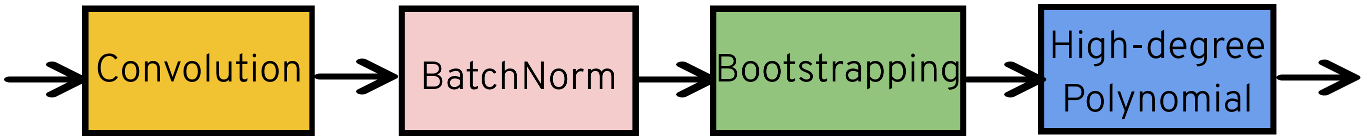

- **Fixed Architecture**

Level 2 Level 0 Level 0 Level 16 Level 2

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Polynomial CNNS

`Polynomials: degree -> depth`

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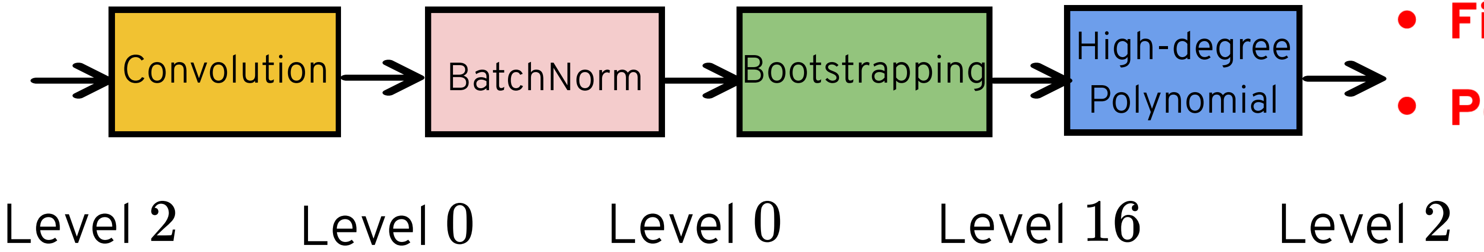

- **Fixed Architecture**
- **Periodic Bootstrapping**

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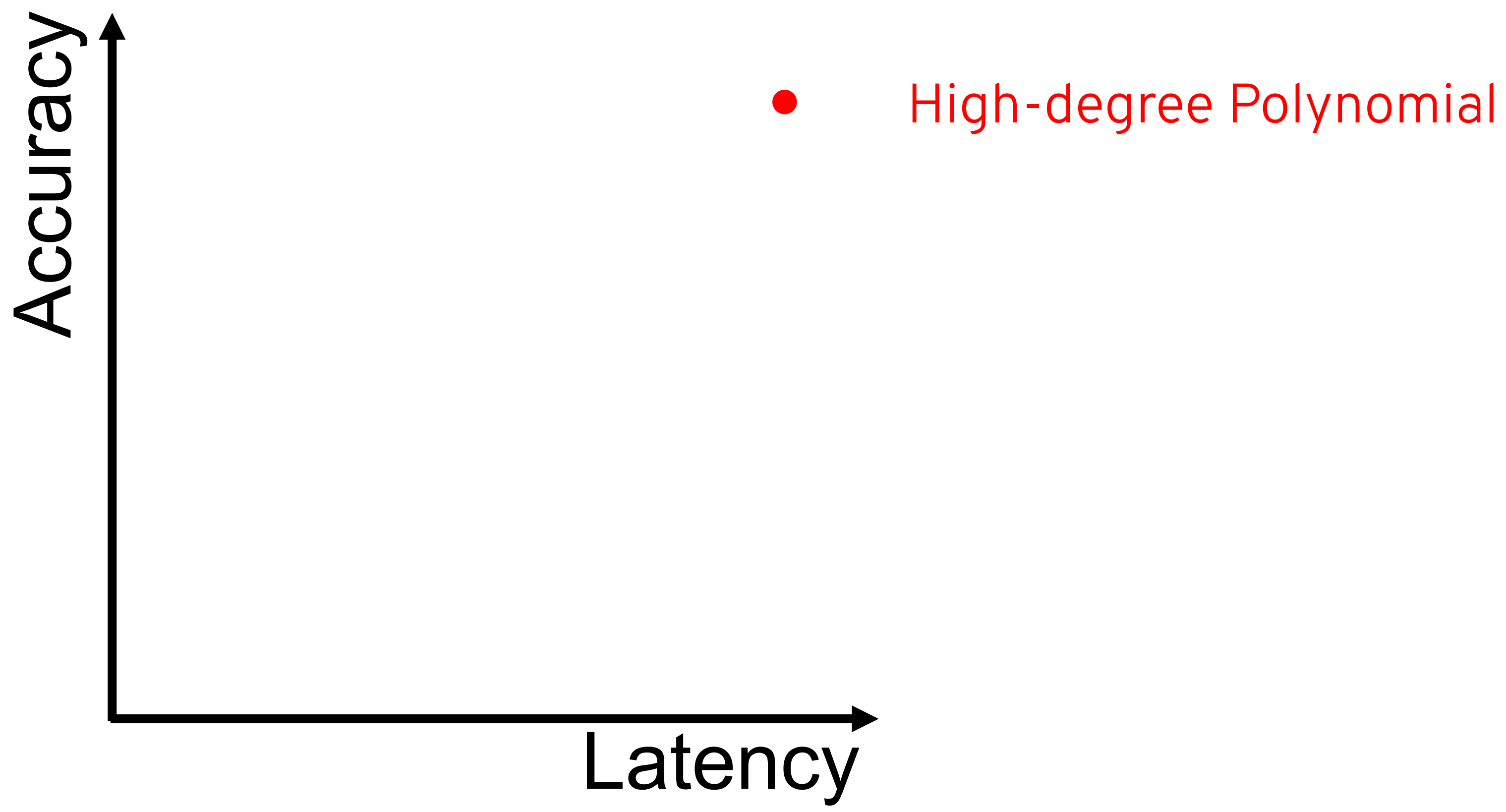
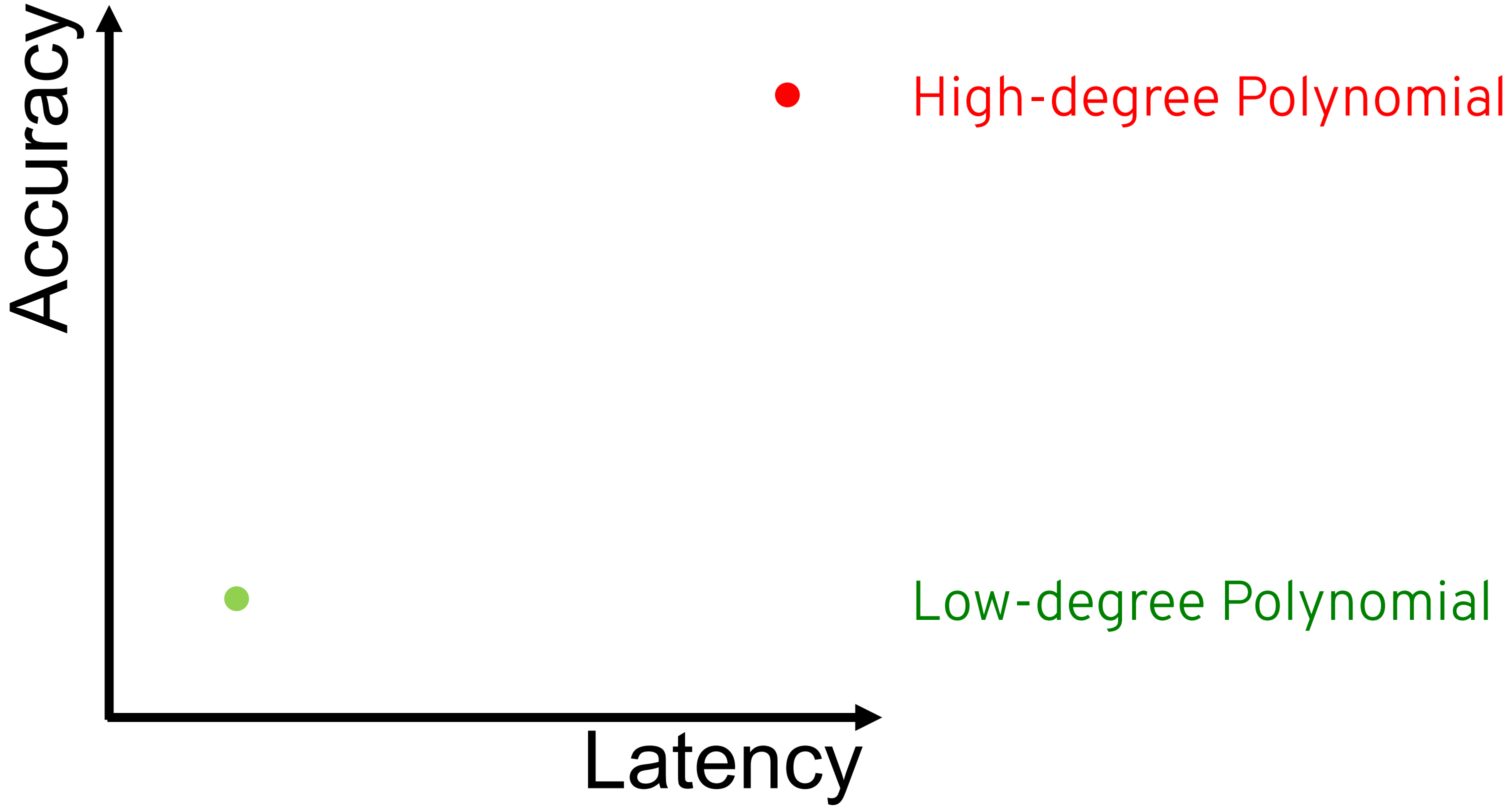
Hand-crafted Design of **Polynomial** for **CNNs** under **FHE**



Hand-crafted Design of **Polynomial** for **CNNs** under **FHE**



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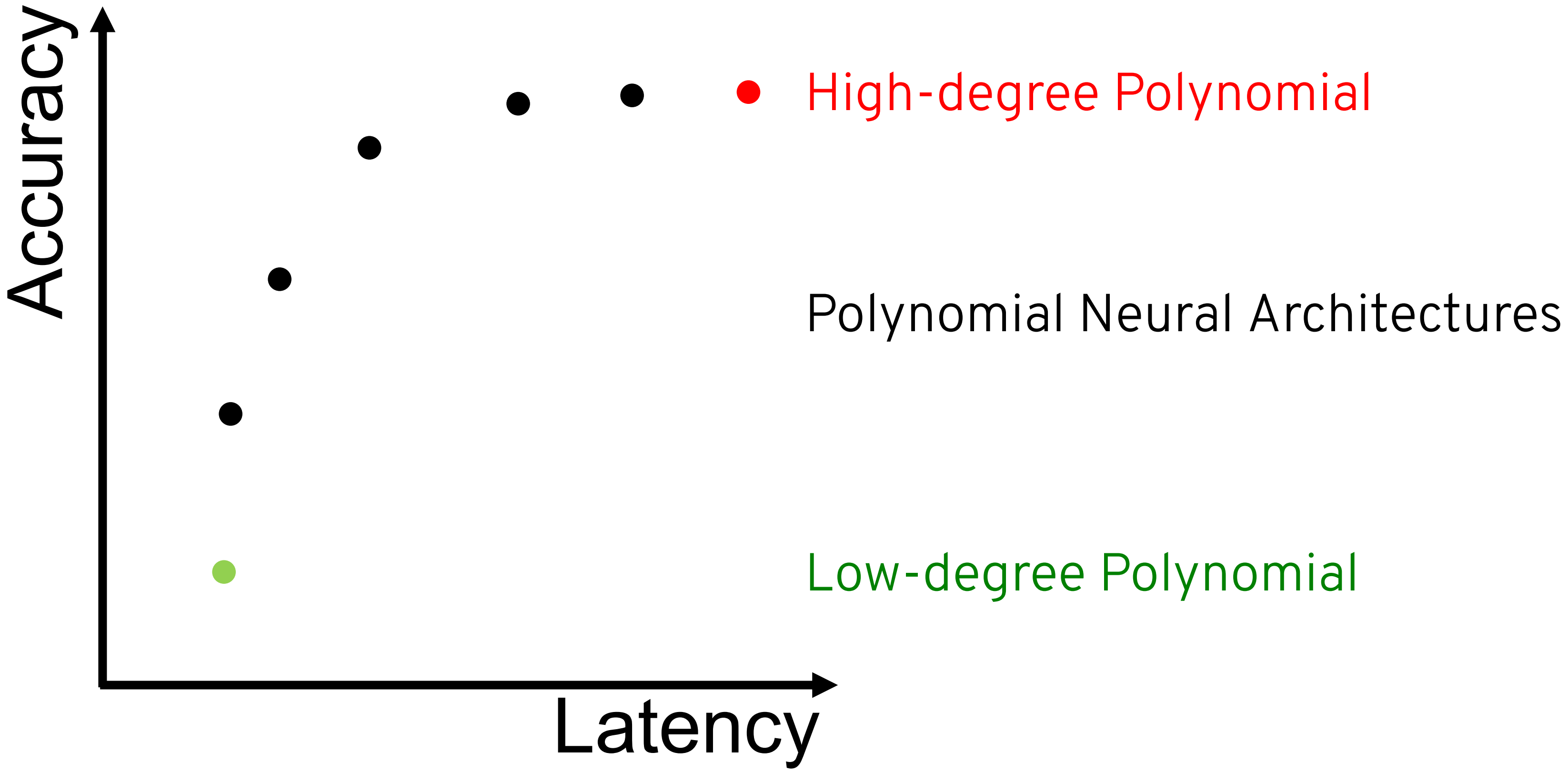

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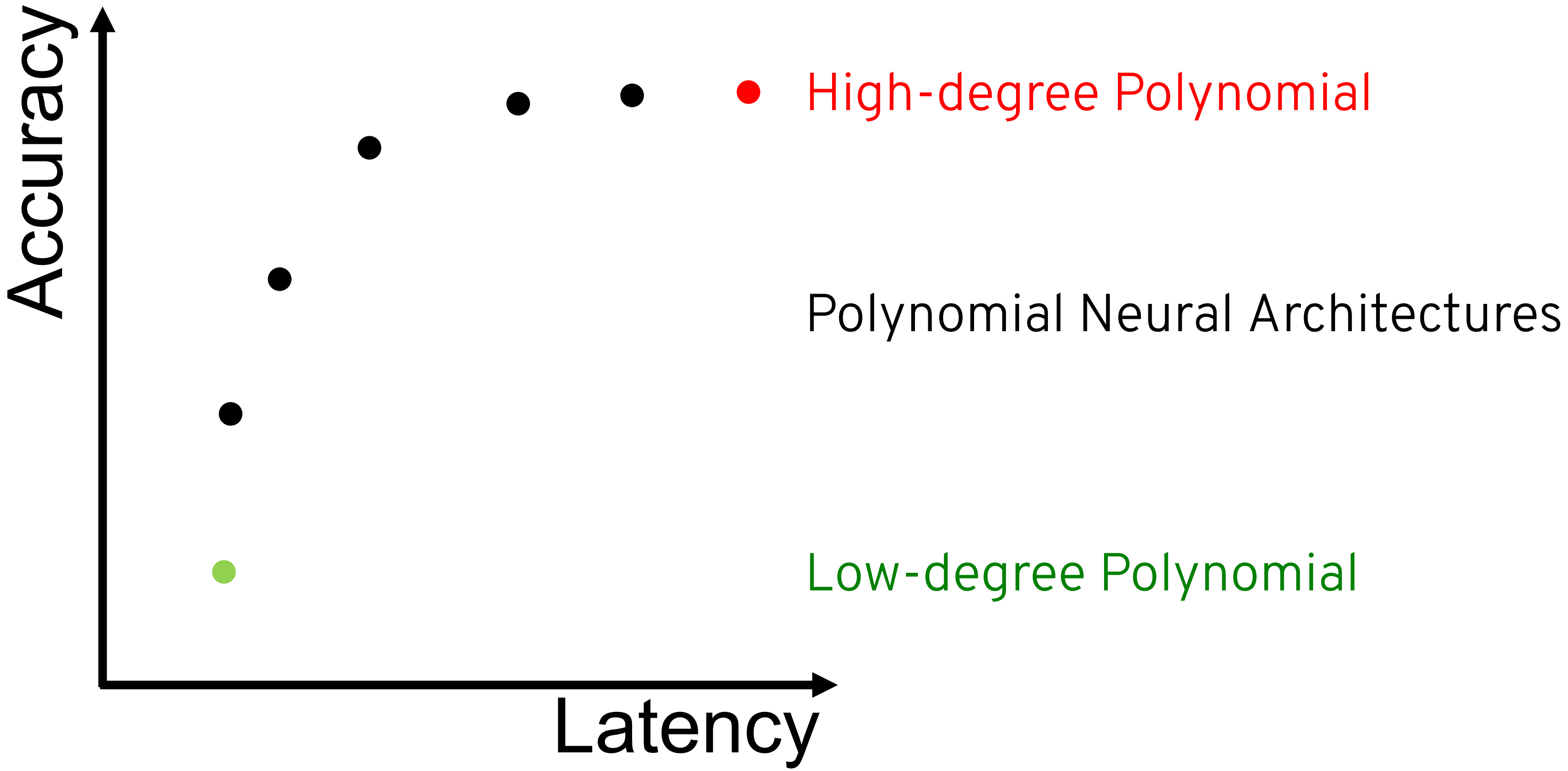


How to obtain all possible polynomial neural architectures?

Key Insight

Optimize the

Key Insight

Optimize the

instead of the polynomial function

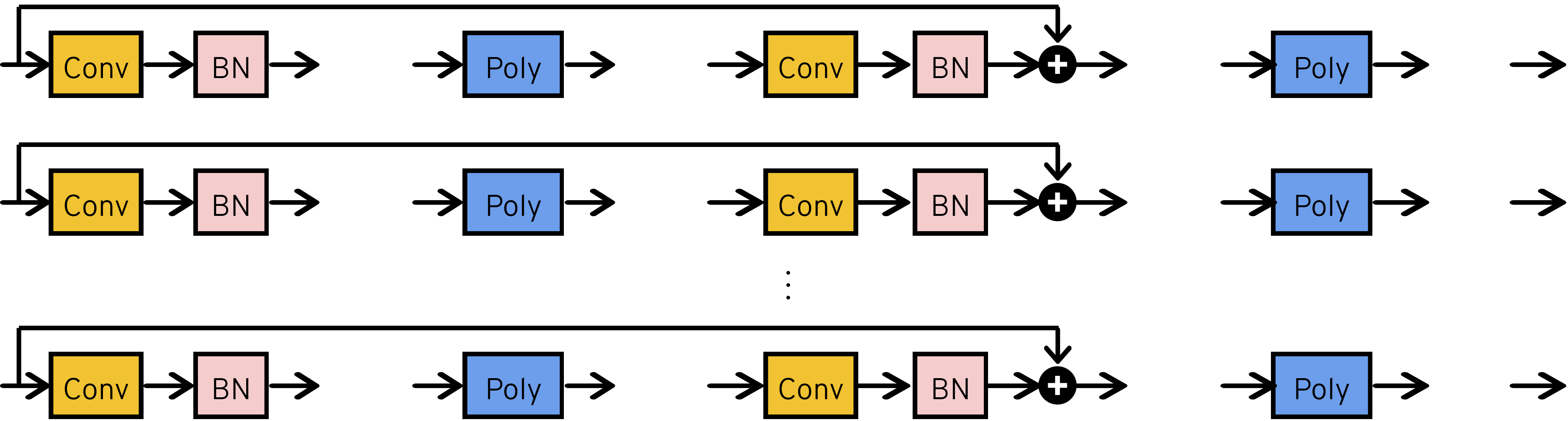
Key Insight

Optimize the

end-to-end polynomial neural **architecture**

instead of the polynomial function

Optimization of End-to-End Polynomial Neural Architecture



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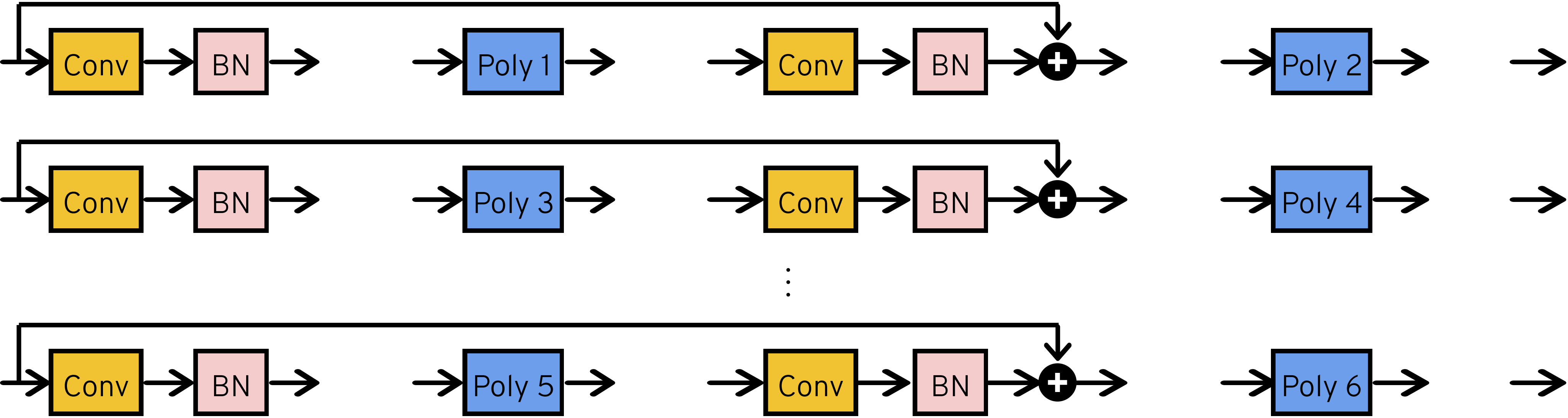
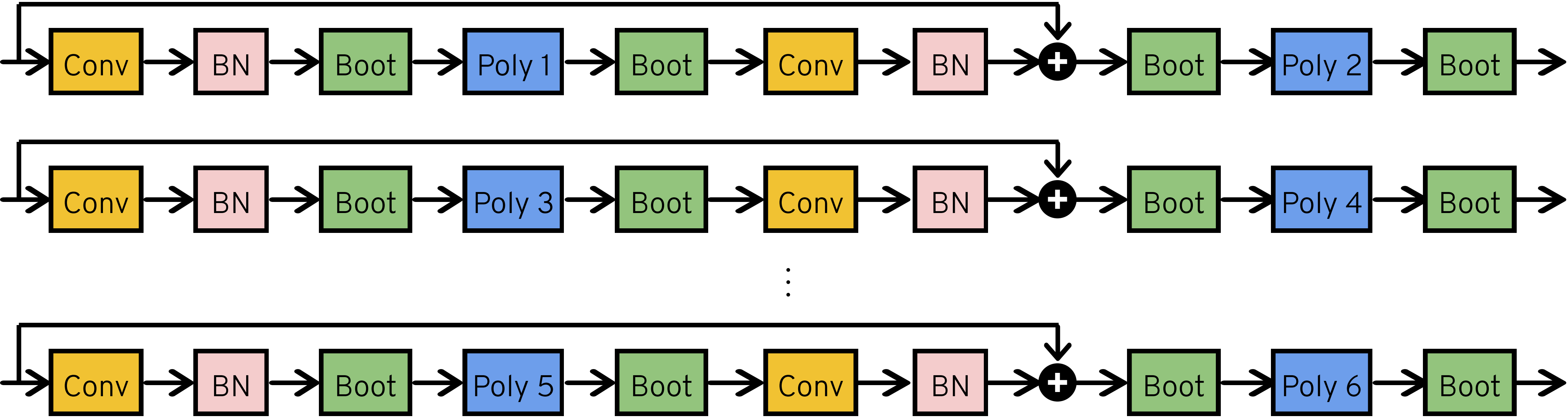
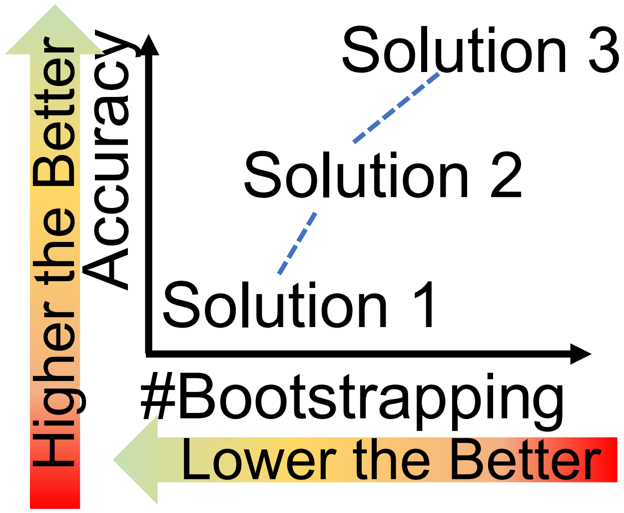


