Like an Open Book? Read Neural Network Architecture with Simple Power Analysis on 32-bit Microcontrollers

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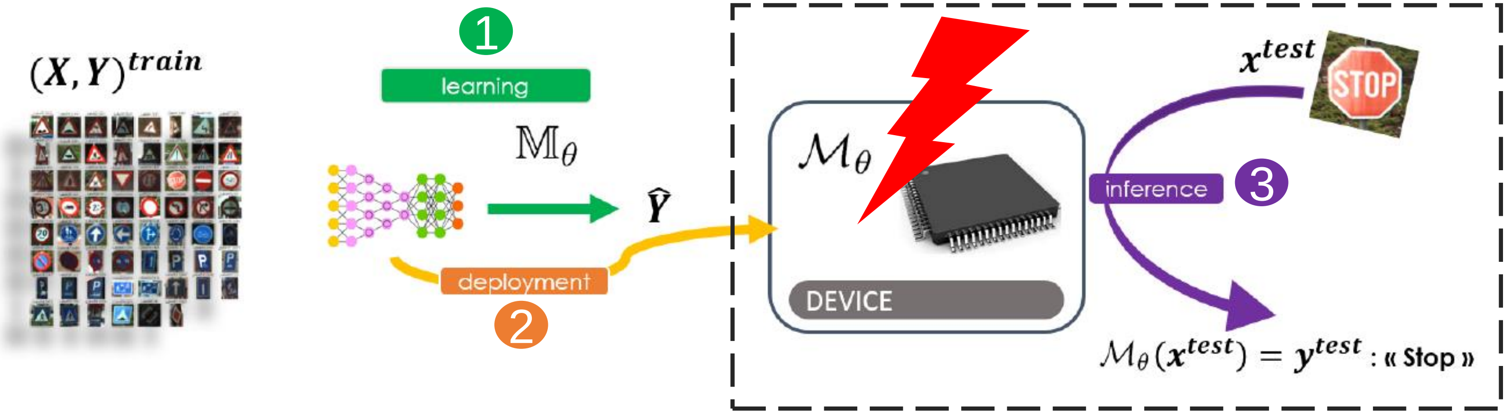
Outline

- Introduction
- Challenges
- Scope and threat model
- Model analysis
- Layer analysis
- Discussion & Perspectives

Threats related to Machine Learning

- Large-scale Machine Learning (ML) model deployment
- Wide variety of applications and HW platforms involved
- Questions about ML security and related attack surface
- Attacking a ML model:
  - Integrity
  - Availability
  - **Confidentiality**

Theoretical / API-based attack
Side channel analysis

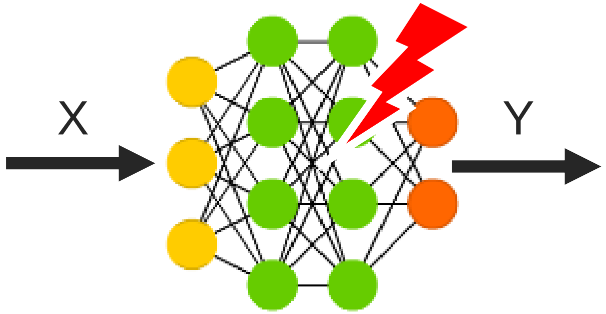


Overall attack surface

Attack Surface

Algorithmic / API-based attacks

Target theoretical flaws – Include adversarial examples, data poisoning, membership inference, model extraction…



Overall attack surface

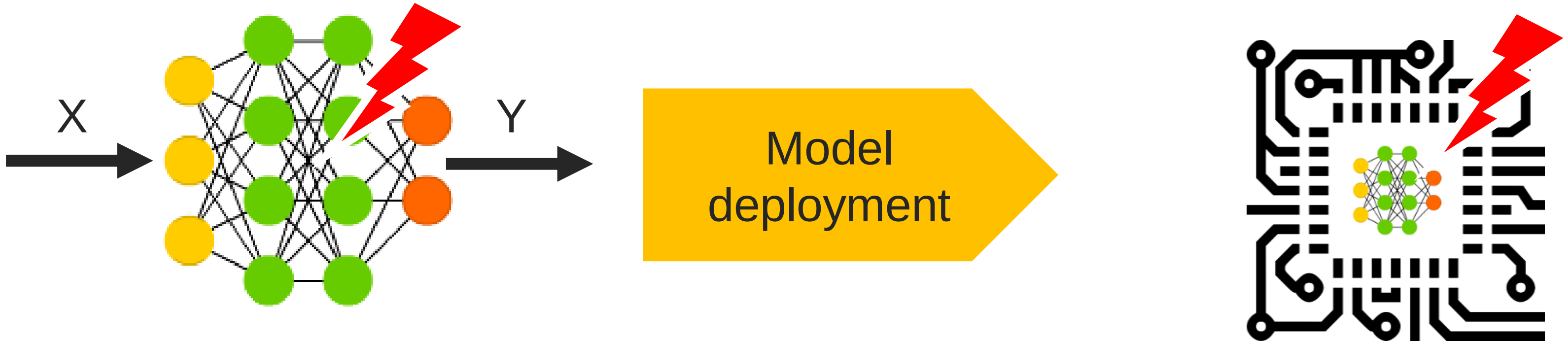
Attack Surface

Algorithmic / API-based attacks

Implementation-based attacks

Target theoretical flaws – Include adversarial examples, data poisoning, membership inference, model extraction…

Target implementation flaws – Include physical attacks like Fault Injection Analysis (FIA) and Side-Channel Analysis (SCA)



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Stakes related to model architecture

- Third-party vs Ad-hoc architectures

- Architecture knowledge is required to carry out various attacks

- Often required for parameters extraction whatever the attack surface considered [1 to 7]

Attack surface / method	Example of attacks requiring architecture knowledge
API-based	Cryptanalytic extraction [1,2] High Accuracy and High Fidelity [3]
FIA-based	Deepsteal [4] Fault Injection & Safe-error [5]
SCA-based	Practical Introduction [6] Reverse-engineering DNN [7]

State of the art of architecture extraction

Attack	Physical target	Targeted models	Used techniques
Duddu *et al.* (2018) [8]	MLaaS	CNN	TA & Regression
Yu *et al.* (2020) [9] Yli *et al.* (2021) [10]	FPGA	BNN	SEMA
Luo *et al.* (2022) [11]	FPGA	CNN & ResNet	SEMA
Chmielewski *et al.* (2021) [12]	GPU	CNN	SEMA & TA
Batina *et al.* (2019) [13]	µC	MLP & CNN	CEMA
Xiang *et al.* (2020) [14]	µC	CNN	SPA & ML
Ours	**µC**	**MLP & CNN**	**SEMA only**

MLaaS: ML as a Service,
TA: Timing Analysis,

SEMA: Simple EM Analysis,
SPA: Simple Power Analysis

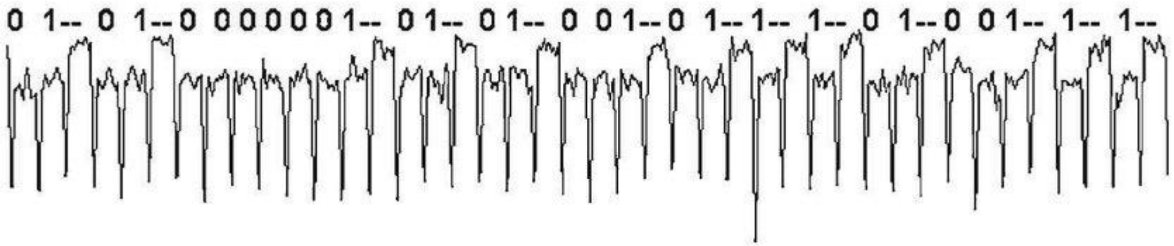
What is a Simple Power / EM Analysis ?

SPA / SEMA:

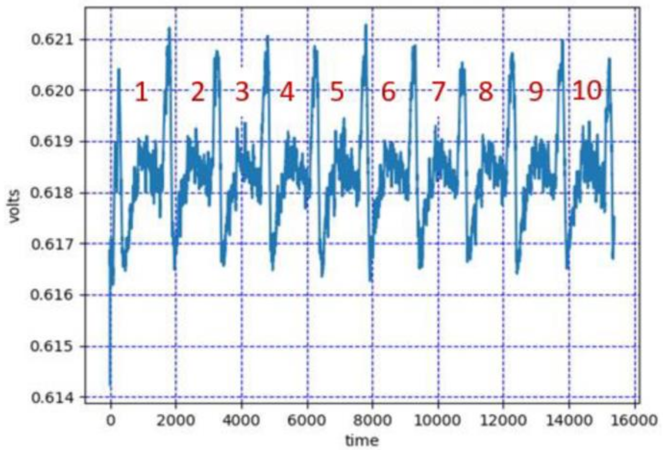
- “Direct” interpretation of power consumption / EM measurements collected

- Can allow to identify parts of codes or even secret information

- Often requires knowledge of used implementation library



SPA on RSA emanations



SPA on AES emanations

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Scope and Threat model

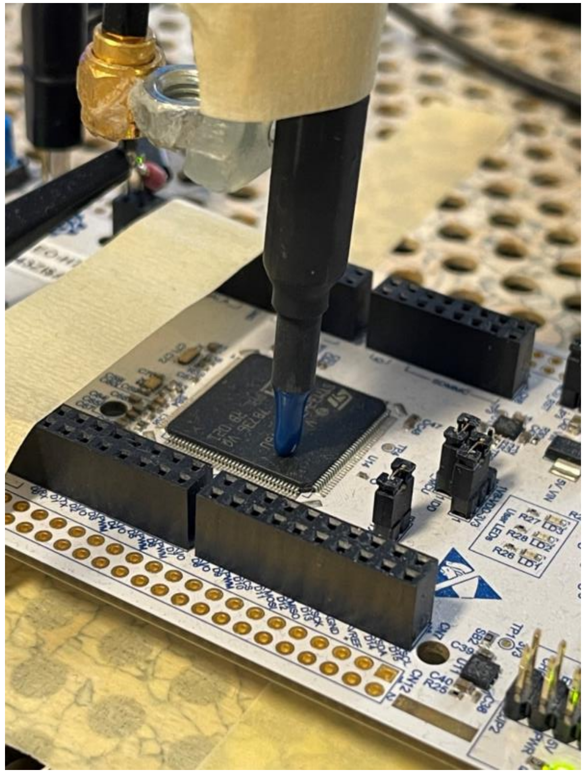
- Goal: extract models architecture as precisely as possible

- Targeted models: quantified (8-bits) and implemented with open-source libraries: **NNoM** [15] & **CMSIS-NN** by ARM [16]

  ➔ Analyse layer C code to anticipate corresponding EM leakages (cache optimisations are disabled)

- Black-box context: no knowledge of model architecture nor parameters

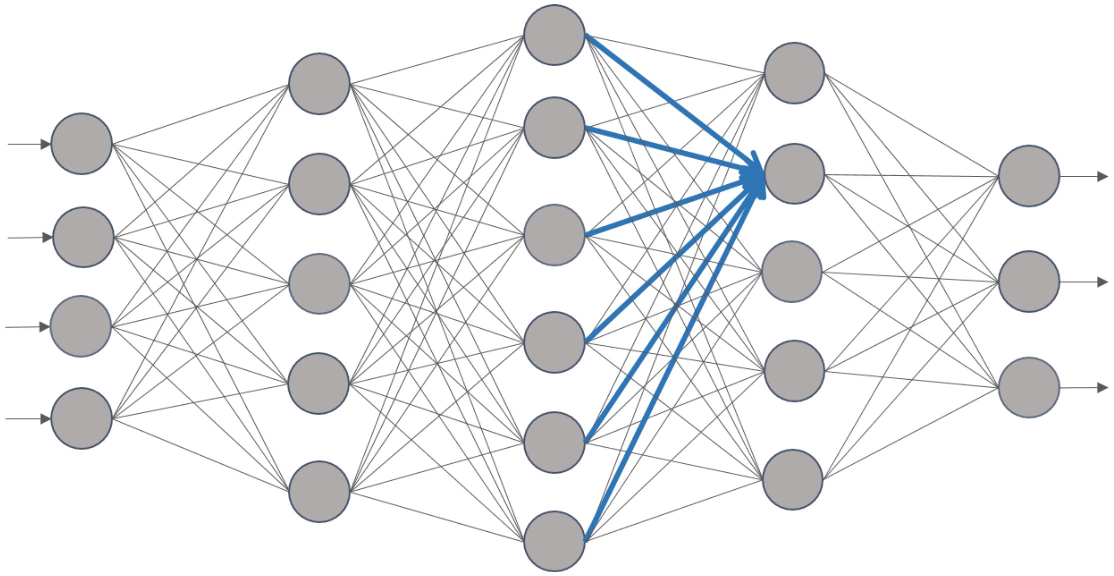
- EM traces acquired with only 1 input: avoids desynchronisation problems & allows to average traces



