深度學習系統與實現

LAB01 - Basic DL framework & model architecture

Dept. of Computer Science and
Information Engineering

National Chiao Tung University

Outline

- LAB 1-1, Train a CNN model via pytorch
- Review of some concept
- LAB 1-2, Use thop to count MACs of your model
- LAB 1-3, Count the MACs / FLOPs of your model via the customized forward hook function
- Notices & Hints
- Questions
- Grading

Prerequisite

- Most of Labs for this semester are based on Pytorch (>=1.2, 1.2 is best for deployment)
- The GPU resource requirements
  - Maxwell (只推薦 980ti, Titan)
  - Pascal (1060 6G 或以上)
  - Turing (1660 6G, 或是 RTX 家族) / Volta (Titan V))

LAB 1-1
Train a CNN model via pytorch

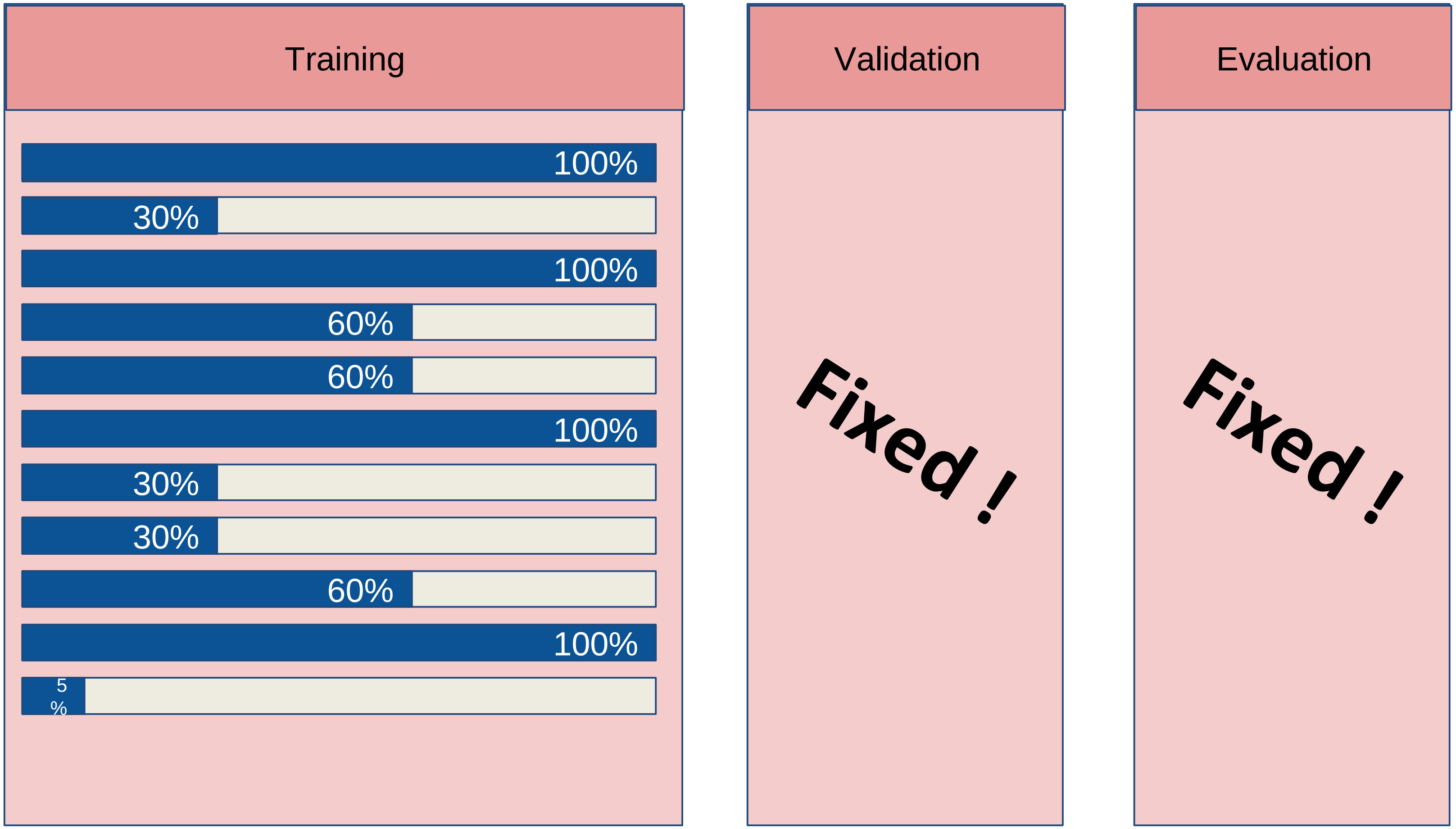
- We provide a cifar10 example on New E3
  - LAB-1-1-example-code.ipynb
- Just need to change the task to the other dataset
- You should show total accuracy (test case)
- You should show accuracy for each class
- We only verify the correctness of your function usage & workflow (total accuracy > 60% is OK!)

