AOC 2025 Final Project

Team 1 : Cache Me If You Can

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Main Purpose And Motivation

本研究的主要目的是在執行卷積神經網路（CNN）推論時，優化系統的能源效率。隨著深度學習模型在邊緣裝置與嵌入式系統中的應用越來越普遍，能源消耗成為一個關鍵課題。根據 ESL 的資料指出，DRAM 存取最多可佔系統總能耗的 70%，因此，如何有效減少資料移動，並選用一個適合實作且修改過的模型放在 Eyeriss 硬體上運行，最終選擇 Mobilenet v1 去改良，去檢測是否符合我們預期結果。成為提升能效的首要任務。

本研究針對此問題提出三大優化策略：

- 最小化資料移動：減少對 DRAM 和全域快取的讀寫次數，降低能量消耗。
- 強化資料重用：在處理單元（Processing Elements）內部實現最大化的資料重用，進一步節省功耗。
- 資料壓縮：運用如游程編碼（Run-Length Coding）與跳過零值的運算（Zero Skipping）等技巧，減少不必要的運算與資料傳輸。

這些方法能夠協助提升 CNN 推論在硬體上的能源效率，延長裝置使用壽命、減少熱功耗、並推動 AI 系統朝向低功耗、高效能的方向發展。

Model Comparison Table

Model	Params	FLOPs	Accuracy	Operators	DRAM Access Optimization
MobileNet	3.5M	334.22M (thop)	(ImageNet) top1=69.48% top5=89.26%	Conv, BN, ReLU6, InvertedResidual	**High:** Low params, high sparsity, but layer shape variation reduces reuse on original Eyeriss. DRAM access ~1-3 MB on v2 with CSC compression.
SqueezeNet	1.2M	349M (MACs)	(ImageNet) top1=57.5% top5=80.3%	Conv, ReLU, MaxPool, AvgPool, Concat, Reshape	**Moderate:** Very low params, fits global buffer (108 kB), but lower reuse due to fire modules. DRAM access ~2-4 MB after pruning.
-	-	-	-	-	--
ResNet50	25.6M	~7.7G (MACs)	(ImageNet) top1=76.15% top5=92.87%	Conv, BN, ReLU, Add, MaxPool	**High:** Stable layer shapes, high data reuse with 3x3 filters, moderate params. Pruned ResNet50 achieves ~3-5 MB DRAM access. Versatile and hardware-friendly.
VGG16	138M	~30.9G (MACs)	(ImageNet) top1=71.59% top5=90.38%	Conv, ReLU, MaxPool	**Low:** High params (528 MB), exceeds global buffer, high DRAM access (~5-10 MB even after pruning). Stable layers but not memory-efficient.
EfficientNet B0	5.3M	~0.78G (MACs)	(ImageNet) top1=77.1% top5=93.3%	Conv, BN, Swish, MBConv	**High:** Low params, high sparsity, but MBConv layer shape variation impacts original Eyeriss. DRAM access ~2-4 MB on v2.
InceptionV3	23.8M	~5.7G (MACs)	(ImageNet) top1=77.9% top5=93.7%	Conv, BN, ReLU, Concat, MaxPool	**Moderate:** High reuse with multi-size filters, but layer shape variation increases DRAM access (~3-6 MB on v2).
DenseNet121	8M	~5.7G (MACs)	(ImageNet) top1=74.98% top5=92.21%	Conv, BN, ReLU, Concat, MaxPool	**High:** Low params, stable layers, high reuse via dense connections. DRAM access ~2-5 MB after pruning.
ConvNeXt Tiny	28.6M	~8.7G (MACs)	(ImageNet) top1=82.1% top5=95.8%	Conv, LayerNorm, GELU, MaxPool	**High:** High reuse with 7x7 filters, stable layers. DRAM access ~3-6 MB. Good for original Eyeriss.

> [!Warning] Why not choose SqueezeNet SqueezeNet **may not easy** to implement in >Eyeriss(mapping parameter).

Software

AI Model Design and Quantization

file path：`Performance_Modeling/mobilenetv1-cifar10.ipynb`

you can run **mobilenetv1-cifar10.ipynb** with kaggle or colab.

Model Choosing : Modified **Mobilenet_v1** with cifar10 dataset

```
import torch
import torch.nn as nn
import torch.ao.quantization as tq

class DepthwiseSeparableConv(nn.Module):
```

```python
    """Depthwise Separable Convolution Block: Depthwise Conv2d + Pointwise Conv2d"""
    def __init__(self, in_channels, out_channels, stride=1):
        super().__init__()
        # Depthwise Convolution (3x3, groups=in_channels)
        self.depthwise = nn.Sequential(
            nn.Conv2d(
                in_channels, in_channels, kernel_size=3, stride=stride, padding=1,
                groups=in_channels, bias=False
            ),
            nn.BatchNorm2d(in_channels),
            nn.ReLU(inplace=True)
        )
        # Pointwise Convolution (1x1)
        self.pointwise = nn.Sequential(
            nn.Conv2d(
                in_channels, out_channels, kernel_size=1, stride=1, padding=0, bias=False
            ),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(inplace=True)
        )

    def forward(self, x):
        x = self.depthwise(x)
        x = self.pointwise(x)
        return x

    def fuse_modules(self):
        """Fuse Conv2d, BatchNorm2d, and ReLU for quantization"""
        tq.fuse_modules(self.depthwise, ['0', '1', '2'], inplace=True)
        tq.fuse_modules(self.pointwise, ['0', '1', '2'], inplace=True)

class MobileNetV1(nn.Module):
    """MobileNetV1 adapted for CIFAR-10 with final output 2x2x1024 → 1x1x1024"""
    def __init__(self, in_channels=3, in_size=32, num_classes=10):
        super().__init__()

        # Initial Conv2d layer
        self.conv1 = nn.Sequential(
            nn.Conv2d(in_channels, 32, kernel_size=3, stride=1, padding=1, bias=False),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True)
        )

        # Depthwise Separable Convolution layers
        self.layers = nn.Sequential(
            DepthwiseSeparableConv(32, 64, stride=1),    # 32x32x64
            DepthwiseSeparableConv(64, 128, stride=2),   # 16x16x128
            DepthwiseSeparableConv(128, 128, stride=1),  # 16x16x128
            DepthwiseSeparableConv(128, 256, stride=2),  # 8x8x256
            DepthwiseSeparableConv(256, 256, stride=1),  # 8x8x256
            DepthwiseSeparableConv(256, 512, stride=2),  # 4x4x512
            DepthwiseSeparableConv(512, 512, stride=1),  # 4x4x512
            DepthwiseSeparableConv(512, 1024, stride=2), # 2x2x1024
        )

        # Global average pooling and fully connected layers
        self.avgpool = nn.AdaptiveAvgPool2d(1)  # 2x2x1024 → 1x1x1024
        self.fc = nn.Linear(1024, num_classes)  # 1024 → 10

    def forward(self, x):
        x = self.conv1(x)
        x = self.layers(x)
        x = self.avgpool(x)                     # 2x2x1024 → 1x1x1024
        x = torch.flatten(x, start_dim=1)       # 1x1x1024 → 1024
        x = self.fc(x)                          # 1024 → 10
        return x

    def fuse_modules(self):
        """Fuse Conv2d, BatchNorm2d, and ReLU for quantization"""
        self.conv1.eval()
        tq.fuse_modules(self.conv1, ['0', '1', '2'], inplace=True)
        for layer in self.layers:
            layer.eval()
            layer.fuse_modules()
        self.eval()

if __name__ == "__main__":
    model = MobileNetV1()
    inputs = torch.randn(1, 3, 32, 32)
    print(model)
```

```
from torchsummary import summary
summary(model, (3, 32, 32), device="cpu")
```

for quantized model, model acheive the following metrics:

- **top-1 accuracy on CIFAR-10 $\ge$ 80% (OK)**
- **accuracy drop $\le$ 1% compared to your full-precision model (OK)**

Workload Analysis

- Similar to environments in Lab2

1. Create and activate virtual environment

```
conda create -n aoc python=3.10 -y
conda activate aoc
```

2.Install packages

```
cd Performance_Modeling
pip install -r requirements.txt
```

FP32 - mobilenetv1.pt

file path： `Performance_Modeling/weights/mobilenetv1.pt`

```
python3 profiling.py weights/mobilenetv1.pt
```

- **accuracy=0.8733** , Model size : 4.40 MB

```
(aoc) f74106092@user:~/profiling_test$ python3 profiling.py weights/mobilenetv1.pt
Model does not have 'fuse_modules' method. Skipping fusion.
Model loaded from weights/mobilenetv1.pt (3.379794 MB)
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
                           Name    Self CPU %      Self CPU   CPU total %     CPU total  CPU time avg       CPU Mem  Self CPU Mem    # of Calls  Total KFLOPs
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
                model_inference        18.72%       1.850ms       100.00%       9.884ms       9.884ms           0 b      -2.71 Mb             1            --
                   aten::conv2d         0.70%      69.096us        63.04%       6.231ms     366.550us       1.33 Mb           0 b            17     54386.688
              aten::convolution         1.50%     147.832us        62.34%       6.162ms     362.486us       1.33 Mb           0 b            17            --
             aten::_convolution         1.28%     126.645us        60.85%       6.014ms     353.790us       1.33 Mb           0 b            17            --
       aten::mkldnn_convolution        37.77%       3.734ms        38.54%       3.809ms     380.888us     880.00 Kb           0 b            10            --
              aten::thnn_conv2d         0.21%      20.557us        20.82%       2.057ms     293.919us     480.00 Kb           0 b             7            --
     aten::_slow_conv2d_forward        20.02%       1.978ms        20.61%       2.037ms     290.982us     480.00 Kb    -108.00 Kb             7            --
               aten::batch_norm         0.36%      36.011us        12.04%       1.190ms      70.020us       1.36 Mb           0 b            17            --
   aten::_batch_norm_impl_index         0.76%      74.695us        11.68%       1.154ms      67.902us       1.36 Mb           0 b            17            --
        aten::native_batch_norm         9.46%     935.079us        10.80%       1.068ms      62.821us       1.36 Mb     -66.75 Kb            17            --
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
Self CPU time total: 9.884ms
```

INT8 - mobilenetv1-power2.pt

file path： `Performance_Modelin/Profiling_Results/weights/mobilenetv1-power2.pt`

```
python3 profiling.py weights/mobilenetv1-power2.pt -b power2
```

- **accuracy=0.8694** , Model size : 1.117842MB

```
(aoc) f74106092@user:~/profiling_test$ python3 profiling.py weights/mobilenetv1-power2.pt -b power2
Fusing modules
/home2/aoc2025/f74106092/miniconda3/envs/aoc/lib/python3.10/site-packages/torch/_utils.py:410: UserWarning: TypedStorage is deprecated. It will be removed in the future and Un
typedStorage will be the only storage class. This should only matter to you if you are using storages directly.  To access UntypedStorage directly, use tensor.untyped_storage(
) instead of tensor.storage()
  device=storage.device,
Model loaded from weights/mobilenetv1-power2.pt (0.86389 MB)
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
                           Name    Self CPU %      Self CPU   CPU total %     CPU total  CPU time avg       CPU Mem  Self CPU Mem    # of Calls
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
                model_inference        48.25%      35.662ms       100.00%      73.910ms      73.910ms           0 b    -347.05 Kb             1
         quantized::conv2d_relu        20.53%      15.172ms        29.18%      21.567ms       1.269ms     340.00 Kb      -1.33 Mb            17
              quantized::linear        18.74%      13.850ms        18.76%      13.868ms      13.868ms          10 b         -40 b             1
                    aten::clone         8.53%       6.305ms         8.55%       6.318ms       3.159ms       5.00 Kb           0 b             2
               aten::contiguous         0.01%       4.518us         8.54%       6.309ms       6.309ms       3.00 Kb           0 b             1
                  aten::flatten         0.02%      12.824us         3.61%       2.668ms       2.668ms       2.00 Kb           0 b             1
             aten::_unsafe_view         3.57%       2.641ms         3.57%       2.641ms       2.641ms           0 b           0 b             1
       aten::quantize_per_tensor         0.10%      75.025us         0.10%      75.025us      75.025us       3.00 Kb       3.00 Kb             1
     aten::_empty_affine_quantized         0.09%      65.184us         0.09%      65.184us       3.104us     347.00 Kb     347.00 Kb            21
                    aten::empty         0.04%      31.823us         0.04%      31.823us       1.675us       1.33 Mb       1.33 Mb            19
-------------------------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------  ------------
Self CPU time total: 73.910ms
```

Analytical Model – mapping parameters

Conv2D Shape Parameter

Parameter	Description
N	batch size
H/W	input height/width
R/S	filter height/width
E/F	output height/width
C	input channels
M	output channels
U	stride
P	padding

RS Dataflow Mapping Parameter

Parameter	Description
m	number of ofmap channels stored in the global buffer
n	number of ofmaps/ifmaps used in a processing pass
e	width of the PE set (strip-mined if nessary)
p	number of filters processed by a PE set
q	number of ifmap/filter channels processed by a PE set
r	number of PE sets for different ifmap/filter channels
t	number of PE sets for different filters

Eyeriss Mapping Result

We use the following mapping result to generate the verification test data for the subsequent testbench.

```
cd Performance_Modeling
python3 main.py ./weights/mobilenetv1-power2.pt
```

CONV.csv

layer	glb_usage	glb_read	glb_write	glb_access	dram_read	dram_write	dram_access	macs	latency	energy_per_layer
mobilenetv1.conv0	33976	150400	163840	314240	7808	32768	40576	884736	240608	13.087224
mobilenetv1.conv1	34472	1462528	1114112	2576640	69888	65536	135424	2686976	1523136	58.60593599999999
mobilenetv1.conv2	35240	2265344	1081344	3346688	110848	32768	143616	2392064	1885632	67.44561599999999
mobilenetv1.conv3	33704	2955776	2129920	5085696	121344	32768	154112	4489216	2768256	91.34985599999999
mobilenetv1.conv4	34088	2298112	1064960	3363072	106752	16384	123136	2244608	1851840	63.210096
mobilenetv1.conv5	33320	3021312	2113536	5134848	162304	16384	178688	4341760	2807168	96.47139199999998
mobilenetv1.conv6	33512	2363648	1056768	3420416	153856	8192	162048	2170880	1920960	71.43575999999997
mobilenetv1.conv7	33128	3152384	2105344	5257728	281088	8192	289280	4268032	2998656	119.71900799999999
mobilenetv1.conv8	16808	2236928	1052672	3289600	543232	4096	547328	2134016	2333056	147.212896