Optimization of **End-to-End Polynomial Neural Architecture**



Optimization of **End-to-End Polynomial Neural Architecture**

Optimization of End-to-End Polynomial Neural Architecture



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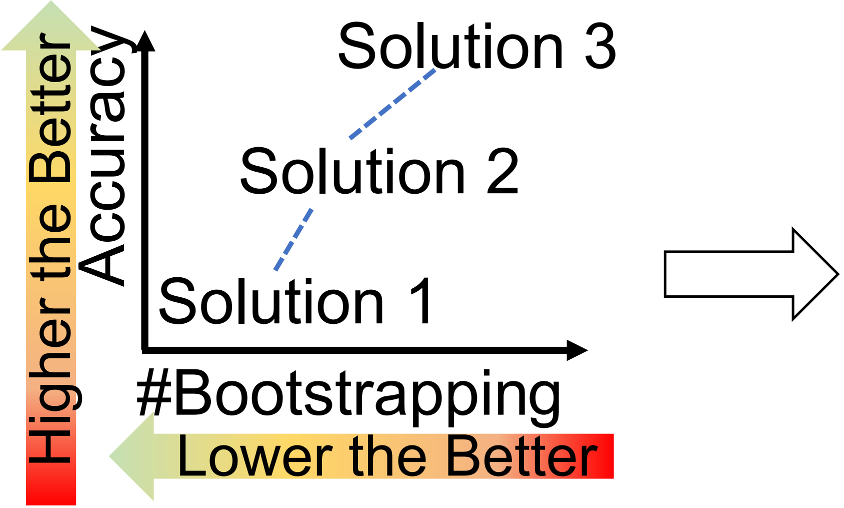

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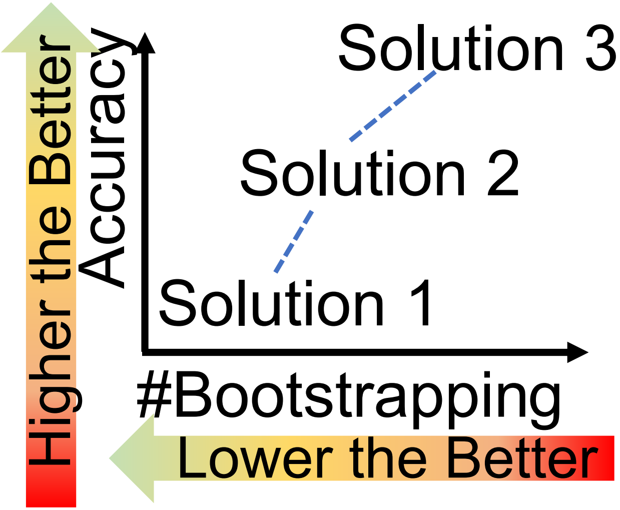

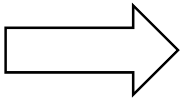

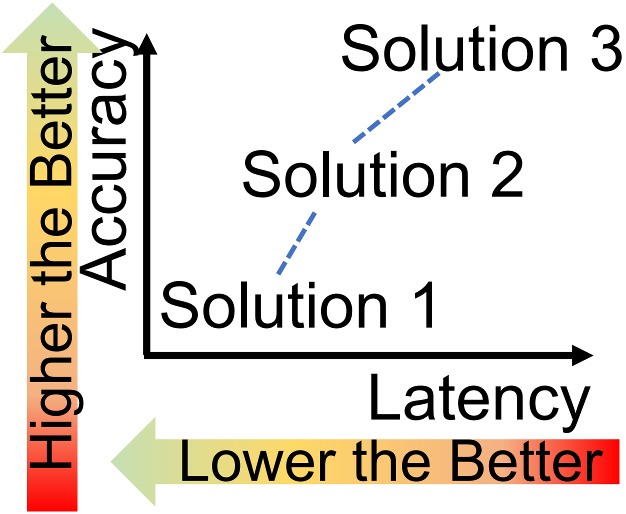

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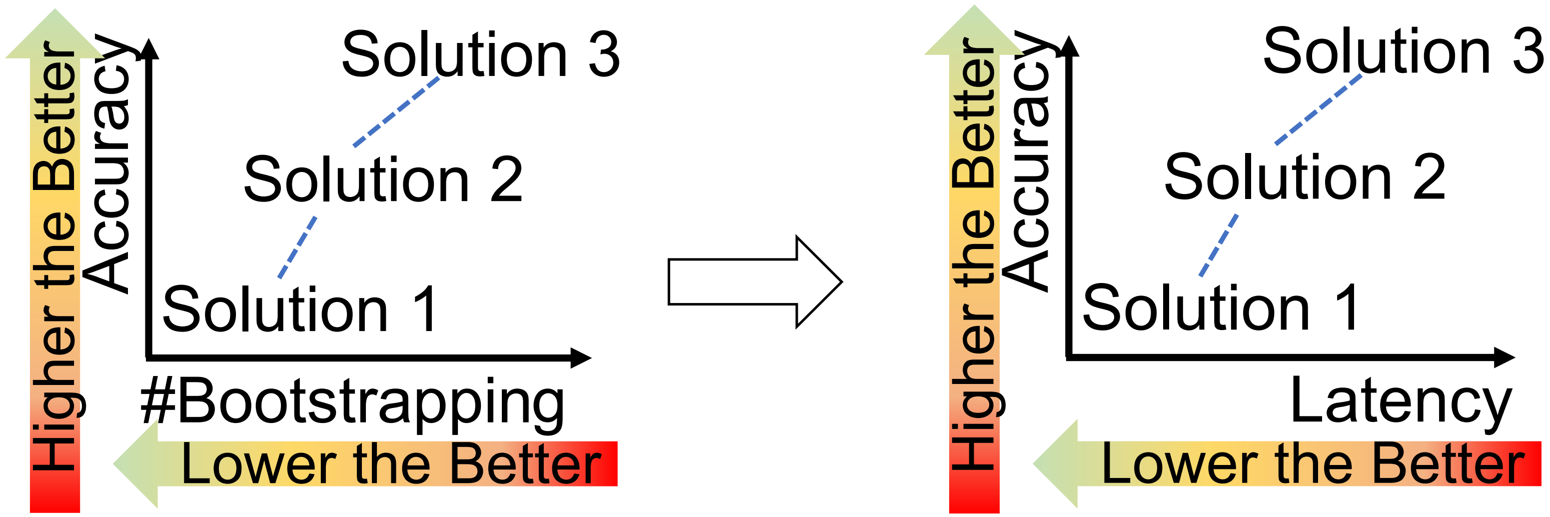
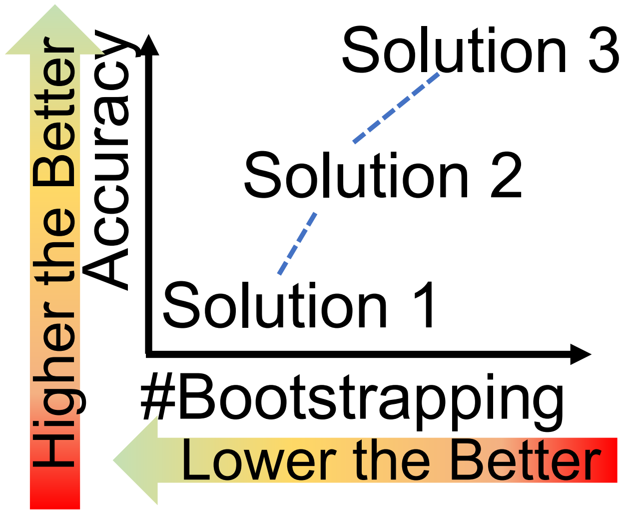
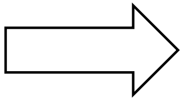
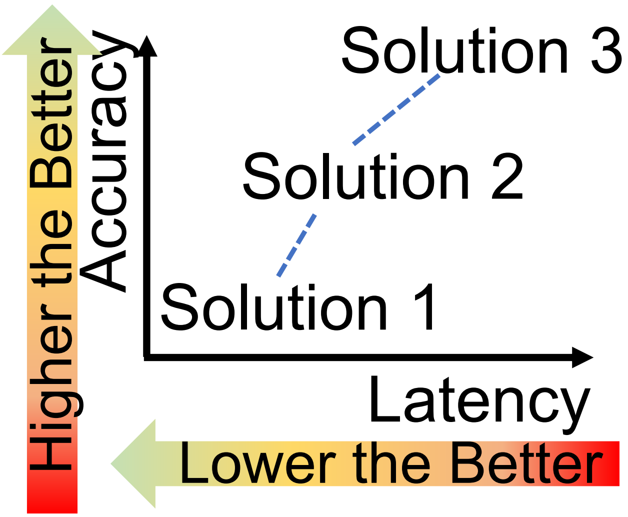


To meet different requirements in real world

Optimization of **End-to-End Polynomial Neural Architecture**



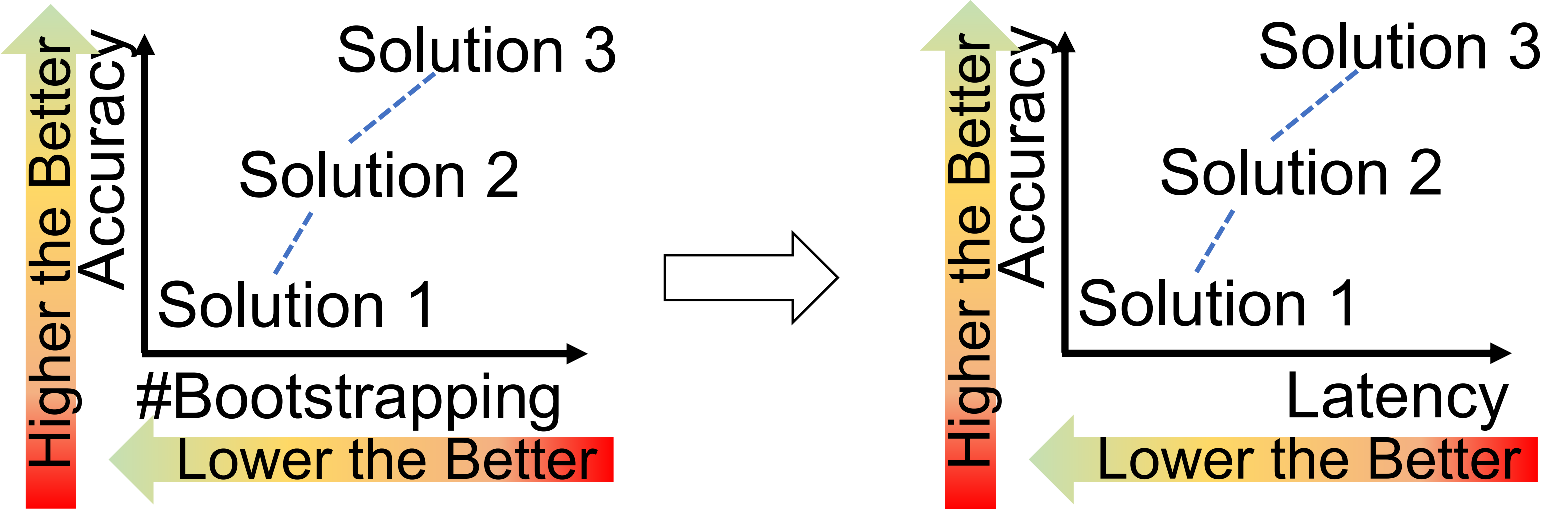




To meet different requirements in real world

- I want a faster response

Optimization of End-to-End Polynomial Neural Architecture



To meet different requirements in real world

- I want a faster response
- I can wait for an accurate result

AutoFHE: Automated Adaption of **CNNs** under **FHE**

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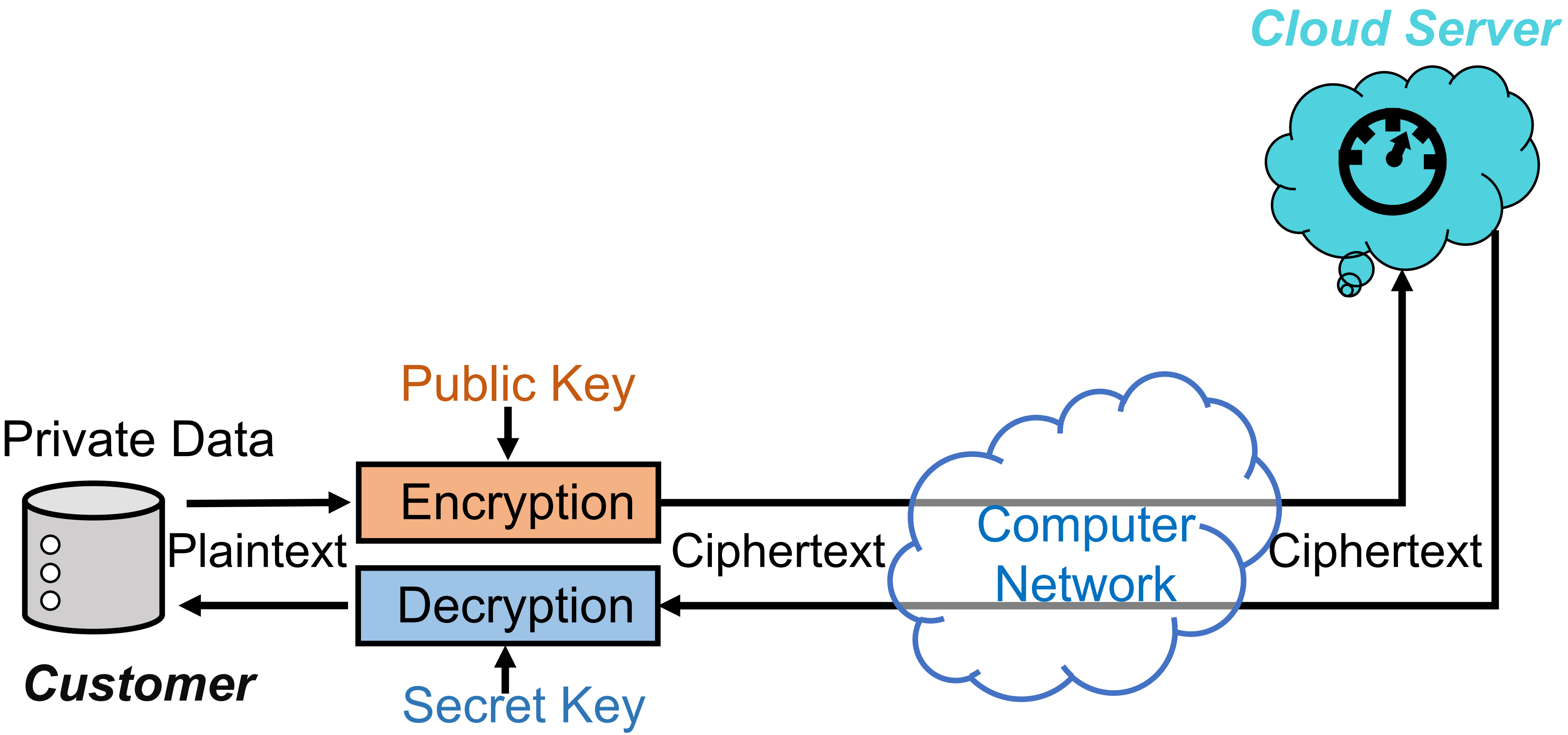

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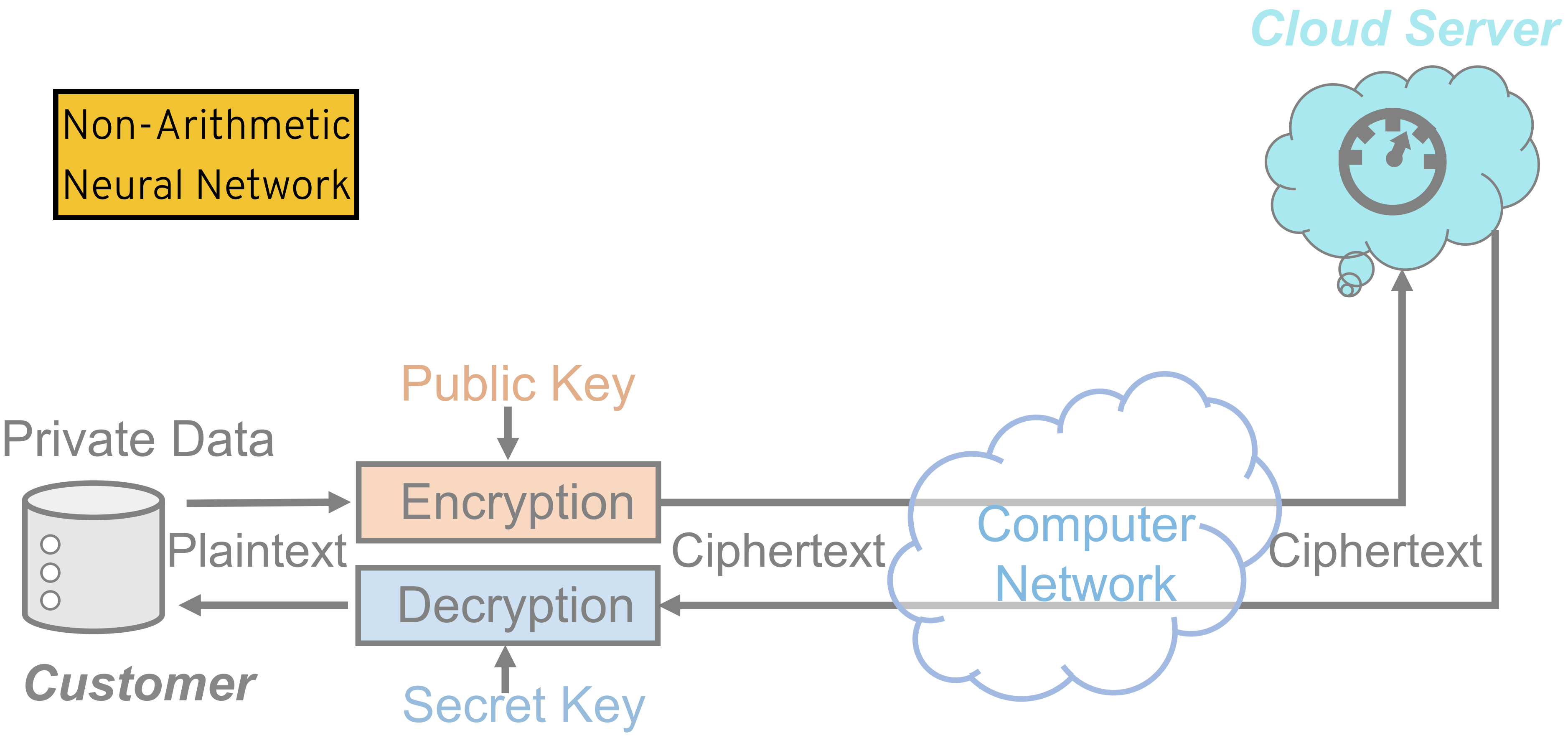

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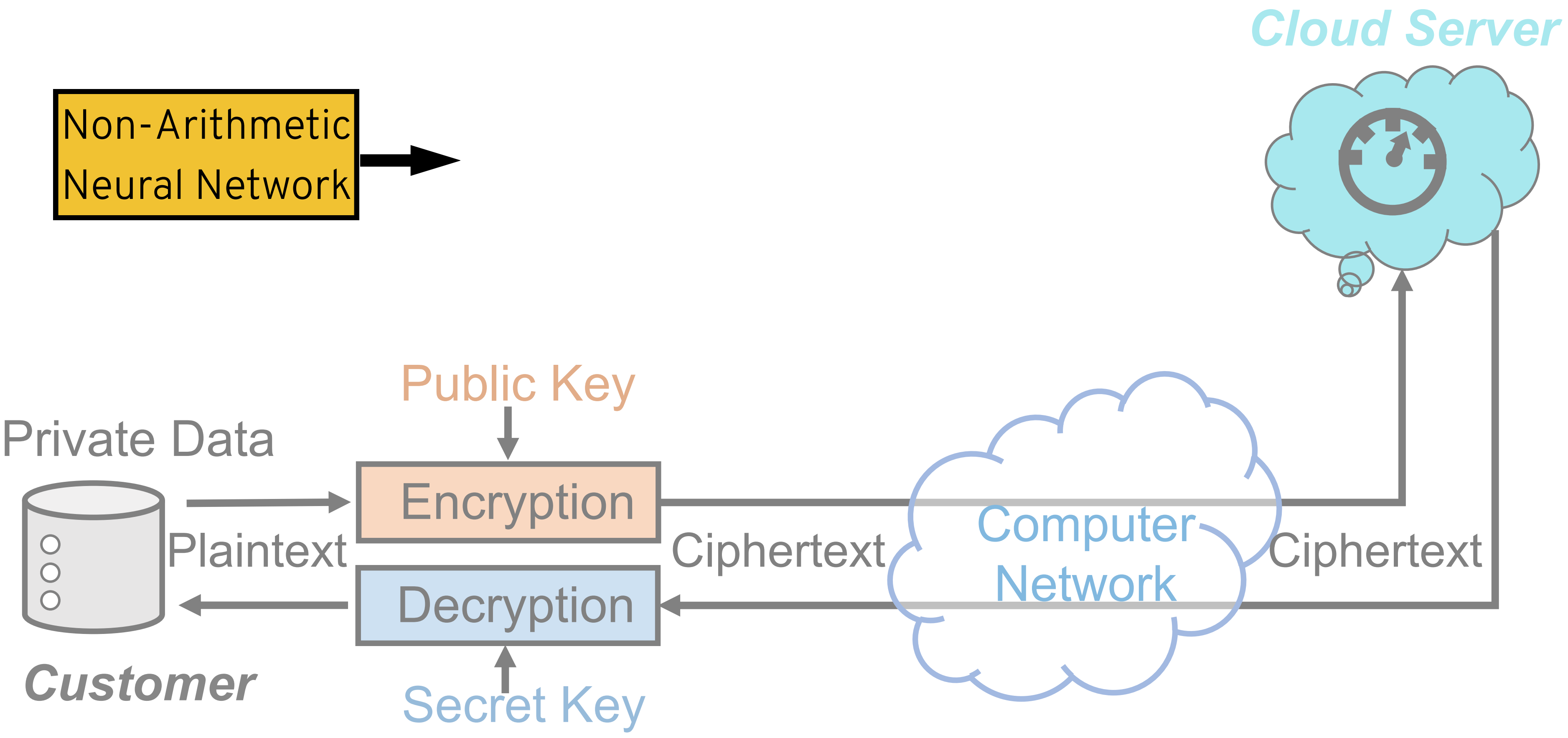