LAB 1-1

Dataset - skewed_food11

- Food11 Download link - https://www.kaggle.com/tohidul/food11
- Transfer to skewed_food11 - build_imbalanced_food11.sh
  - step 1. copy the script file into the dataset folder /food11
  - step 2. run this script file (build_imbalanced_food11.sh)

LAB 1-1
Dataset - skewed_food11



LAB 1-1
Output format (ref.)

```
Lab 1-1:
Test set: Top 1 Accuracy: 2925/3347 (87%) , Top 3 Accuracy: 3264/3347 (98%)
Class 0 :  302/368    82.07%
Class 1 :  100/148    67.57%
Class 2 :  460/500    92.00%
Class 3 :  268/335    80.00%
Class 4 :  237/287    82.58%
Class 5 :  410/432    94.91%
Class 6 :  141/147    95.92%
Class 7 :  93 /96     96.88%
Class 8 :  263/303    86.80%
Class 9 :  482/500    96.40%
Class 10:  169/231    73.16%
```

Review of some concept

- Metrics of model efficiency
- MACs
- FLOPs

Metrics of model efficiency

- the increased model complexity leads to a higher computational burden
- infeasible to deploy on the edge where the compute capacity is limited
- How should we evaluate the efficiency (complexity) of a neural network?

Reference- Ch.2 of Efficient Deep Neural Networks

How to evaluate complexity

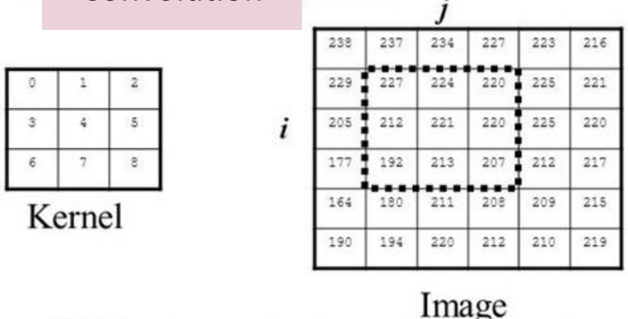
- Measurement
  - via some profiling tools, to record runtime of each ops
  - consider the real cases, ex: memory behavior ...
  - most of DL frameworks provide their own profiler
    - TensorFlow's profiler, PyTorch's profiler(only record timestamp)
- Theoretical metrics
  - MACs
  - FLOPs

[reference[1] - CSC508. Convolution Operators](#)
[reference[2] - Wiki, Multiply-accumulate Operation](#)

MACs

- In computing, especially digital signal processing, the multiply–accumulate(MAC) is a common operation
- Most layers in CNN model can be composed of many MAC operations - like "convolution"
- It's common used to estimate complexity