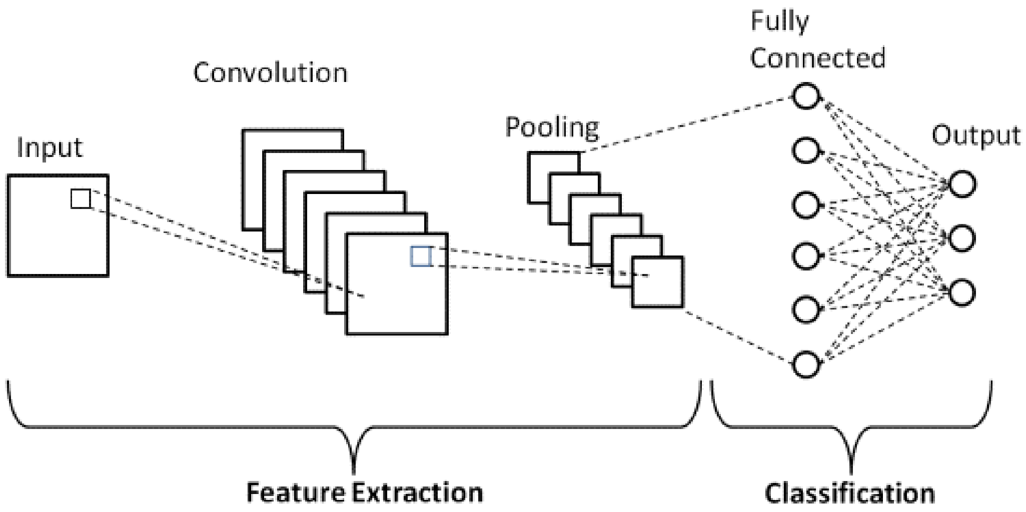
Scope and Threat model

- Studied architectures:

MultiLayer Perceptron (MLP)

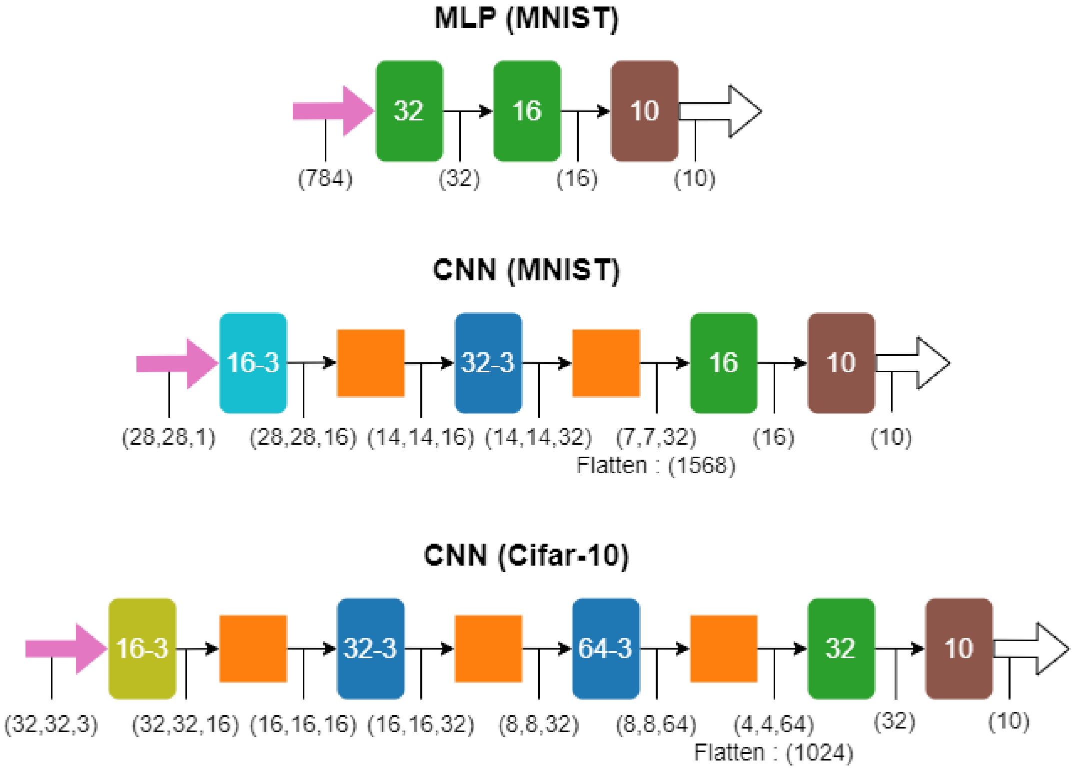


Convolutional Neural Networks (CNN)



Scope and Threat model

- 3 different targeted models:



Target	Hyper-parameter	Notation
Conv. layer	Output shape	H_{out}
	# Kernels	K
	Kernel size	Z
	Stride, Padding	S, P
MaxPool layer	Output shape	H_{out}
	Filter size	Z_{pool}
Dense layer	# Neurons	N_e
Activation layer	ReLU or not	Ø
Model	# Layers	L
	Layers nature	Ø

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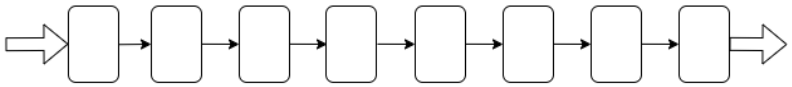
Model Analysis

Analyse the overall shape of inference trace:

1. Find the number of layers:
    - Straightforward or can rely on frequency spectrum



2. Identify their nature:
    - Use layer execution time (complexity)
    - Use patterns of specific layer
3. Extract hyper-parameters of each of them

Model Analysis

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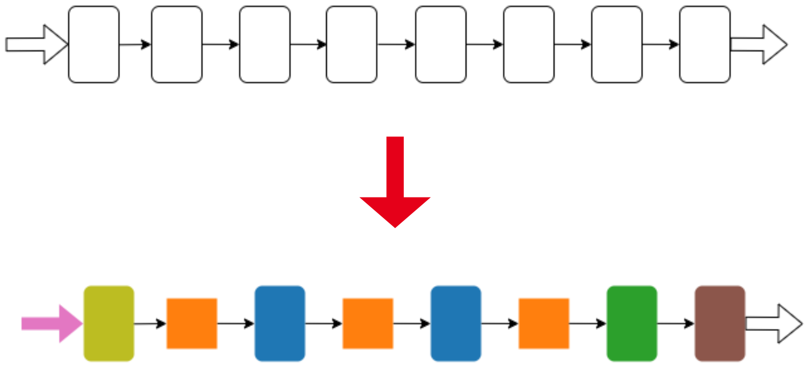