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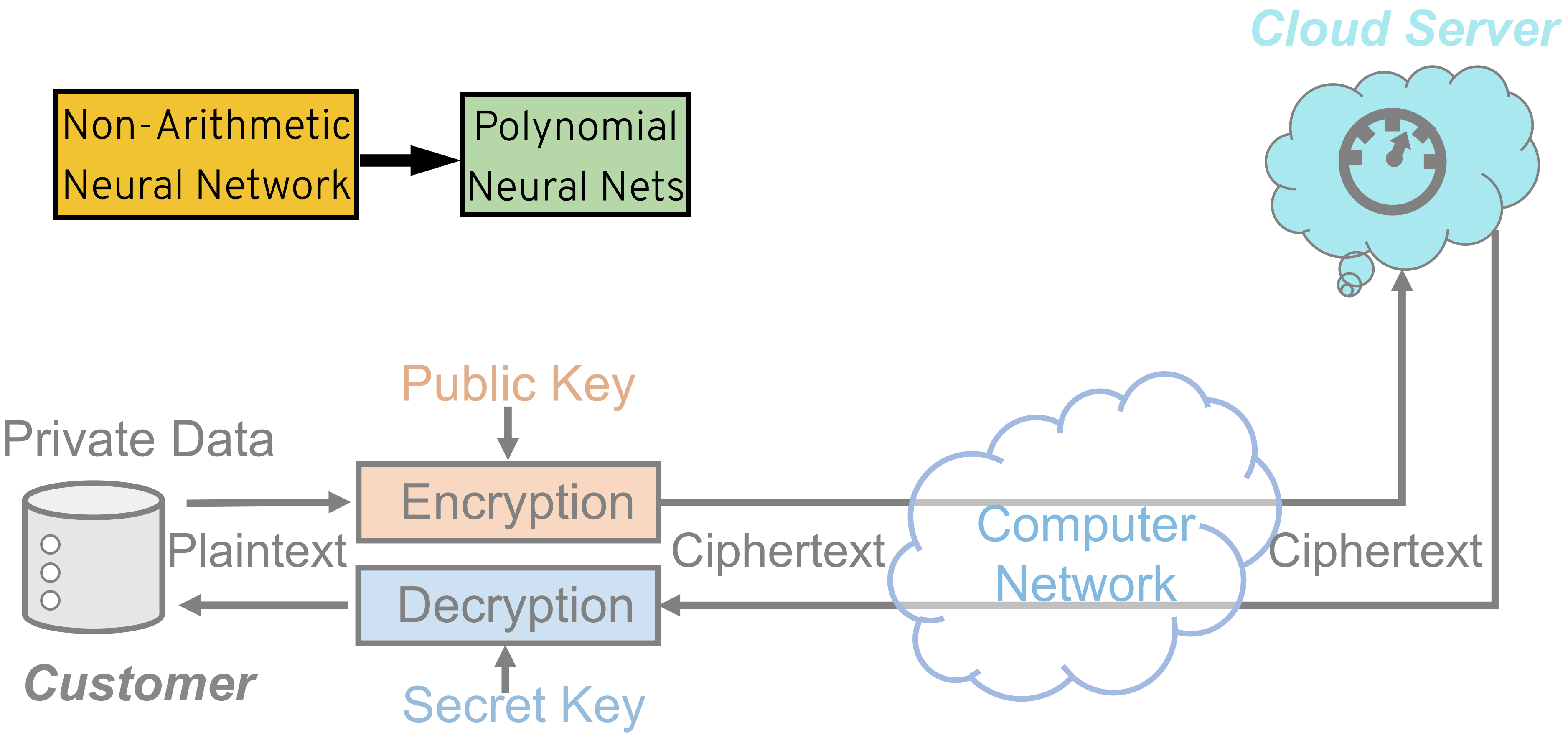

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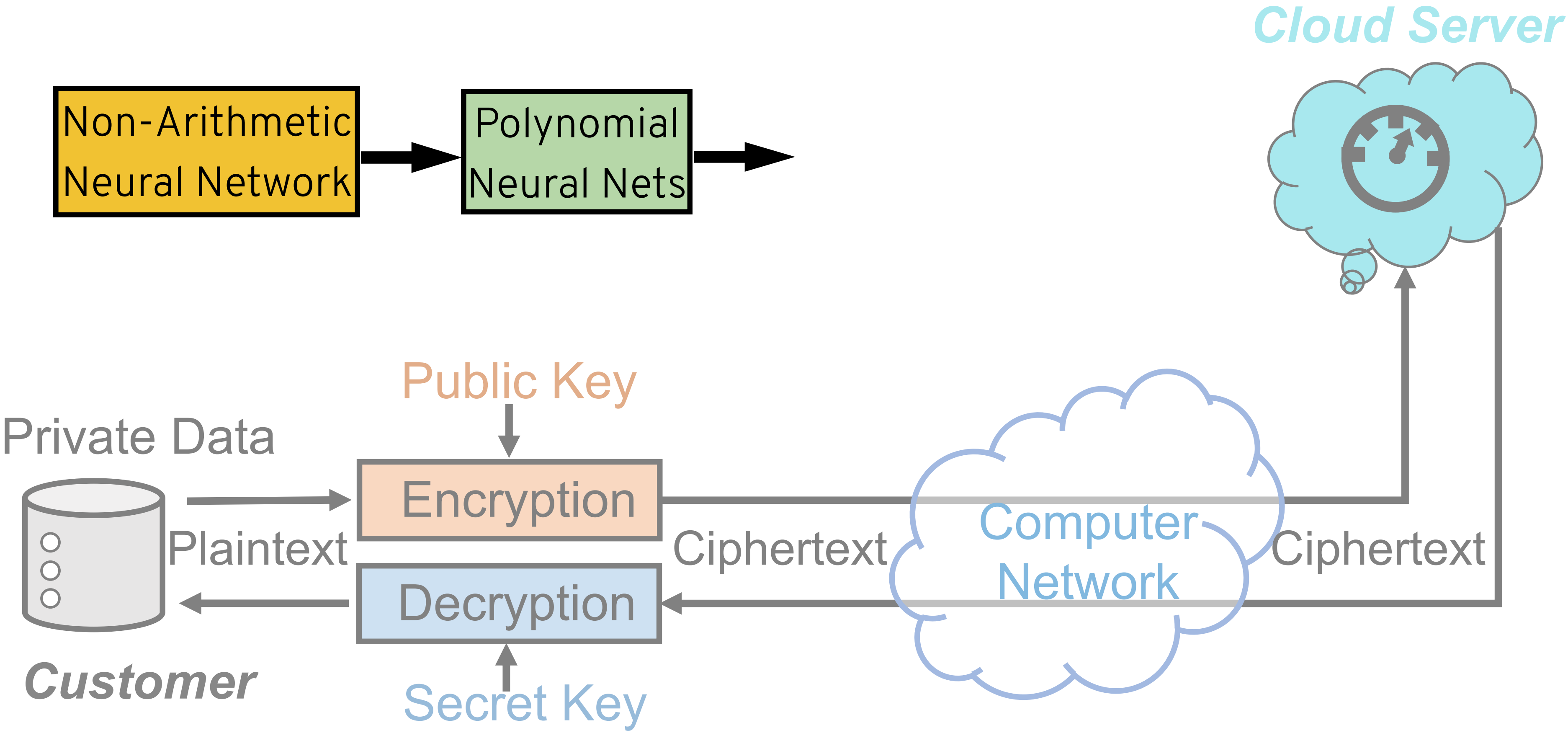

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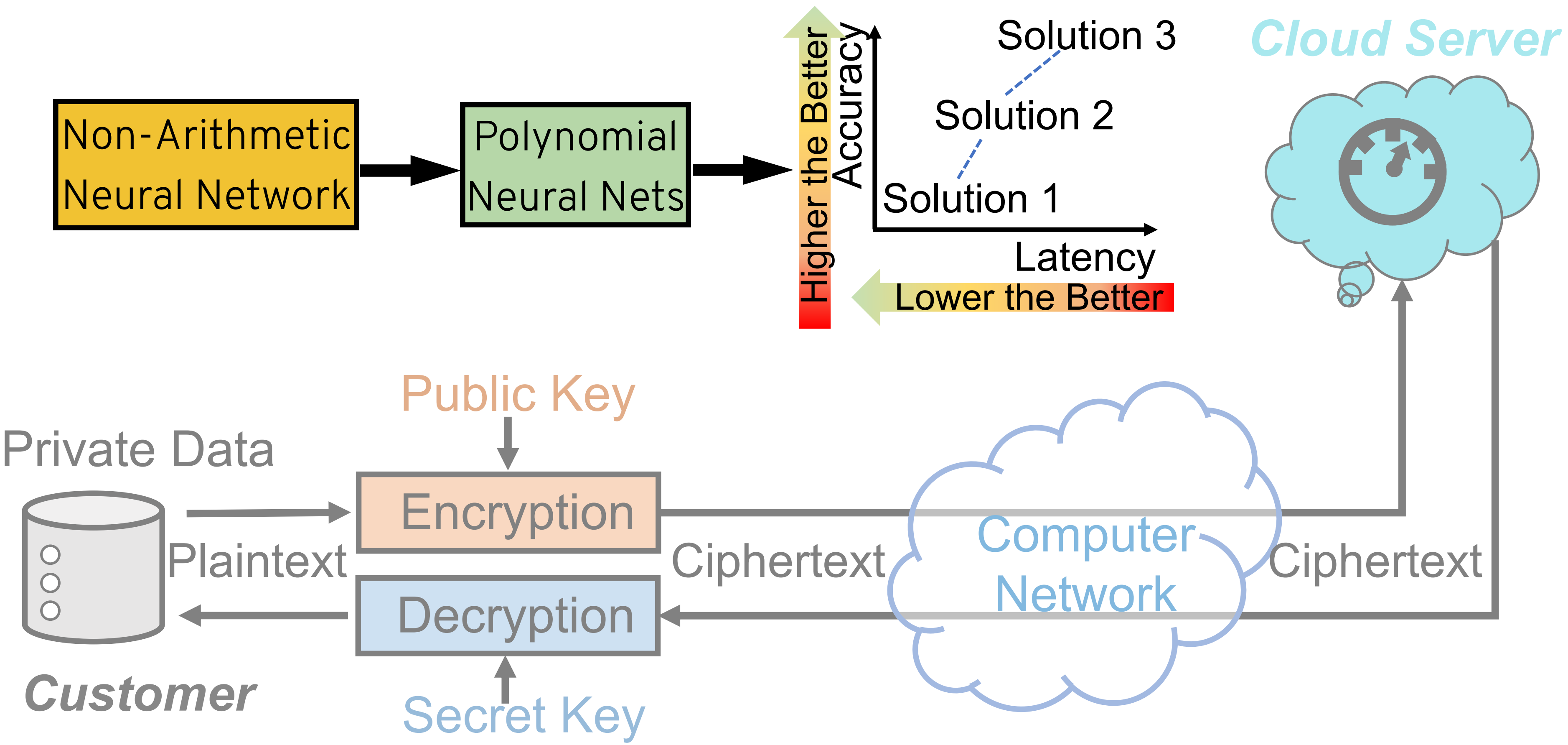

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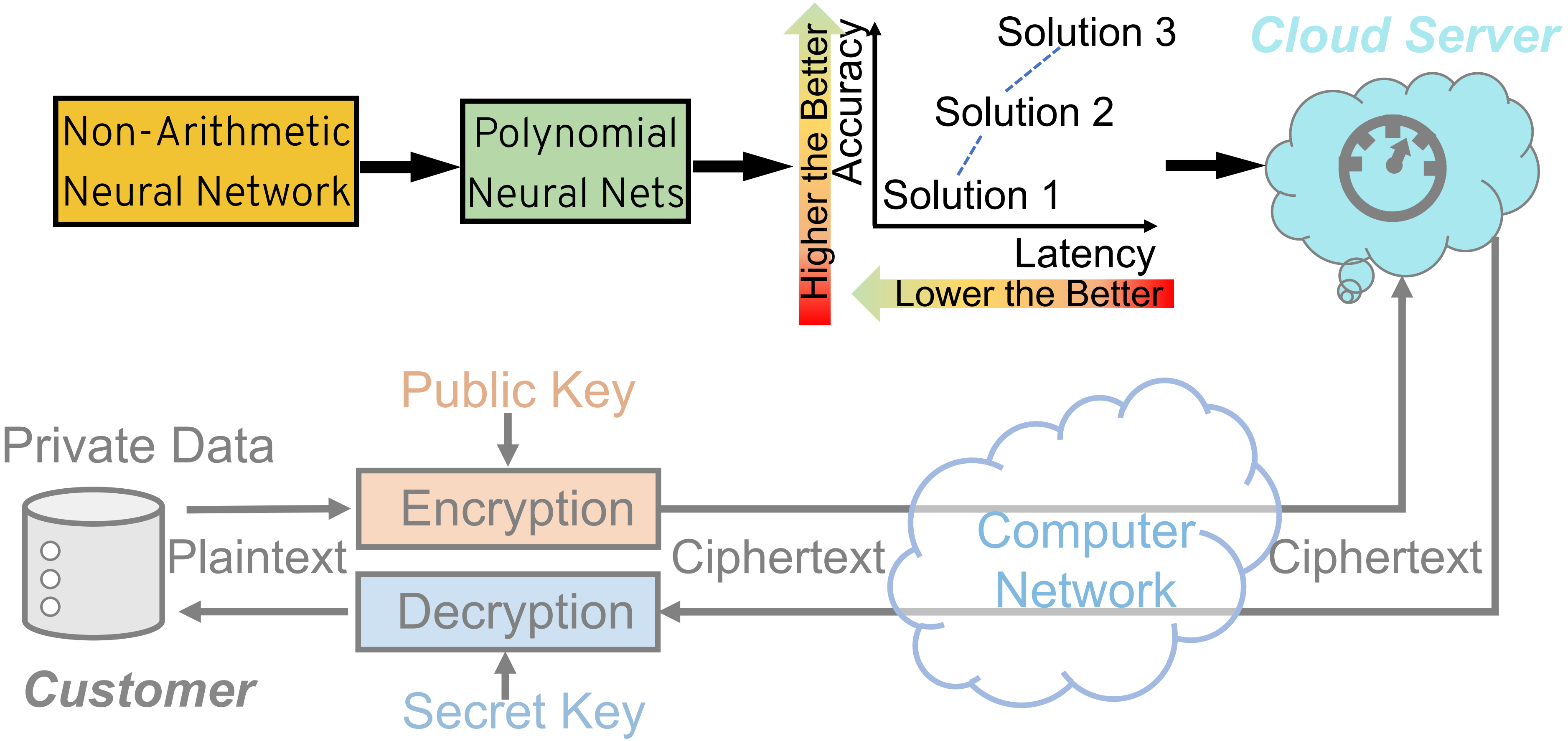

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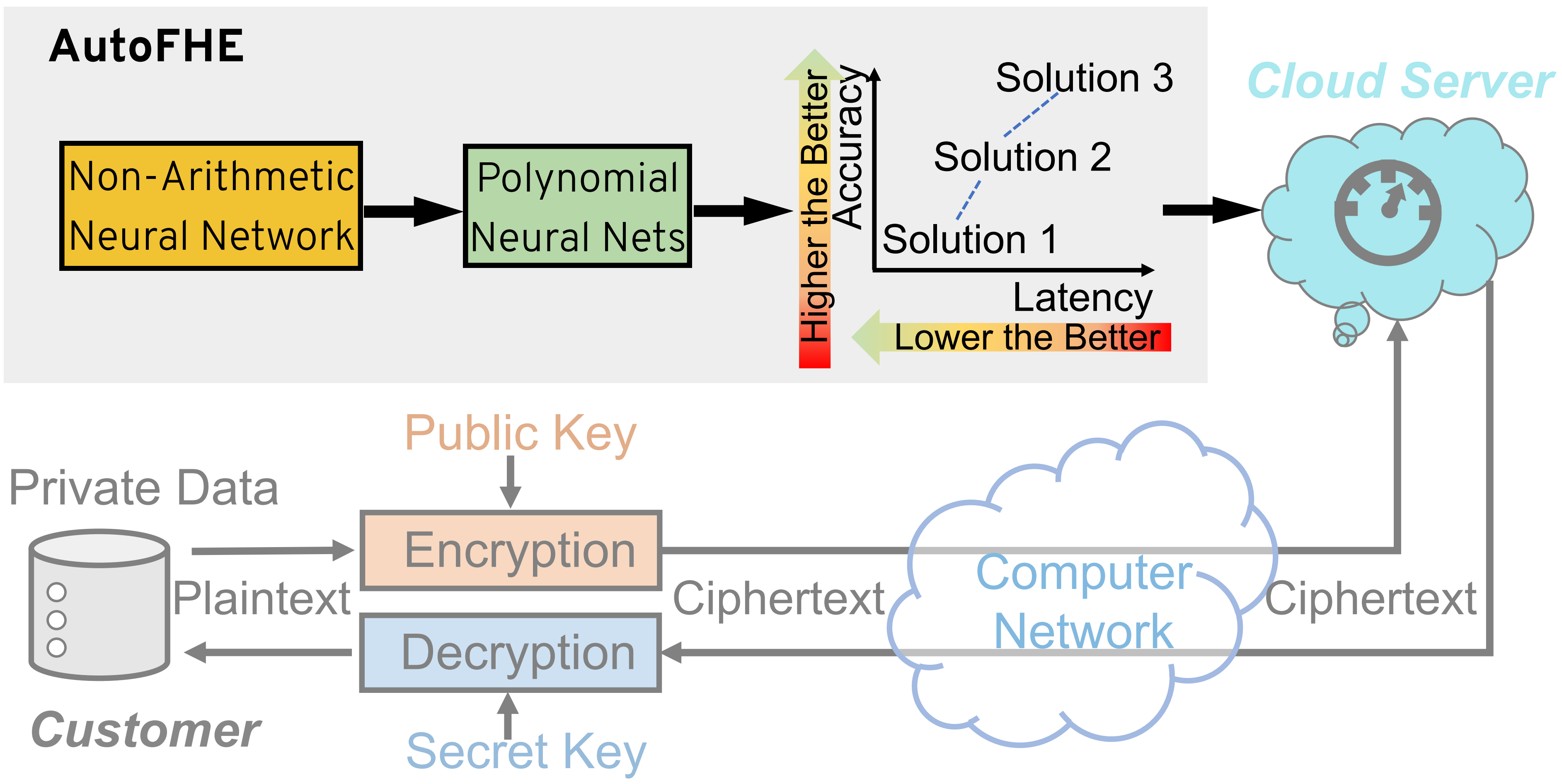

EvoReLU: Evolutionary Mixed-Degree Polynomial Approximation of **ReLU**

EvoReLU: Evolutionary Mixed-Degree Polynomial Approximation of ReLU

Forward Propagation

$$\mathrm{EvoReLU}(x) = \begin{cases} x, & d = 1 \\ \alpha_2 x^2 + \alpha_1 x + \alpha_0, & d = 2 \\ x \cdot \left(\mathcal{F}(x) + 0.5\right), & d > 2 \end{cases}$$

High-degree composite polynomial [2]:

$$\mathcal{F}(x) = (f_K^{d_K} \circ \cdots \circ f_k^{d_k} \circ \cdots \circ f_1^{d_1})(x), 1 \leq k \leq K$$

[2] Lee, Eunsang, Joon-Woo Lee, Jong-Seon No, and Young-Sik Kim. "Minimax approximation of sign function by composite polynomial for homomorphic comparison." *IEEE Transactions on Dependable and Secure Computing* 19, no. 6 (2021): 3711-3727.

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- **Pruning**: DeepReDuce, SAFENet, Delphi

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EvoReLU: Evolutionary Mixed-Degree Polynomial Approximation of ReLU

Forward Propagation

$$\text{EvoReLU}(x) = \begin{cases} x, & d = 1 \\ \alpha_2 x^2 + \alpha_1 x + \alpha_0, & d = 2 \\ x \cdot (\mathcal{F}(x) + 0.5), & d > 2 \end{cases}$$

High-degree composite polynomial [2]:

$$\mathcal{F}(x) = (f_K^{d_K} \circ \cdots \circ f_k^{d_k} \circ \cdots \circ f_1^{d_1})(x), 1 \leq k \leq K$$

- **Pruning**: DeepReDuce, SAFENet, Delphi
- **Quadratic**: LoLa, CryptoNets, HEMET

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Differentiable Evolution

- **Pruning**: DeepReDuce, SAFENet, Delphi
- **Quadratic**: LoLa, CryptoNets, HEMET
- **High-degree approximation**: MPCNN

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EvoReLU: Evolutionary Mixed-Degree Polynomial Approximation of ReLU

Backward Propagation

$$\frac{\partial \mathrm{EvoReLU}(x)}{\partial x} = \begin{cases} 1, & d = 1 \\ 2\alpha_2 x + \alpha_1, & d = 2 \\ \partial \mathrm{ReLU}(x)/\partial x, & d > 2 \end{cases}$$

EvoReLU: Evolutionary Mixed-Degree Polynomial Approximation of ReLU

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$$\frac{\partial \mathrm{EvoReLU}(x)}{\partial x} = \begin{cases} 1, & d = 1 \\ 2\alpha_2 x + \alpha_1, & d = 2 \\ \partial \mathrm{ReLU}(x)/\partial x, & d > 2 \end{cases}$$

- Gradient

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- Gradient
- Gradient

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- Gradient
- Gradient
- Straight-through estimated gradient

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- Gradient
- Gradient
- Straight-through estimated gradient

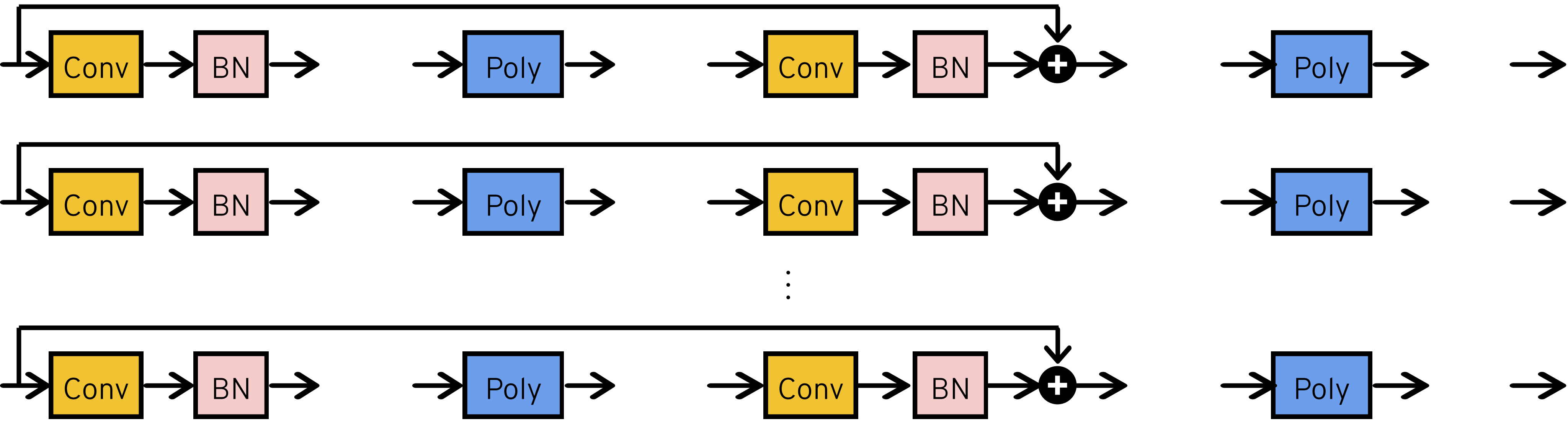
- **Make training more stable**

How to **optimize** end-to-end polynomial neural architecture?

How to **optimize** end-to-end polynomial neural architecture?