Convolution

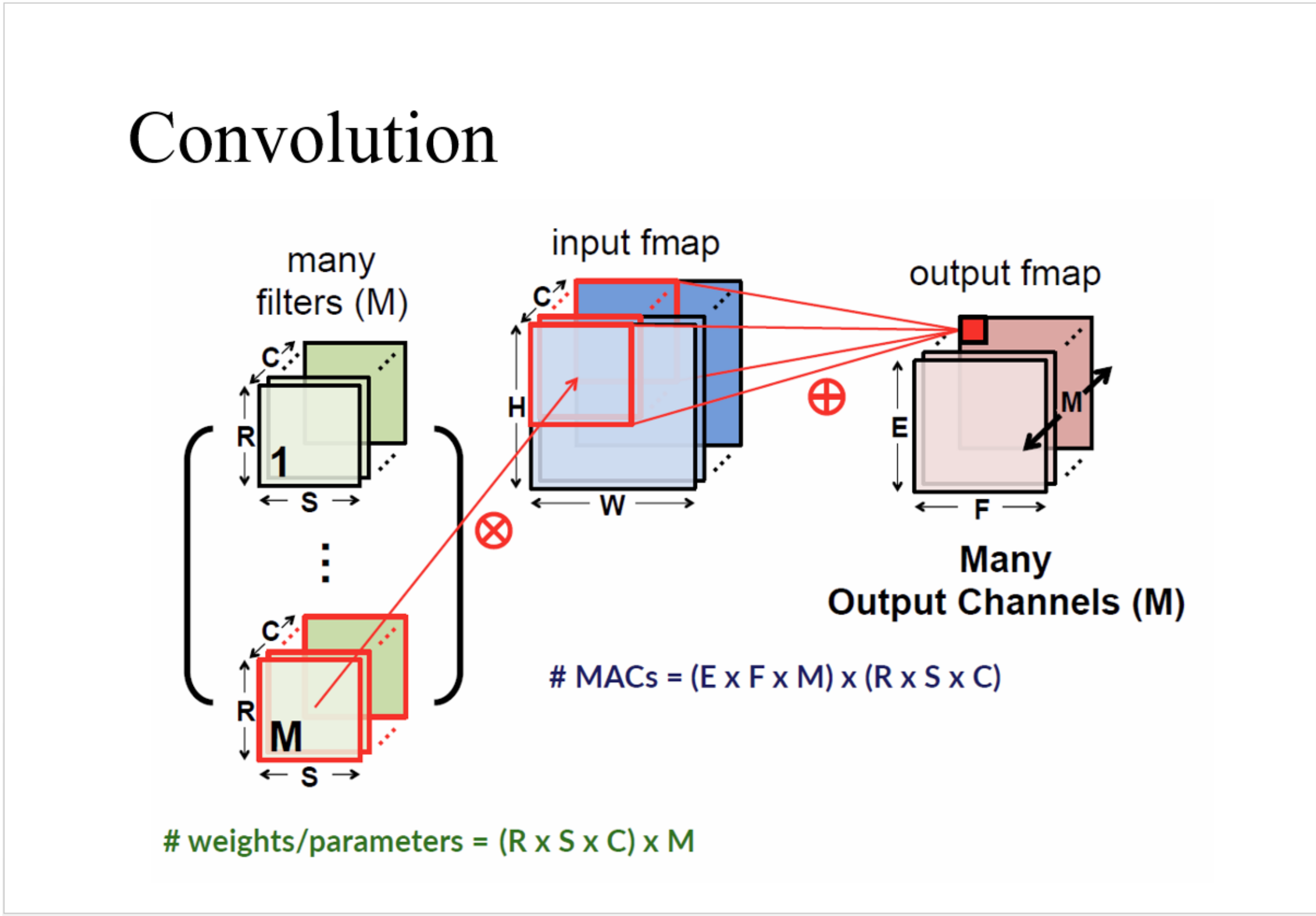


$$R[i][j] = (0*227)+(1*224)+(2*220)+ (3*212)+(4*221)+(5*220)+ (6*192)+(7*213)+(8*207)$$

MAC Op

$$a \leftarrow a + (b \times c)$$

MACs - example



FLOPs

- Count number of floating-point operations
- Rely on your instruction set architecture & implement method
- In most paper, just use MACs to represent FLOPs, but they are totally different
- If implement the convolution with "dot product instruction" rather than "MAC" ?