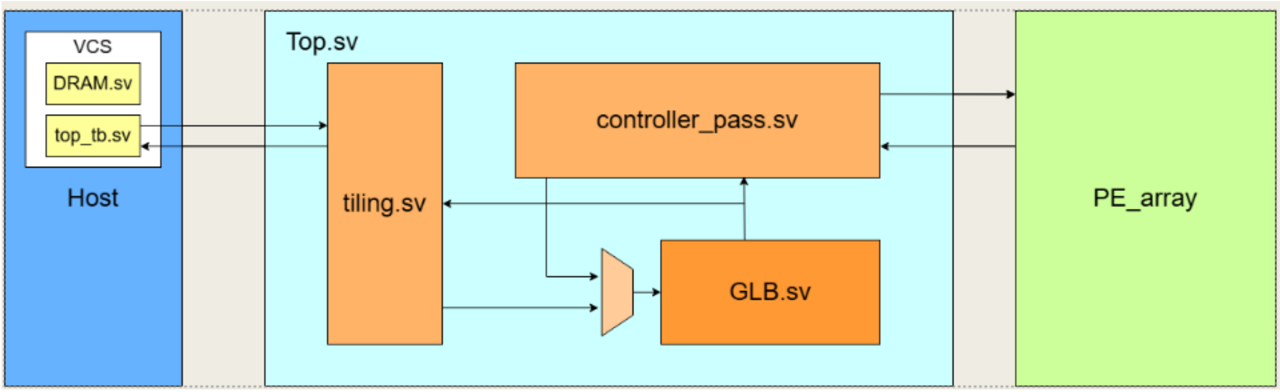
> [!Warning] Because the algorithm for the first 3x3 convolution in the first layer of eyeriss.py is different from the depthwise separable convolution, it has been recalculated separately.

FC_layer.csv

layer	glb_usage	glb_read	glb_write	glb_access	dram_read	dram_write	dram_access	macs	latency	energy_per_layer	power_per
FC_layer0	4456	1334032	177152	1511184	1070184	1024	1071208	10240	2094652	229.89758299999997	21950.9095

Hardware

Overall architecture



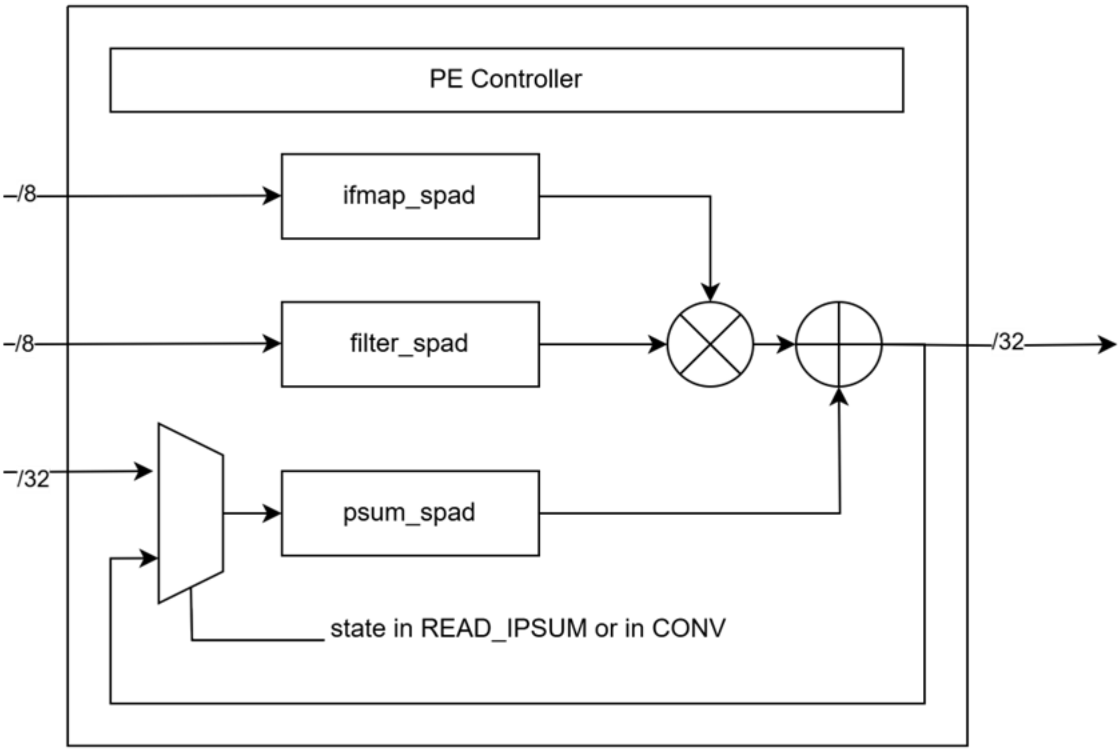
PE config modification

9	8	7	6	5	4	3	2	1	0
mode	p-1		F-1					q-1	

12	11	10	9	8	7	6	5	4	3	2	1	0
depthwise	FILTER_RS - 1		U - 1	p-1		F-1					q-1	

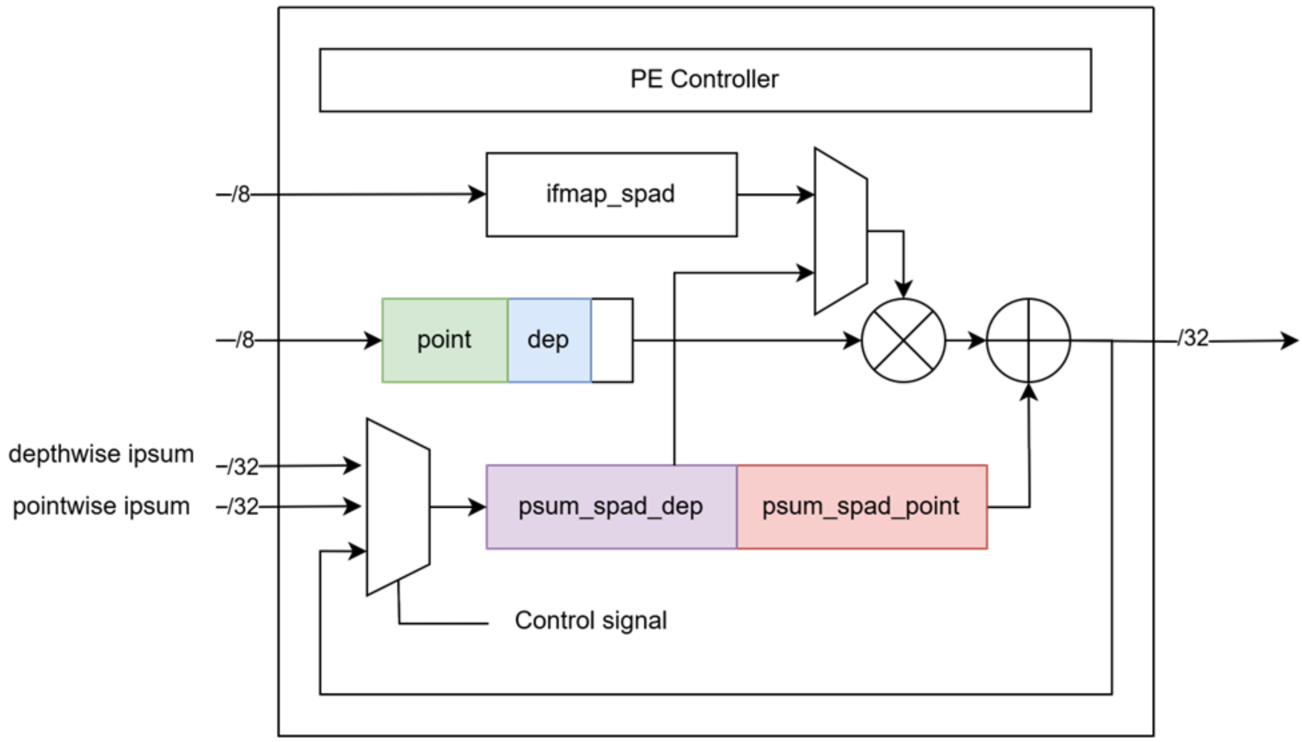
為了支援MobileNet depthwise separable convolution 多了`depthwise`, `FILTER_RS-1`為可以支援kernel size from 1 to 3，將`mode`改為`U-1`用以支援stride = 1 or 2。