Multi-Objective evolutionary optimization

Joint Search for **Layerwise EvoReLU** and **Bootstrapping Operations**



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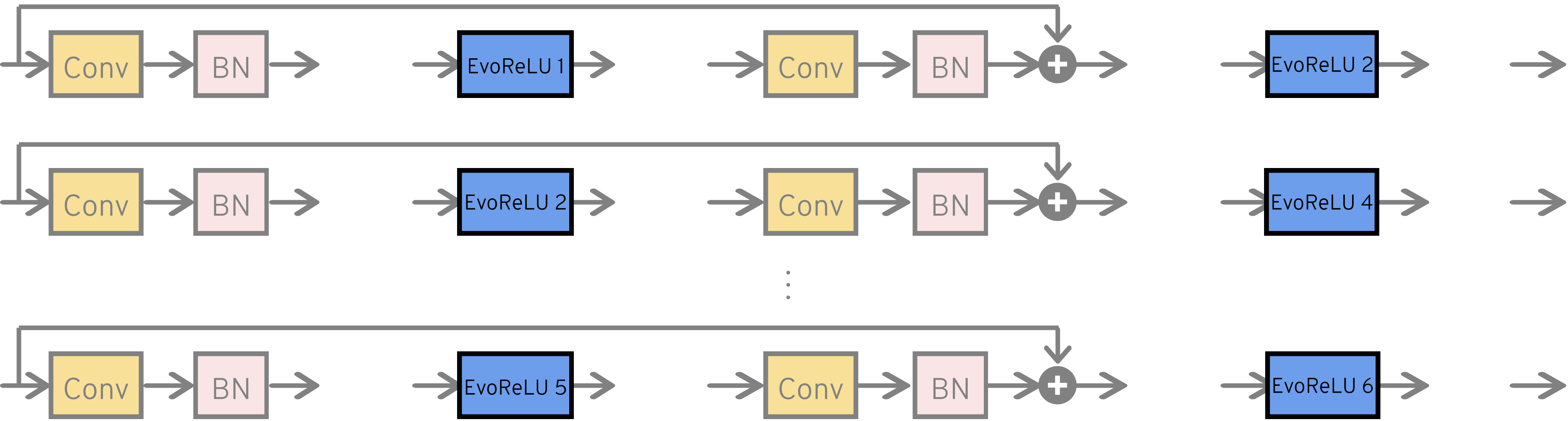

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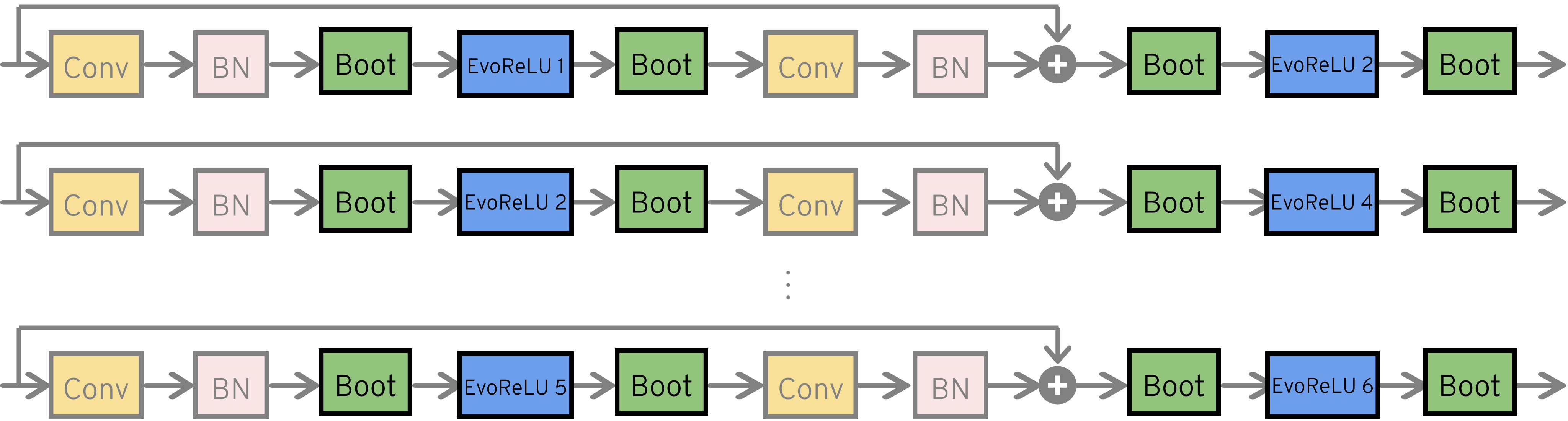

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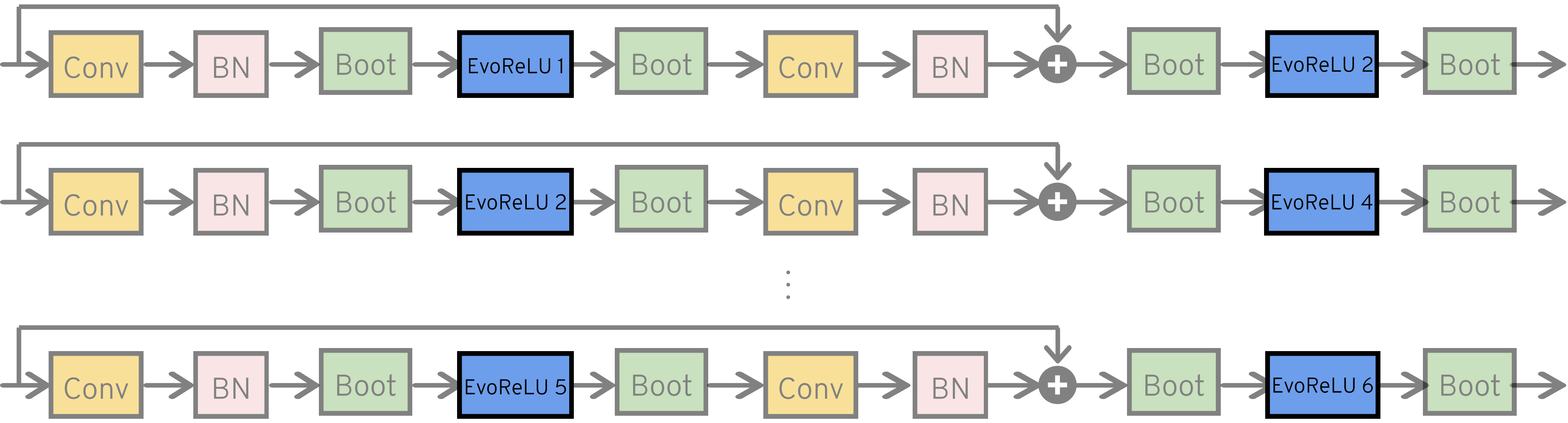
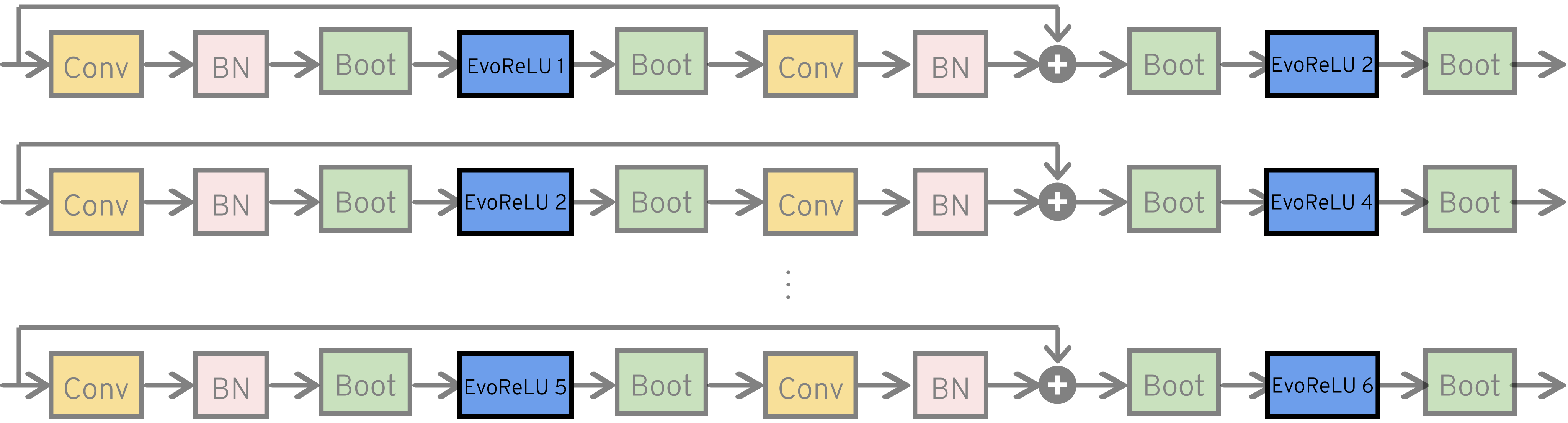


Joint search problem

Joint Search for **Layerwise EvoReLU** and **Bootstrapping Operations**



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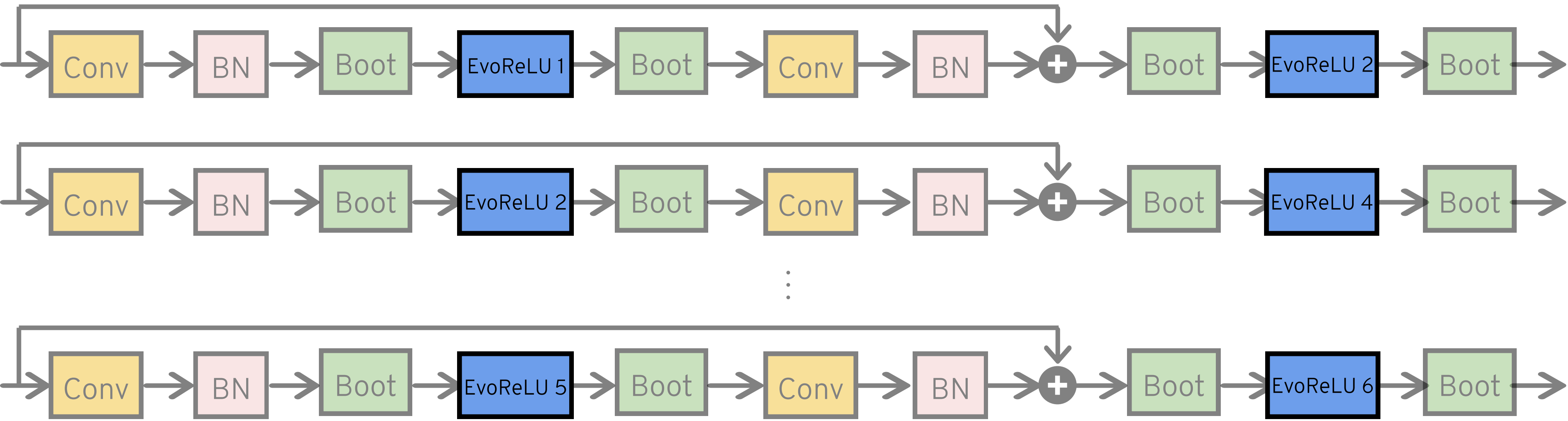
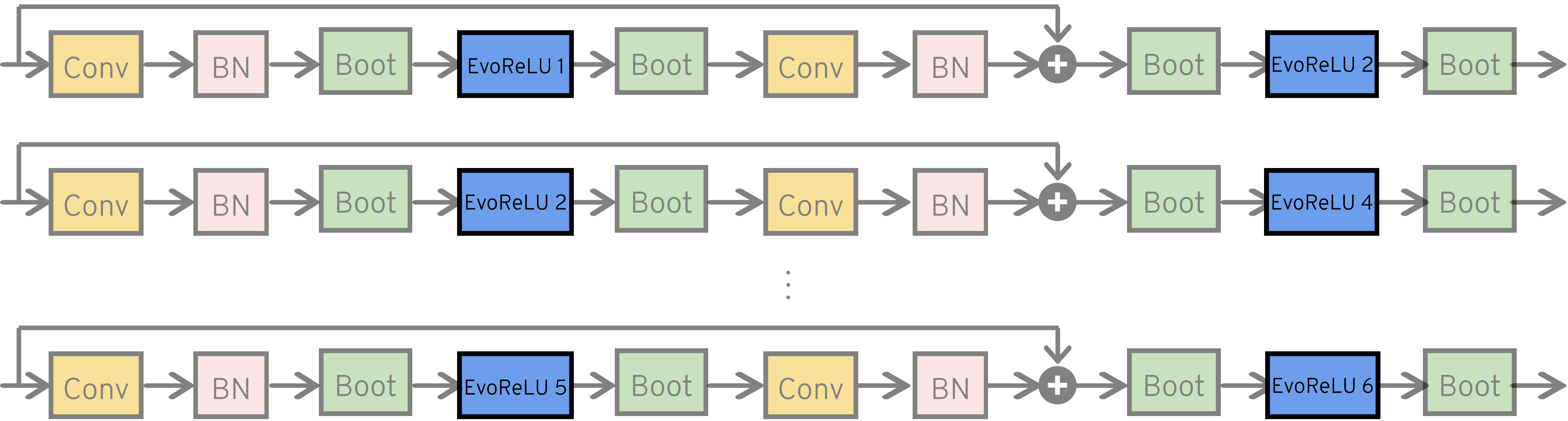


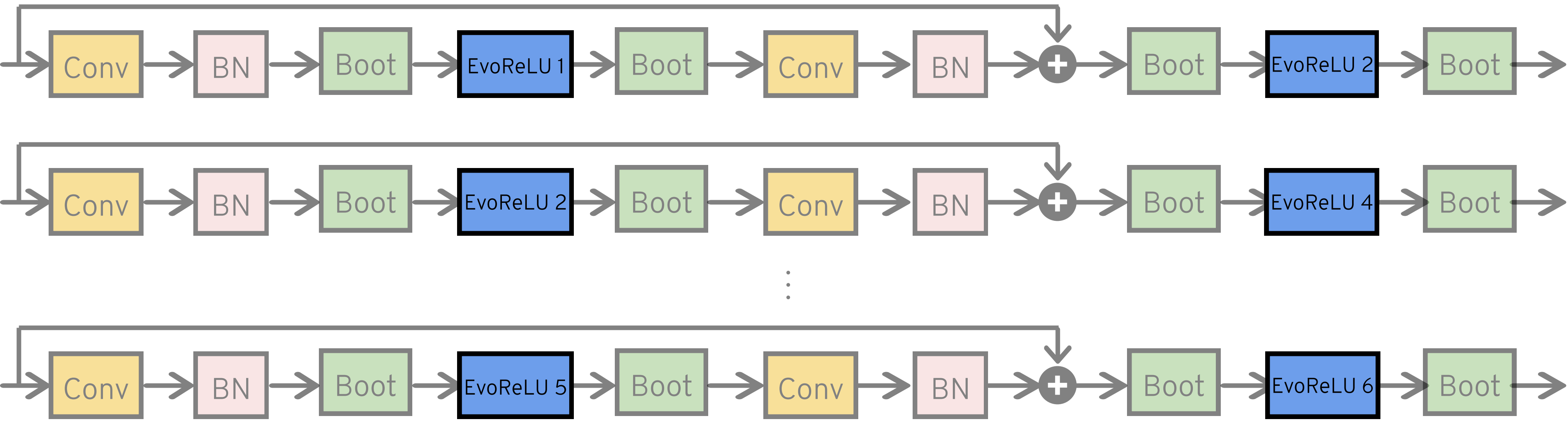
Joint search problem ⇨ Multi-objective optimization

Joint Search for **Layerwise EvoReLU** and **Bootstrapping Operations**



Joint search problem → Multi-objective optimization →

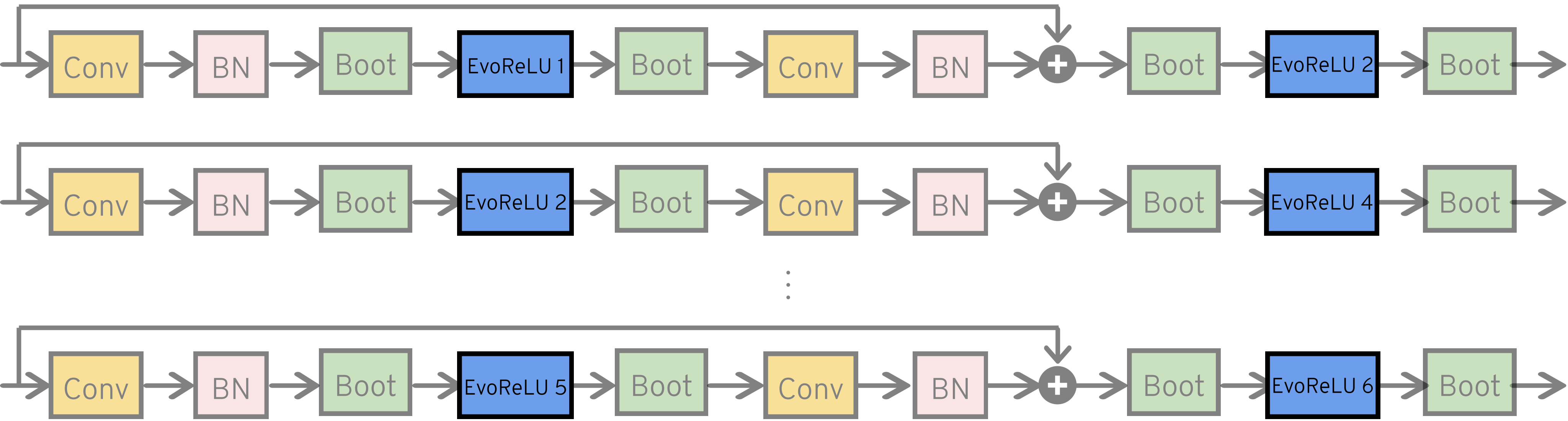
Joint Search for **Layerwise EvoReLU** and **Bootstrapping Operations**



Joint search problem ⇨ Multi-objective optimization ⇨

- **Flexible Architecture**

Joint Search for **Layerwise EvoReLU** and **Bootstrapping Operations**



Joint search problem → Multi-objective optimization →

- **Flexible Architecture**
- **On-demand Bootstrapping**

Multi-Objective Optimization

Multi-Objective Optimization

Single Objective

- Accuracy
- Latency

Multi-Objective Optimization

Single Objective

- Accuracy
- Latency

Scalarization of Multiple Objectives

$$\alpha \cdot \text{Accuracy} + \beta \cdot \text{Latency}$$

Multi-Objective Optimization

Single Objective

- Accuracy
- Latency

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- Only generate a single solution

Multi-Objective Optimization

Single Objective

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- Latency

Scalarization of Multiple Objectives

$$\alpha \cdot \text{Accuracy} + \beta \cdot \text{Latency}$$

- Only generate a single solution
- Hard to tune balancing weights

Multi-Objective Optimization

Single Objective

- Accuracy
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$$\alpha \cdot \text{Accuracy} + \beta \cdot \text{Latency}$$

- Only generate a single solution
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- Not Pareto optimal

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Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \#\text{Bootstrapping}\}$$

Multi-Objective Optimization

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Scalarization of Multiple Objectives

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- Only generate a single solution
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- Not Pareto optimal

Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \#\text{Bootstrapping}\}$$

- Multiple solutions on the Pareto front

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- Accuracy
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Scalarization of Multiple Objectives

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- Only generate a single solution
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Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \#\text{Bootstrapping}\}$$

- Multiple solutions on the Pareto front
- No need to tune weights

Multi-Objective Optimization

Single Objective

- Accuracy
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- Multiple solutions on the Pareto front
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Multi-Objective Optimization

Multi-Objective Optimization

Multi-Objective Optimization

$$\min\{1-\text{Accuracy}, \text{Depth of polys}\}$$

Multi-Objective Optimization

Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \text{Depth of polys}\}$$

Level 4

Multi-Objective Optimization

Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \text{Depth of polys}\}$$

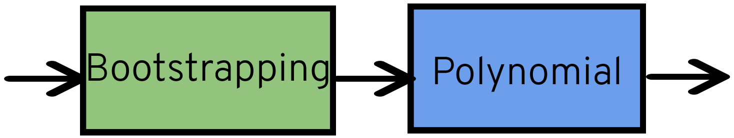
Level 4

Multi-Objective Optimization

Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \text{Depth of polys}\}$$

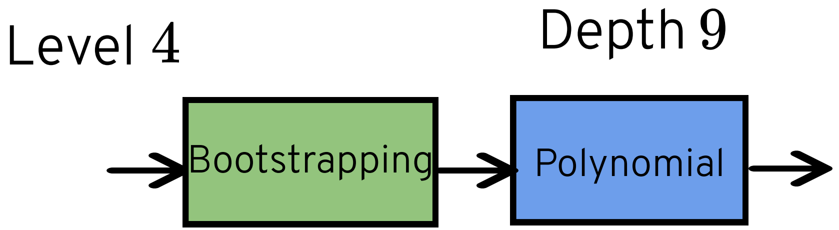
Level 4



Multi-Objective Optimization

Multi-Objective Optimization

$$\min\{1 - \text{Accuracy}, \textcolor{red}{\text{Depth of polys}}\}$$



Multi-Objective Optimization

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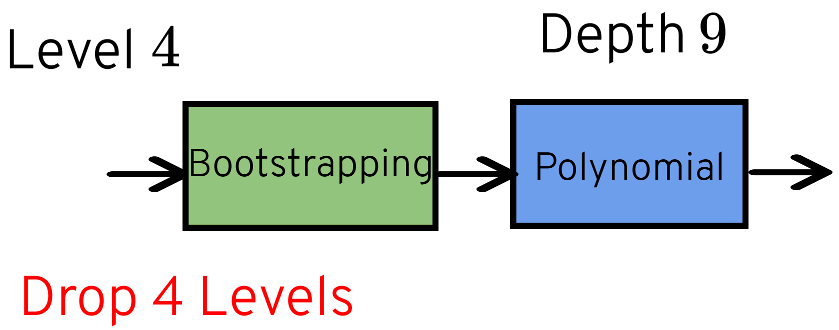

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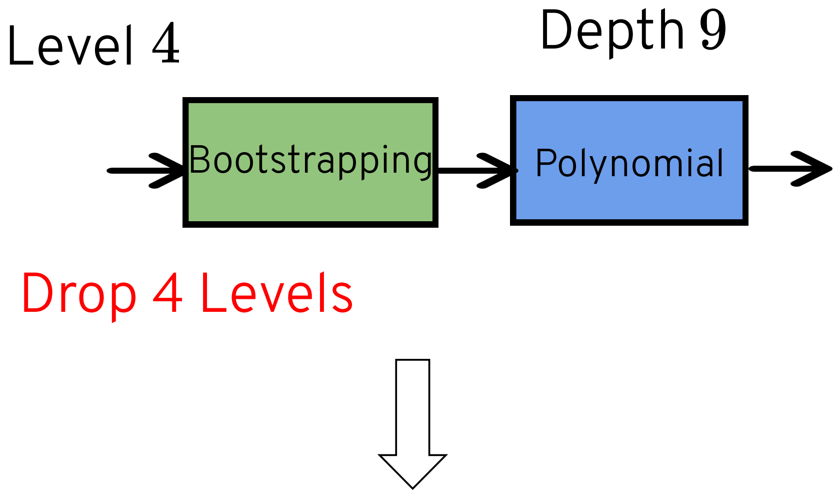


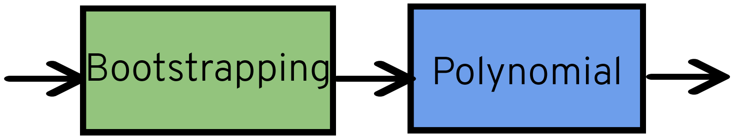
Multi-Objective Optimization

Multi-Objective Optimization

$$\min \{1 - \text{Accuracy}, \text{Depth of polys}\}$$

Level 4

Depth 9



Drop 4 Levels

- Not necessarily reduce bootstrapping operations

Multi-Objective Optimization

Multi-Objective Optimization

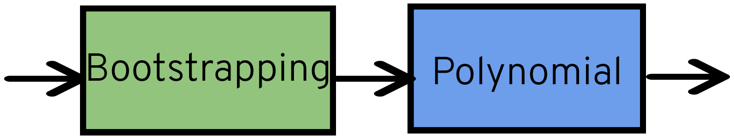
$$\min\{1 - \text{Accuracy}, \text{Depth of polys}\}$$

Multi-Objective Optimization

$$\min\{1 - \text{Accuracy}, \#\text{Bootstrapping}\}$$

Level 4

Depth 9



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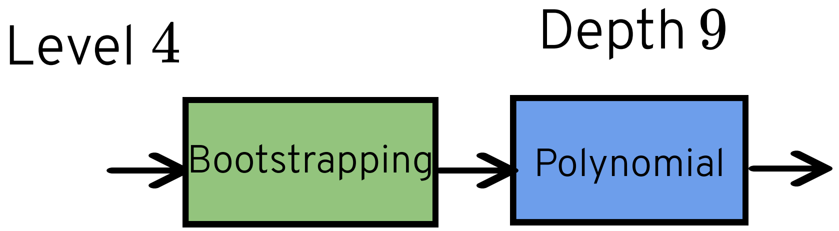

Drop 4 Levels

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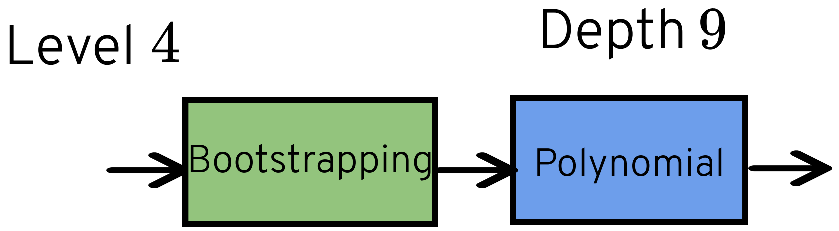


