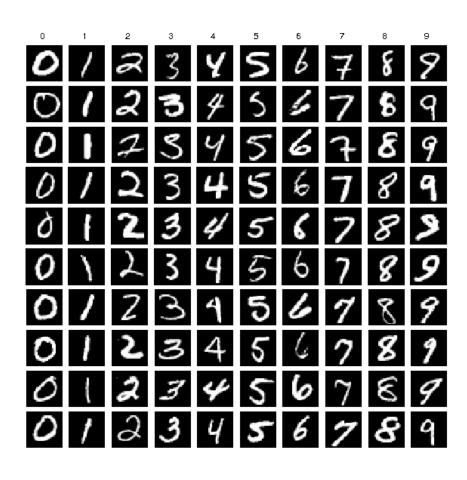
# CIFAR-10

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2020.04.20.

# Class Lab – 기초 과제 일정

- 1. XOR (~4/05)
- 2. MNIST (~4/19)
- 3. CIFAR-10 (~5/03)



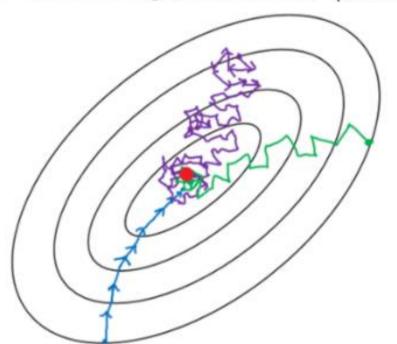
 The database contains 60,000 training images, 10,000 validation images, and 10,000 testing images with 10 classes.

- Shape of each data: [28, 28]

- Range : 0.0 to 1.0

#### Mini-Batch

- Batch gradient descent (batch size = n)
- Mini-batch gradient Descent (1 < batch size < n)</p>
- Stochastic gradient descent (batch size = 1)



### Weight Initialization

(1) Xavier Normal Initialization

$$W \sim N(0, Var(W))$$

$$Var(W) = \sqrt{rac{2}{n_{in} + n_{out}}}$$

(2) He Normal Initialization

$$W \sim N(0, Var(W))$$

$$Var(W) = \sqrt{rac{2}{n_{in}}}$$

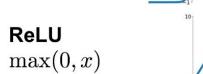
#### Activation Function

### Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

#### tanh

tanh(x)



# Leaky ReLU $\max(0.1x, x)$



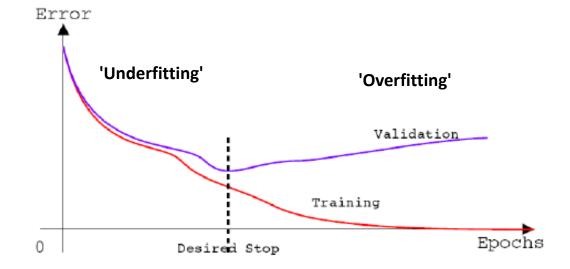
#### **Maxout**

 $\max(w_1^T x + b_1, w_2^T x + b_2)$ 

#### **ELU**

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

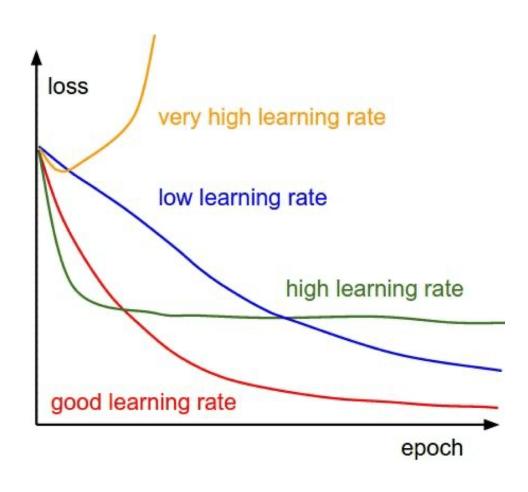
## Early Stopping



Parameter Norm Penalties

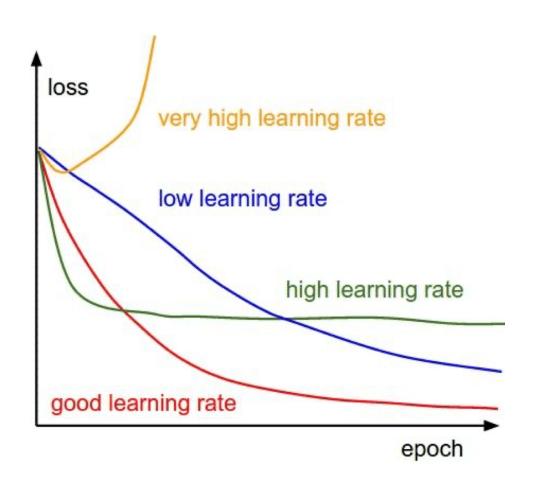
Weight decay: 
$$E_t = \frac{1}{N_t} \sum_{n \in D_t} E_n + \frac{\Lambda}{2} \frac{||w||^2}{\text{L2-norm}}$$
 
$$w^{t+1} = w^t - \epsilon (\frac{1}{N_t} \sum \nabla E_n + \lambda w^t)$$
 Weight restriction: 
$$||w||^2 < c$$