PE (Process Element)



與Lab3大部分相同，但因應上面config改變，多了一些控制邏輯。

SUPER (Super Ultra Processing Element RRR bon wo kai stream)



`filter_spad`可以同時存放pointwise filter與depthwise filter，進行depthwise convolution時會將depthwise psum存進`psum_spad`上半部，再以depthiwse psum作為pointwise psum 的 ifmap 與 pointwise filter 相乘得到depthwise separable convolution 結果。

Formula deduction

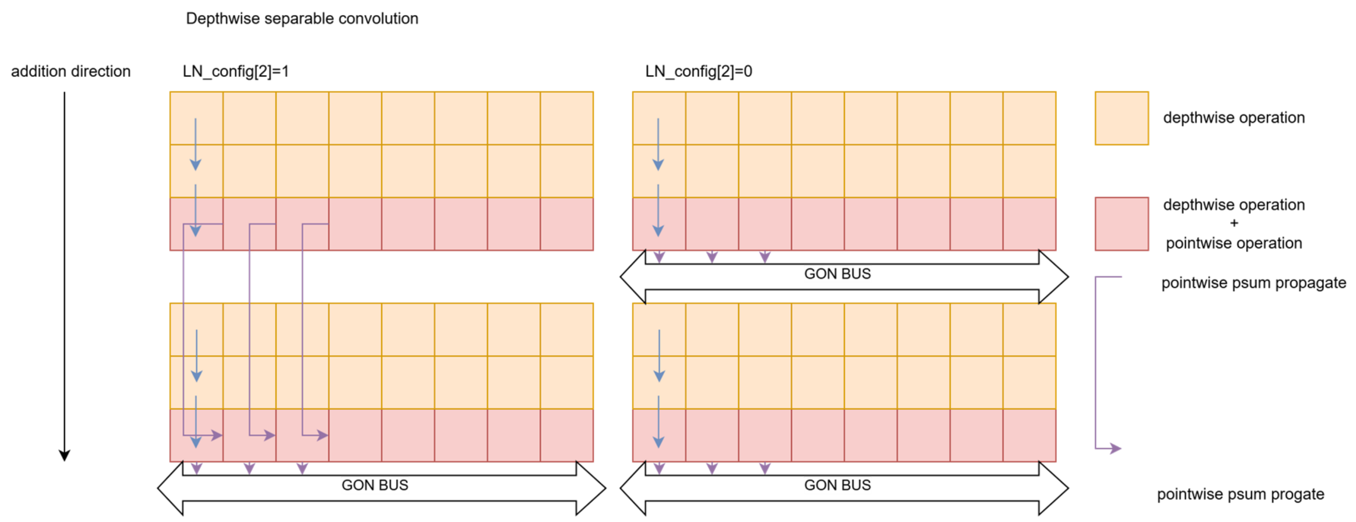
$$y_{m,e,f} = b_m^{\text{pointwise}} + \sum_c \left(b_c^{\text{depthwise}} + \sum_r \sum_s x_{c,\,Ue+r,\,Uf+s} \cdot w^T_{m,\,c,\,r,\,s} \right) \cdot w^{\text{pointwise}}_{m,c}$$

$$\text{assume } s_w \text{of depthiwse and pointwise same}$$

$$\begin{aligned}
s_y(\bar{y}_{m,e,f} - 128) &= s_x s_w \bar{b}_m^{\text{pointwise}} + \sum_c \left(s_x s_w \bar{b}_c^{\text{depthwise}} + \sum_r \sum_s s_x(\bar{x}_{c,\,Ue+r,\,Uf+s} - 128) \cdot s_w \bar{w}^T_{m,\,c,\,r,\,s} \right) \cdot s_w \bar{w}^{\text{pointwise}}_{m,c} \\
&= s_x s_w \bar{b}_m^{\text{pointwise}} + s_x s_w \sum_c \left(\bar{b}_c^{\text{depthwise}} + \sum_r \sum_s (\bar{x}_{c,\,Ue+r,\,Uf+s} - 128) \cdot \bar{w}^T_{m,\,c,\,r,\,s} \right) s_w \bar{w}^{\text{pointwise}}_{m,c} \\
&= s_x s_w \left(\bar{b}_m^{\text{pointwise}} + s_w \sum_c \left(\bar{b}_c^{\text{depthwise}} + \sum_r \sum_s (\bar{x}_{c,\,Ue+r,\,Uf+s} - 128) \cdot \bar{w}^T_{m,\,c,\,r,\,s} \right) \bar{w}^{\text{pointwise}}_{m,c} \right) \\
\bar{y}_{m,e,f} &= \frac{s_x s_w}{s_y} \left(\bar{b}_m^{\text{pointwise}} + s_w \sum_c \left(\bar{b}_c^{\text{depthwise}} + \sum_r \sum_s (\bar{x}_{c,\,Ue+r,\,Uf+s} - 128) \cdot \bar{w}^T_{m,\,c,\,r,\,s} \right) \bar{w}^{\text{pointwise}}_{m,c} \right) + 128 \\
\text{assume bias} &= 0 \\
\bar{y}_{m,e,f} &= \text{clamp}\left(\frac{s_x s_w^2}{s_y} \left(\sum_c \sum_r \sum_s (\bar{x}_{c,\,Ue+r,\,Uf+s} - 128) \cdot \bar{w}^T_{m,\,c,\,r,\,s} \bar{w}^{\text{pointwise}}_{m,c} \right) + 128,\ 0,\ 255 \right)
\end{aligned}$$