Drop 4 Levels

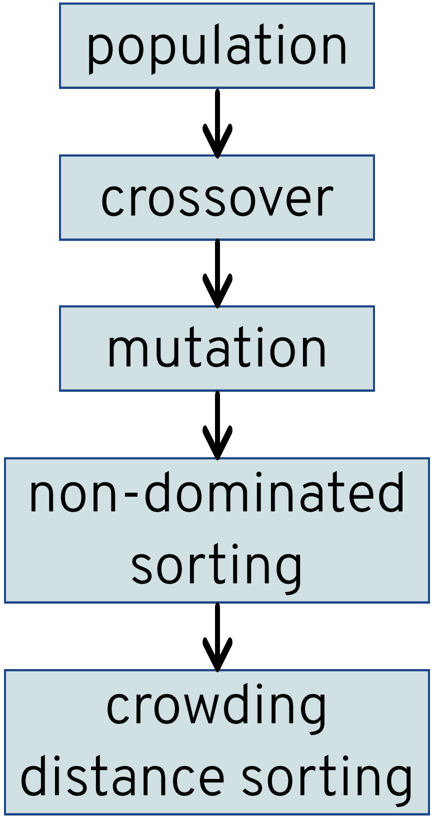
- Not necessarily reduce bootstrapping operations

Multi-Objective Optimization

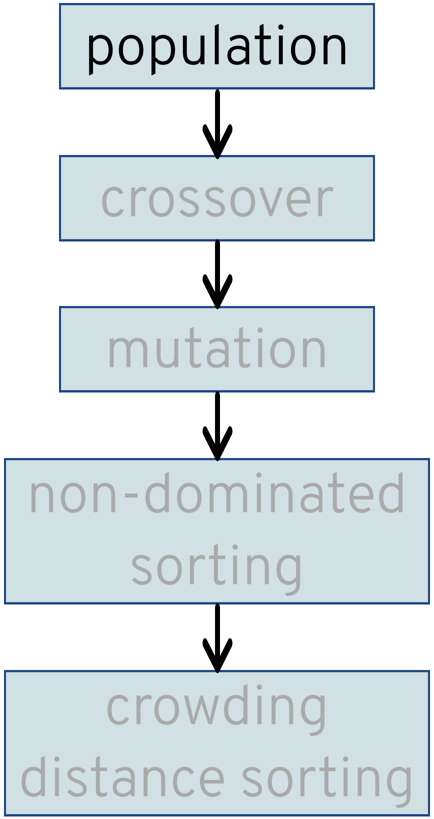
$$\min\{1 - \text{Accuracy}, \#\text{Bootstrapping}\}$$

- Directly reduce bootstrapping operations

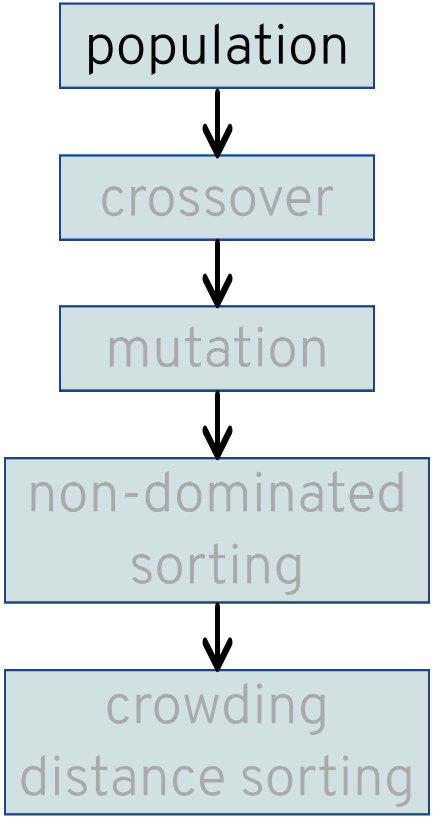
Evolutionary Multi-Objective Optimization



Evolutionary Multi-Objective Optimization



Evolutionary Multi-Objective Optimization



$$x_1 : \mathrm{EvoReLU}_{11}, \mathrm{EvoReLU}_{12}, \mathrm{EvoReLU}_{13}, \mathrm{EvoReLU}_{14}, \cdots$$

$$x_2 : \mathrm{EvoReLU}_{21}, \mathrm{EvoReLU}_{22}, \mathrm{EvoReLU}_{23}, \mathrm{EvoReLU}_{24}, \cdots$$

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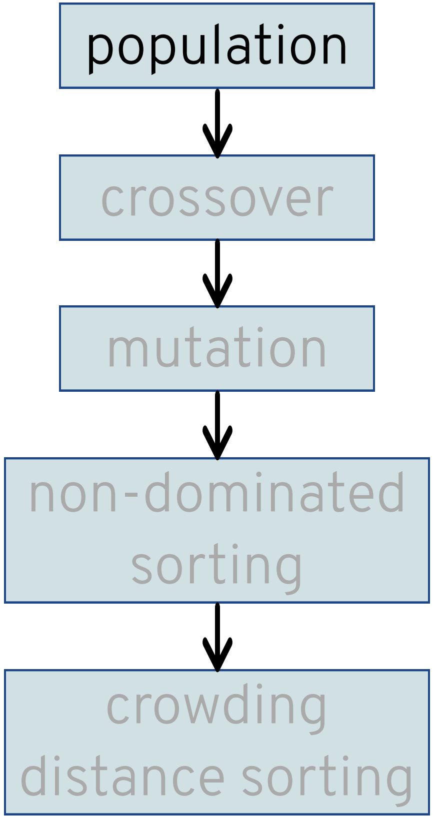
Evolutionary Multi-Objective Optimization



→ #Layers

$x_1 : \mathrm{EvoReLU}_{11}, \mathrm{EvoReLU}_{12}, \mathrm{EvoReLU}_{13}, \mathrm{EvoReLU}_{14}, \cdots$

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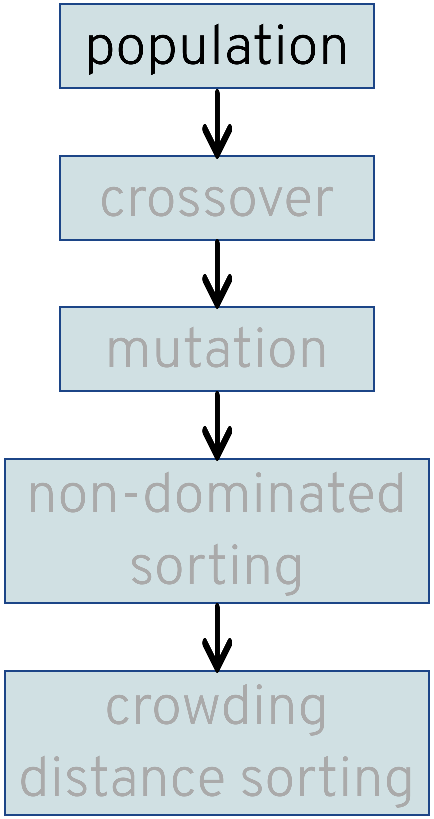
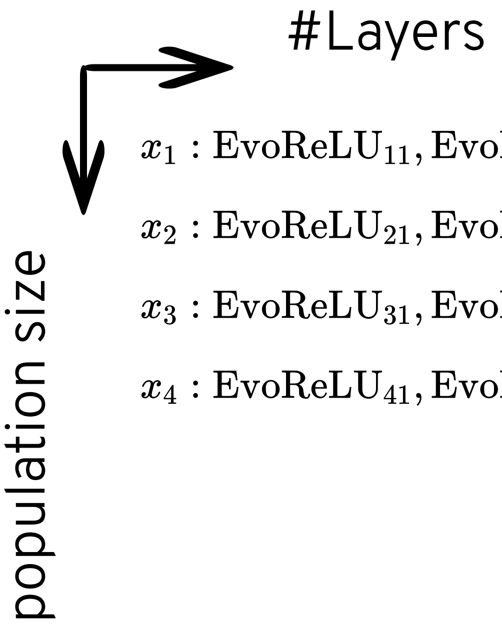
Evolutionary Multi-Objective Optimization





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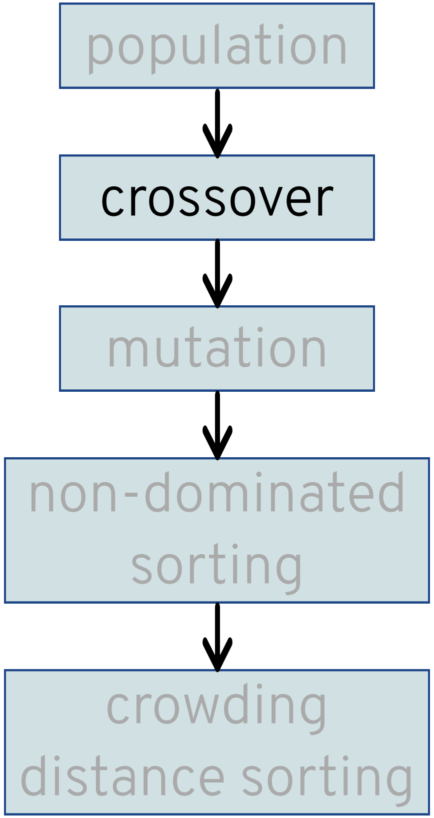
Evolutionary Multi-Objective Optimization



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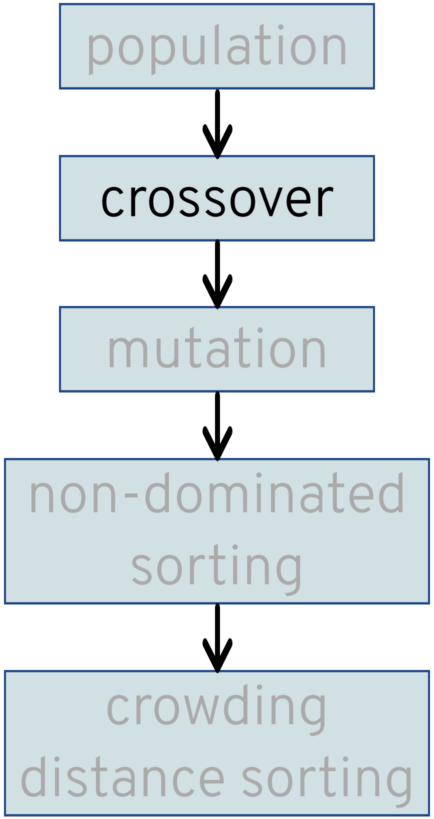
Evolutionary Multi-Objective Optimization



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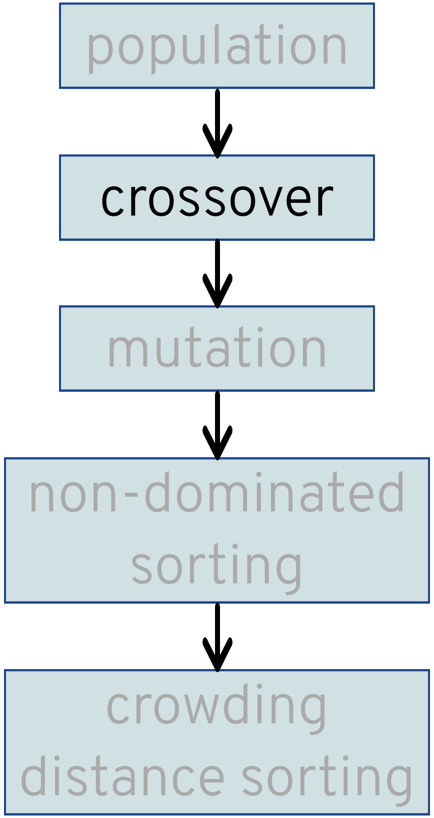
Evolutionary Multi-Objective Optimization



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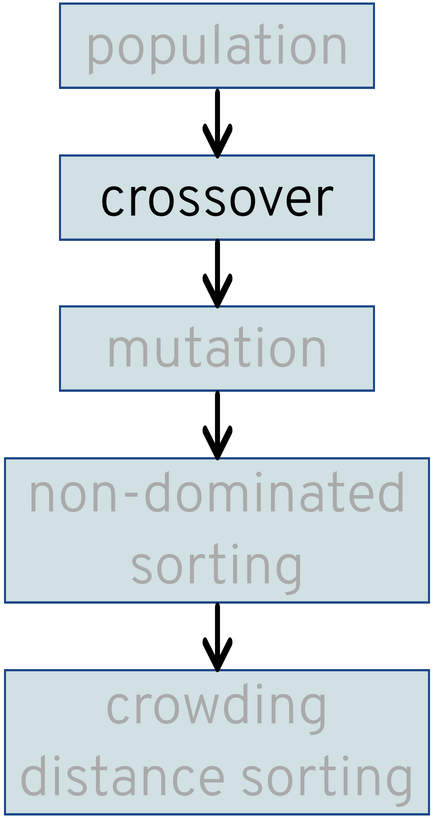
Evolutionary Multi-Objective Optimization



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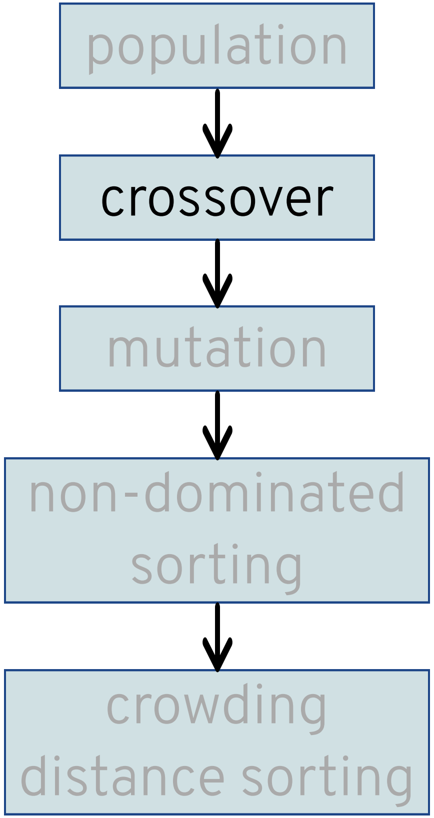
Evolutionary Multi-Objective Optimization



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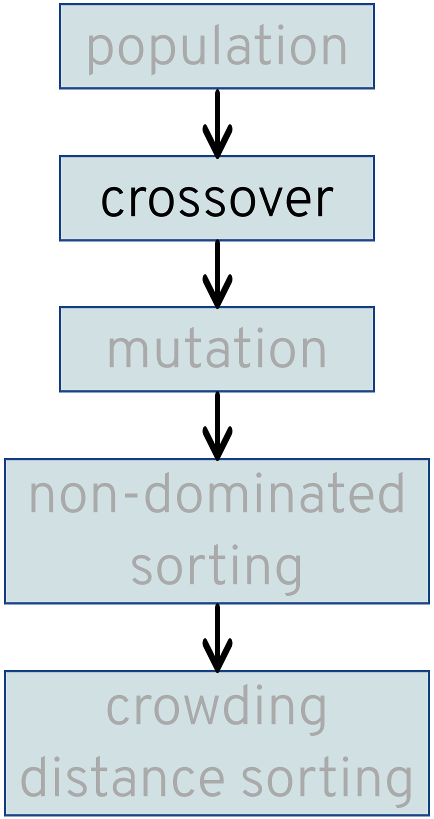
$$x_1' : \mathrm{EvoReLU}_{21}, \mathrm{EvoReLU}_{12}, \mathrm{EvoReLU}_{23}, \mathrm{EvoReLU}_{14}, \cdots$$

Evolutionary Multi-Objective Optimization



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$$\Downarrow$$

$$x_1' : \text{EvoReLU}_{21}, \text{EvoReLU}_{12}, \text{EvoReLU}_{23}, \text{EvoReLU}_{14}, \cdots$$

$$x_2' : \text{EvoReLU}_{11}, \text{EvoReLU}_{22}, \text{EvoReLU}_{13}, \text{EvoReLU}_{24}, \cdots$$

Evolutionary Multi-Objective Optimization

population

↓

crossover

↓

mutation

↓

non-dominated sorting

↓

crowding distance sorting

$$x_1 : \mathrm{EvoReLU}_{11}, \mathrm{EvoReLU}_{12}, \mathrm{EvoReLU}_{13}, \mathrm{EvoReLU}_{14}, \cdots$$

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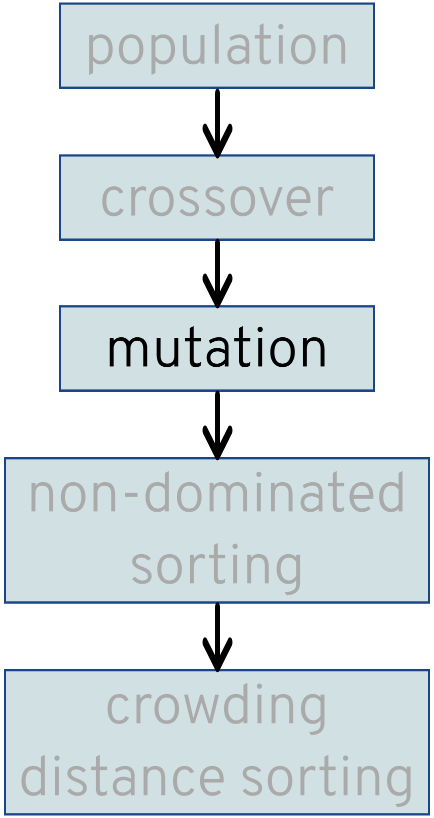
Evolutionary Multi-Objective Optimization



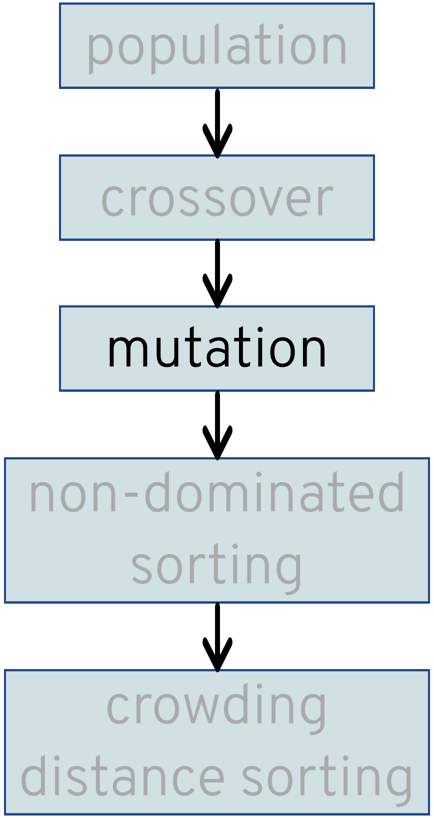
$$x_1 : \mathrm{EvoReLU}_{11}, \mathrm{EvoReLU}_{12}, \boxed{\mathrm{EvoReLU}_{13},} \mathrm{EvoReLU}_{14}, \cdots$$

$$x_2 : \mathrm{EvoReLU}_{21}, \mathrm{EvoReLU}_{22}, \boxed{\mathrm{EvoReLU}_{23},} \mathrm{EvoReLU}_{24}, \cdots$$

$$x_3 : \boxed{\mathrm{EvoReLU}_{31},} \mathrm{EvoReLU}_{32}, \mathrm{EvoReLU}_{33}, \mathrm{EvoReLU}_{34}, \cdots$$

$$x_4 : \mathrm{EvoReLU}_{41}, \boxed{\mathrm{EvoReLU}_{42},} \mathrm{EvoReLU}_{43}, \mathrm{EvoReLU}_{44}, \cdots$$

Evolutionary Multi-Objective Optimization



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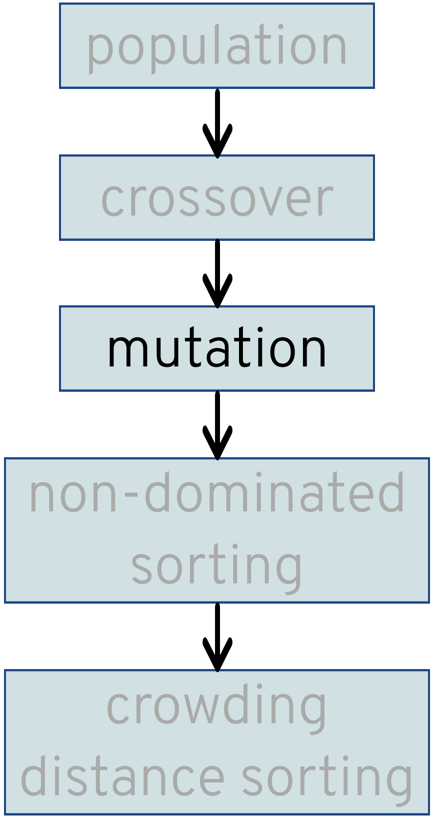
Evolutionary Multi-Objective Optimization



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$$x_4 : \mathrm{EvoReLU}_{41}, \boxed{\mathrm{EvoReLU}_{42},} \mathrm{EvoReLU}_{43}, \mathrm{EvoReLU}_{44}, \cdots$$

$$\Downarrow$$

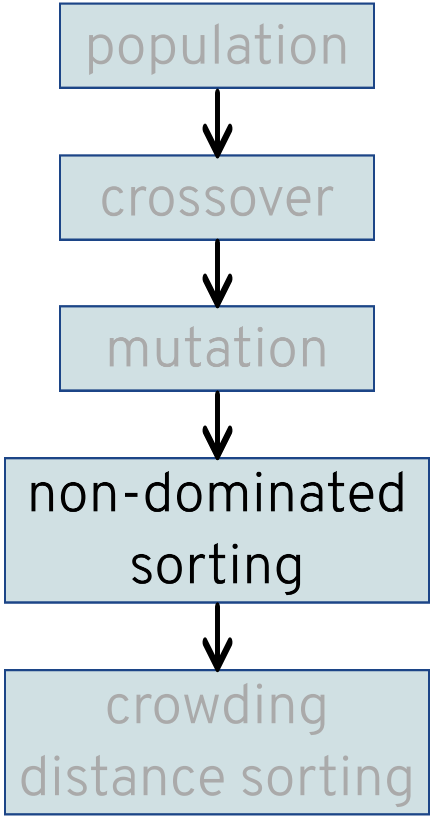
$$x'_1 : \mathrm{EvoReLU}_{11}, \mathrm{EvoReLU}_{12}, \color{red}{\mathrm{EvoReLU}'_{13}}, \mathrm{EvoReLU}_{14}, \cdots$$

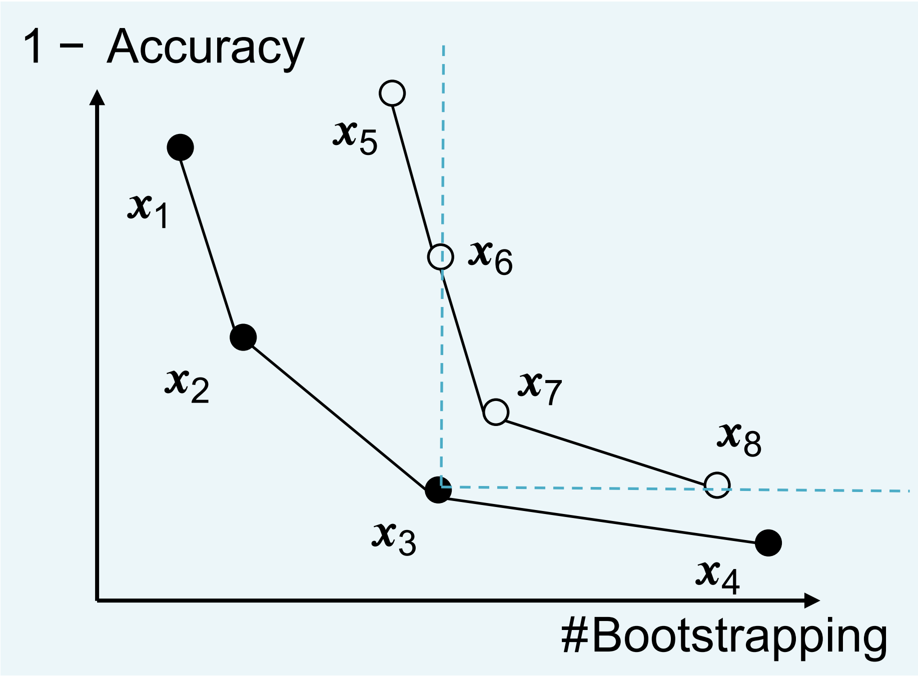
$$x'_2 : \mathrm{EvoReLU}_{21}, \mathrm{EvoReLU}_{22}, \color{red}{\mathrm{EvoReLU}'_{23}}, \mathrm{EvoReLU}_{24}, \cdots$$

$$x'_3 : \color{red}{\mathrm{EvoReLU}'_{31}}, \mathrm{EvoReLU}_{32}, \mathrm{EvoReLU}_{33}, \mathrm{EvoReLU}_{34}, \cdots$$

$$x'_4 : \mathrm{EvoReLU}_{41}, \color{red}{\mathrm{EvoReLU}'_{42}}, \mathrm{EvoReLU}_{43}, \mathrm{EvoReLU}_{44}, \cdots$$

