Optimal DNN Primitive Selection with Partitioned Boolean Quadratic Programming

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ACM Code generation and Optimization (CGO) Conference

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February 02, 2020

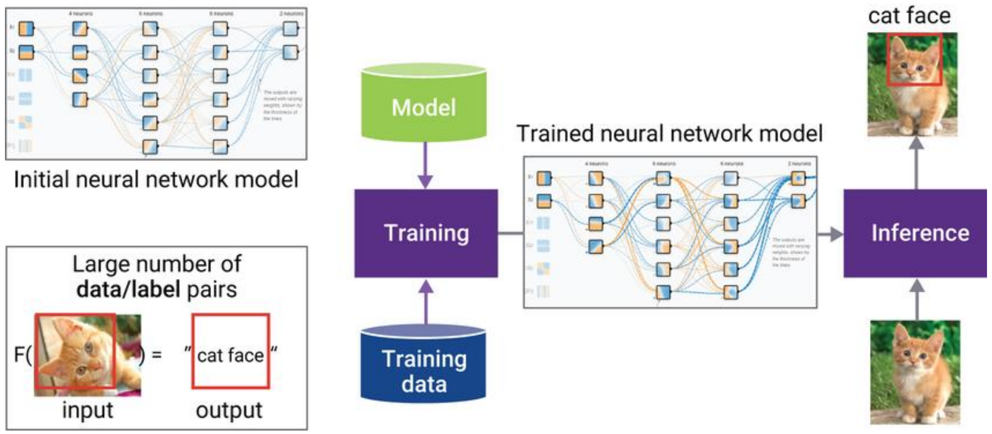
Neural Acceleration Study

Contents of presentation

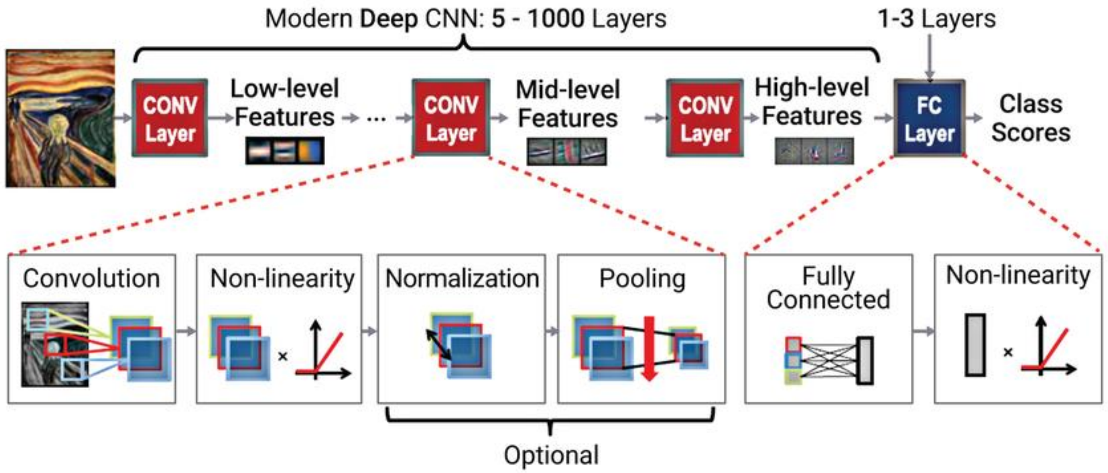
- **Introduction and Background**
  - Fast acceleration, Acceleration HW, Convolutional neural network (CNN)
  - Convolution shapes, Primitives (DNN convolution algorithm)
- **Key contribution: Primitive selection**
  - Partitioned Boolean quadratic assignment problem (PBQP) based selection
- **Performance**
- **Conclusion and Discussion**

Introduction: Fast Acceleration

- **Fast inference or training**
  - Inference: Image classification, Acoustic speech recognition
  - Training: ImageNet, TIMIT learning, Etc.
  - The goal of fast acceleration is to classify or learn data quickly
  - Target: Convolution or Fully-connected layer



Neural network models in deep learning framework[1]



Modern convolutional neural networks [1]

[1] https://www.synopsys.com/designware-ip/technical-bulletin/building-efficient-deep-learning-dwtb_q318.html

Introduction: Acceleration HW

- **From processor to dedicated accelerator**
  - Processor: CPU (x86, ARM, RISC-V), GPU (NVIDIA, AMD), DSP (CEVA, Qualcomm)
  - Dedicated accelerator: ASIC/FPGA based accelerator