Model Analysis

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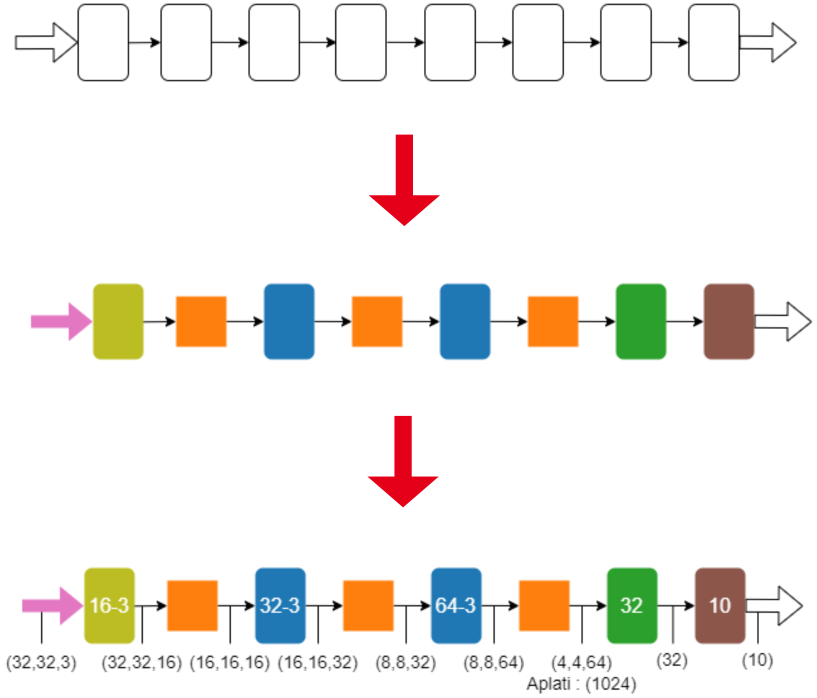
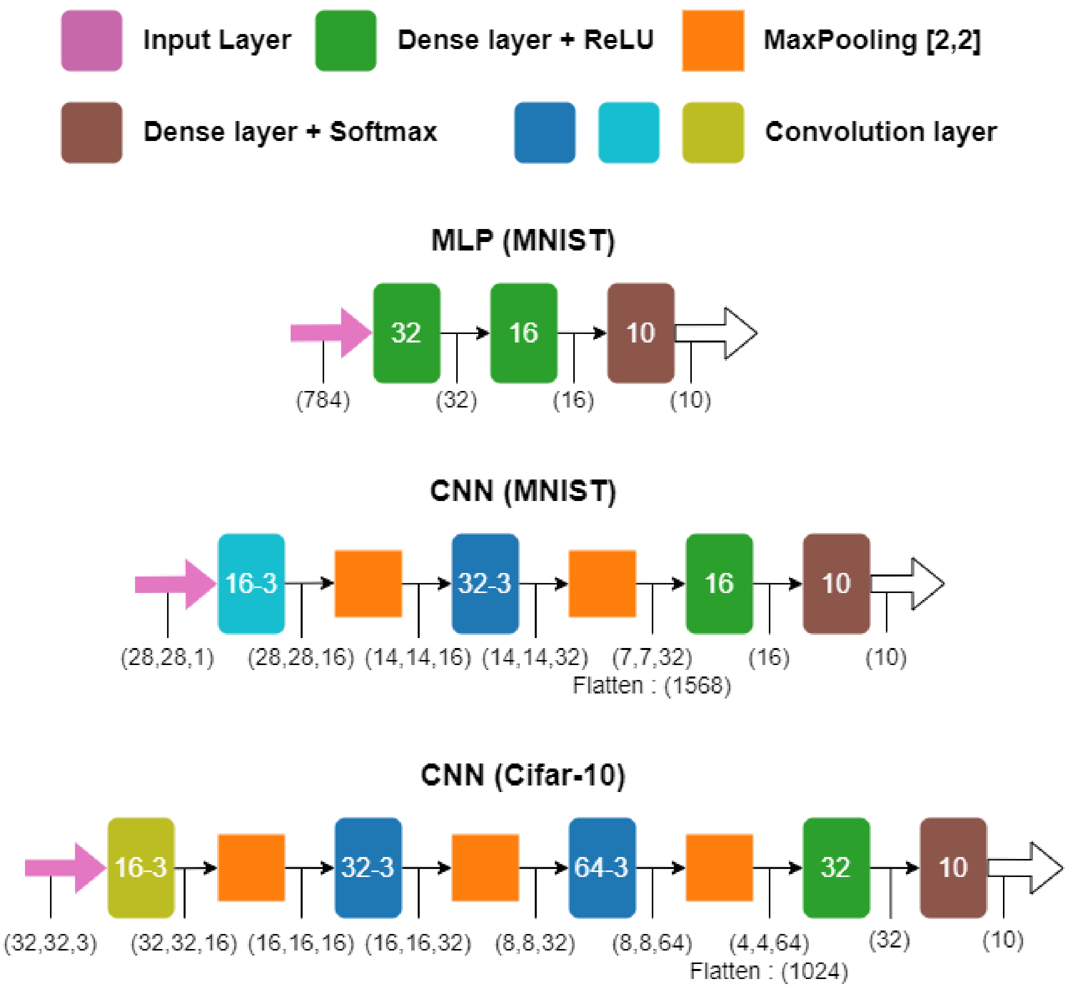
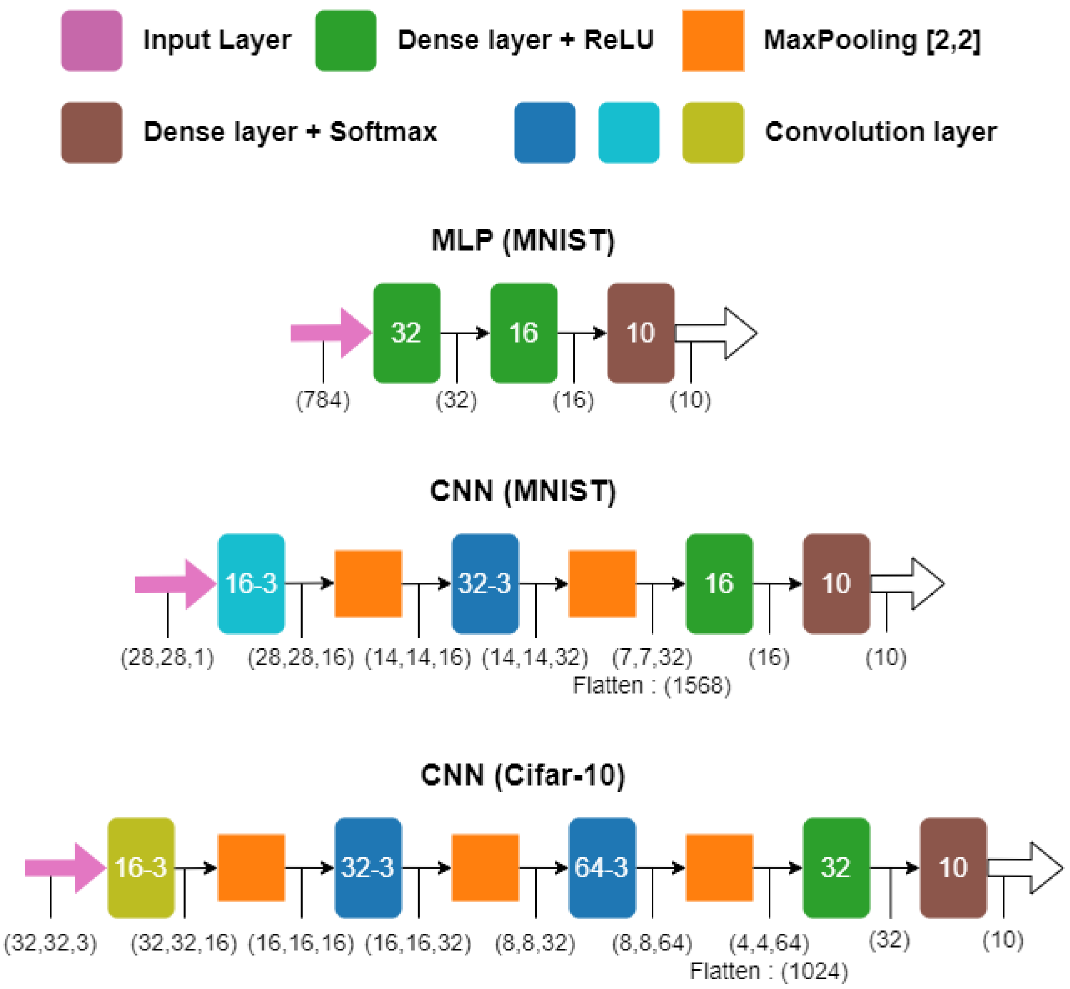
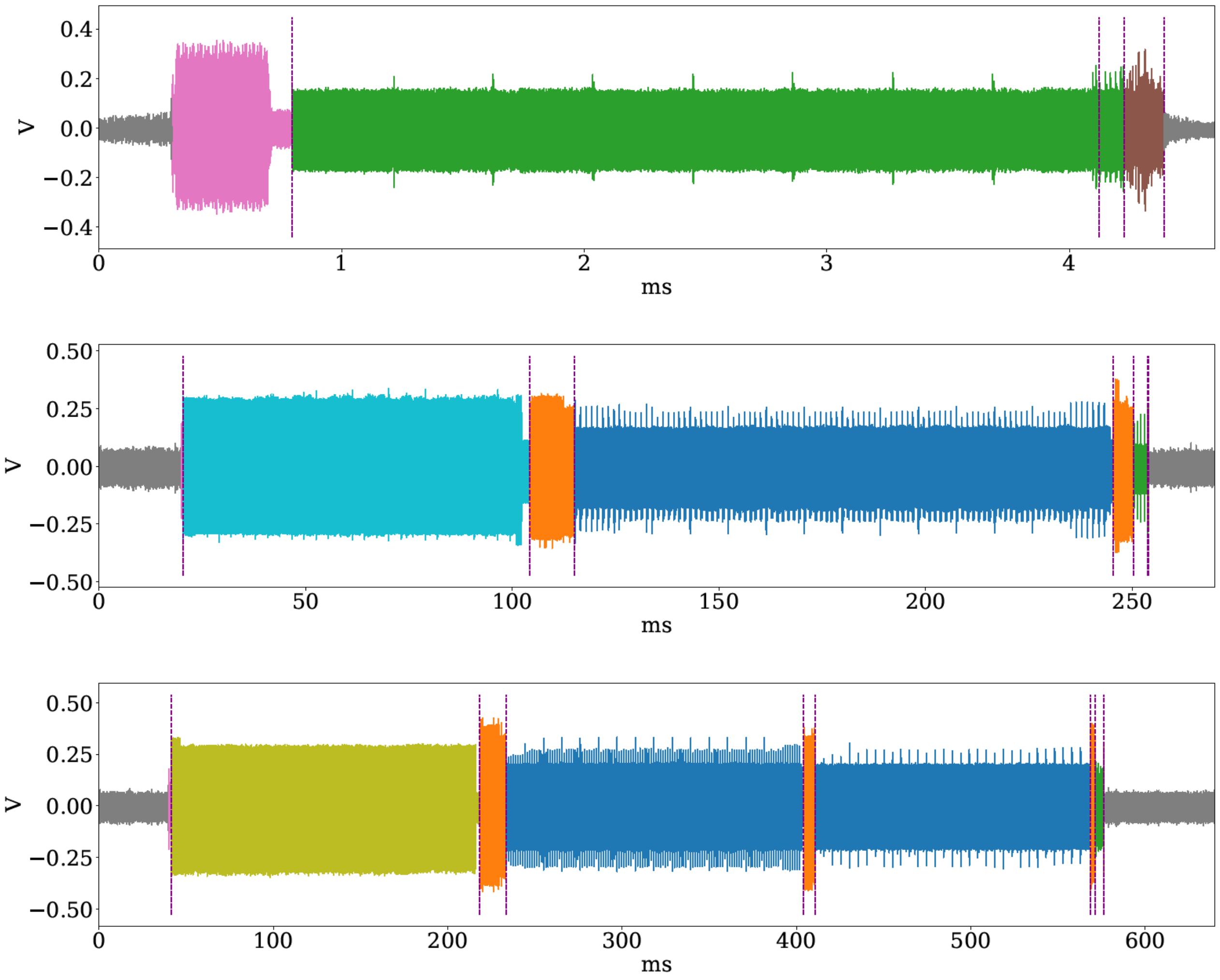


Model Analysis

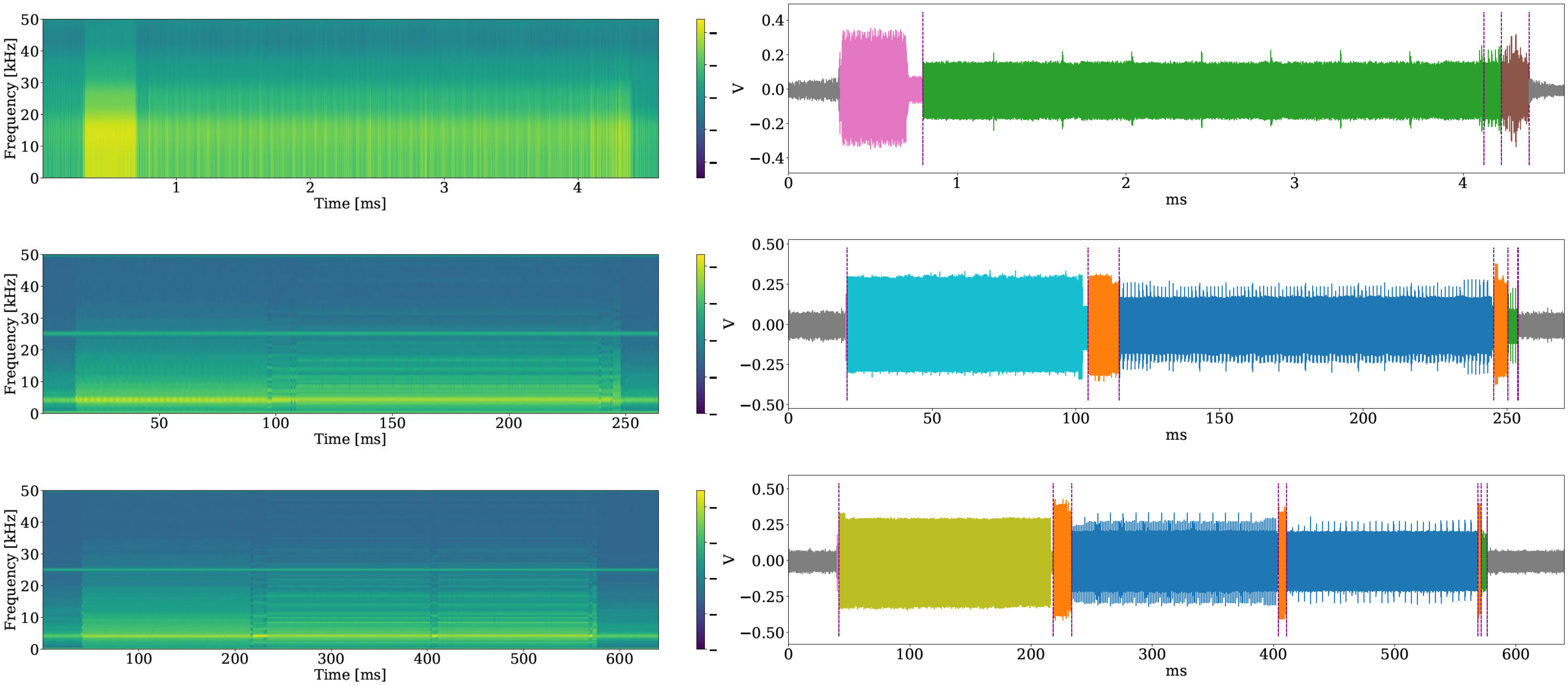


Model Analysis



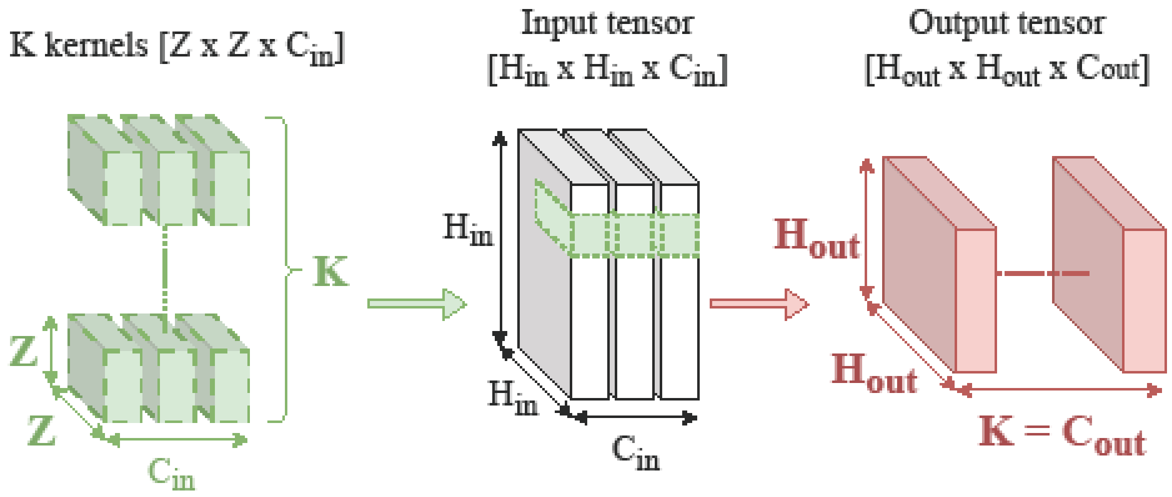


Model Analysis



Outline

Convolution layers



- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P

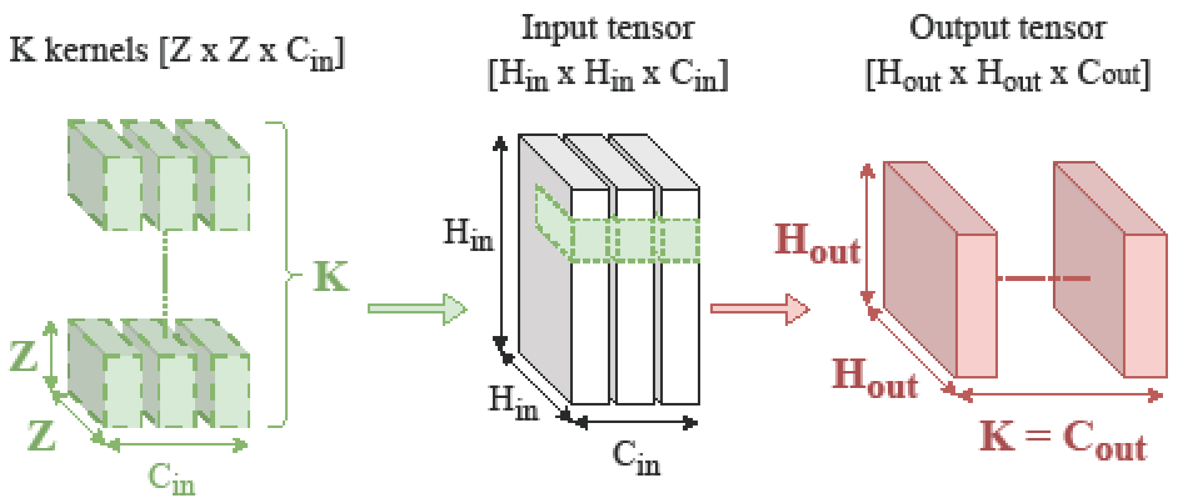
Algorithm 1 General convolution implementation