Evolutionary Multi-Objective Optimization



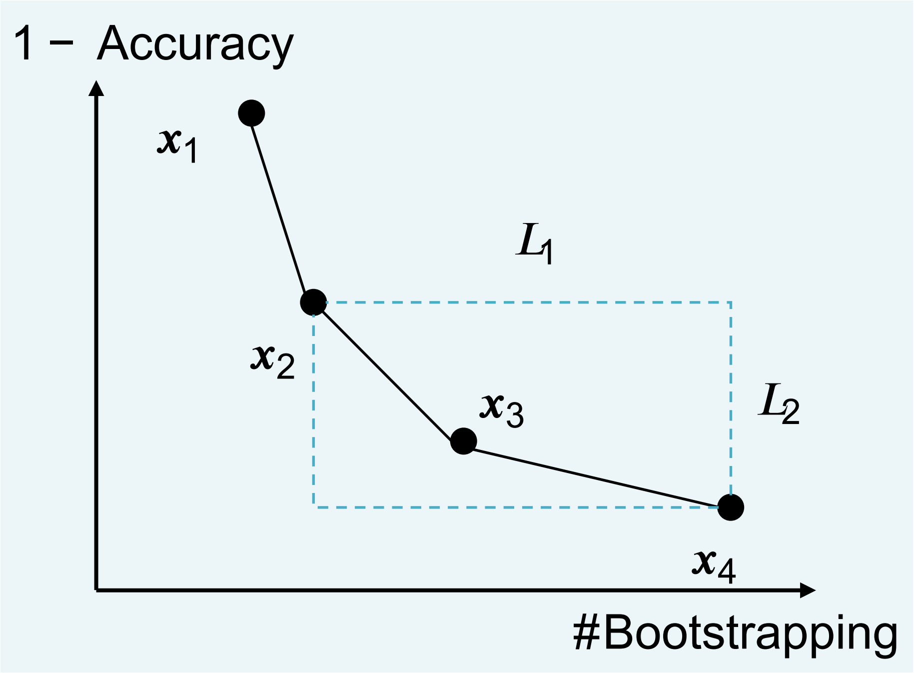


x_3 dominates $x_6, x_7,$ and x_8

i.e. x_3 is better than $x_6, x_7,$ and x_8

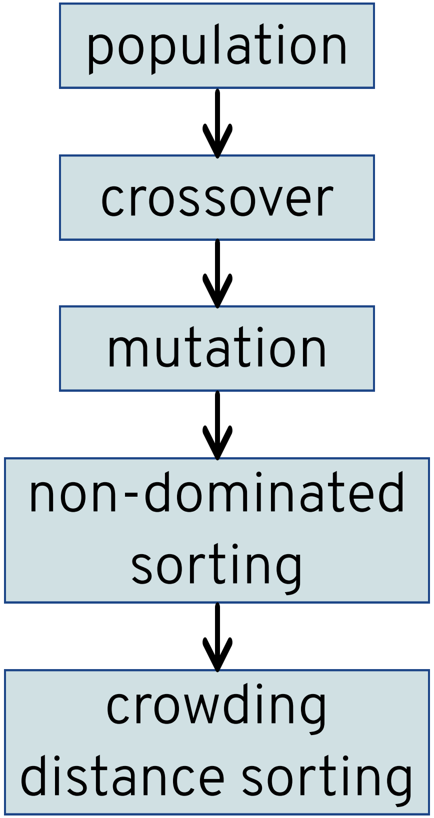
Evolutionary Multi-Objective Optimization

population
↓
crossover
↓
mutation
↓
non-dominated sorting
↓
crowding distance sorting

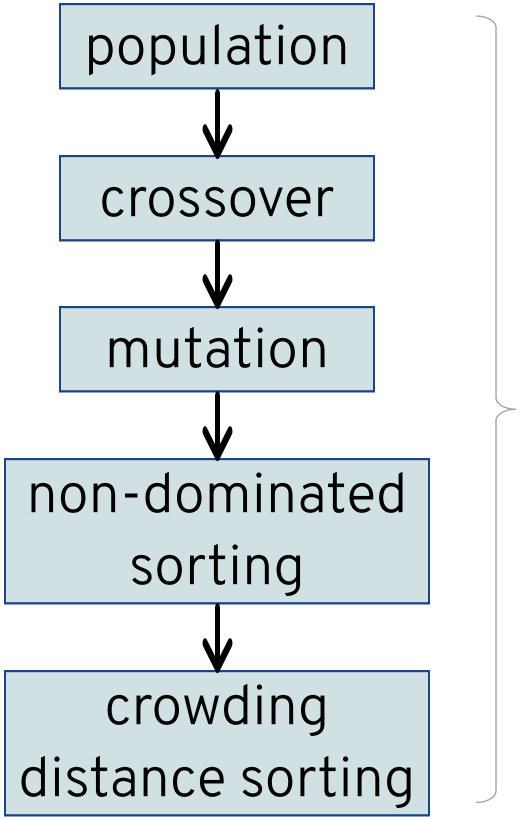


crowding distance of x_3 is $\frac{L_1 + L_2}{2}$

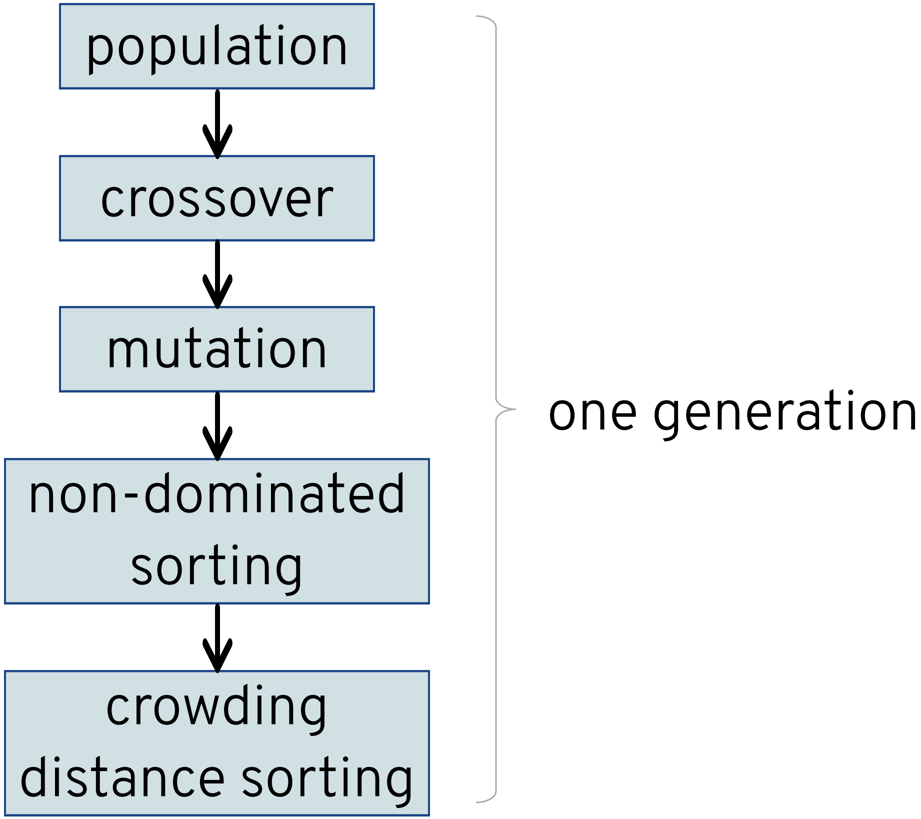
Evolutionary Multi-Objective Optimization



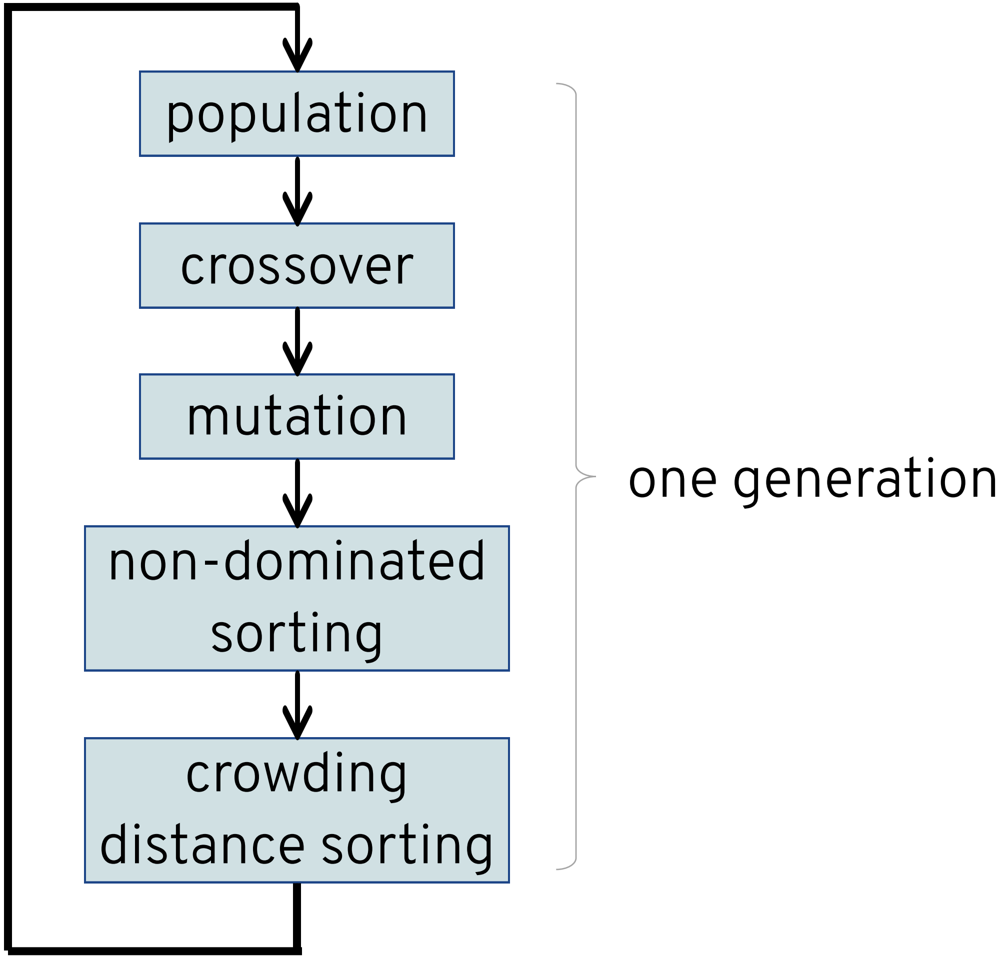
Evolutionary Multi-Objective Optimization



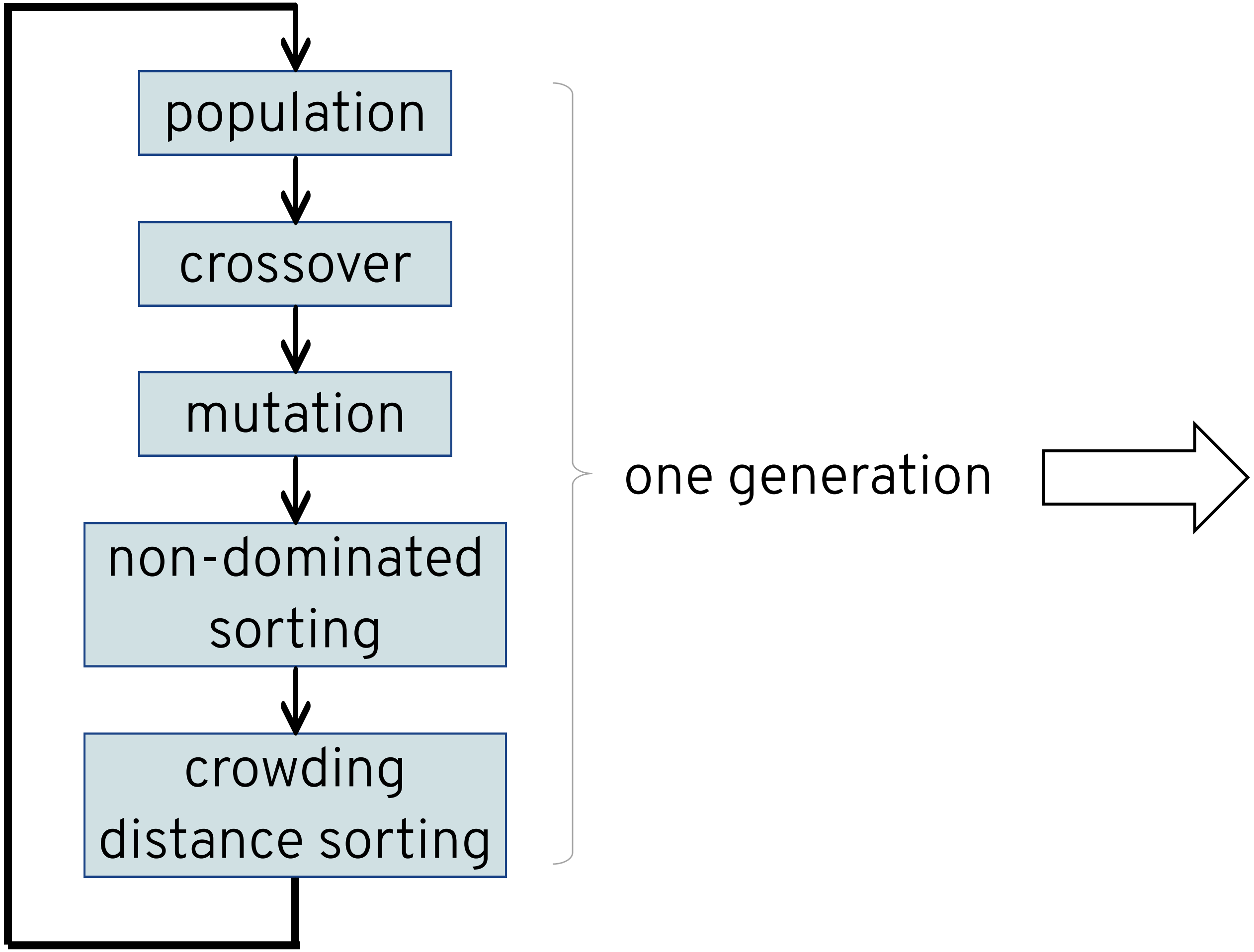
Evolutionary Multi-Objective Optimization



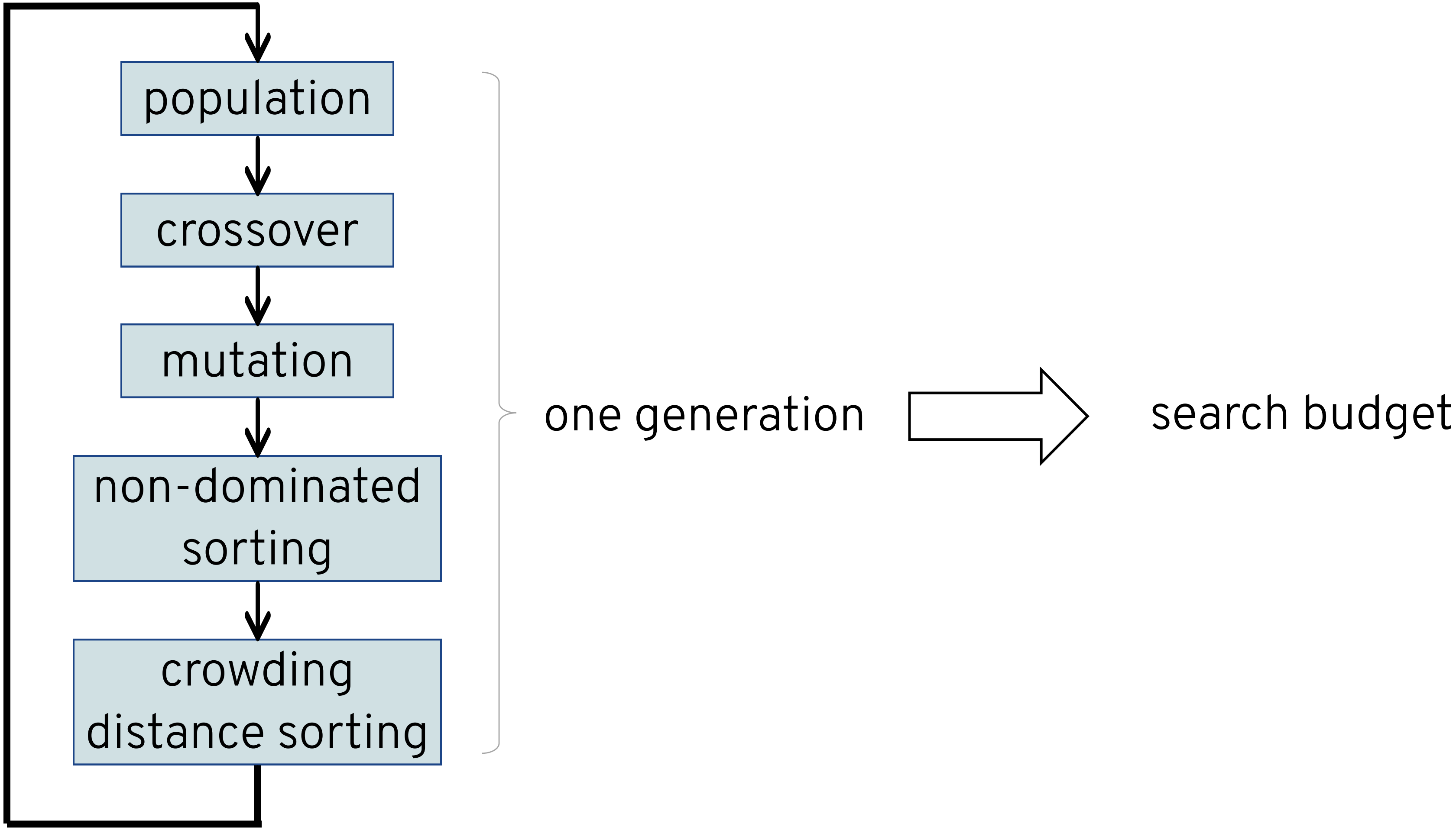
Evolutionary Multi-Objective Optimization



Evolutionary Multi-Objective Optimization



Evolutionary Multi-Objective Optimization



How to **fine-tune** polynomial CNNs?

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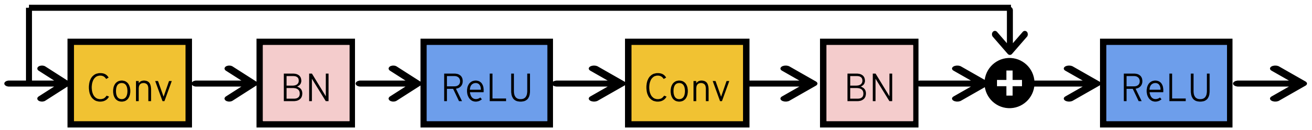
Neural network adaption

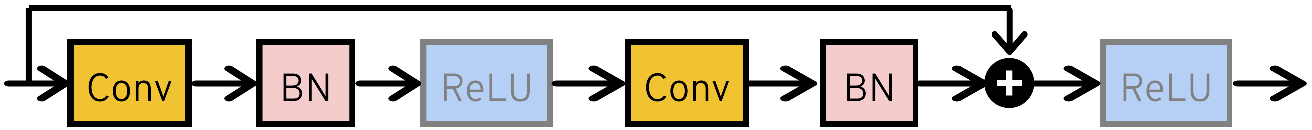
Trainable Weight Adaption and **Knowledge Transferring**

ReLU Network



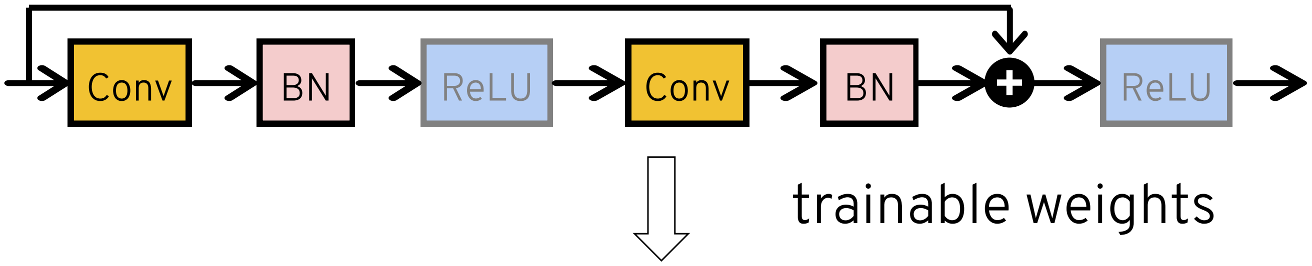
Trainable Weight Adaption and **Knowledge Transferring**

ReLU Network



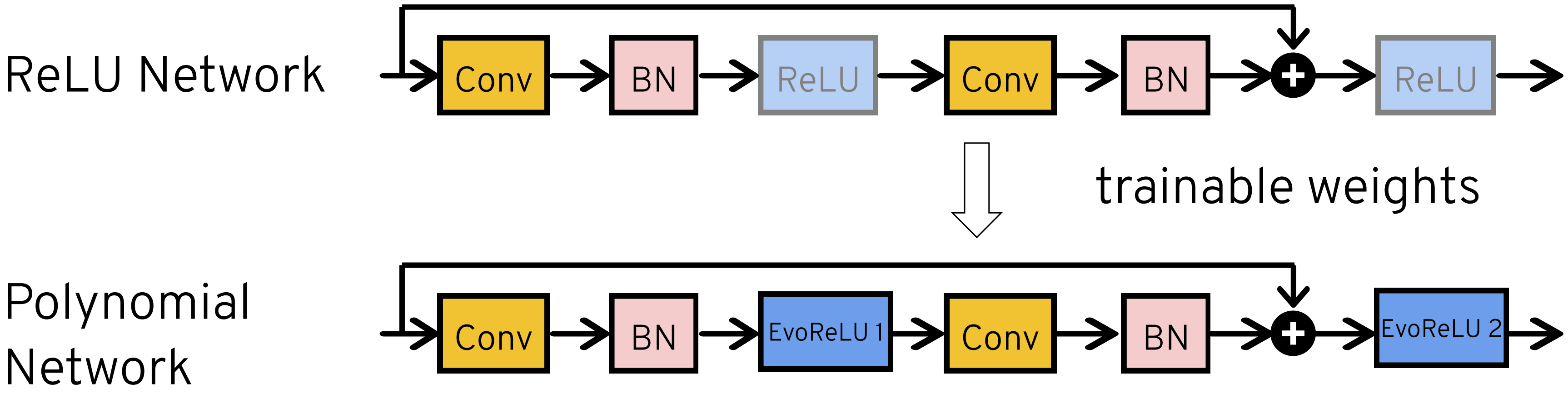
Trainable Weight Adaption and **Knowledge Transferring**