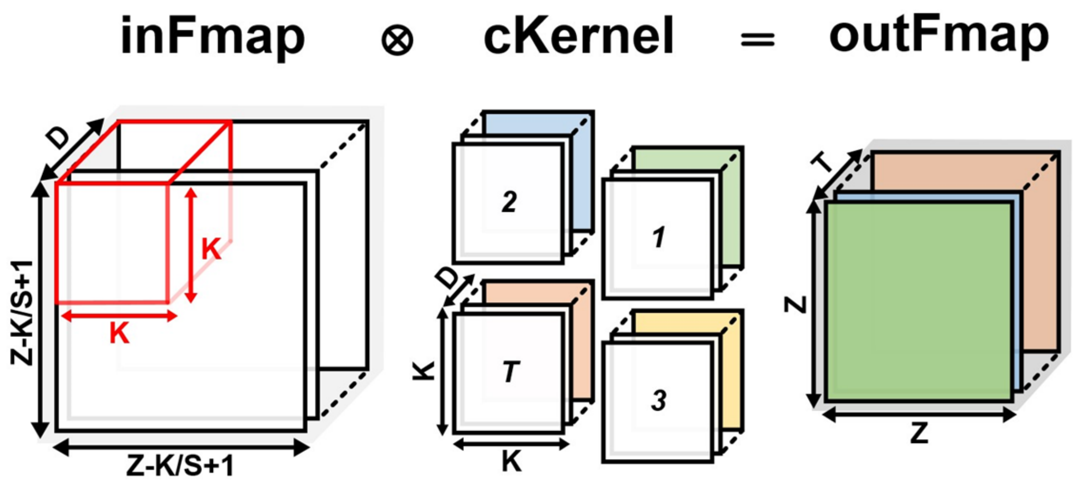
CPU: Ryzen Threadripper

GPU: VOTLA, TURING, PASCAL

FPGA: ALVEO

Introduction: Convolutional NN (CNN)

- **Convolution: Key operation in CNN**
  - Multiply and Accumulate (MAC) operation between feature map (inFmap) and kernel (cKernel)
  - Total number of MAC operation is <u>*$O(Z \times Z \times D \times K^2 \times T)$*</u>



Graph of convolution layer[2]

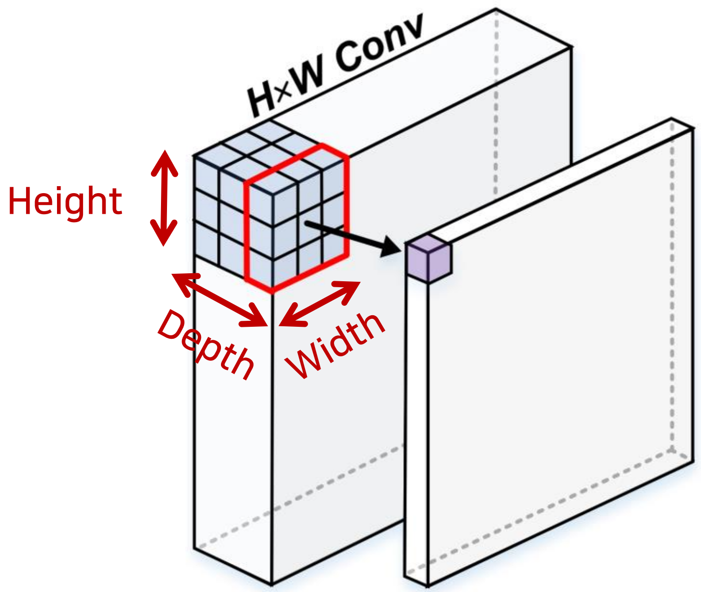
```
for (t=0; t<T; t++) {                       // type index of kernel
 for (r=0; r<Z; r=r+S) {                    // row index of feature map
  for (c=0; c<Z; c=c+S) {                   // col index of feature map
   for (d=0; c<D; d++) {                    // depth index of feature map
    for (i=0; i<K; i++) {                   // row index of kernel
     for (j=0; j<K; j++) {                  // col index of kernel
      outFmap[t][r][c]+=inFmap[d][r+i][c+j]*cKernel[t][d][i][j]
    }}}
  outFmap [t][r][c]= activation(outFmap[t][r][c])}}}
```

Pseudo code of convolution layer[2]

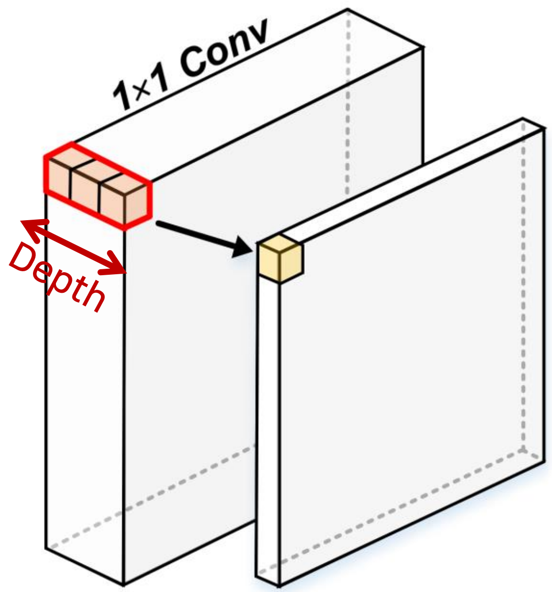
[2] CENNA: Cost-effective neural network accelerator, S. Park, et.al., *electronics*, 2020

Background: Convolution shapes

- **Layer used in convolutional neural network**
  - H×W convolution (Height×Width×Depth), 1×1 convolution (1×1×Depth)
  - Different optimal primitives in each layer