FLOPs - example

A.1 FLOPs COMPUTATION

To compute the number of floating-point operations (FLOPs), we $\boxed{\text{assume}}$ convolution is implemented as a sliding window and that the nonlinearity function is computed for free. For convolutional kernels we have:

$$\text{FLOPs} = 2HW(C_{in}K^2 + 1)C_{out}, \tag{11}$$

where H, W and C_{in} are height, width and number of channels of the input feature map, K is the kernel width (assumed to be symmetric), and C_{out} is the number of output channels.

For fully connected layers we compute FLOPs as:

$$\text{FLOPs} = (2I - 1)O, \tag{12}$$

where I is the input dimensionality and O is the output dimensionality.

[reference - Pruning Convolutional Neural Networks for Source Efficient Inference [ICLR '17, Pavlo Molchanov, NVIDIA]]

LAB 1-2

Use thop to count MACs of your model

- THOP: PyTorch-OpCounter
- Choose some models from torchvision
  - at least 2 kinds (recommend - ResNet, MobileNetV2)
- How to use

```
from torchvision.models import resnet50
from thop import profile
model = resnet50()
input = torch.randn(1, 3, 224, 224)
macs, params = profile(model, inputs=(input, ))
```

- Output format

```
Lab 1-2:
Total params:  2.238M
Total MACs:   312.879M
```

LAB 1-3

Count the MACs / FLOPs of your model via the customized forward hook function

- you also need to count the FLOPs in LAB 1-3
  - should be different with your MACs results
- need to show layer-wise MACs information
- customize your own MACs calculator for each layer
- hook function example - pytorch_hook_sample.py

```
def my_hook_function(self, input, output):
    print("Op:{}".format(str(self.__class__.__name__)))
    for param in self.parameters():
        print("params shape: {}".format(list(param.size())))

def main():
    model = SampleNet()
    model.conv1.register_forward_hook(my_hook_function)
    input_data = torch.randn(1, 3, 224, 224)
    out = model(input_data)
```

reference - forward & backward function hooks

LAB 1-3 Output Format

- You don't need to follow the format, but you need to provide each layer's information with the following items
  - op_type
  - input_shape
  - output_shape
  - params
  - MACs

```
Lab 1-3:
op_type             input_shape         output_shape        params              MACs
----------------------------------------------------------------------------------------------------
Conv2d              [1, 3, 224, 224]    [1, 64, 112, 112]   9408                118013952
...                 ...                 ...                 ...                 ...
...                 ...                 ...                 ...                 ...
Linear              [1, 512]            [1, 11]             5643                5632
----------------------------------------------------------------------------------------------------
Total params: 11.182 M
Total MACs:  1.816G
```

Notices & Hints

- Please carefully confirm which layers need to count MACs (hint: compare with the works from thop)
- How many FLOPs for the non-linear layer ?
- Do we need to count MACs for pooling layer ?

Questions

- You can try to answer the following questions in your report (TAs will ask you during the DEMO)
  - Do you get the same result from 'thop' & your own functions ? If not, please explain.
  - How could you get a difference result between FLOPs and MACs ?
  - Is MACs/FLOPs a good metric to estimate the real inference latency ? If not, please explain.

reference - ShuffleNet V2: Practical Guidelines for EfficientCNN Architecture Design [ECCV '18, Ningning Ma]

Grading

- LAB 1-1 (60%)
- LAB 1-2 (15%)
- LAB 1-3 (25%)
- Bonus (10%)
  - In LAB 1-3, if your selected model contains the following special layers, TAs will give extra points
    - Dilated (Atrous) Convolution, Deconvolution, Others(ask TAs)
- Submission: source code + report (.ipynb is accepted)(E3)
  - zip format (ex: DLSR_lab1_{group id}.zip)
  - 未依照上述命名格式者，扣該Lab成績5分
- Deadline : 2020/03/23, 23:59 (Mon)(2 week)
- Demo : (TAs will announce date on New-E3 later)

Total:

110

Report Spec.

- EX:
  - Introduction
  - Experiment setup
  - Result
  - Discussion
  - Other ...

Reference

- Stanford Course : CS231n
  - http://cs231n.stanford.edu/
- Pytorch Document:
  - https://pytorch.org/docs/stable/index.html
- pytorch_OpCounter:
  - https://github.com/Lyken17/pytorch-OpCounter