Input: Input tensor I_{in} of size $H_{in}^2 \cdot C_{in}$, ker (Kernel tensor), S, P, Output size I_{out} of size $H_{out}^2 \cdot C_{out}$

Output: Filled I_{out}

for $i_y \leftarrow 0,\ i_y < H_{out},\ i_y++1$ **do** ▷ Iterate over H_{out} (y-axis)
  for $i_x \leftarrow 0,\ i_x < H_{out},\ i_x++1$ **do** ▷ idem (x-axis)
    $\text{buff}_{in} \leftarrow im2col(I_{in}, i_y, i_x, S, P, H_{in}, C_{in})$ ▷ Apply Im2col conversion
    if $len(\text{buff}_{in}) == 2 \times C_{in} \times Z^2$ **then** ▷ Checks if 2 input columns are set
      $GeMM(\text{buff}_{in}, ker, C_{out}, C_{in} \times Z^2, I_{out})$ ▷ Perform matrix-product
      $\text{buff}_{in} \leftarrow 0$ ▷ Buffer reset
    end if
  end for
end for

Convolution layers



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Output: Filled I_{out}

for $i_y \leftarrow 0,\ i_y < H_{out},\ i_y{+}{+}1$ **do** ▷ Iterate over H_{out} (y-axis)
  for $i_x \leftarrow 0,\ i_x < H_{out},\ i_x{+}{+}1$ **do** ▷ idem (x-axis)
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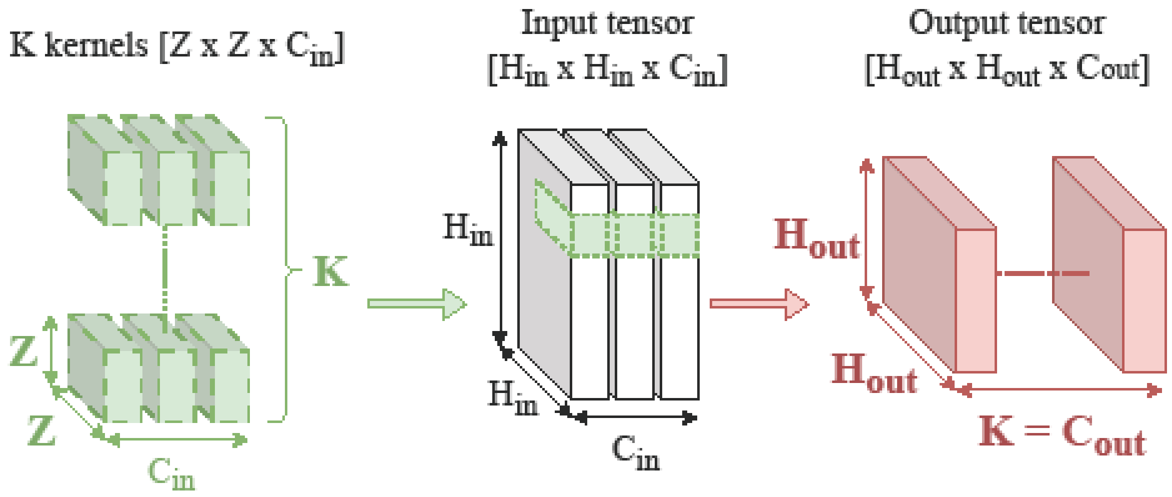
      $\mathrm{buff}_{in} \leftarrow 0$ ▷ Buffer reset
    end if
  end for
end for

$H_{out} \times H_{out}$ iterations

GeMM function called $H_{out} \times (H_{out}/2)$ times

Convolution layers



- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P

Algorithm 1 General convolution implementation

Input: Input tensor I_{in} of size $H_{in}^2 \cdot C_{in}$, ker (Kernel tensor), S, P, Output size I_{out} of size $H_{out}^2 \cdot C_{out}$

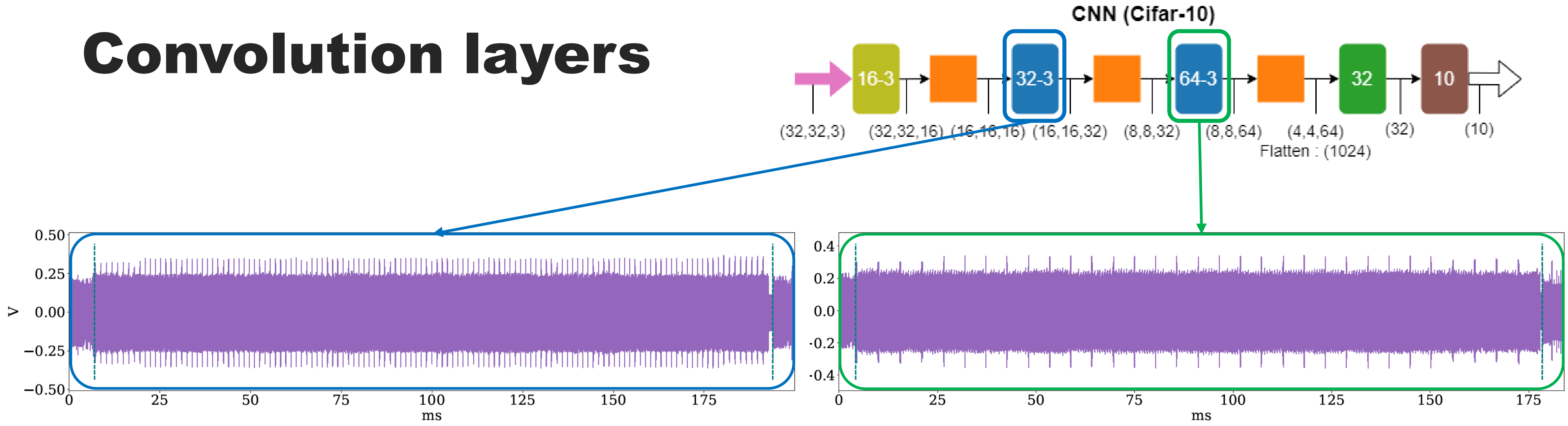
Output: Filled I_{out}

```
for i_y ← 0, i_y < H_out, i_y + +1 do                          ▷ Iterate over H_out (y-axis)
    for i_x ← 0, i_x < H_out, i_x + +1 do                      ▷ idem (x-axis)
        buff_in ← im2col(I_in, i_y, i_x, S, P, H_in, C_in)     ▷ Apply Im2col conversion
        if len(buff_in) == 2 × C_in × Z^2 then                 ▷ Checks if 2 input columns are set
            GeMM(buff_in, ker, C_out, C_in × Z^2, I_out)       ▷ Perform matrix-product
            buff_in ← 0                                        ▷ Buffer reset
        end if
    end for
end for
```

With N_p the number of pattern corresponding to GeMM function call:

$$H_{out} = \sqrt{2 \times N_p}$$

Convolution layers



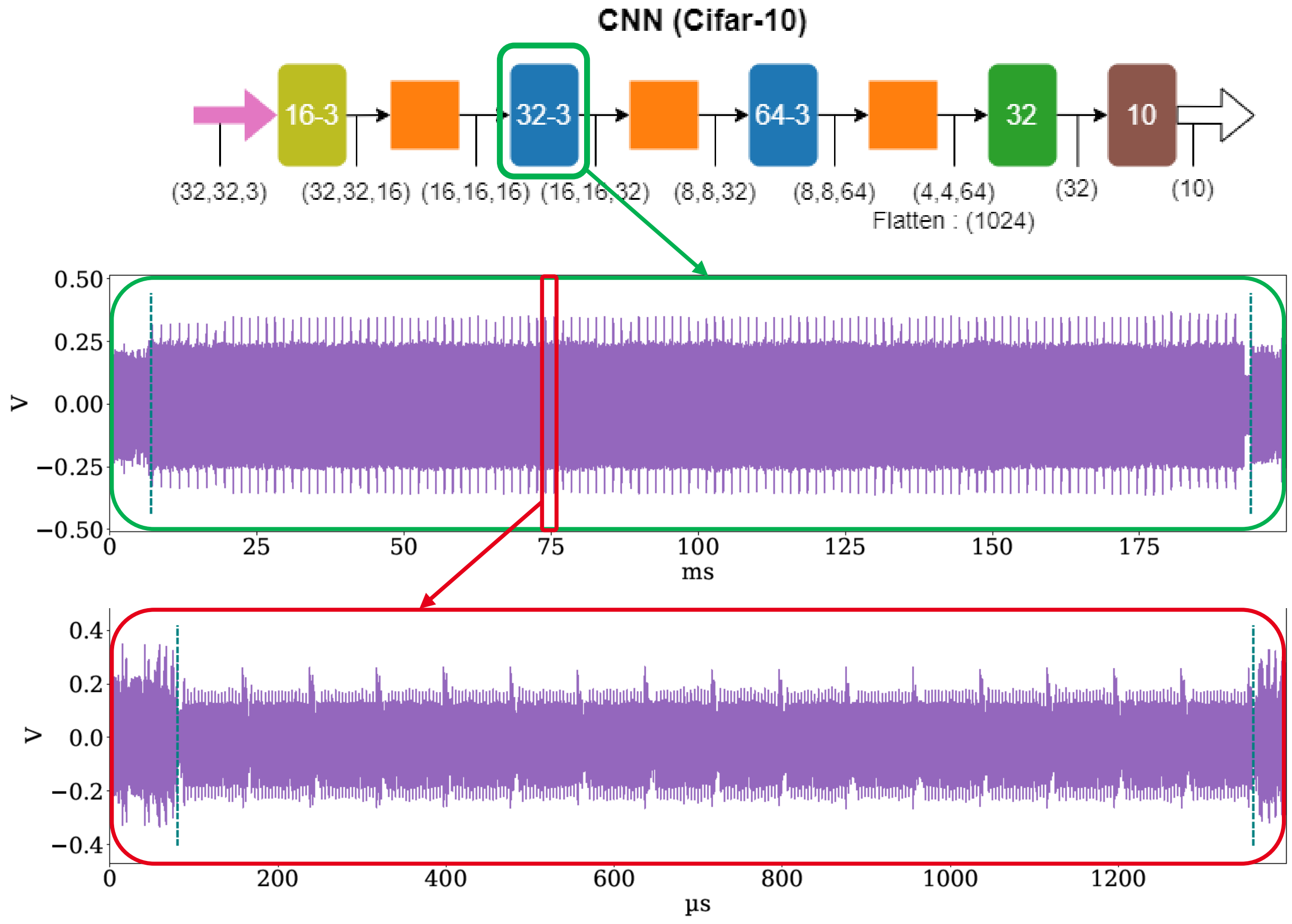
$N_p = 128$ iterations $\Leftrightarrow H_{out} = 16$

$N_p = 32$ iterations $\Leftrightarrow H_{out} = 8$

- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P
- → $\boldsymbol{H_{out} = \sqrt{2 \times N_p}}$

Convolution layers

- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P
- Russian dolls effect to get K



Convolution layers

- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P
- Russian dolls effect to get K

Algorithm 1 Matrix-product for convolution (**GeMM**)