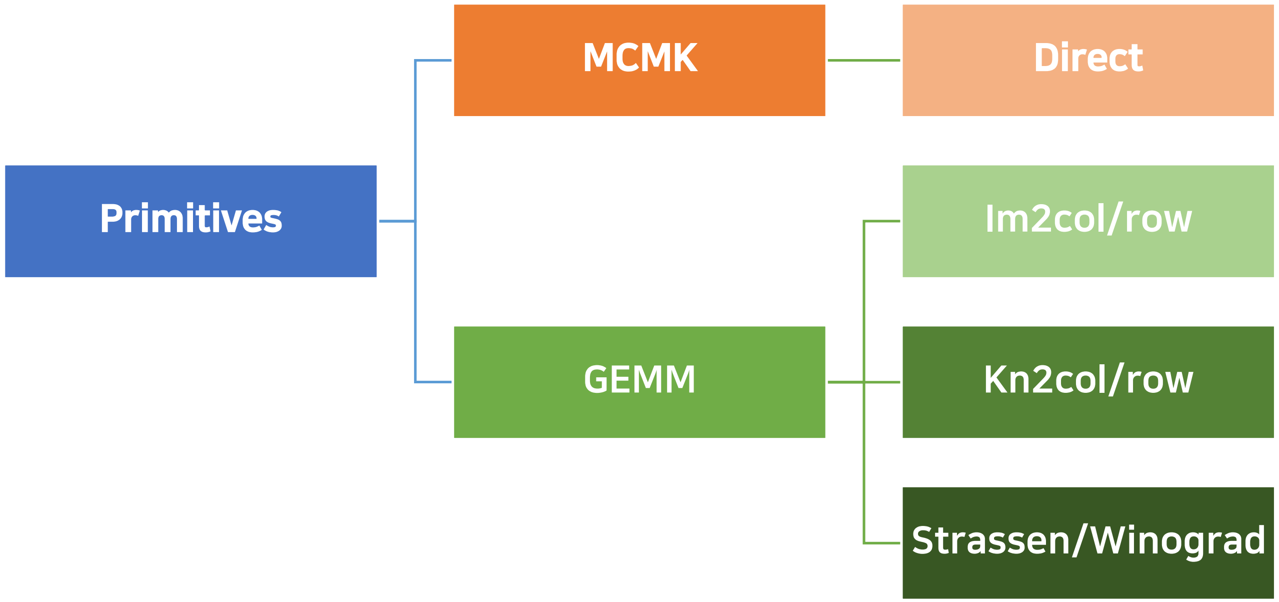
H×W convolution layer



1×1 convolution layer

Background: Primitives

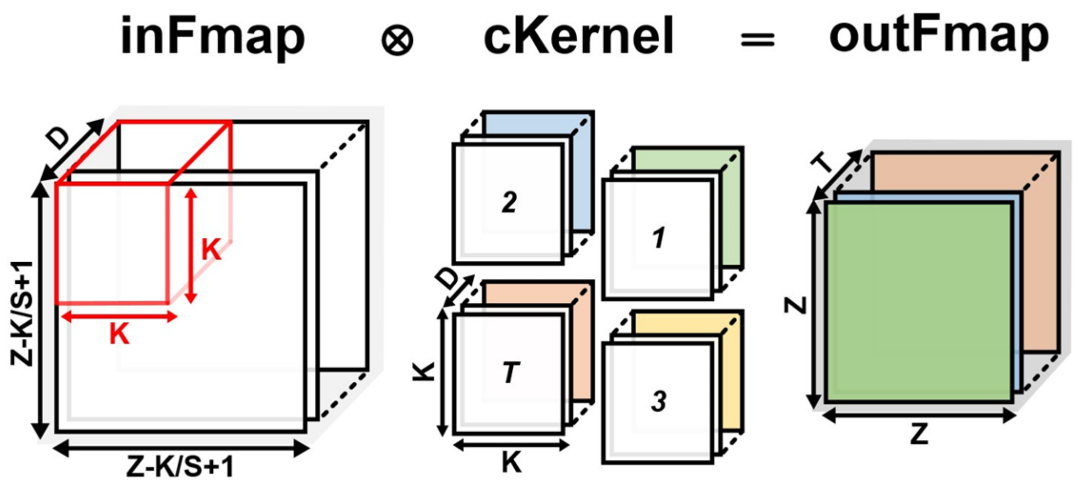
- **Definition: Belonging to a very early period (원시적인)**
  - In CNN, method to implement one of each of the types of layer in DNN
  - Ex) Convolution layer in CNN, Recurrent layer in GRU/LSTM



Hierarchy of DNN Primitives

Background: Primitives

- **Multi Channel Multi Kernel (MCMK)**
  - The most intuitive way to implement a convolutional layer
  - Implemented using multiple For loop statement (6~7 levels)
  - Most inefficient primitive in data locality



Graph of convolution layer[2]

