# swDNN:A Library for Accelerating Deep Learning Applications on Sunway TaihuLight

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- Introduction
- 2 Architecture
- Register Communication
- 4 Instruction Pipelines
- Experiment

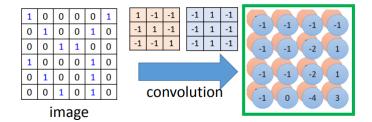
# Sunway TaihuLight

- A supercomputer that ranks the first in the world.
- Over 100 Pflops computing capacity.
- Sunway TaihuLight is power by a new SW26010 many-core processor.
- Not only the fastest but also the greenest supercomputer in the world.

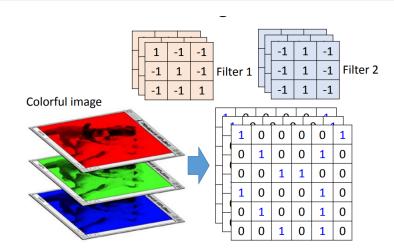
## SW26010

- Peak double-precision performance of 3.06 Tflops.
- 300 watts power consumption.
- Combine both management cores and computing core clusters on a core group.
- Support a user-controlled fast buffer for each computing cores.
- Rigister communication between computing cores.
- Each computing core consists of two execution pipelines.

# Convolution layer



## Convolution layer



# Peseudo code of a convolutional layer

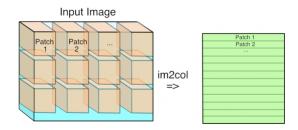
Table I: Parameters of convolutional layers

Parameter	Meaning
$N_i$	Number of input feature maps
$N_o$	Number of output feature maps
$R_i$	Height of input image
$C_i$	Width of input image
$R_o$	Height of output image
$C_o$	Width of output image
$K_r$	Height of filter kernel
$K_c$	Width of filter kernel

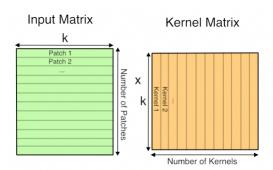
# Pseudo code of a convolutional layer

```
for cB = 0 to B
 for cR_0 = 0 to R_0
  for cC_0 = 0 to C_0
    for cN_o = 0 to N_o
     for cK_r = 0 to K_r
      for cK_c = 0 to K_c
        for cN_i = 0 to N_i
         \operatorname{out}[cB][cR_o][cC_o][cN_o] +=
\inf[cB][cR_o + cK_r][cC_o + cK_c][cN_i]*filter[cN_o][cK_r][cK_c][cN_i]
```

# General Matrix-Multiplication(GEMM)



## **GEMM**



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#### Architecture

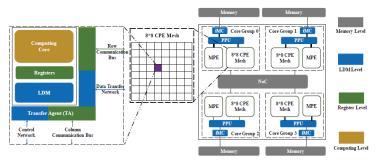


Figure 1: The general architecture of the SW26010 many-core processor.

# Unique features

- Each CG has an MPE.
- Users can explicitly set the size of each CG's private memory space, and the size of shared memory space.
- Support a 64kb user-controlled fast buffer for each computing cores.
- Rigister communication between computing cores.
- Each computing core consists of two execution pipelines.

## Challenges

- Low memory bandwidth.
  - SW26010:36 GB/s for each CG, 144 GB/S for entire processor.
  - NVIDIA K80GPU: 480 GB/S for entire processor.
- CPEs do not have a shared buffer to rely on a fine-grained data sharing scheme.

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# Register Communication

- Motivation
  - Fine-grained.
  - No shared memory in a CG.
- Architecture
  - 8 row communication buses.
  - 8 col communication buses.
  - Broadcast.

$$W*D_i=D_o$$

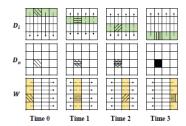


Figure 3: Schematic of register communication on CPEs for matrix multiplication.

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#### P1 and P0

- Each CPE consists of two execution pipelines.
  - P0 : floating-pointer, vector operations.
  - P1 : Control transfer, load/store and register communication operations.
- The two execution pipelines share an Instruction Decoder and an instruction queue.
- In each cycle, two instructions in the front of the queue are issued into two pipelines.

## Instructions scheduling rules

- Both instructions have no conflicts with the unifinished instructions issued before.
- The two insturctions have no RAW or WAW conflicts.
- The two instructions can be handled by two execution pipelines separately.

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## Experiment

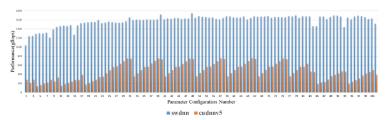


Figure 7: Double-precision performance results of our convolution kernels with different  $(N_i, N_o)$  ranging from (64, 64) to (384, 384), compared with the K40m GPU results with cuDNNv5.  $(B = 128, \text{ output image } = 64 \times 64, \text{ filter } = 3 \times 3)$