Input: buff_{in}, ker, C_{out}, $C_{in} \times Z^2$, I_{out}, $bias$ (bias tensor)
Output: Partly filled I_{out}

```
rowCnt ← C_out >> 1                                          ▷ Set rowCnt = K/2
for rowCnt > 0, rowCnt − −1 do                                ▷ Iterate over K/2
    sum, sum1, sum2, sum3 = init_sum(bias, C_in × Z^2)
    colCnt ← (C_in × Z^2) >> 2                                ▷ Set colCnt
    for colCnt > 0, colCnt − −1 do
        simd_mac(sum, sum1, sum2, sum3, buff_in, ker)
    end for
    if (C_in × Z^2) & 0x3 then
        Manage_colCnt_remainder(sum, sum1, sum2, sum3, buff_in, bias, C_in × Z^2)
    end if
    apply_mac(sum, sum1, sum2, sum3, C_out, I_out)
end for
if C_out & 0x3 then                                           ▷ Check presence of remainders
    sum, sum1 = init_sum(bias, C_in × Z^2)
    colCnt ← (C_in × Z^2) >> 2                                ▷ Set colCnt
    for colCnt > 0, colCnt − −1 do
        simd_mac(sum, sum1, buff_in, ker)
    end for
    if (C_in × Z^2) & 0x3 then
        Manage_colCnt_remainder(sum, sum1, buff_in, bias, C_in × Z^2)
    end if
    apply_mac(sum, sum1, C_out, I_out)
end if
```

Convolution layers

- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P
- Russian dolls effect to get K
- With $\mathrm{N_p}$ the number of visible patterns corresponding to iterations of `for` loop (3-11):

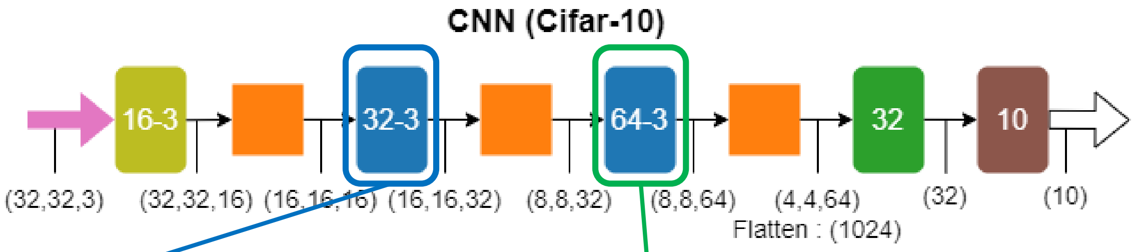
$$rowCnt\colon K = C_{out} = 2 \times N_p$$

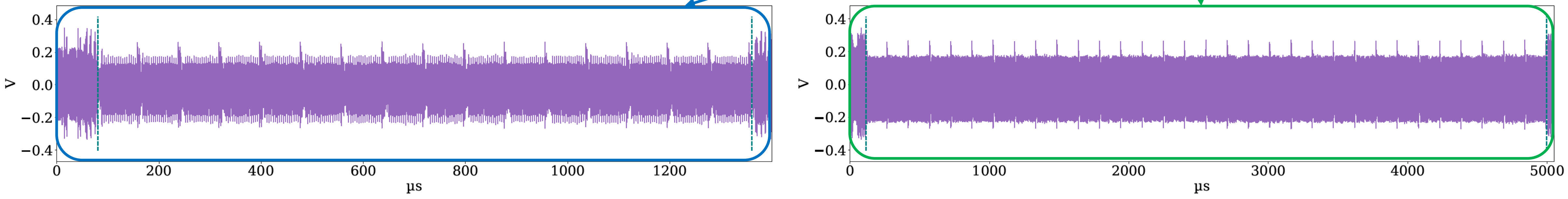
Algorithm 1 Matrix-product for convolution (**GeMM**)

Input: buff$_{in}$, ker, C_{out}, $C_{in} \times Z^2$, I_{out}, $bias$ (bias tensor)
Output: Partly filled I_{out}

1: $rowCnt \leftarrow C_{out} >> 1$ ▷ Set $rowCnt = K/2$
2: **for** $rowCnt > 0,\ rowCnt - -1$ **do** ▷ Iterate over $K/2$
3: $sum, sum1, sum2, sum3 = init\_sum(bias, C_{in} \times Z^2)$
4: $colCnt \leftarrow (C_{in} \times Z^2) >> 2$ ▷ Set $colCnt$
5: **for** $colCnt > 0,\ colCnt - -1$ **do**
6: $simd\_mac(sum, sum1, sum2, sum3, \mathrm{buff}_{in}, ker)$
7: **end for**
8: **if** $(C_{in} \times Z^2)$ & 0x3 **then**
9: $Manage\_colCnt\_remainder(sum, sum1, sum2, sum3, \mathrm{buff}_{in}, bias, C_{in} \times Z^2)$
10: **end if**
11: $apply\_mac(sum, sum1, sum2, sum3, C_{out}, I_{out})$
12: **end for**
13: **if** C_{out} & 0x3 **then** ▷ Check presence of remainders
14: $sum, sum1 = init\_sum(bias, C_{in} \times Z^2)$
15: $colCnt \leftarrow (C_{in} \times Z^2) >> 2$ ▷ Set $colCnt$
16: **for** $colCnt > 0,\ colCnt - -1$ **do**
17: $simd\_mac(sum, sum1, \mathrm{buff}_{in}, ker)$
18: **end for**
19: **if** $(C_{in} \times Z^2)$ & 0x3 **then**
20: $Manage\_colCnt\_remainder(sum, sum1, \mathrm{buff}_{in}, bias, C_{in} \times Z^2)$
21: **end if**
22: $apply\_mac(sum, sum1, C_{out}, I_{out})$
23: **end if**

Convolution layers





$N_p = 16$ iterations $\Leftrightarrow K = 32$

$N_p = 32$ iterations $\Leftrightarrow K = 64$

- With $\mathrm{N_p}$ the number of visible patterns corresponding to iterations of first `for` loop:

$$rowCnt\colon\ K = C_{out} = 2 \times N_p$$

Convolution layers

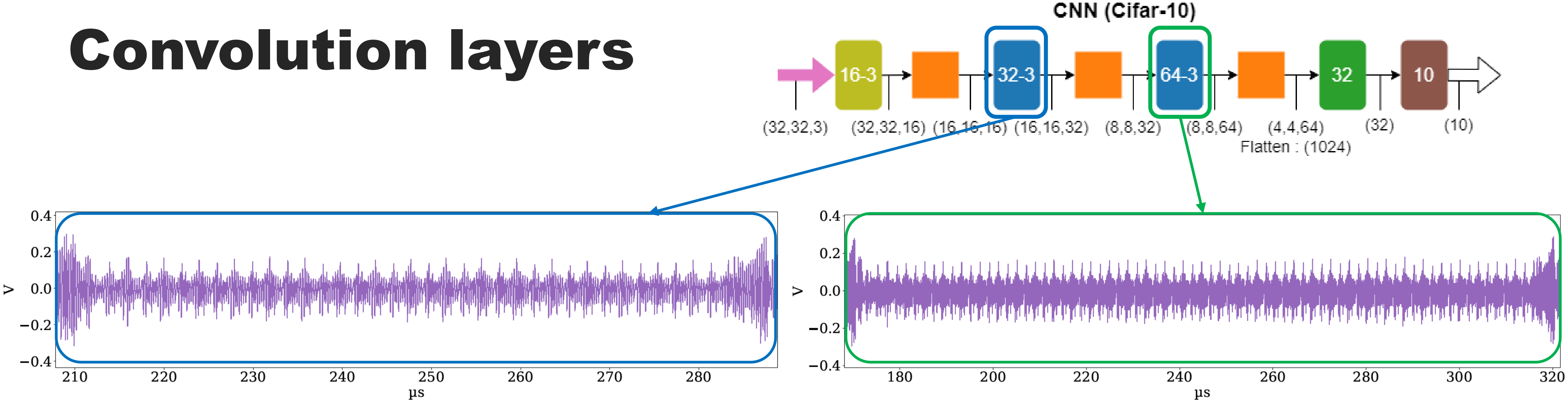
- Allows to extract: H_{out}, K and Z
- Allows to deduce: S and P
- Russian dolls effect to get K and Z
- $rowCnt$: $K = C_{out} = 2 \times N_p$
- $colCnt$: $Z = \sqrt{\frac{(4 \times N_p)}{C_{in}}}$

Algorithm 1 Matrix-product for convolution (**GeMM**)

Input: buff$_{in}$, ker, C_{out}, $C_{in} \times Z^2$, I_{out}, $bias$ (bias tensor)
Output: Partly filled I_{out}

```
rowCnt ← C_out >> 1                                          ▷ Set rowCnt = K/2
for rowCnt > 0, rowCnt − −1 do                               ▷ Iterate over K/2
    sum, sum1, sum2, sum3 = init_sum(bias, C_in × Z^2)
    colCnt ← (C_in × Z^2) >> 2                               ▷ Set colCnt
    for colCnt > 0, colCnt − −1 do
        simd_mac(sum, sum1, sum2, sum3, buff_in, ker)
    end for
    if (C_in × Z^2) & 0x3 then
        Manage_colCnt_remainder(sum, sum1, sum2, sum3, buff_in, bias, C_in × Z^2)
    end if
    apply_mac(sum, sum1, sum2, sum3, C_out, I_out)
end for
if C_out & 0x3 then                                          ▷ Check presence of remainders
    sum, sum1 = init_sum(bias, C_in × Z^2)
    colCnt ← (C_in × Z^2) >> 2                               ▷ Set colCnt
    for colCnt > 0, colCnt − −1 do
        simd_mac(sum, sum1, buff_in, ker)
    end for
    if (C_in × Z^2) & 0x3 then
        Manage_colCnt_remainder(sum, sum1, buff_in, bias, C_in × Z^2)
    end if
    apply_mac(sum, sum1, C_out, I_out)
end if
```

Convolution layers



$N_p = 36$ iterations $\Leftrightarrow Z = 3$ with $C_{in} = 16$

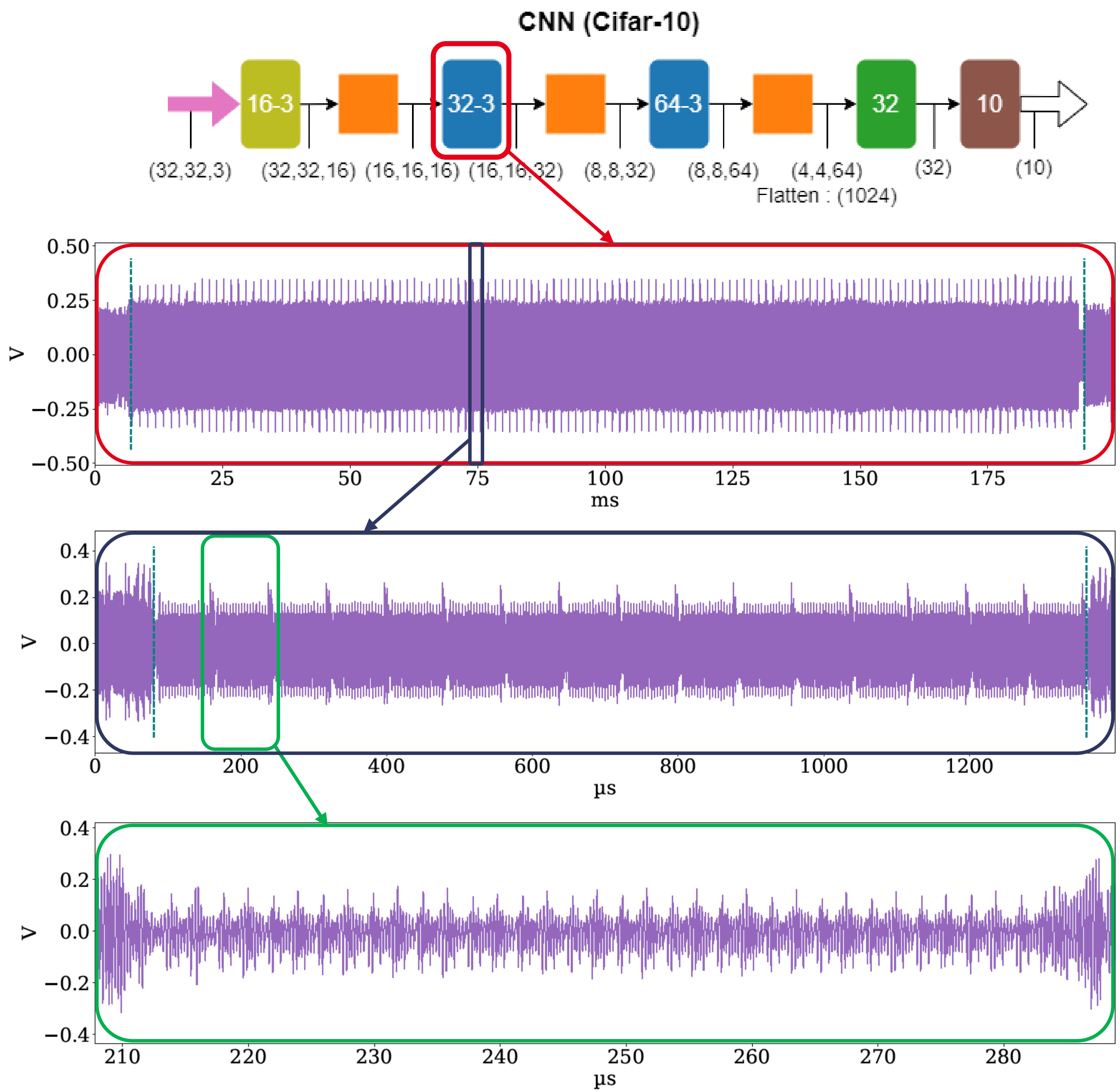
$N_p = 72$ iterations $\Leftrightarrow Z = 3$ with $C_{in} = 32$