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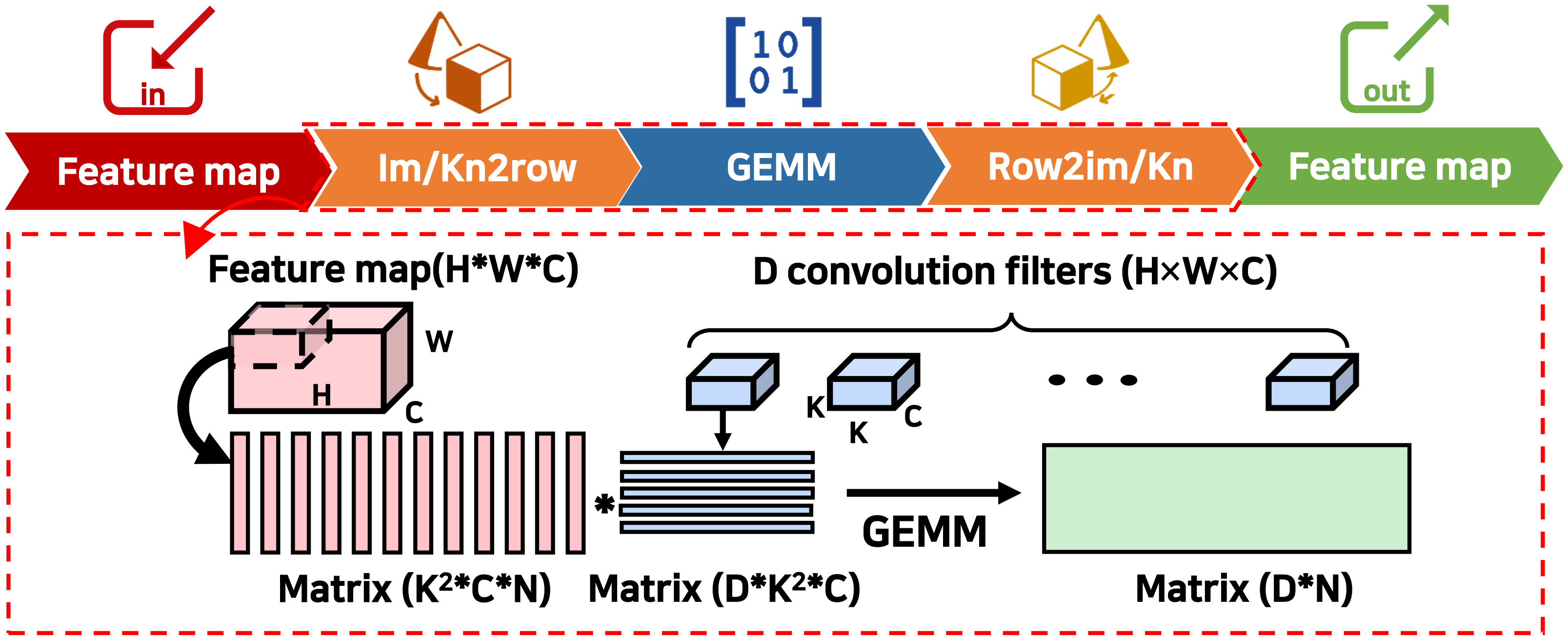
   for (d=0; c<D; d++) {                       // depth index of feature map
    for (i=0; i<K; i++) {                      // row index of kernel
     for (j=0; j<K; j++) {                     // col index of kernel
      outFmap[t][r][c]+=inFmap[d][r+i][c+j]*cKernel[t][d][i][j]
    }}}
   outFmap [t][r][c]= activation(outFmap[t][r][c])}}}
```

Pseudo code of convolution layer[2]

Background: Primitives

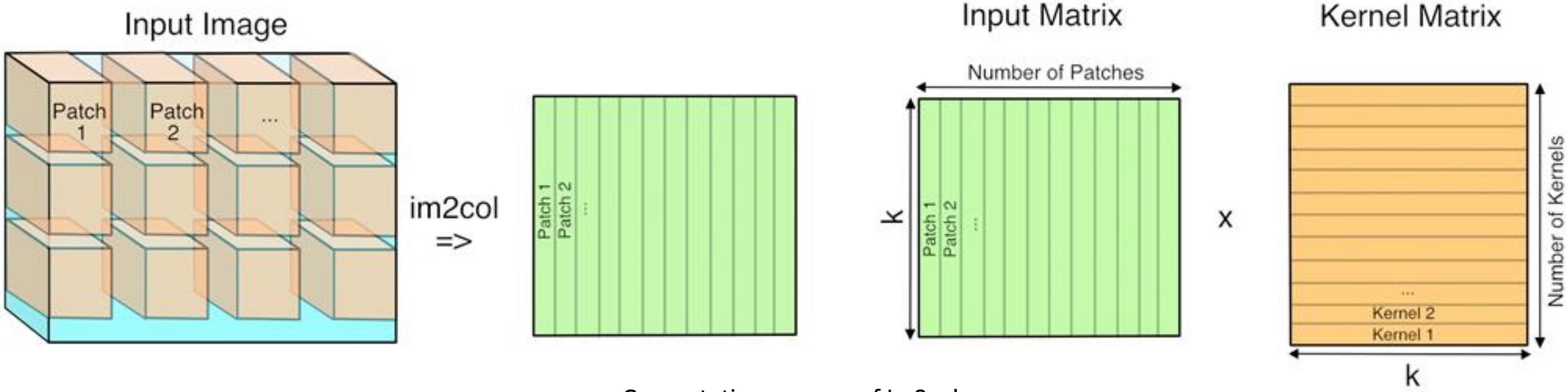
- **General matrix multiplication (GEMM)**
  - Transforming convolution operation to matrix multiplication
  - Transformation processor for matrix multiplication, results obtained through matrix multiplication
  - Advantages of data locality over MCMK



GEMM based Im2col

Background: Primitives

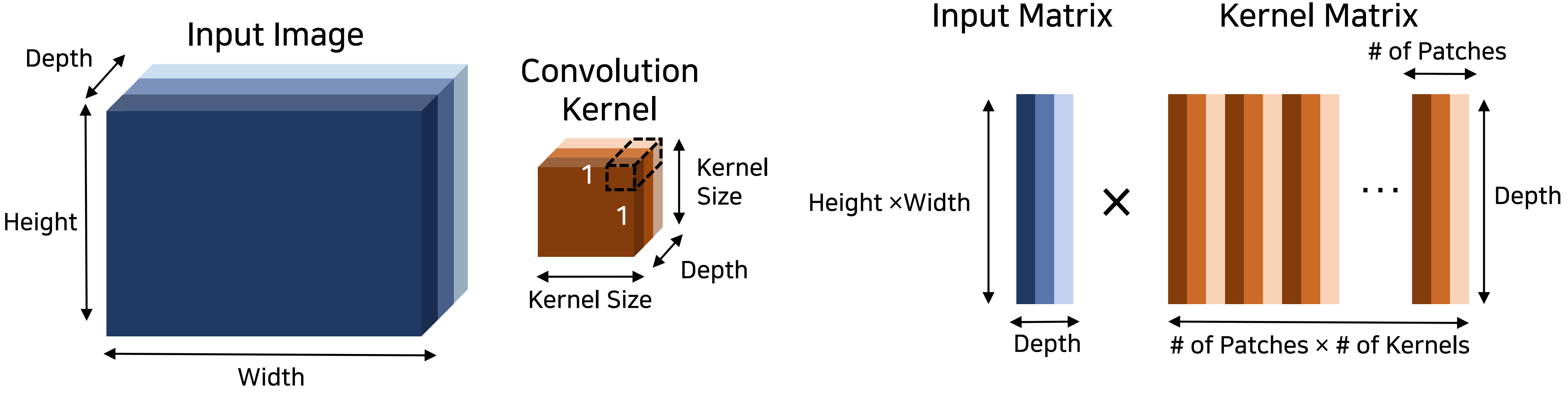
- **Image to column/row (Im2col/row)**
  - Converting feature map into patches to math the kernel size
  - Ex) Kernel width × height × depth × N (N is # of patches)
  - Appropriate for H×W convolution layer (data locality for horizonal/vertical orientations)
  - Im2col's transposed image to row (Im2row) is mainly used



Computation process of Im2col

Background: Primitives

- **Kernel to column/row (Kn2col/row)[3]**