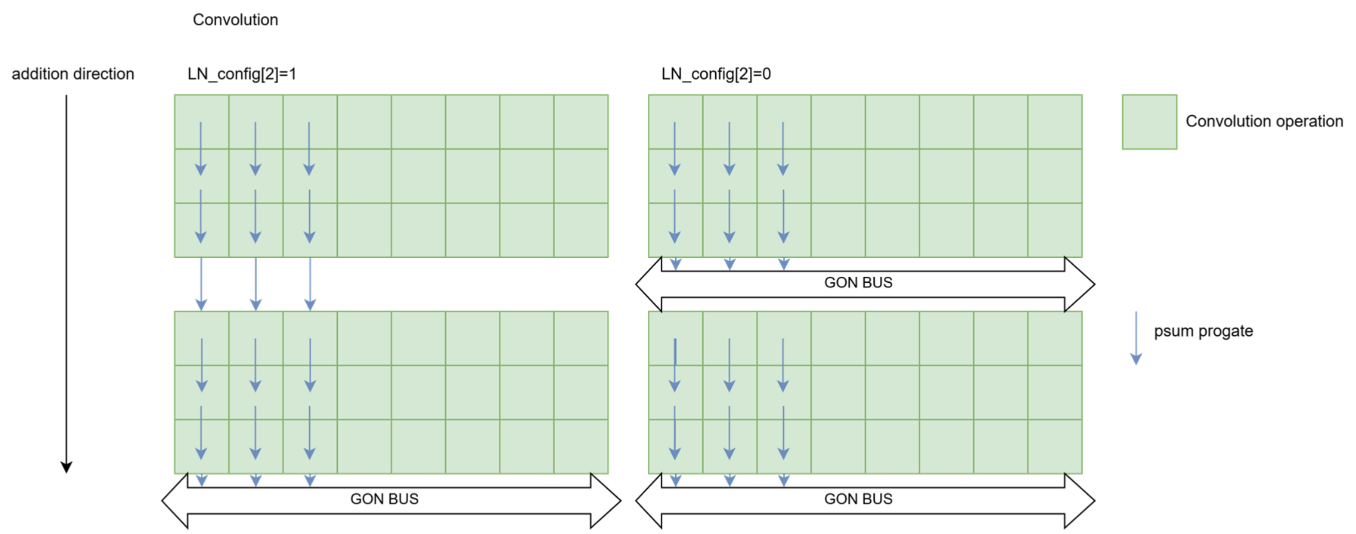
由上式得出可以直接將depthiwse 結果直接做pointwise 結果。

Depthwise separable convolution



最後一排depthwise的row會變成由SUPER 組成的row，做最後的結果，若LN_config[2]=1，就會將SUPER 相接。

Normal convolution



SUPER也可以執行一般convolution，此時整個PE array行為就會與原本一樣。 這樣的好處可以將一次depthwise separable convolution在一次pass中做完，不用做一次depthwise後存入glb再做pointwise才得到結果，壞處是需要更大的乘法器。

Controller for one pass

Controller_pass 負責協調 Eyeriss PE array 與 Global Buffer（GLB）間的資料傳輸，控制整個卷積運算中一個 pass 的資料流程，並根據參數設定啟動資料載入、PE 配置、卷積輸入與結果寫回等操作。以下為模組的主要功能說明與架構解析：

1. **I/O port definition**

- interface to Top module

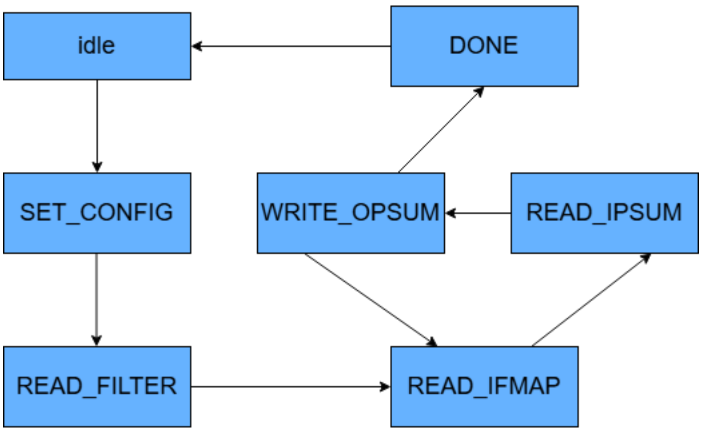
Name	I/O	Bits	Explanation
start	Input	1	start signal
bias_ipsum_sel	Input	1	select which ipsum in this pass is used, bias or ipsum
op_config	Input	32	ctrl register define in lab4
mapping_param	Input	32	ctrl register define in lab4
shape_param1	Input	32	ctrl register define in lab4
shape_param2	Input	32	ctrl register define in lab4
filter_baseaddr	Input	32	filter base address in glb
ifmap_baseaddr	Input	32	ifmap base addressin glb
bias_baseaddr	Input	32	bias base addressin glb
opsum_baseaddr	Input	32	opsum base addressin glb
done	Output	1	done signal

- interface to PE array

```
/* same as lab3 */
```

- interface to glb

Name	I/O	Bits	Explanation
glb_we	Output	4	write enable
glb_w_addr	Output	32	write address
glb_w_data	Output	32	write data
glb_re	Output	4	read enable
glb_r_addr	Output	32	read address
glb_r_data	Input	32	read data



2. **State Diagram**

- 當接受到`start` signal時，會從`idle`進入`SET_CONFIG`狀態，開始scan ID給PE array
- Scan configuration完成後，會開始依序read filter, ifmap, ipsum
- 將PE array運算完的opsum寫回GLB中，並重複read ifmap, ipsum
- 直到所有`opsum`都已寫回glb中，跳轉至DONE狀態，此時將`pass_done` signal拉起，告知外界pass已做完，並回至`idle`

3. **PE ID setup and scanning chain**

- 使用 pe_array_id_generator 模組，根據輸入參數（如 p, q, r, t, e 等）計算整體 PE 陣列中的 XID、YID 分布。
- XID 掃描鏈、YID 掃描鏈對應 set_XID、set_YID 訊號，依據掃描順序送入每個 PE。
- LN（Local Neighbors） 設定鏈透過 set_LN 與 LN_config_in 一次性配置。

4. **Tag calculation logic**

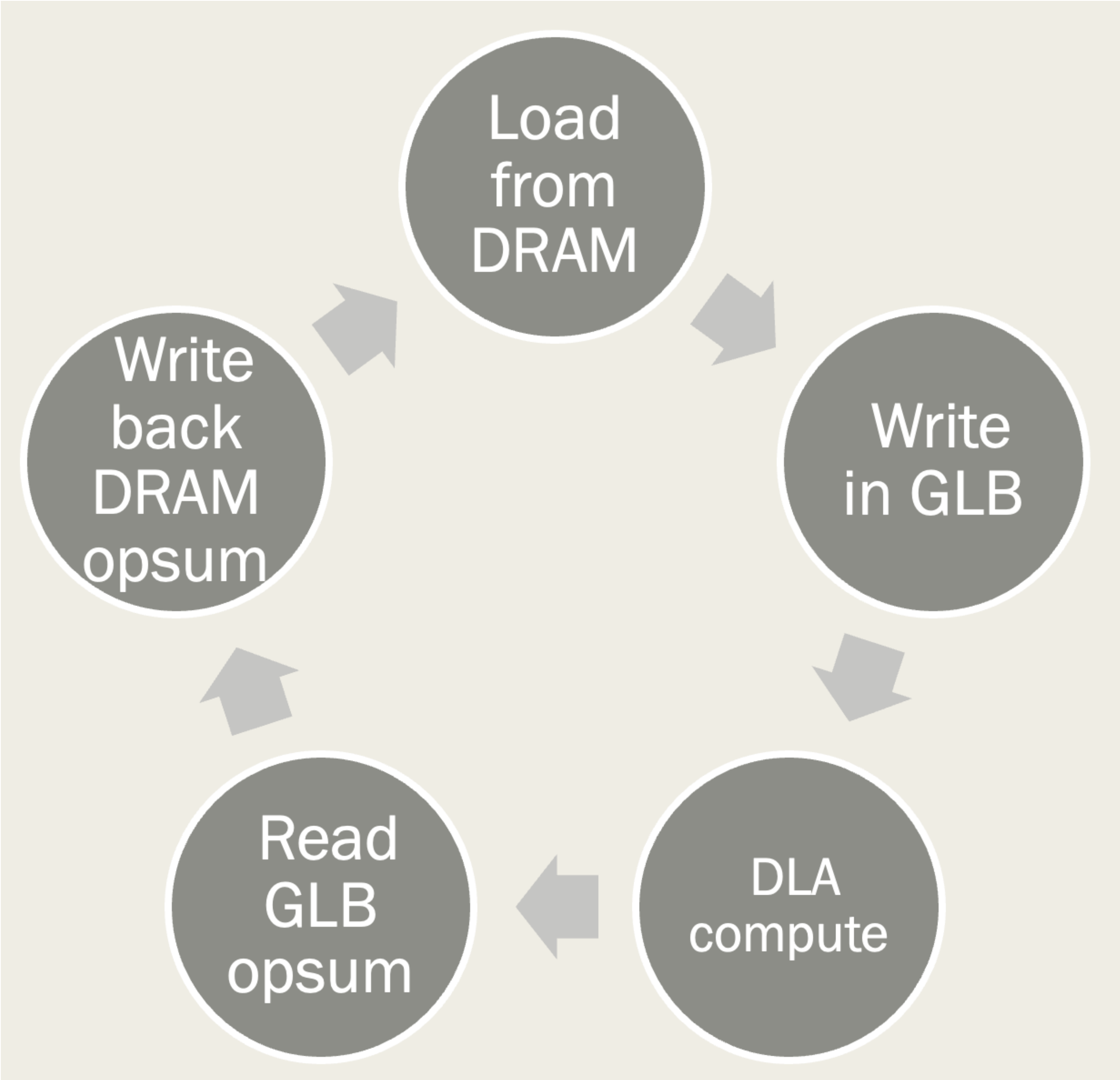
- 參考lab3 PE array的testbench
- 為了處理Stride=2，相比於前者，增加額外的計數器u_ct來計算下次load ifmap的數量和tag位置