ReLU Network

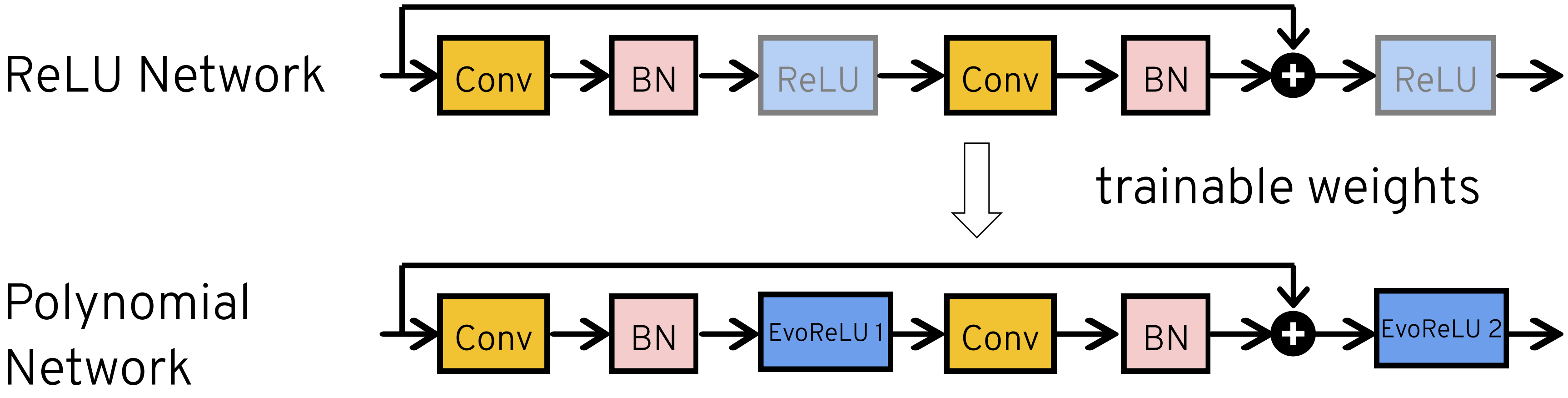


trainable weights

Trainable Weight Adaption and **Knowledge Transferring**



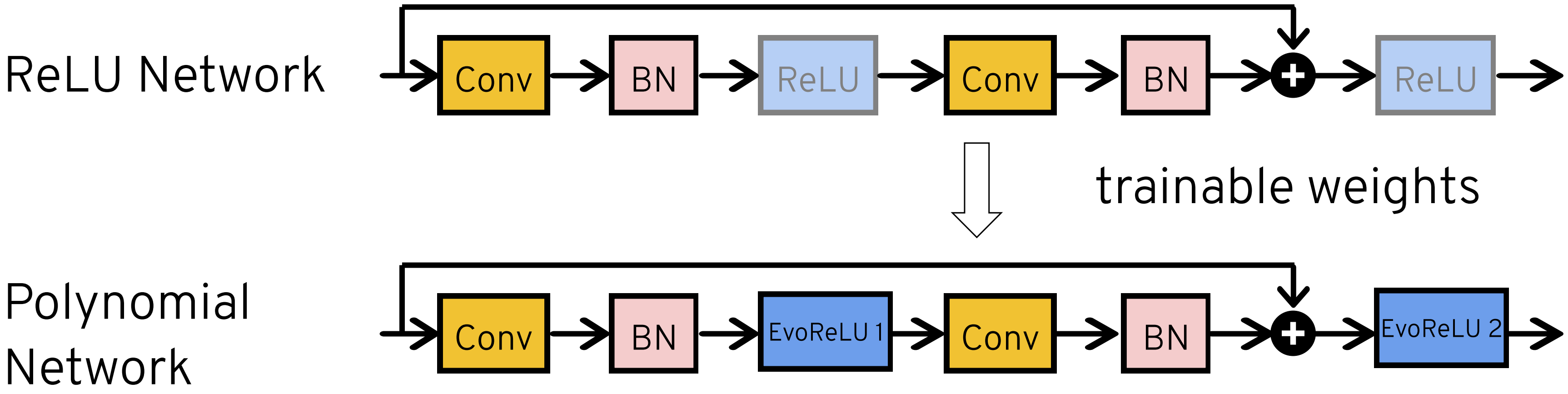
Trainable Weight Adaption and **Knowledge Transferring**



Fine-tuning objective

$$\mathcal{L}_{train} = (1-\tau)\mathcal{L}_{CE} + \tau\mathcal{L}_{KL}$$

Trainable Weight Adaption and **Knowledge Transferring**

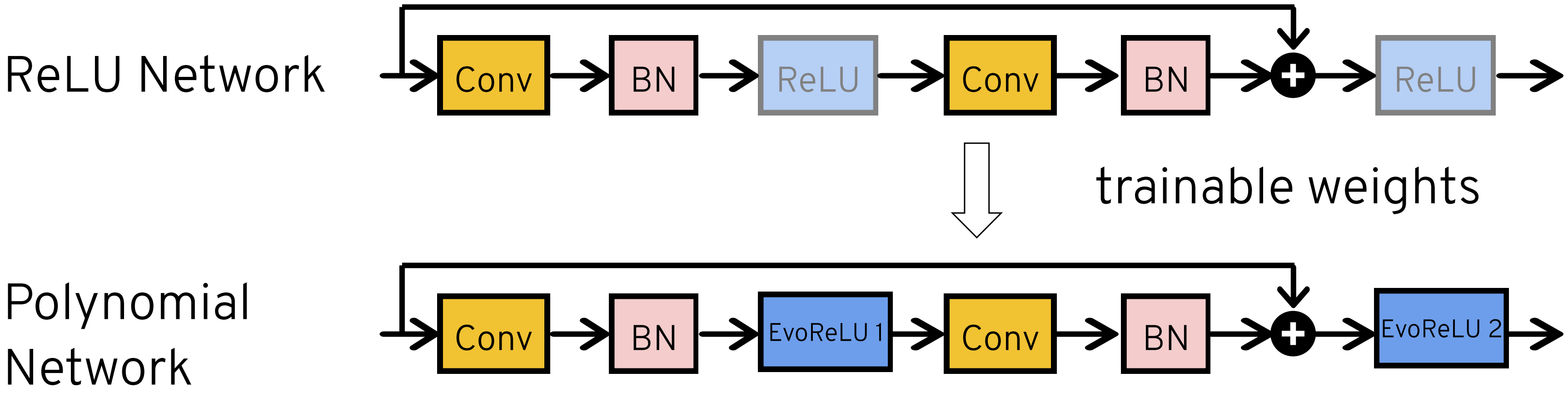


Fine-tuning objective

$$\mathcal{L}_{train} = (1-\tau)\mathcal{L}_{CE} + \tau\mathcal{L}_{KL}$$

- Inherit representation learning ability

Trainable Weight Adaption and **Knowledge Transferring**



Fine-tuning objective

$$\mathcal{L}_{train} = (1-\tau)\mathcal{L}_{CE} + \tau\mathcal{L}_{KL}$$

- Inherit representation learning ability
- Adapt trainable weights to EvoReLU

Experiments on encrypted CIFAR10 dataset under FHE

Experimental Setup

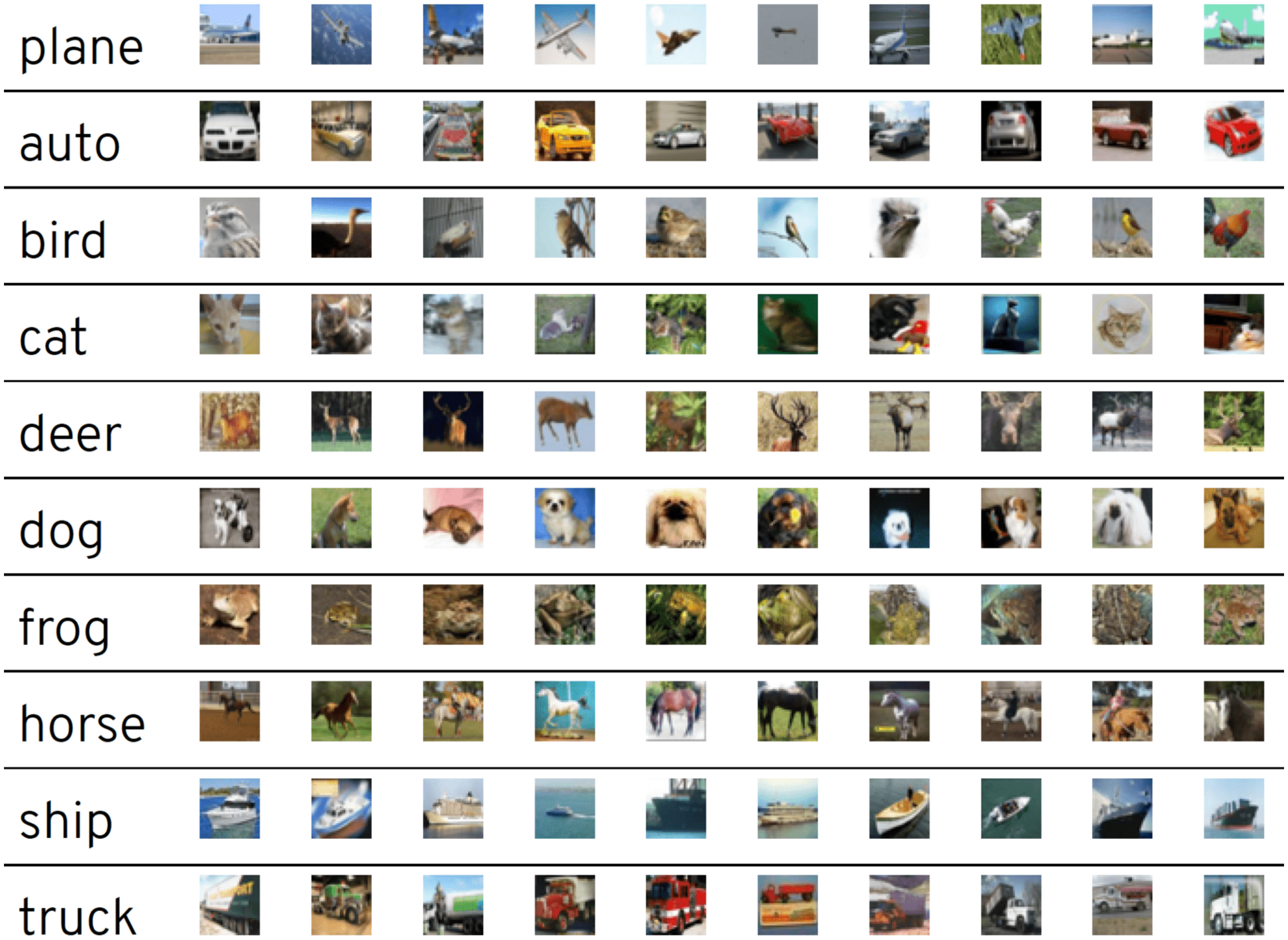
Experimental Setup

Dataset: CIFAR10

50,000 training images

10,000 test images

32x32 resolution, 10 classes



[3]Alex Krizhevsky. CIFAR example images (online).

Experimental Setup

Dataset: CIFAR10

50,000 training images

10,000 test images

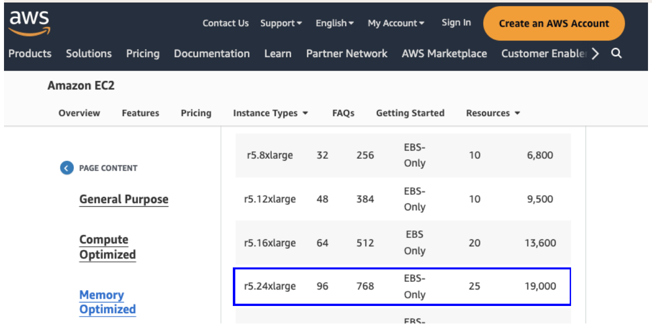
32x32 resolution, 10 classes

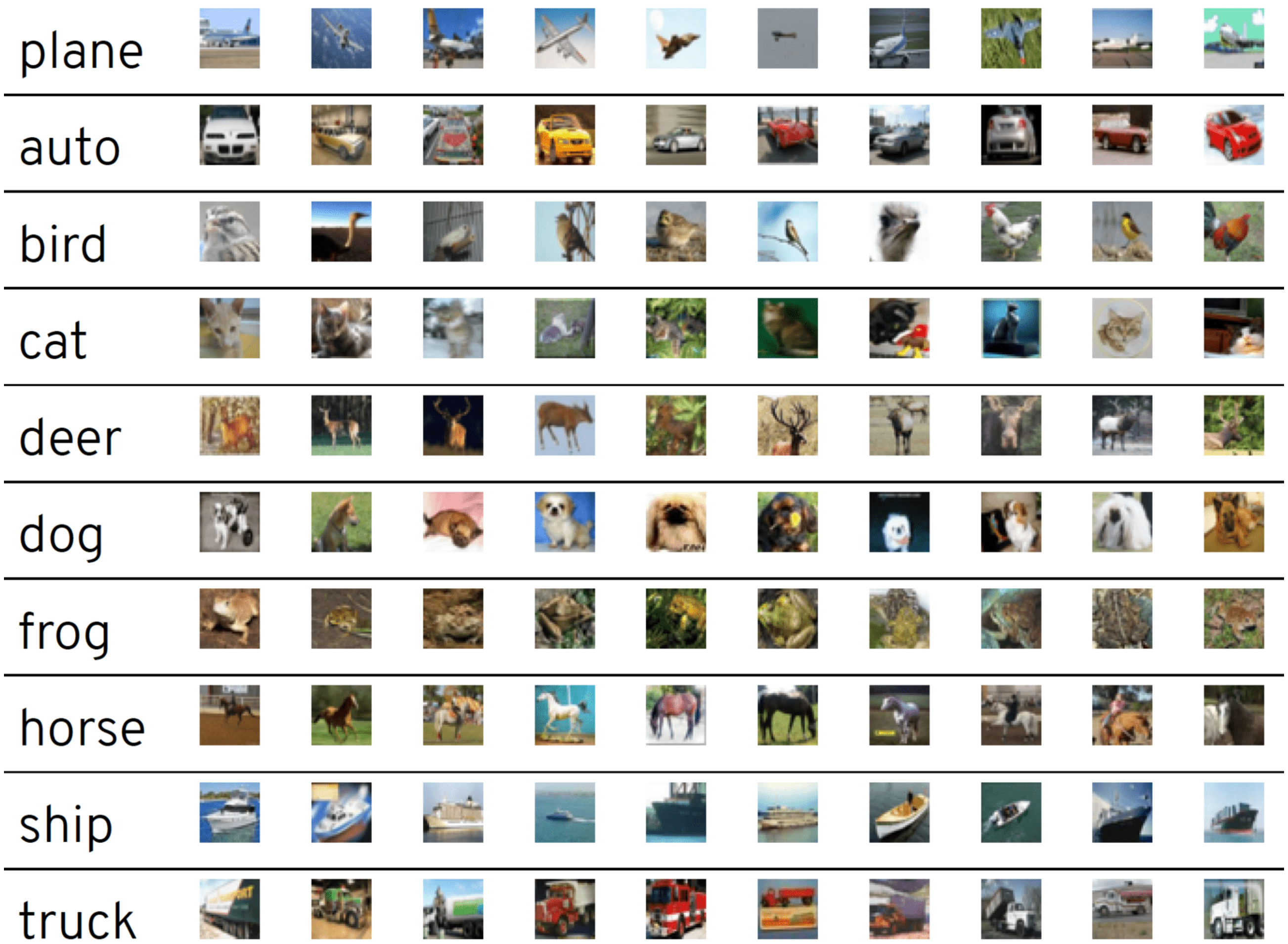
Hardware & Software

Amazon AWS, r5.24xlarge

96 CPUs, 768 GB RAM

Microsoft SEAL, 3.6

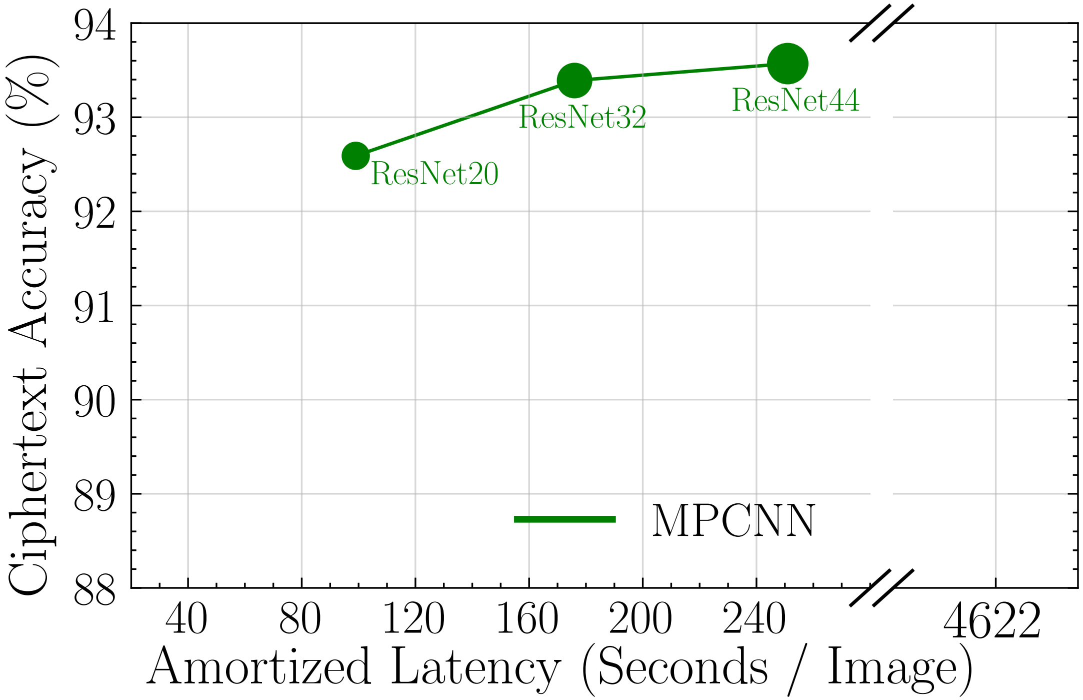




[3]Alex Krizhevsky. CIFAR example images (online).

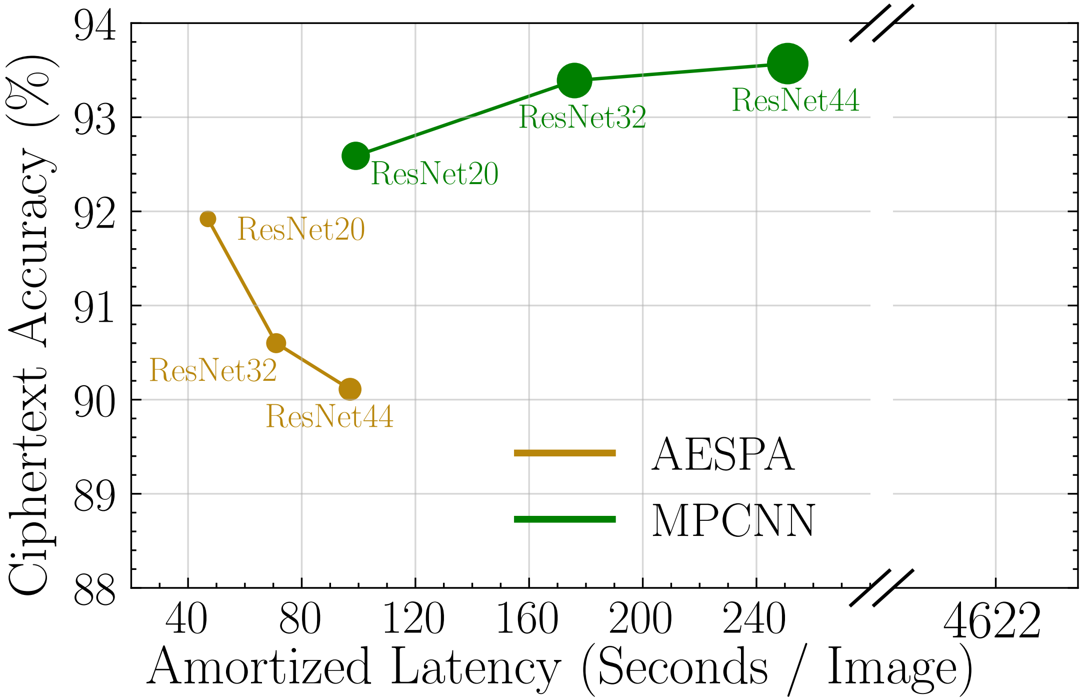
Latency and **Accuracy Trade-offs** under **FHE**

Approach	**MPCNN**
Venue	ICML22
Scheme	CKKS
Polynomial	high-degree
Layerwise	no
Strategy	approx
Arch	manual



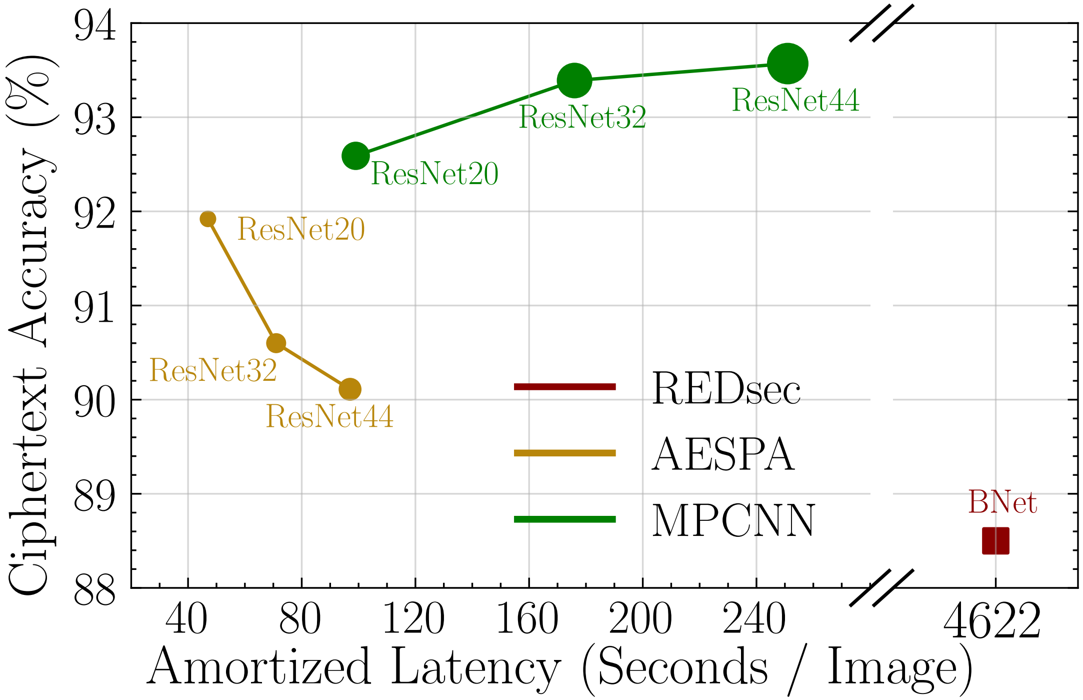
Latency and **Accuracy Trade-offs** under **FHE**

Approach	**MPCNN**	**AESPA**
Venue	ICML22	arXiv22
Scheme	CKKS	CKKS
Polynomial	high-degree	low-degree
Layerwise	no	no
Strategy	approx	train
Arch	manual	manual



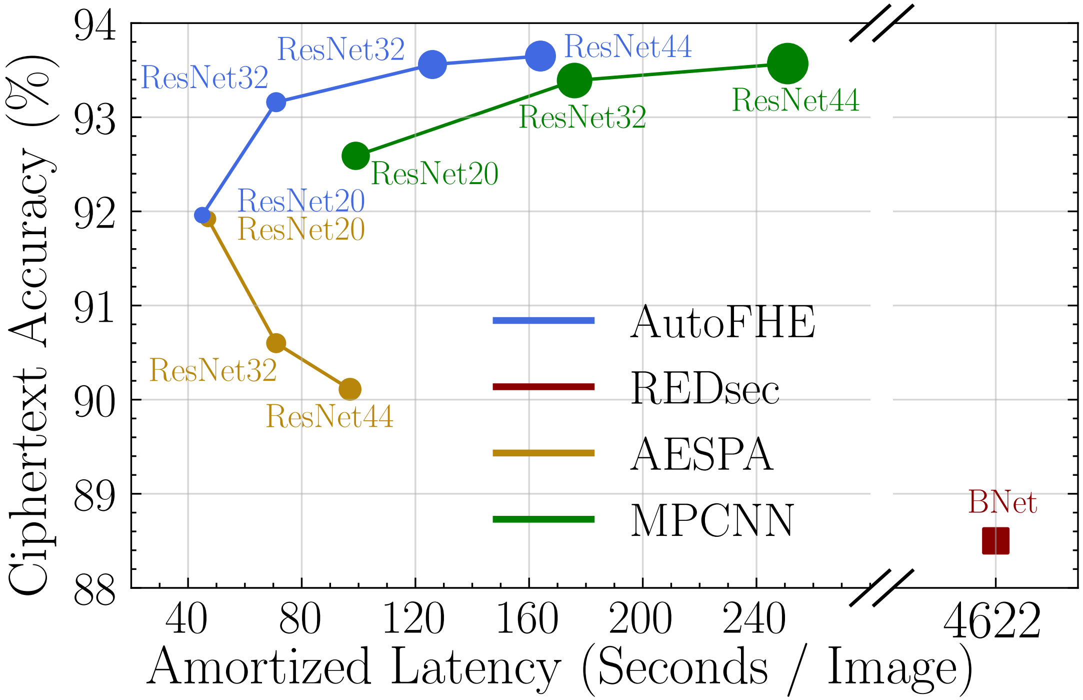
Latency and **Accuracy Trade-offs** under **FHE**