- With $\mathrm{N_p}$ the number of visible patterns corresponding to iterations of second `for` loop:

$$colCnt\colon Z = \sqrt{\frac{(4 \times N_p)}{C_{in}}}$$

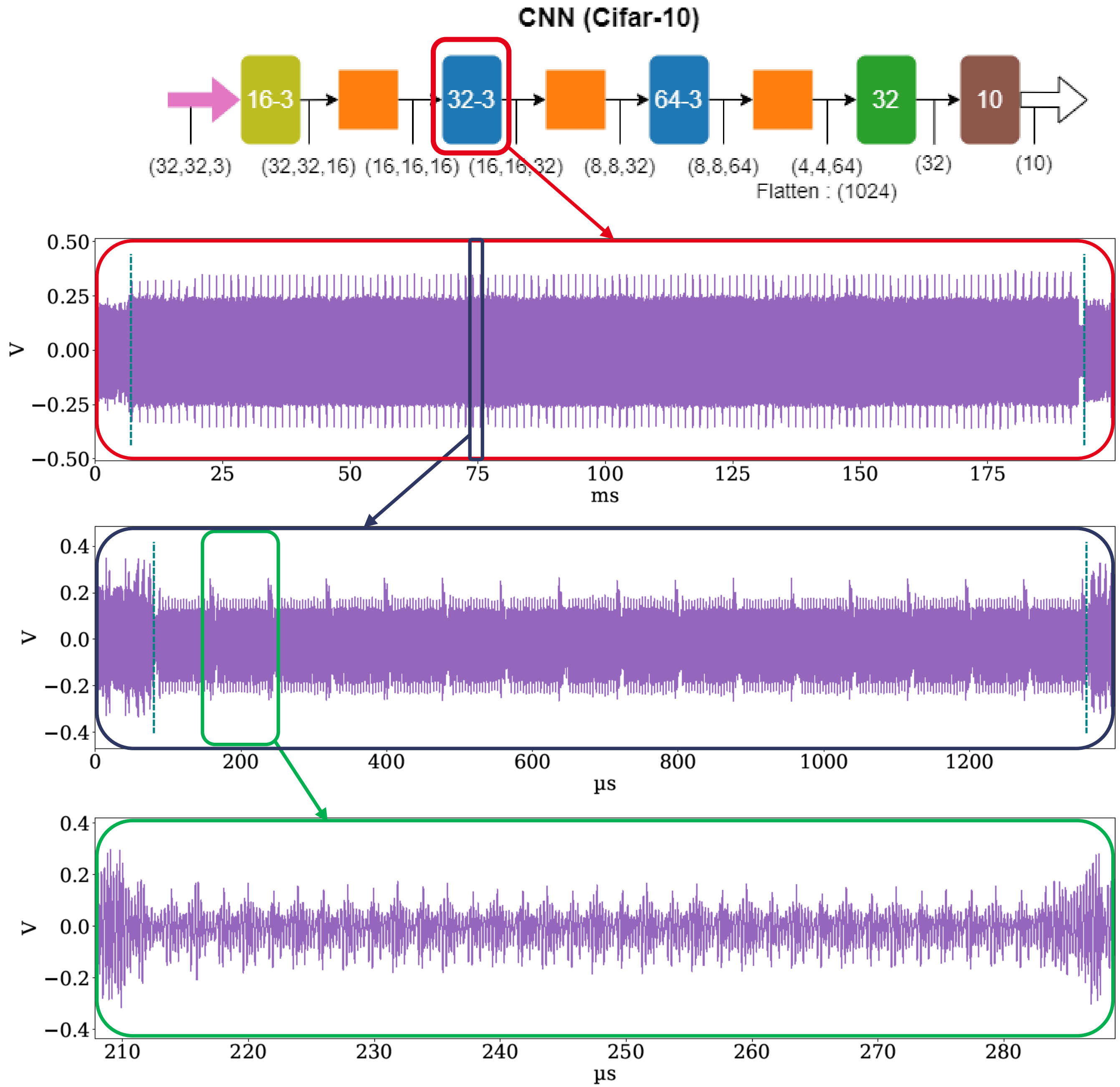
Convolution layers

- Look at `for` loops iterations
- Russian Dolls effect
- Allows to extract:
  - H_{out}
  - K
  - Z

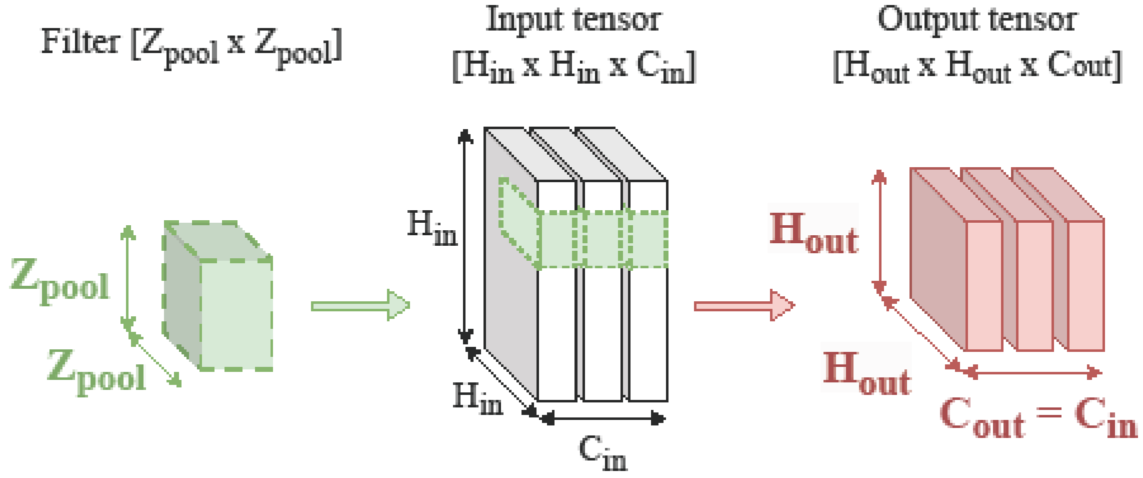


Convolution layers

- Look at `for` loops iterations
- Russian Dolls effect
- Allows to extract:
  - H_{out}
  - K
  - Z
- Then deducing:
  - S and P as $P \leq Z$



MaxPool layers



- Allows to extract H_{out} and deduce Z_{pool}
- 2 distinct parts

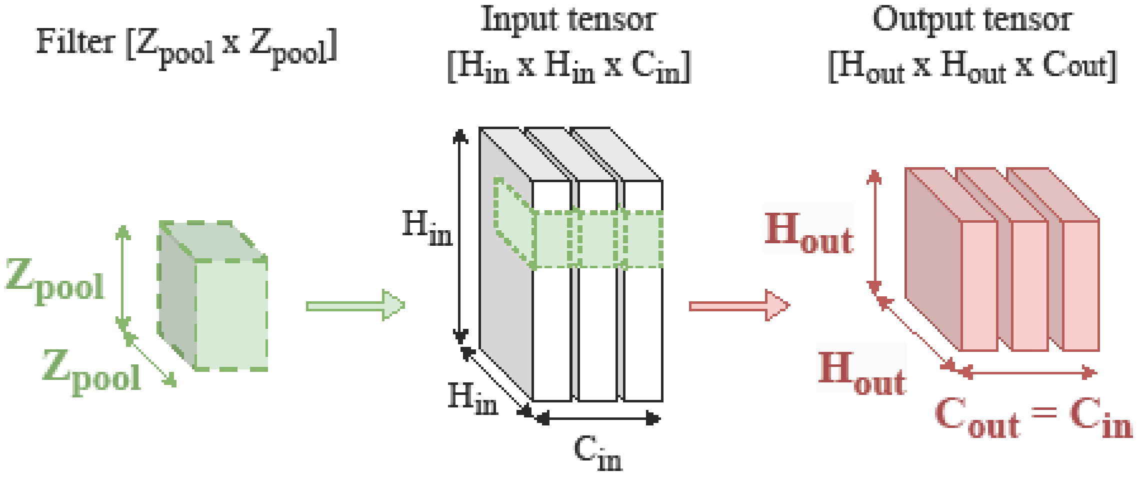
$$H_{out} = \frac{H_{in}}{Z_{pool}}$$

Algorithm 1 MaxPool - `arm_maxpool_q7_HWC`

Input: Input tensor I_{in} of size $H_{in}^2 \cdot C_{in}$, Output tensor I_{out} of size $H_{out}^2 \cdot C_{out}$, P, S, H_{ker}
Output: Filled I_{out}

for $i_y \leftarrow 0,\ i_y < H_{in},\ i_y++1$ **do** ▷ Pooling along x-axis
    for $i_x \leftarrow 0,\ i_x < H_{out},\ i_x++1$ **do**
        $win_{start}, win_{stop} \leftarrow set\_window(i_y, i_x, I_{in}, H_{ker}, P, S)$
        $compare\_and\_remplace\_if\_larger(win_{start}, win_{stop}, i_y, i_x, I_{in})$
    end for
end for
for $i_y \leftarrow 0,\ i_y < H_{out},\ i_y++1$ **do** ▷ Pooling along y-axis, iterates directly over H_{out}
    $row_{start}, row_{stop} \leftarrow set\_rows(i_y, I_{in}, I_{out}, H_{ker}, P, S)$
    $compare\_replace\_then\_apply(row_{start}, row_{stop}, I_{in}, I_{out})$
end for

MaxPool layers



- Allows to extract H_{out} and deduce Z_{pool}
- 2 distinct parts

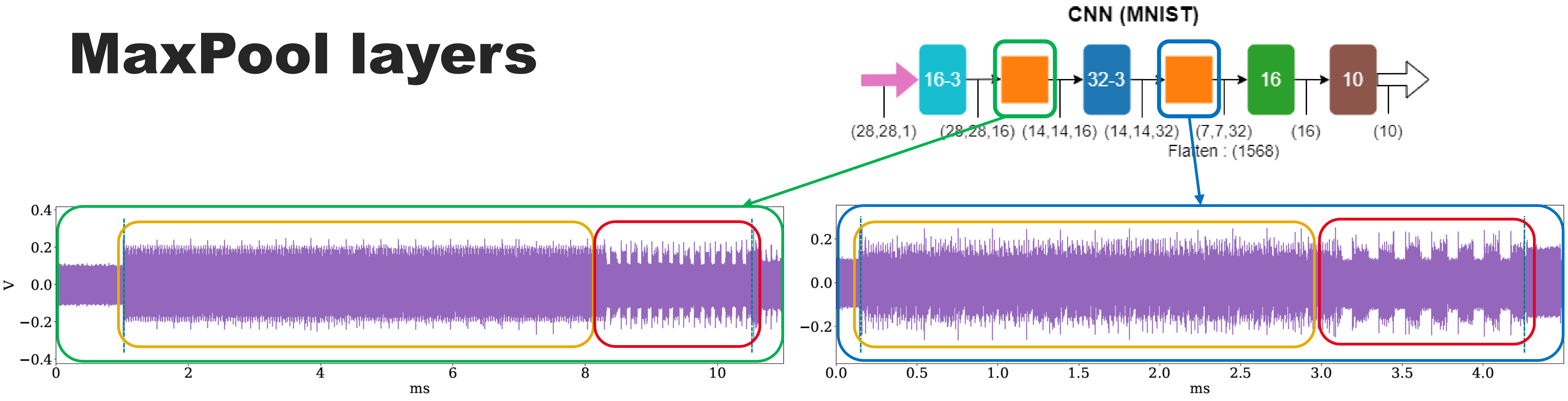
$$H_{out} = \frac{H_{in}}{Z_{pool}}$$

Algorithm 1 MaxPool - `arm_maxpool_q7_HWC`

Input: Input tensor I_{in} of size $H_{in}^2 \cdot C_{in}$, Output tensor I_{out} of size $H_{out}^2 \cdot C_{out}$, P, S, H_{ker}
Output: Filled I_{out}

```
for i_y ← 0, i_y < H_in, i_y++1 do                 ▷ Pooling along x-axis
    for i_x ← 0, i_x < H_out, i_x++1 do
        win_start, win_stop ← set_window(i_y, i_x, I_in, H_ker, P, S)
        compare_and_remplace_if_larger(win_start, win_stop, i_y, i_x, I_in)
    end for
end for
for i_y ← 0, i_y < H_out, i_y++1 do    ▷ Pooling along y-axis, iterates directly over H_out
    row_start, row_stop ← set_rows(i_y, I_in, I_out, H_ker, P, S)
    compare_replace_then_apply(row_start, row_stop, I_in, I_out)
end for
```