5. **Address calculation and glb control**

- 利用各個代表不同dimension的計數器chn_ct, col_ct, row_ct來計算當前read/write的address
- 為了更好模擬現實中的sram，我們將glb設計為read會有一個cycle的delay，以此為基準設計handshake signal

Controller for one layer (tiling)

- 依照 mapping_param、shape_param1、shape_param2 決定從 DRAM 讀取多少資料，並寫入 GLB。
- 支援多種 tile/filter/channel/stride/padding 組合。



參數解析

透過 `mapping_param` 與 `shape_param1`/`shape_param2`，解析出分塊所需的各種參數（如分塊大小、padding、stride、filter 尺寸、channel 數等），並計算出各種資料的實際寬高。

狀態機控制

模組內部以狀態機（state machine）方式運作，主要狀態包含：

1. `IDLE`：等待啟動信號（`start`）。
2. `LOAD_IFMAP_DRAM_R` / `LOAD_IFMAP_GLB_W`：從 DRAM 讀取 ifmap，寫入 GLB。
3. `LOAD_FILTER_DRAM_R` / `LOAD_FILTER_GLB_W`：從 DRAM 讀取 filter，寫入 GLB。
4. `LOAD_BIAS_DRAM_R` / `LOAD_BIAS_GLB_W`：從 DRAM 讀取 bias，寫入 GLB。
5. `WRITE_OPSUM_GLB` / `WRITE_OPSUM_DRAM`：從 GLB 讀取 opsum，寫回 DRAM。
6. `RESET_OPSUM`：重設 GLB 中 opsum 區域爲 0。
7. `FINISH` / `DONE`：流程結束，等待下一次啟動。

地址計算

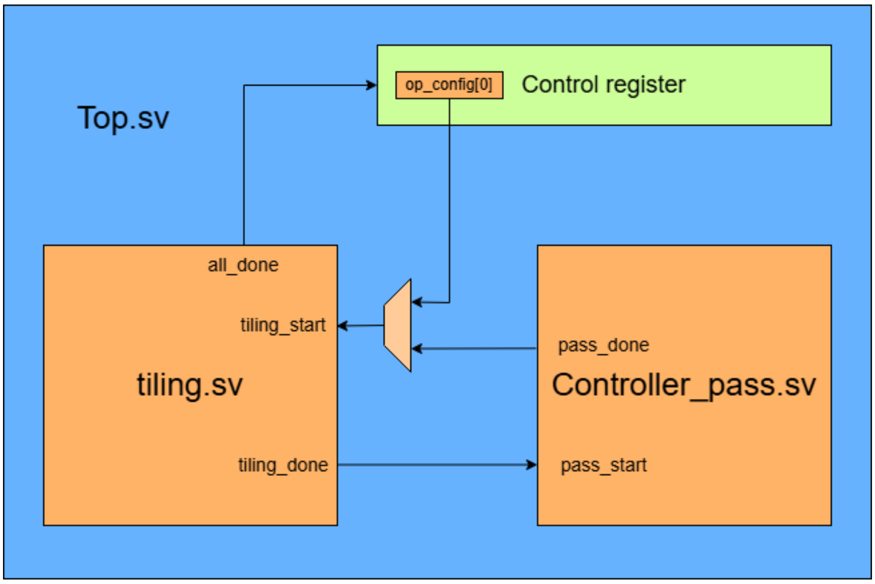
針對 `ifmap`、`filter`、`bias`、`opsum` 等資料，分別設計了對應的地址計算 function，根據分塊參數與 base address 動態產生 DRAM/GLB 的存取位址。

資料搬移流程

1. 依據狀態機流程，依序將 `ifmap`、`filter`、`bias` 由 DRAM 讀取並寫入 GLB。

2. 運算完成後，將 opsum 由 GLB 讀取並寫回 DRAM。
3. 每一階段皆有對應的計數器與條件判斷，確保分塊搬移正確進行。
4. 支援多層次分塊與多次搬移，直到所有資料處理完畢。
5. 流程重啟與結束
6. 當一輪分塊搬移結束後，根據參數判斷是否還有剩餘資料需要處理，若有則重啟流程，否則進入 DONE 狀態。

Control flow



- When the testbench writes `1` to `op_config[0]`, it triggers the DLA to begin operation.
- The `tiling.sv` module detects this start signal and begins transferring data into the GLB.
- Once data movement is complete, `tiling.sv` sends a `tiling_done` signal to notify `Controller_pass.sv` to initiate a computation pass.
- After the pass is completed, `Controller.sv` asserts a `pass_done` signal to inform `tiling.sv`. The `tiling.sv` module then starts writing the partial sums (opsum) back to DRAM and proceeds to load the data for the next pass.
- This alternating sequence continues—data movement followed by computation—until `tiling.sv` detects that there is no more data to load, indicating that the entire layer has been processed.
- At this point, an `all_done` signal is sent to the host to indicate that the DLA has finished processing. Additionally, `op_config[0]` is cleared back to `0` to prevent the DLA from being unintentionally restarted.