  - Converting convolution kernel into patches to math 1×1 convolution
  - Ex) Kernel width (5) × height (5) × depth (3) -> width (1) × height (1) × depth (3) × patches (25)
  - Appropriate for 1×1 convolution layer (data locality for channel orientations)
  - Kn2col's transposed image to row (Kn2row) is mainly used



Computation process of Kn2col (Left), GEMM in Kn2col (Right)

[3] https://www.slideshare.net/embeddedvision/even-faster-cnns-exploring-the-new-class-of-winograd-algorithms-a-presentation-from-arm

Background: Primitives

- **Strassen, Winograd matrix multiplication[4]**
  - Multiplication requires more overhead than adder (Latency, Power consumption)
  - To compute 2×3, 3×1 matrix multiplication
  - Naïve (Mul: 6, Add: 4), Winograd (Mul: 4, Add: 8, Shift: 2)

$$F(2,3) = \begin{bmatrix} d_0 & d_1 & d_2 \\ d_1 & d_2 & d_3 \end{bmatrix} \begin{bmatrix} g_0 \\ g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} m_1 + m_2 + m_3 \\ m_2 - m_3 - m_4 \end{bmatrix}$$

$$m_1 = (d_0 - d_2) g_0 \qquad m_2 = (d_1 + d_2) \frac{g_0 + g_1 + g_2}{2}$$

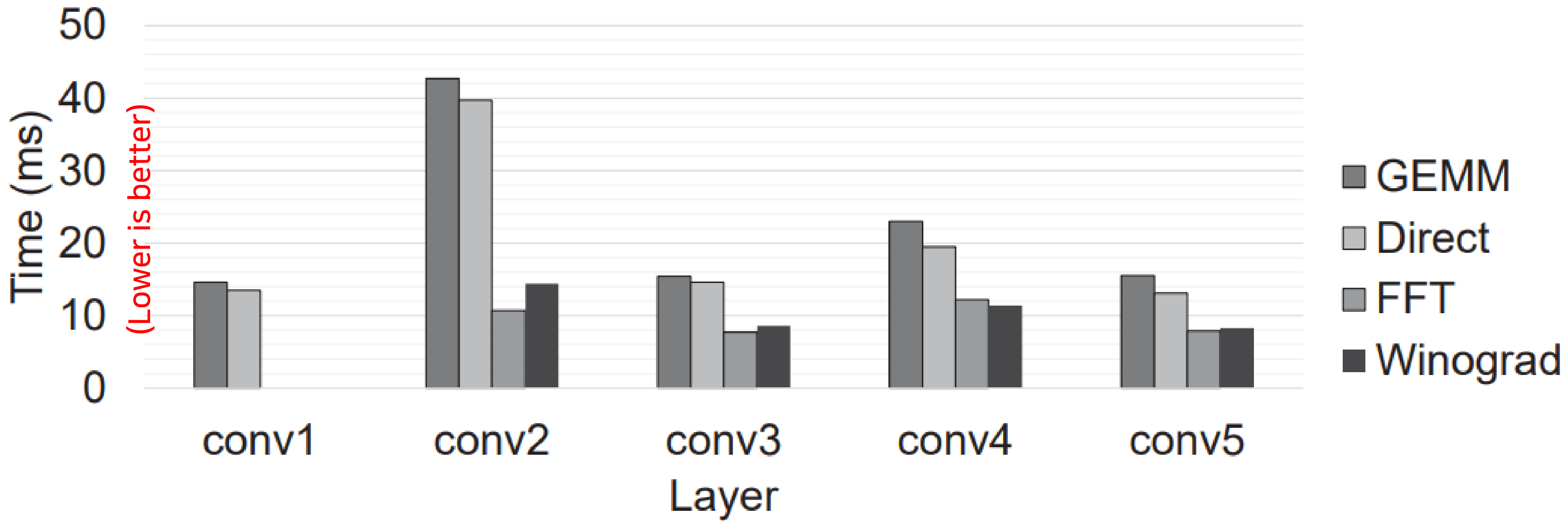
$$m_4 = (d_1 - d_3) g_2 \qquad m_3 = (d_2 - d_1) \frac{g_0 - g_1 + g_2}{2}$$

Equation of Winograd matrix multiplication

[4] Fast Algorithms for Convolutional Neural Networks , A. Lavin, https://arxiv.org/pdf/1509.09308.pdf