MaxPool layers



$N_p = 14$ iterations $\Leftrightarrow H_{out} = 14$

$N_p = 7$ iterations $\Leftrightarrow H_{out} = 7$

- Look at `for` loops iterations
- Two distinct parts: one easier to analyse

- Allows to extract: H_{out}
- Allows to deduce: Z_{pool}

Dense layers

- Neurons managed by groups of 4
- Patterns length depends on input shape

Algorithm 1 Dense layer - `arm_fully_connected_q7_opt`

Input: Input vector I_{in} of size H_{in}, weight vector ker of size N_e, bias matrix $bias$ of size N_e, output vector I_{out} of size H_{out}, P, S, H_{ker}

Output: Filled I_{out}

$rowCnt \leftarrow N_e >> 2$ ▷ Nb. neurons divided by 4

for $rowCnt > 0,\ rowCnt - -1$ **do** ▷ Iterate directly over $N_e/4$

$sum, sum1, sum2, sum3 = init\_sum\_with\_bias(bias, rowCnt)$

$colCnt \leftarrow H_{in} >> 2$

for $colCnt > 0,\ colCnt - -1$ **do**

$simd\_mac(sum, sum1, sum2, sum3, ker, colCnt)$

end for

$apply\_mac(sum, sum1, sum2, sum3, rowCnt, I_{out})$

end for

$rowCnt \leftarrow N_e\ \&\ 0x3$ ▷ Manage remainders if any

for $rowCnt > 0,\ rowCnt - -1$ **do**

$sum = init\_sum\_with\_bias(bias, rowCnt)$

$colCnt \leftarrow H_{in} >> 2$

for $colCnt > 0,\ colCnt - -1$ **do**

$mac(sum, ker, colCnt)$

end for

$apply\_mac(sum, rowCnt, I_{out})$

end for

Dense layers

- Neurons managed by groups of 4
- Patterns length depends on input shape
- Allows to extract:
  - $N_e = 4 \times N_p$

Algorithm 1 Dense layer - `arm_fully_connected_q7_opt`

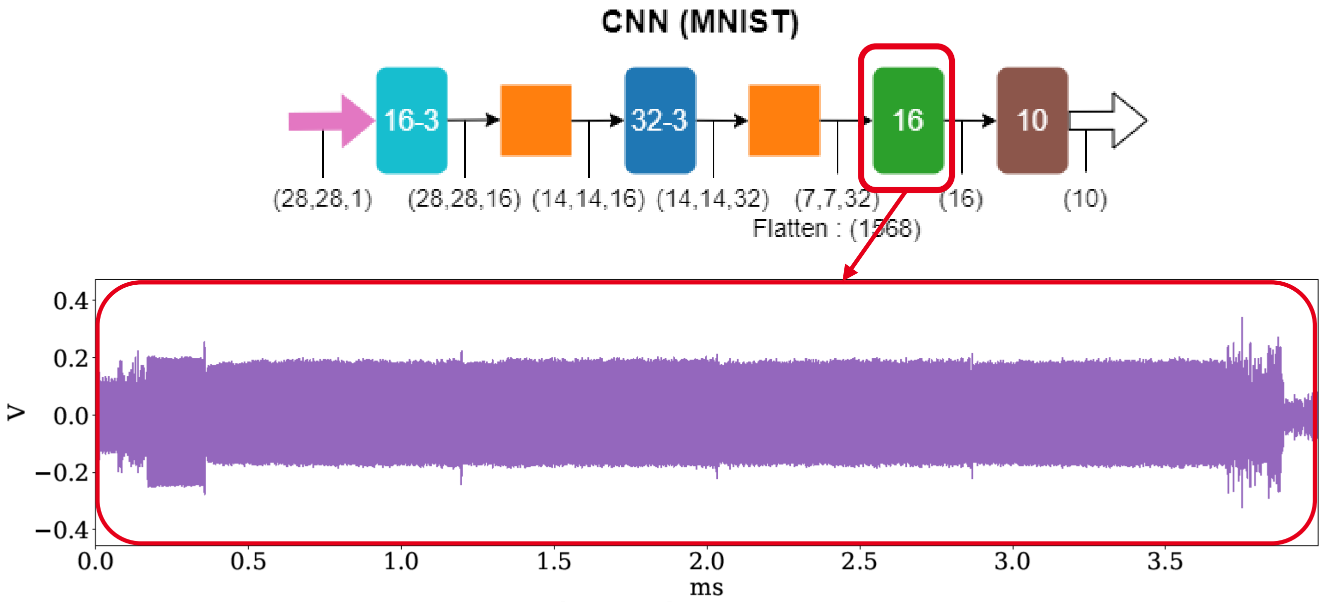
Input: Input vector I_{in} of size H_{in}, weight vector ker of size N_e, bias matrix $bias$ of size N_e, output vector I_{out} of size H_{out}, P, S, H_{ker}

Output: Filled I_{out}

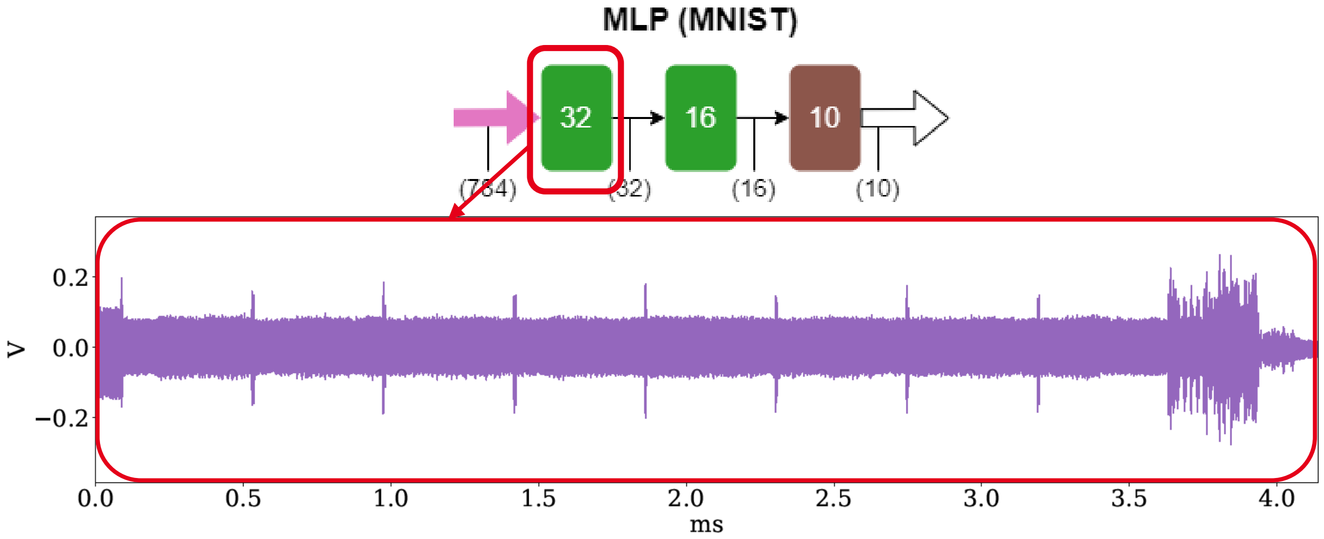
```
rowCnt ← N_e >> 2                                        ▷ Nb. neurons divided by 4
for rowCnt > 0, rowCnt − −1 do                           ▷ Iterate directly over N_e/4
    sum, sum1, sum2, sum3 = init_sum_with_bias(bias, rowCnt)
    colCnt ← H_in >> 2
    for colCnt > 0, colCnt − −1 do
        simd_mac(sum, sum1, sum2, sum3, ker, colCnt)
    end for
    apply_mac(sum, sum1, sum2, sum3, rowCnt, I_out)
end for
rowCnt ← N_e & 0x3                                       ▷ Manage remainders if any
for rowCnt > 0, rowCnt − −1 do
    sum = init_sum_with_bias(bias, rowCnt)
    colCnt ← H_in >> 2
    for colCnt > 0, colCnt − −1 do
        mac(sum, ker, colCnt)
    end for
    apply_mac(sum, rowCnt, I_out)
end for
```

Dense layers

- Neuron managed by groups of 4
- Patterns length depends on input shape
- Allows to extract:
  - $N_e = 4 \times N_p$
- Usual cases when $N_e \% \, 4 = 0$



$N_p = 4$ iterations $\Leftrightarrow N_e = 16$



$N_p = 8$ iterations $\Leftrightarrow N_e = 32$

Dense layers

- Neuron managed by groups of 4
- Patterns length depends on input shape
- Allows to extract:
  - $N_e = 4 \times N_p$
- Usual cases when $N_e \% \, 4 = 0$
- Special cases when $N_e \% \, 4 \neq 0$

Algorithm 1 Dense layer - `arm_fully_connected_q7_opt`

Input: Input vector I_{in} of size H_{in}, weight vector ker of size N_e, bias matrix $bias$ of size N_e, output vector I_{out} of size H_{out}, P, S, H_{ker}