Tiling.cpp

使用C/C++驗證moblienet 每個layer 的tiling 邏輯，輸入為整層layer `ifmap.txt`, `filter.txt`, `bias.txt`,將tiling 與運算完結果與`golden.txt`比對，用以驗證tiling邏輯。

TVM

Similar to Lab5.0 : Enviroment Setup

```
conda create -n tvm-lab
conda activate tvm-lab
conda install python=3.11
conda install llvmdev=18 -c conda-forge
```

```
pip3 install torch torchvision --index-url https://download.pytorch.org/whl/cpu
pip3 install onnx
pip3 install graphviz
pip3 install -e /opt/tvm/python
```

1. Codegen with TVM compiler

Enter TVM Folder

```
conda activate tvm-lab
cd TVM
```

Build the model

```
make build_model
```

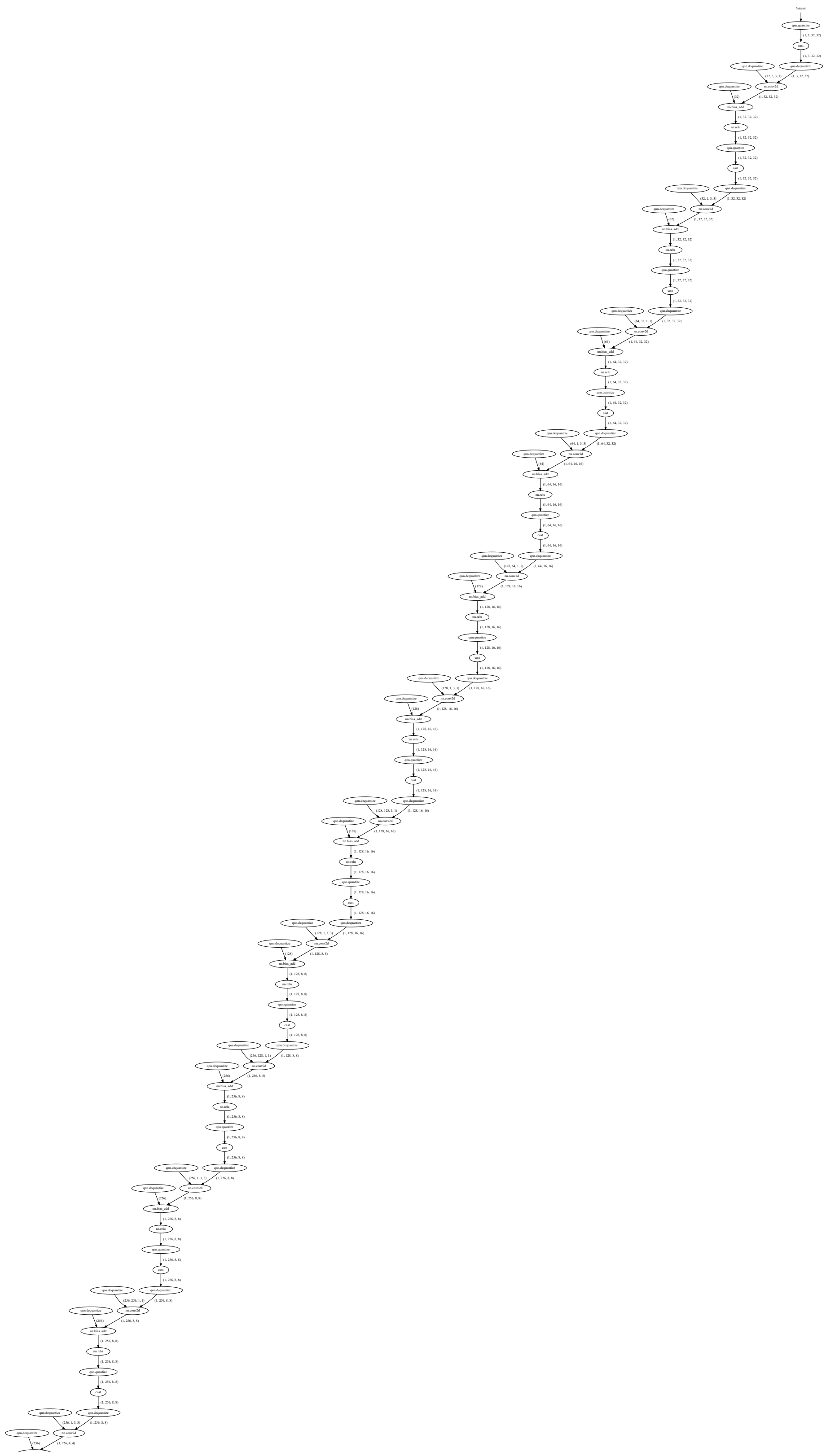
visuTVM: Relay Graph Visualizer

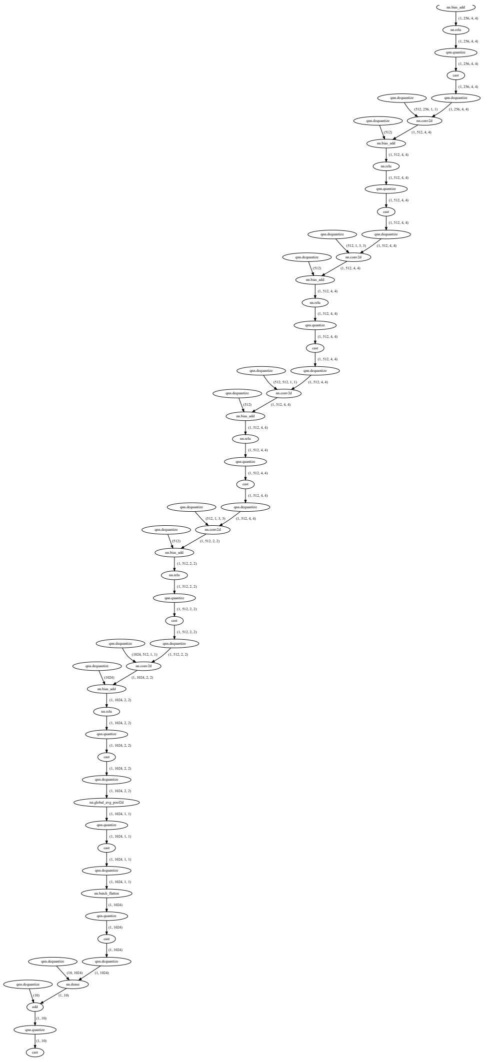
To generate visualizations of the Relay graph:

```
make visuTVM
```

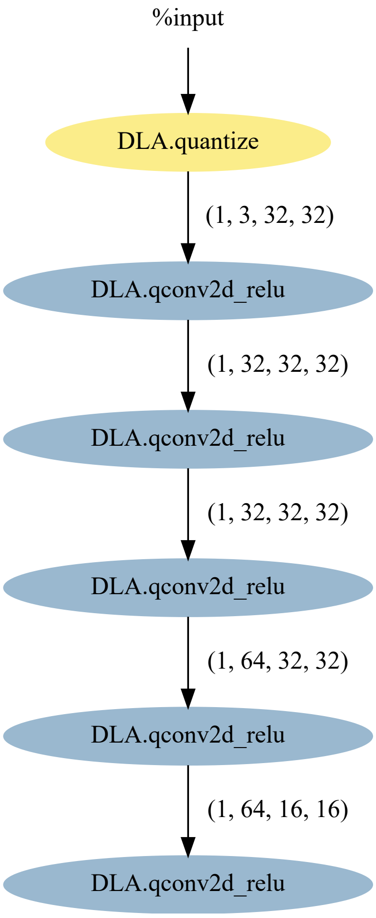
This command produces two SVG images representing the Relay graph:

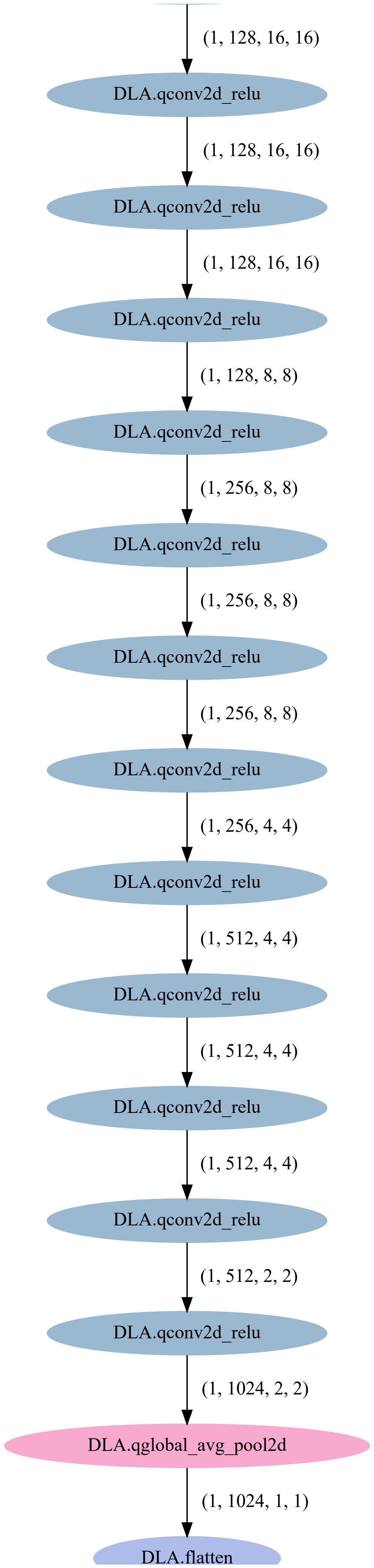
- `./output/visu_VGG8_relay_ir.svg`: The original Relay IR (before the MergeComposite pass)
- `./output/visu_VGG8_relay_ir_pass.svg`: The Relay IR after pattern fusion and annotation passes
  - mobilenetv1_relay_ir

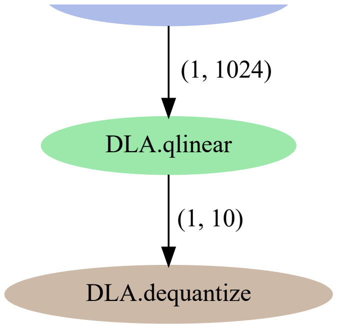




- mobilenetv1_relay_ir_pass




(1, 128, 16, 16)
DLA.qconv2d_relu
(1, 128, 16, 16)
DLA.qconv2d_relu
(1, 128, 16, 16)
DLA.qconv2d_relu
(1, 128, 8, 8)
DLA.qconv2d_relu
(1, 256, 8, 8)
DLA.qconv2d_relu
(1, 256, 8, 8)
DLA.qconv2d_relu
(1, 256, 8, 8)
DLA.qconv2d_relu
(1, 256, 4, 4)
DLA.qconv2d_relu
(1, 512, 4, 4)
DLA.qconv2d_relu
(1, 512, 4, 4)
DLA.qconv2d_relu
(1, 512, 4, 4)
DLA.qconv2d_relu
(1, 512, 2, 2)
DLA.qconv2d_relu
(1, 1024, 2, 2)
DLA.qglobal_avg_pool2d
(1, 1024, 1, 1)
DLA.flatten



2. Simulation and Performance Analysis (Failed)

For more config in compiling cpu-only version runtime, move into `testbench/cpu`, then use `make usage` for more details about configurations.

```
cd testbench/cpu
make usage
```

```
Usage: make [target]

Available targets:
  all                       - Build the project (default target)
  test     [CLASS][INDEX]   - Run the compiled executable with test input
  valgrind [CLASS][INDEX]   - Run Valgrind Massif to analyze memory usage
  test_full                 - Run with 100 test input
  valgrind_full             - Run Valgrind Massifwith 100 test input
  clean                     - Remove all generated files

Environment Variables:
  CLASS=<num>    - Set class index for testing (default: 4)
  INDEX=<num>    - Set test index (default: 9)
```

It is needed to `make clean` before any new configuration applied.

- `make test` is the single shot of indecated image.
- `make test_full` will implement 100 images.

> [!Tip] Model Accuracy This modified Mobilnet_v1 model achieves 86.94% accuracy on the CIFAR-10 dataset.

But,our result is not fit in Mobilnet_v1 model accuracy.

3. Single Test

Our result

```
(base) f74106092@user:~/TVM/testbench/cpu$ make test CLASS=2 INDEX=3
Run test
===============[ single test ]===============
Input file: ../../output/bin/input.bin
Weight file: ../../output/bin/weight.bin
Class index: 2
Image index: 3
=============================================
Image Test: 3/10 image class         bird
Model output
=============================================
[    airplane]   7.070%
[  automobile]   9.893%
[        bird]  12.953%
[         cat]  15.809%
[        deer]  10.572%
[         dog]   6.694%
[        frog]   9.893%
[       horse]   6.564%
[        ship]   7.949%
[       truck]  12.604%
=============================================
```

Expected Results

```
(base) f74106092@user:~/aoc2025-lab5/testbench/cpu$ make test CLASS=2 INDEX=3
Run test
===============[ single test ]===============
Input file: ../../output/bin/input.bin
Weight file: ../../output/bin/weight.bin
Class index: 2
Image index: 3
=============================================
Image Test: 3/10 image class         bird


=============================================
[    airplane]   0.022%
[  automobile]   0.001%
[        bird]  99.802%
[         cat]   0.038%
[        deer]   0.015%
[         dog]   0.016%
[        frog]   0.091%
[       horse]   0.006%
[        ship]   0.007%
[       truck]   0.001%
=============================================
```

The problem we will figure out in future.

Simulation

Makefile main options

options	function
`pe%`	Unit test for PE in No.`%` testbench with Verilator.
`super%`	Unit test for SUPER in No.`%` testbench with Verilator.
`array%`	Unit test for PE Array in No.`%` testbench with Verilator.
`ppu%`	Unit test for PPU in No.`%` testbench with Verilator.
`gen_test_data_for_array`	Generate normal convolution one pass testbench data for array.
`gen_test_data_for_depthwise_array`	Generate depthwise separable convolution one pass testbench data for array.
`gen_test_data_for_pe`	Generate normal convolution testbench data for PE.
`gen_test_data_for_depthwise_pe`	Generate depthwise separable convolution testbench data for SUPER.
`gen_test_data_for_mobilenet`	Generate normal convolution testbench data for MobileNetV1.
`gen_test_data_for_mobilenet_depthwise`	Generate depthwise separable convolution testbench data for MobileNetV1.
`gen_test_data_for_mobilenet_linear`	Generate FC layer testbench data for MobileNetV1.
`gen_ID_CONV`	Generate CONV layer ID for specific mapping parameter by `ID_gen.cpp`.
`gen_ID_LINEAR`	Generate FC layer ID for specific mapping parameter by `ID_gen.cpp`.
`vcs_id_gen`	Generate layer ID for specific mapping parameter by `ID_gen_combinational.v`.
`vcs%`	Generate GLB mirror for No.`%` testbench as inital data in GLB, simulate one pass normal/depthwise separable convolution in module which consist of `PE_array`, `GLB`, `Controller_pass` with vcs.
`clean`	Remove unnecessary files.

> [!Warning] `%` is a interger number which reperesent No.`%` testcase. If you replace `%` with `_all` in the options above, >the Makefile will run all test cases.

Usage

Type

```
make <options>
```

Makefile of tiling.cpp

options	function
`layer0`~`layer9`	Execute C++ simulation of tiling of all 10 layers of our MobileNetV1 model.

options	function
`clean`	Remove unnecessary files.