Key contribution: Why selection ?

- **Different optimal primitives in each layer[5]**
  - Optimal primitives depending on device, layer type
  - Heuristic primitive selection running neural network in cuDNN

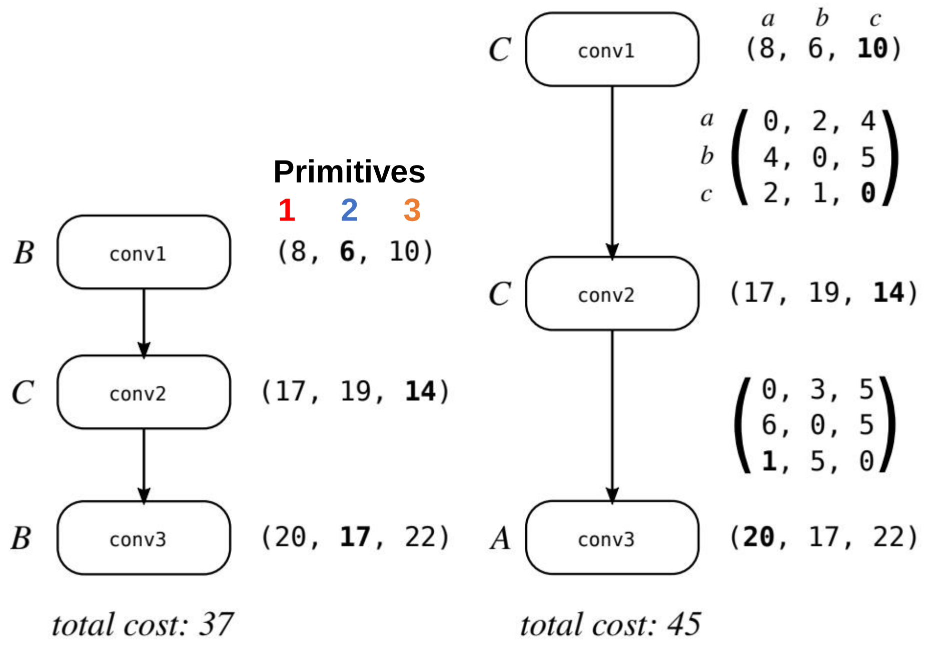


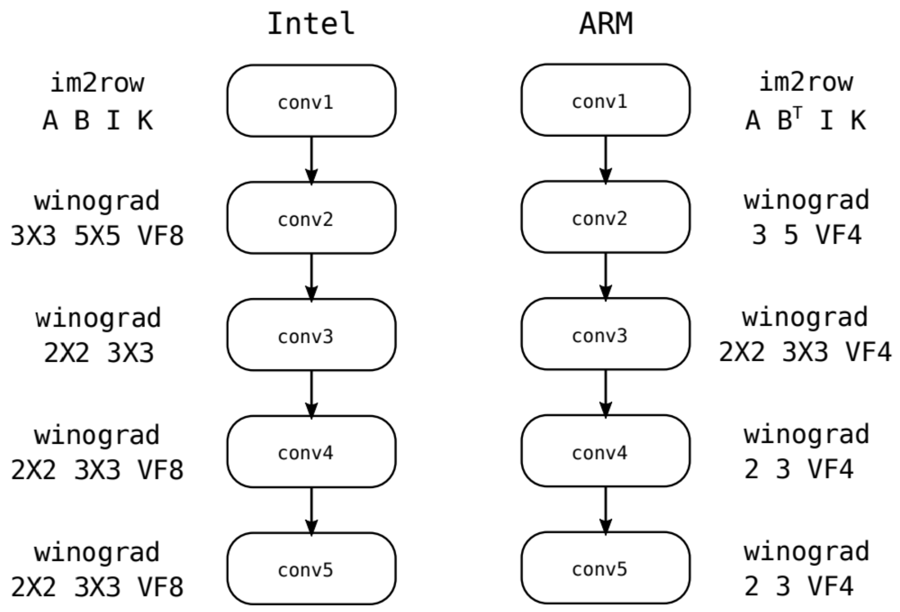
Optimal primitives in AlexNet

[5] Performance Analysis of CNN Frameworks for GPUs, J. Lee, et.al., *IEEE ISPASS*, 2017

Key contribution: Primitive selection

- **Select the primitive with the lowest cost (Latency)**
  - Set **the target device** and choose **the lowest cost primitive**
  - **Pre-computed cost affected by C, H, W, δ, K, M**
  - <u>Cost incurred between primitives</u> using Partitioned Boolean Quadratic Programming (PBQP)
  - **Ex) data format conversion between primitives**





Performance: Intel Haswell

Network	SUM2D	L.OPT	PBQP	CAFFE
(S) AlexNet	711.75	231.75	100	419.565
(S) GoogleNet	1401	465.25	249	1267.07
(M) AlexNet	712.25	186	44.25	286.518
(M) GoogleNet	1400.25	261.5	123.5	919.196

- **PBQP-solver on x86 device**
  - Primitive selection on Caffe v1.0
  - **BLAS: OpenBLAS, MKL-DNN**
  - **Single thread (MKL-DNN is Slightly better in AlexNet,GoogLeNet, not in VGG)**
  - **Multi thread (PBQP is always best)**