Output: Filled I_{out}

$rowCnt \leftarrow N_e >> 2$ ▷ Nb. neurons divided by 4

for $rowCnt > 0, \; rowCnt - -1$ **do** ▷ Iterate directly over $N_e/4$

    $sum, sum1, sum2, sum3 = init\_sum\_with\_bias(bias, rowCnt)$

    $colCnt \leftarrow H_{in} >> 2$

    for $colCnt > 0, \; colCnt - -1$ **do**

        $simd\_mac(sum, sum1, sum2, sum3, ker, colCnt)$

    end for

    $apply\_mac(sum, sum1, sum2, sum3, rowCnt, I_{out})$

end for

$rowCnt \leftarrow N_e \; \& \; 0x3$ ▷ Manage remainders if any

for $rowCnt > 0, \; rowCnt - -1$ **do**

    $sum = init\_sum\_with\_bias(bias, rowCnt)$

    $colCnt \leftarrow H_{in} >> 2$

    for $colCnt > 0, \; colCnt - -1$ **do**

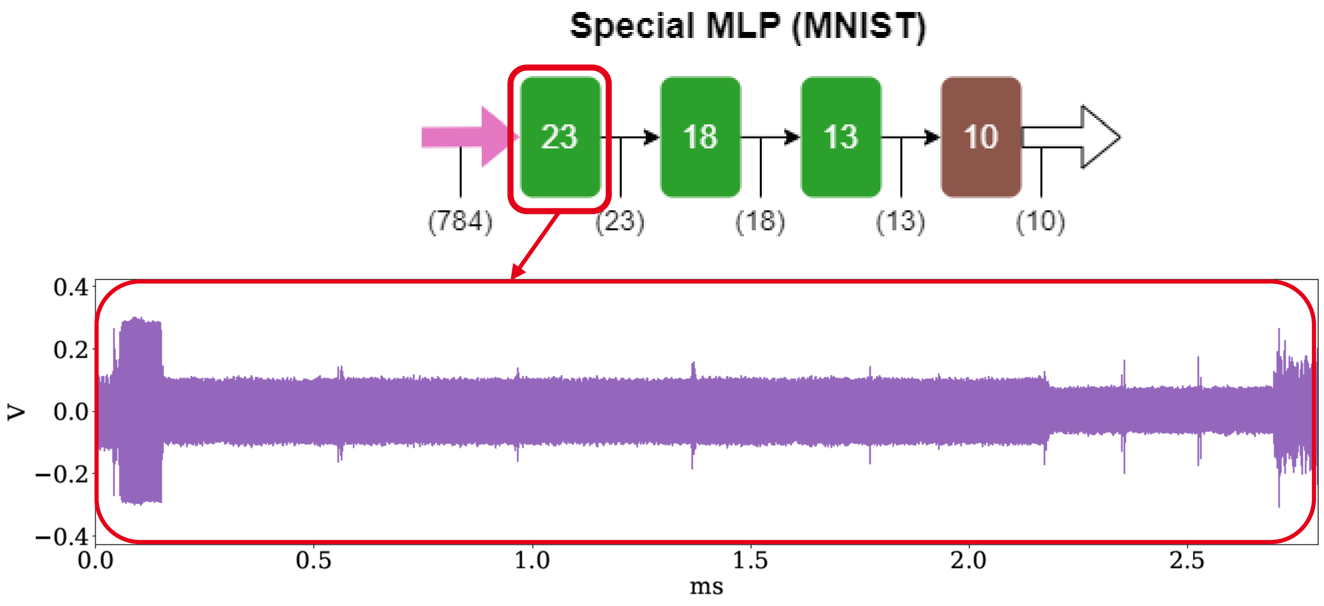
        $mac(sum, ker, colCnt)$

    end for

    $apply\_mac(sum, rowCnt, I_{out})$

end for

Dense layers

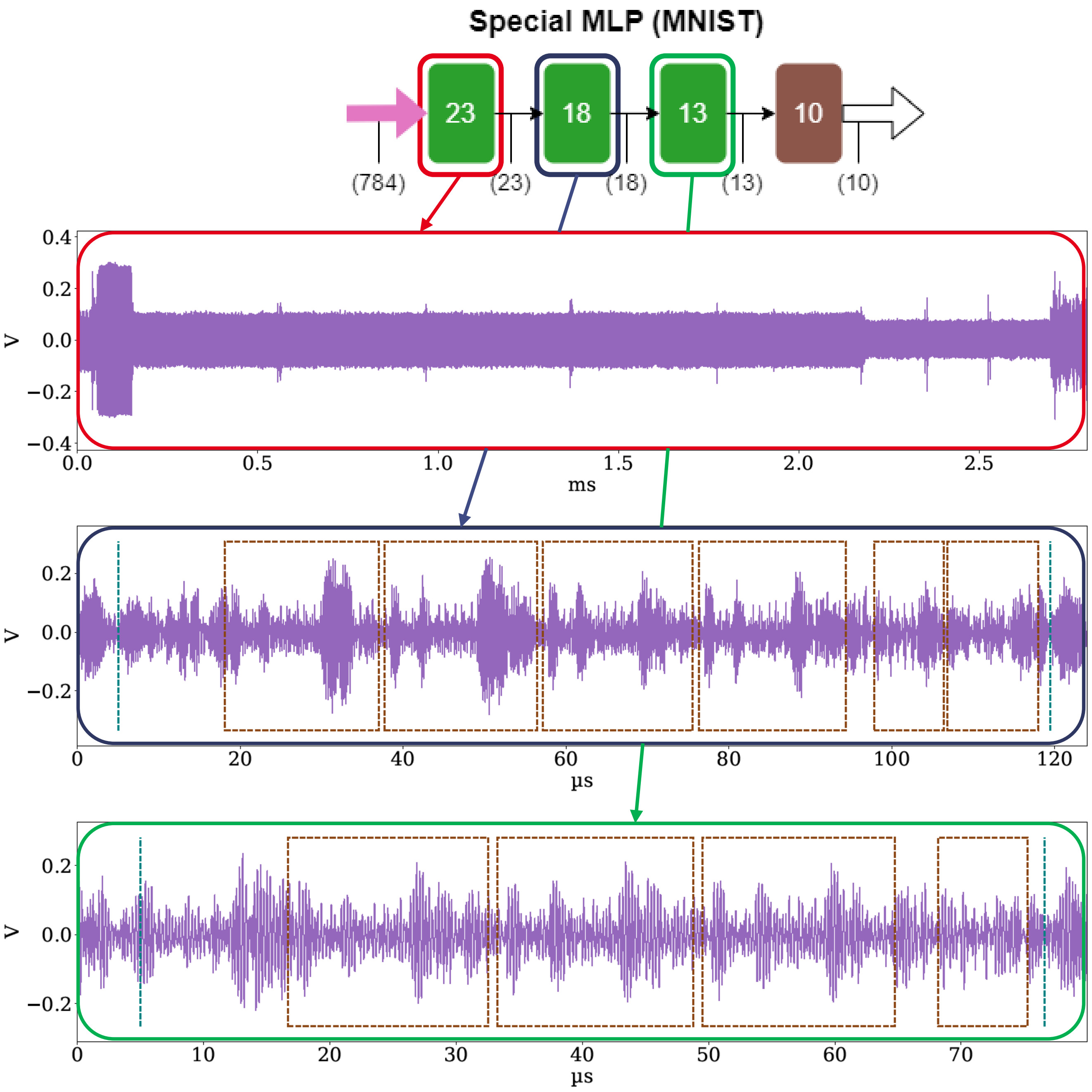


$N_p = 5 + 3$ iterations $\Leftrightarrow N_e = 4 \times 5 + 3 = 23$

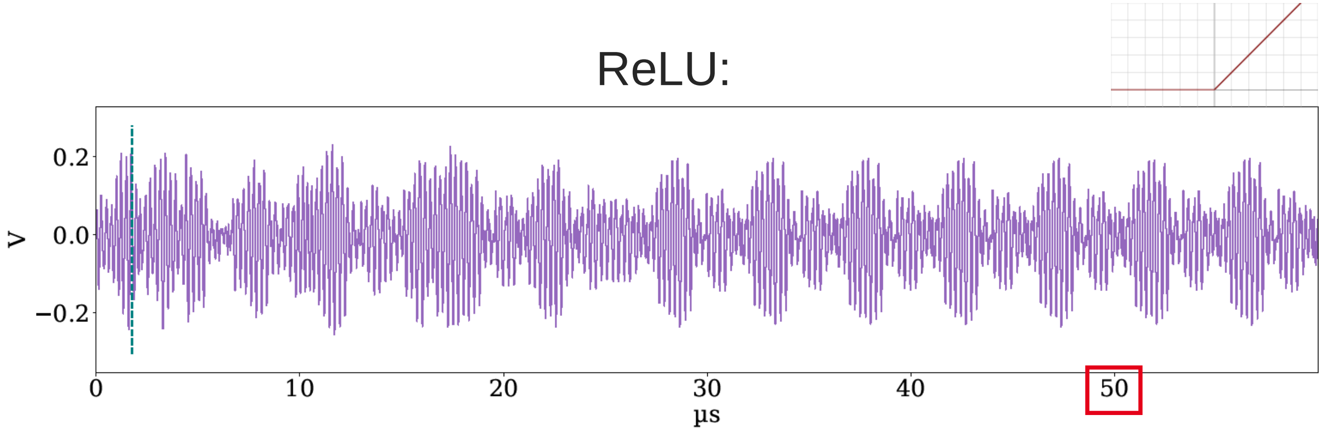
- Neuron managed by groups of 4
- Patterns length depends on input shape
- Allows to extract:
  - $N_e = 4 \times N_p$
- Usual cases when $N_e \% \, 4 = 0$
- Special cases when $N_e \% \, 4 \neq 0$

Dense layers

- Neuron managed by groups of 4
- Patterns length depends on input shape
- Allows to extract:
  - $N_e = 4 \times N_p$
- Usual cases when $N_e \% \, 4 = 0$
- Special cases when $N_e \% \, 4 \neq 0$
- Illustration with additional triggers



Activation layers



- Distinguish ReLU from Tanh and Sigmoid
- Can use duration of activation layers
- EM patterns give additional hints

Layer	ReLU	Sigmoid	Tanh
0	1,84 ms	8,24 ms	8,24 ms
1	0,92 ms	3,21 ms	3,58 ms
2	7,60 µs	15,6 µs	20,64 µs

Activation layers

- Distinguish ReLU from Tanh and Sigmoid
- Can use duration of activation layers
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Layer	ReLU	Sigmoid	Tanh
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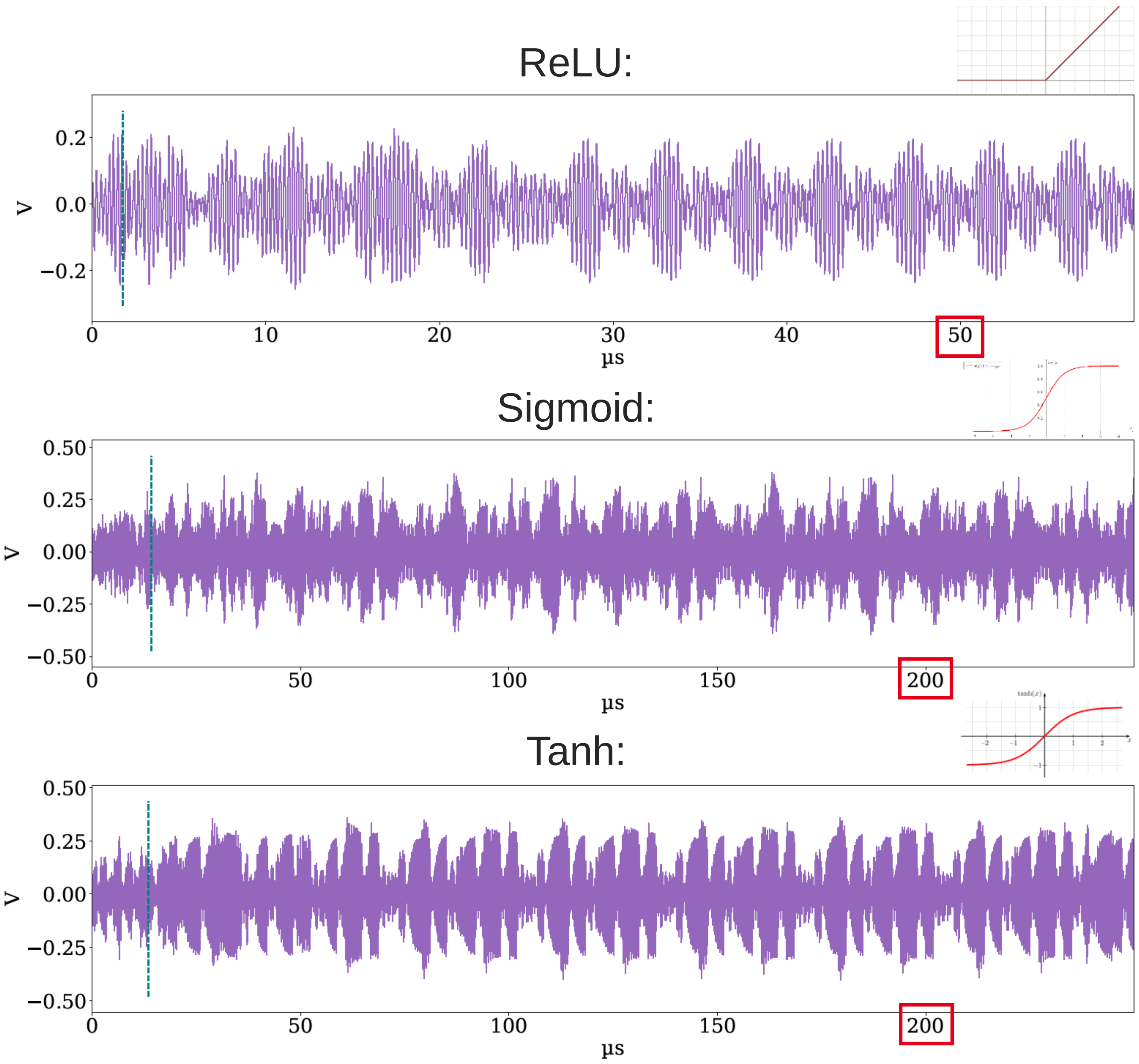

Outline

- Introduction
- Challenges
- Scope and threat model
- Model analysis
- Layer analysis
- Discussion & Perspectives

Discussions and Perspectives

- Several works studying architecture extraction
- Attack surface for such a threat is significantly extended by SCA
- No need of complex exploitation methods (e.g., heavy supervised profiling step)
- Important step for parameters extraction [1 to 7]
- Some more complex cases allowing to approximate hyper-parameter (could be handled with pattern detection tools)
- Critical need to protect architecture from extraction [11, 17, 18]
- Hard challenges to develop efficient protections 32-bit microcontrollers

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Thank you for your attention

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