Approach	**MPCNN**	**AESPA**	**REDsec**
Venue	ICML22	arXiv22	NDSS23
Scheme	CKKS	CKKS	TFHE
Polynomial	high-degree	low-degree	n/a
Layerwise	no	no	n/a
Strategy	approx	train	train
Arch	manual	manual	manual

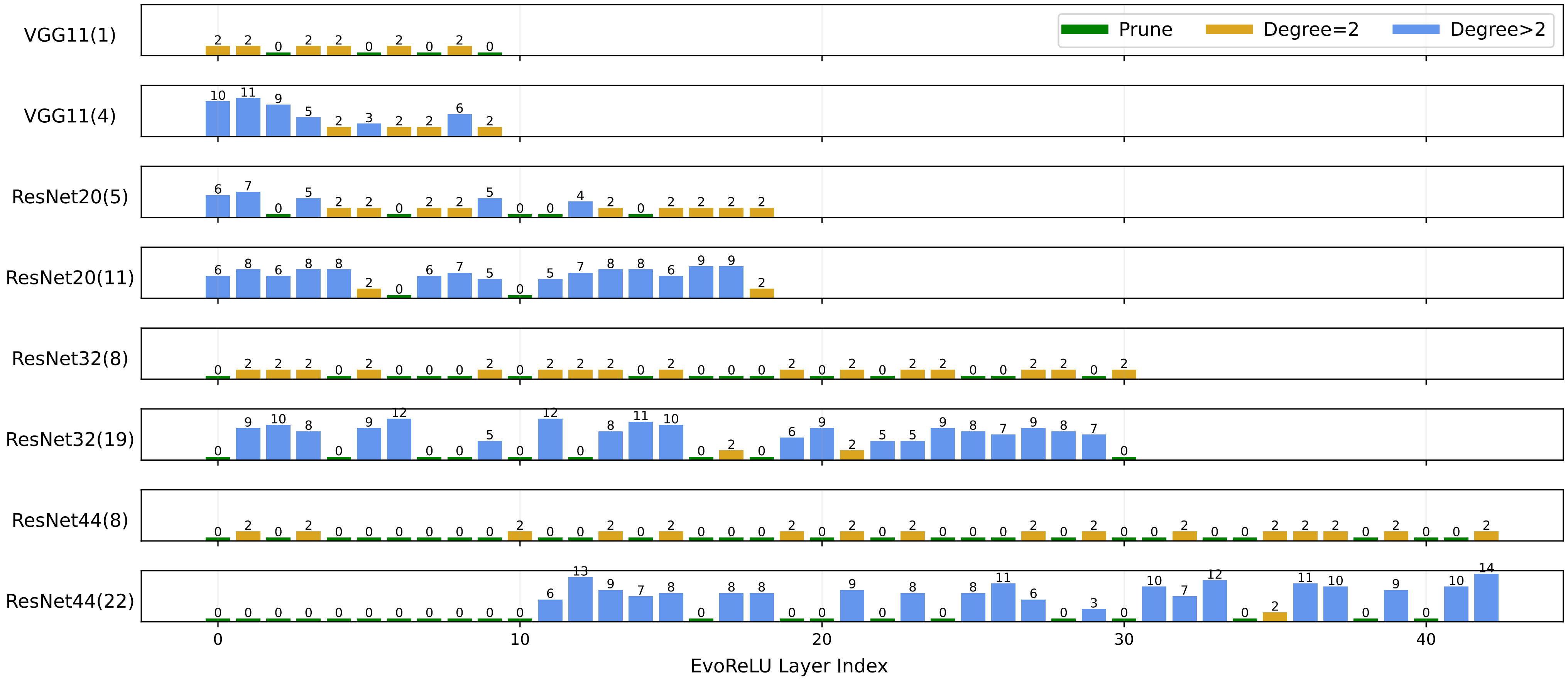


Latency and **Accuracy Trade-offs** under **FHE**

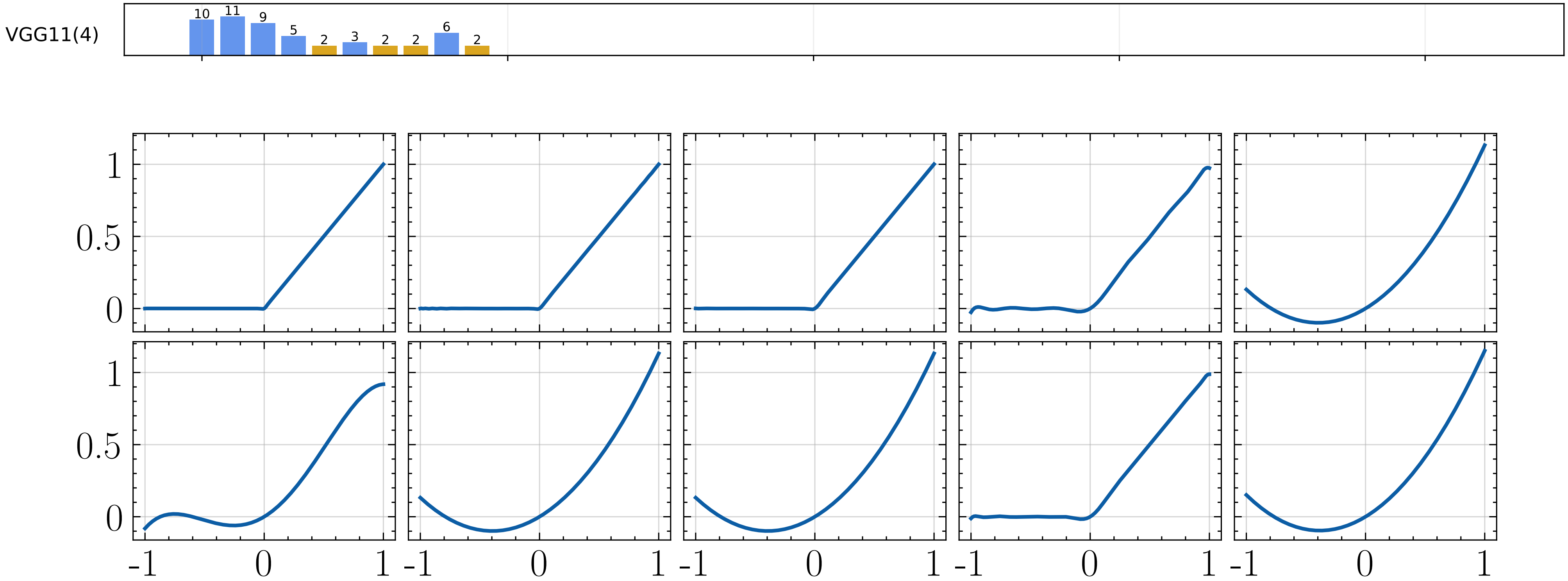
Approach	**MPCNN**	**AESPA**	**REDsec**	**AutoFHE**
Venue	ICML22	arXiv22	NDSS23	USENIX24
Scheme	CKKS	CKKS	TFHE	CKKS
Polynomial	high-degree	low-degree	n/a	mixed
Layerwise	no	no	n/a	**yes**
Strategy	approx	train	train	**adapt**
Arch	manual	manual	manual	**search**



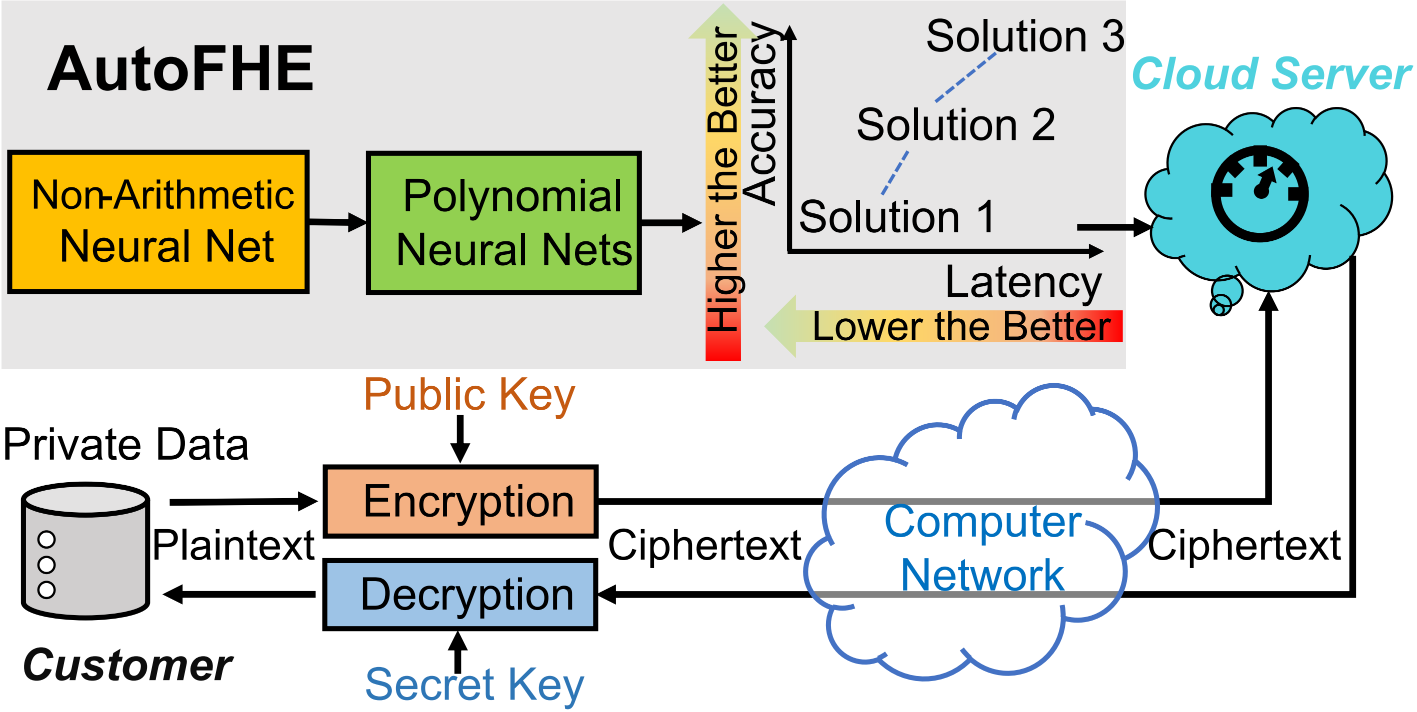
Multiplicative Depth of **Layerwise EvoReLU**



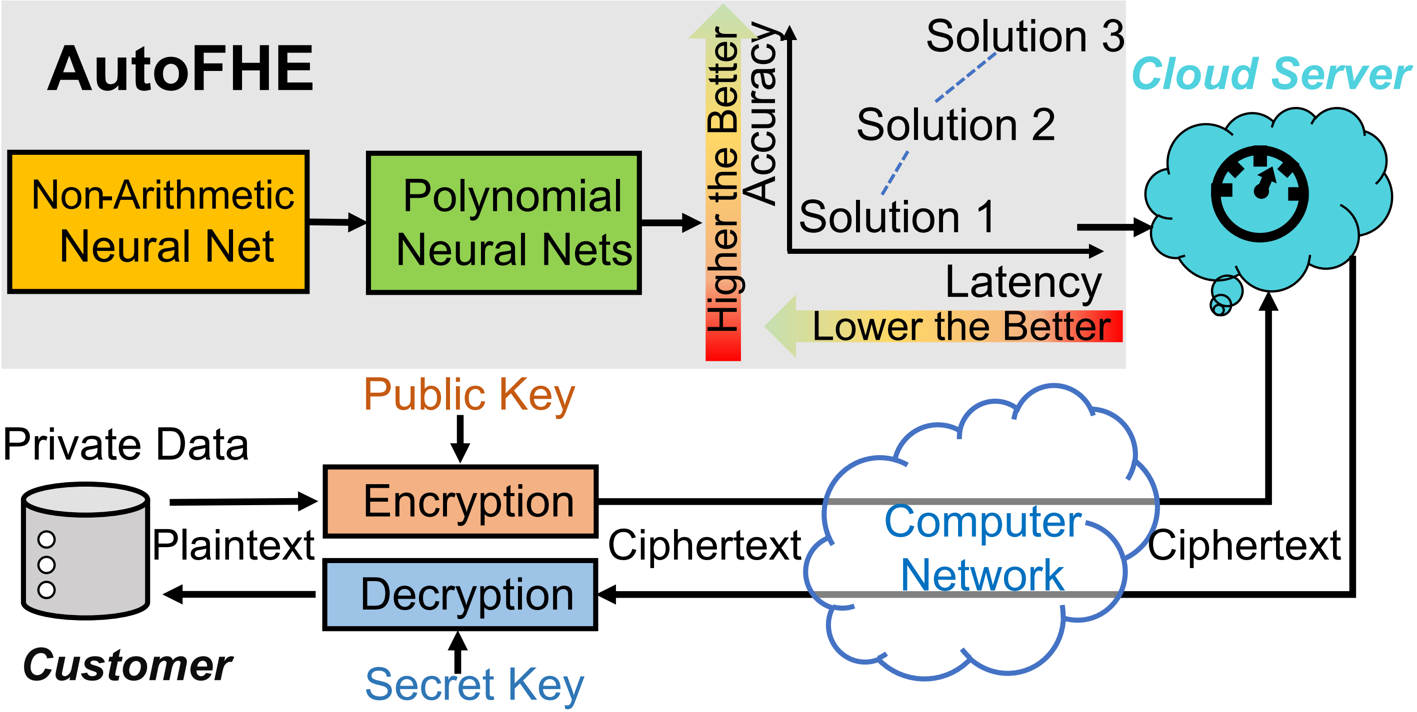
Layerwise EvoReLU



Conclusion

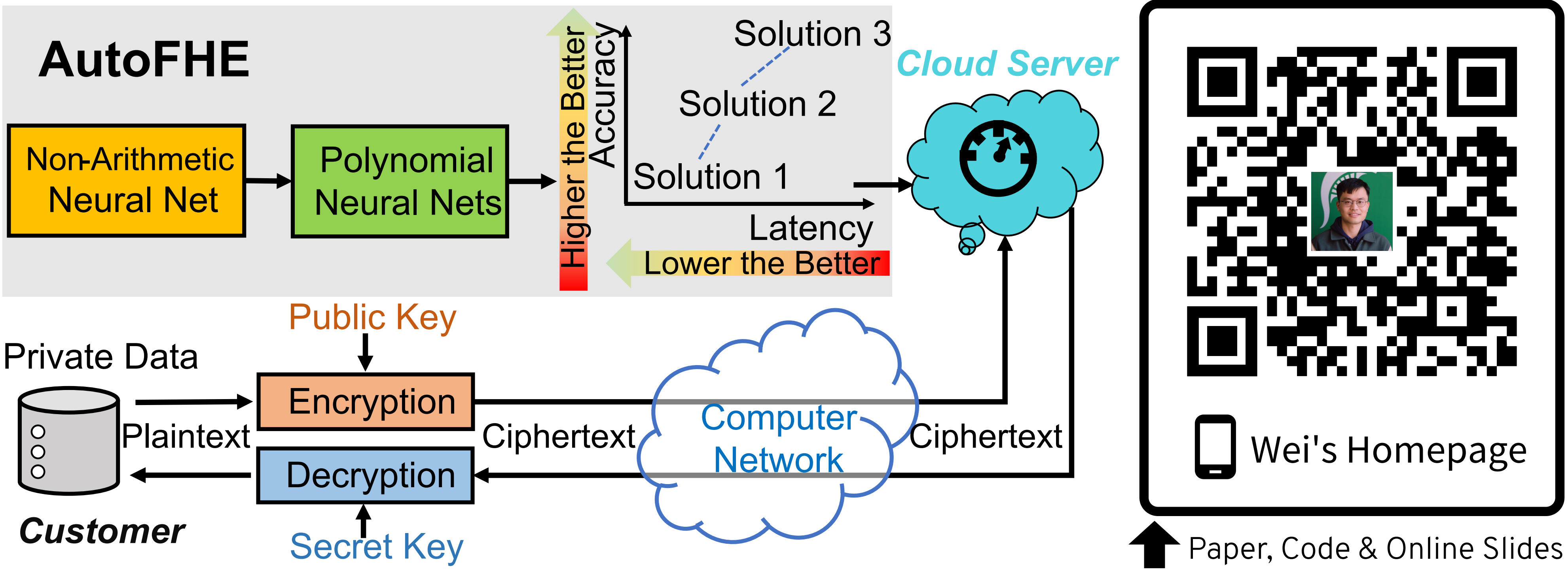


Paper, Code & Online Slides



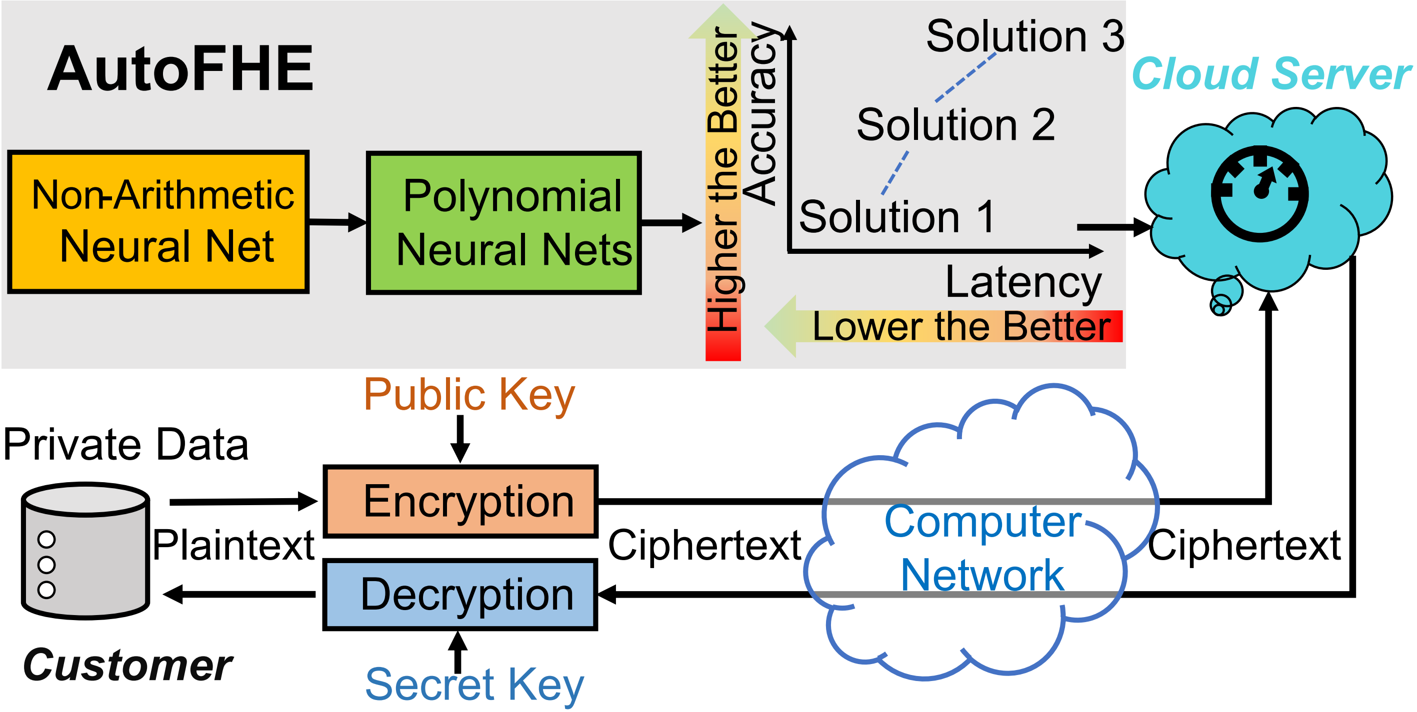
Paper, Code & Online Slides

AutoFHE optimizes end-to-end polynomial neural architecture



AutoFHE optimizes end-to-end polynomial neural architecture

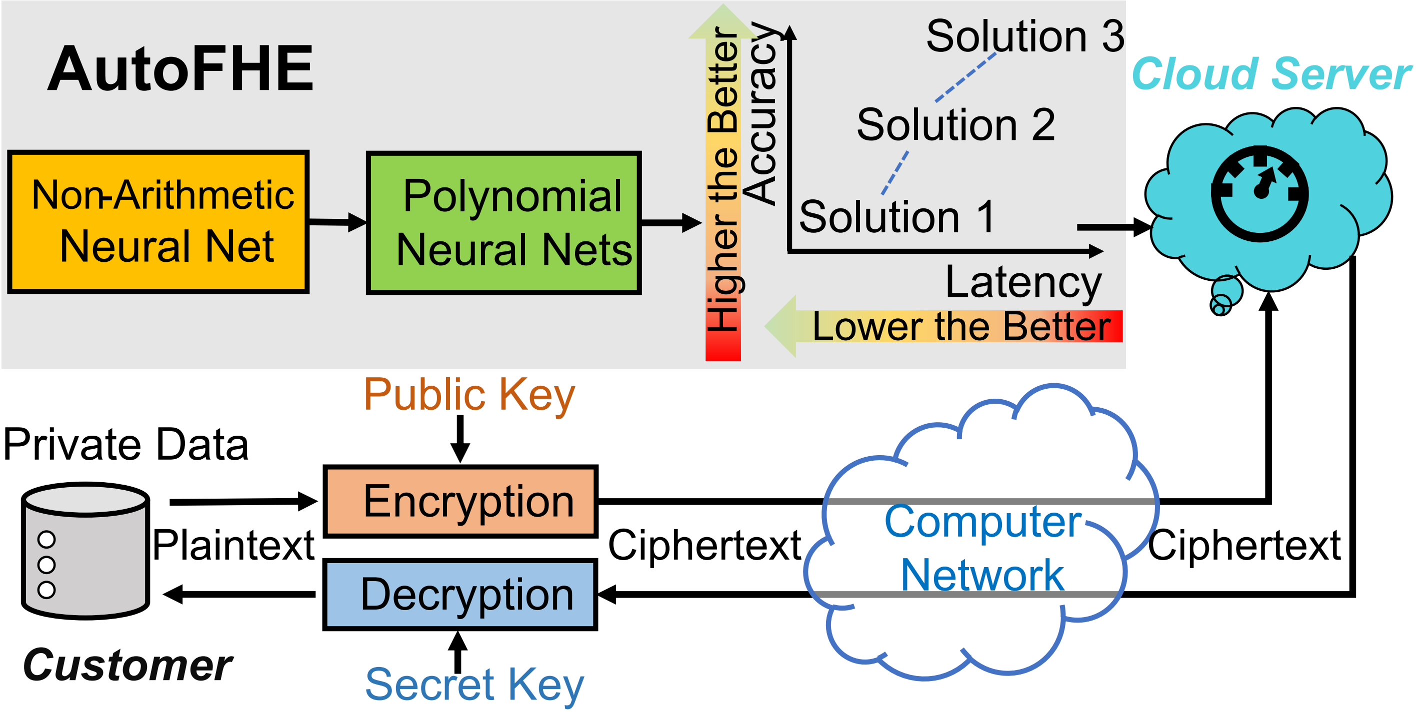
- Multi-objective optimization generates Pareto-effective solutions to meet different requirements



Paper, Code & Online Slides

AutoFHE optimizes end-to-end polynomial neural architecture

- Multi-objective optimization generates Pareto-effective solutions to meet different requirements
- Joint optimization of layerwise EvoReLU and bootstrapping results in optimal polynomial neural architectures



Paper, Code & Online Slides

AutoFHE optimizes end-to-end polynomial neural architecture

- Multi-objective optimization generates Pareto-effective solutions to meet different requirements
- Joint optimization of layerwise EvoReLU and bootstrapping results in optimal polynomial neural architectures
- Adapted neural networks can inherit representation learning ability from ReLU networks