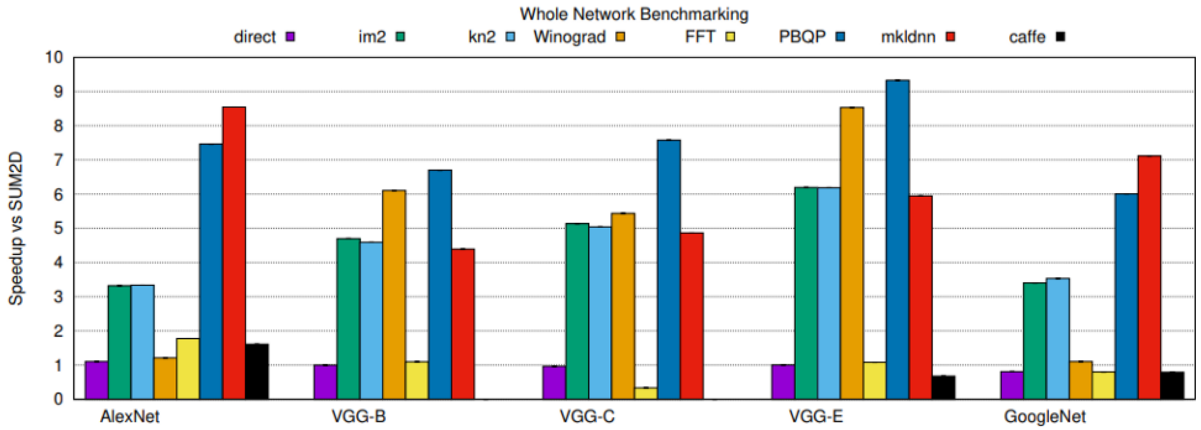


Figure 5. Single-Threaded: Comparison of approaches with PBQP selection on **Intel Haswell**

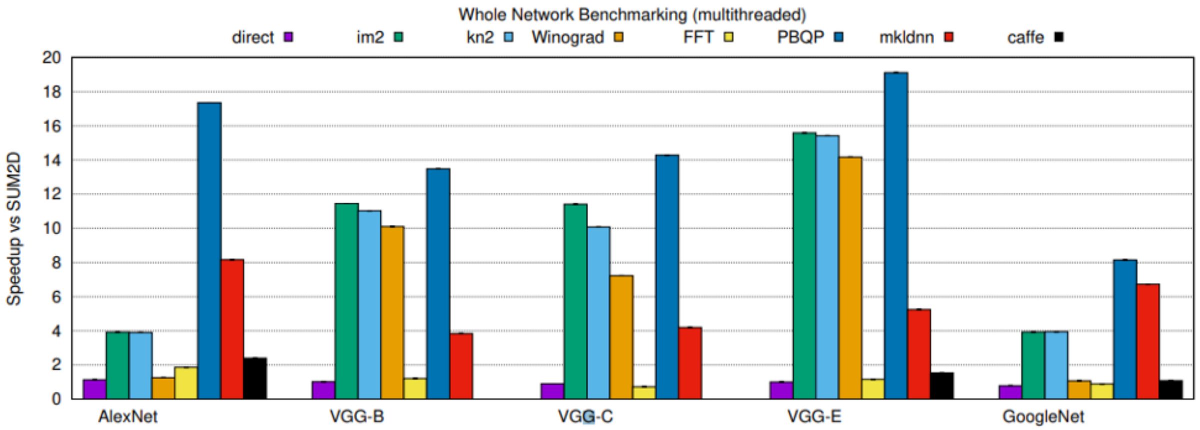
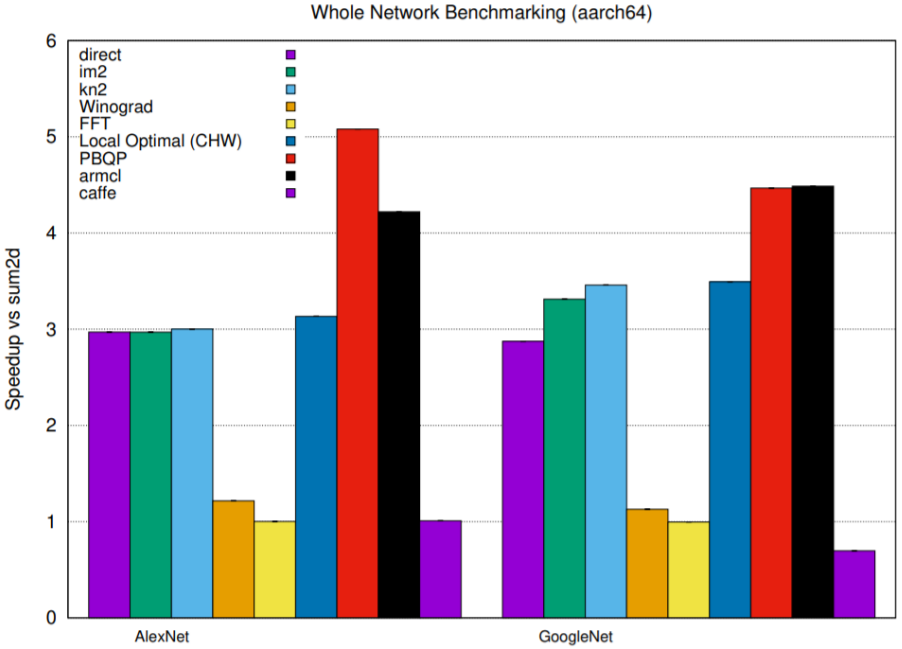


Figure 6. Multi-Threaded: Comparison of approaches with PBQP selection on **Intel Haswell**

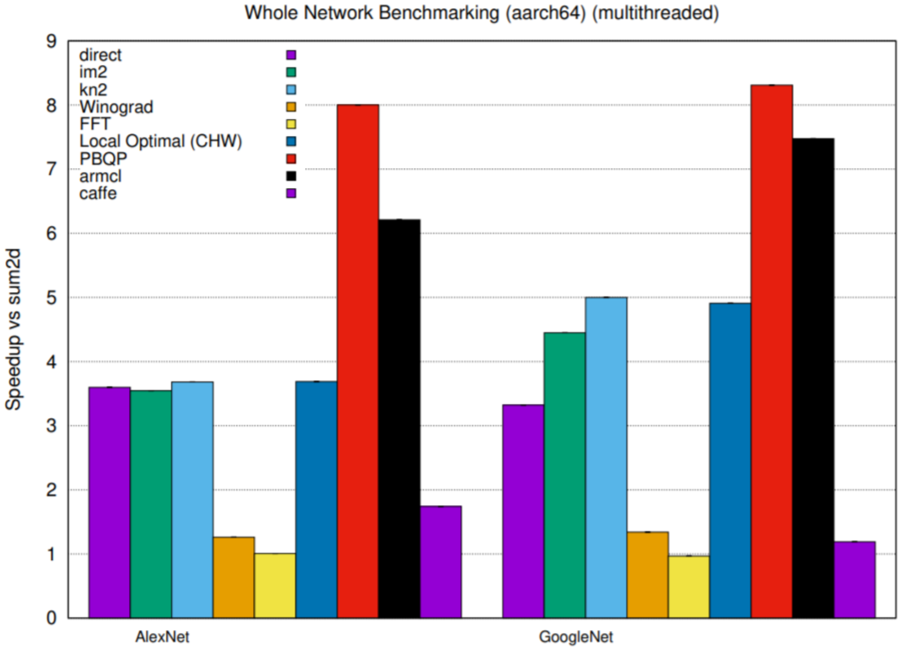
Performance: ARM Cortex-A57

- **PBQP-solver on ARM device**
  - Primitive selection on Caffe v1.0
  - BLAS: OpenBLAS, ARM's ComputeLibrary

Network	SUM2D	L.OPT	PBQP	CAFFE
(S) AlexNet	2369.5	744.25	461	2341.09
(S) GoogleNet	4544.75	1695.25	1025	5782.4
(M) AlexNet	2432.5	639.25	294	1342.62
(M) GoogleNet	4509.75	919.25	547.5	3707.91



(a) Single-Threaded Comparison of approaches with PBQP selection on **ARM Cortex-A57**



(b) Multi-Threaded Comparison of approaches with PBQP selection on **ARM Cortex-A57**

Conclusion and Discussion

- **Extremely effective to select the optimal primitives**
  - However, it is effective only pre-computed device
  - Similar concept (cuDNN, Tensorflow XLA)

Conclusion and Discussion: cuDNN

- **Don't trust the primitive selection in cuDNN**
  - cuDNN finds the most optimal primitive while the convolution is calculated
  - If the latency is odd, check the primitive !

4.78. cudnnGetConvolutionBackwardDataAlgorithm

```
cudnnStatus_t cudnnGetConvolutionBackwardDataAlgorithm(
    cudnnHandle_t                       handle,
    const cudnnFilterDescriptor_t       wDesc,
    const cudnnTensorDescriptor_t       dyDesc,
    const cudnnConvolutionDescriptor_t  convDesc,
    const cudnnTensorDescriptor_t       dxDesc,
    cudnnConvolutionBwdDataPreference_t preference,
    size_t                              memoryLimitInByte
    cudnnConvolutionBwdDataAlgo_t      *algo)
```

This function serves as a heuristic for obtaining the best suited algorithm f
given layer specifications. Based on the input preference, this function wi
fastest algorithm within a given memory limit. For an exhaustive search fo
`cudnnFindConvolutionBackwardDataAlgorithm`.

For the following terms, the short-form versions shown in the paranthesis are used in the table below, for brevity:

- CUDNN_CONVOLUTION_FWD_ALGO_IMPLICIT_GEMM (**_IMPLICIT_GEMM**)
- CUDNN_CONVOLUTION_FWD_ALGO_IMPLICIT_PRECOMP_GEMM (**_IMPLICIT_PRECOMP_GEMM**)
- CUDNN_CONVOLUTION_FWD_ALGO_GEMM (**_GEMM**)
- CUDNN_CONVOLUTION_FWD_ALGO_DIRECT (**_DIRECT**)
- CUDNN_CONVOLUTION_FWD_ALGO_FFT (**_FFT**)
- CUDNN_CONVOLUTION_FWD_ALGO_FFT_TILING (**_FFT_TILING**)
- CUDNN_CONVOLUTION_FWD_ALGO_WINOGRAD (**_WINOGRAD**)
- CUDNN_CONVOLUTION_FWD_ALGO_WINOGRAD_NONFUSED (**_WINOGRAD_NONFUSED**)
- CUDNN_TENSOR_NCHW (**_NCHW**)
- CUDNN_TENSOR_NHWC (**_NHWC**)
- CUDNN_TENSOR_NCHW_VECT_C (**_NCHW_VECT_C**)

Thank you