# **Learning Rate Decay**



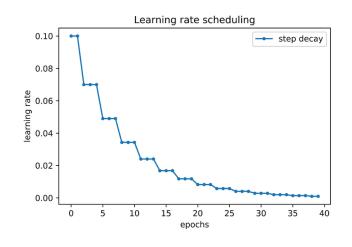
We should choose proper learning rate to find global optimum.

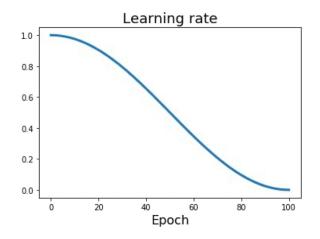
# **Choosing Proper Learning Rate**

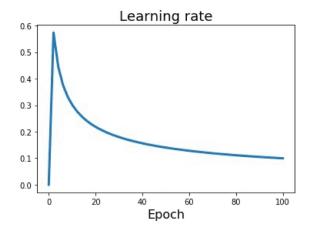


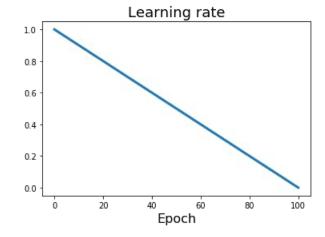
We should choose proper learning rate to find global optimum.

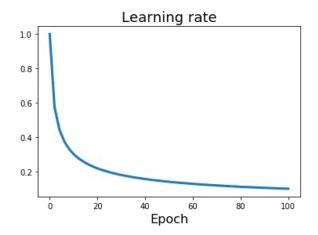
# Learning Rate Scheduling (Learning Rate Decay)



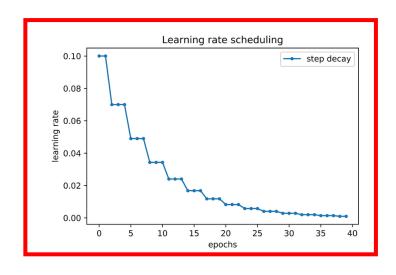


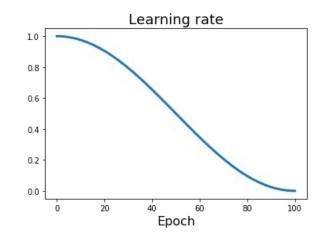


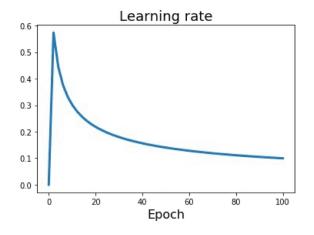


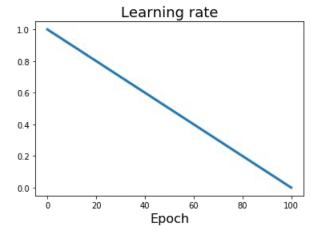


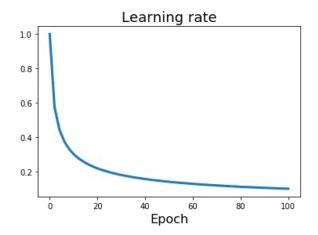
# Learning Rate Scheduling (Learning Rate Decay)





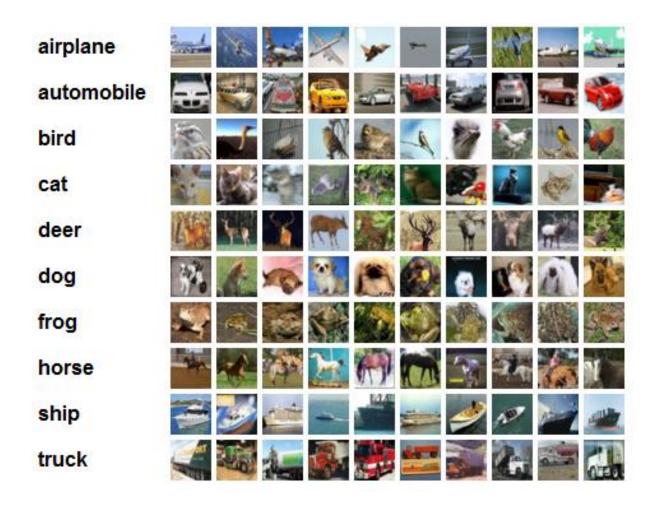






We use step decay method in training ResNet32.

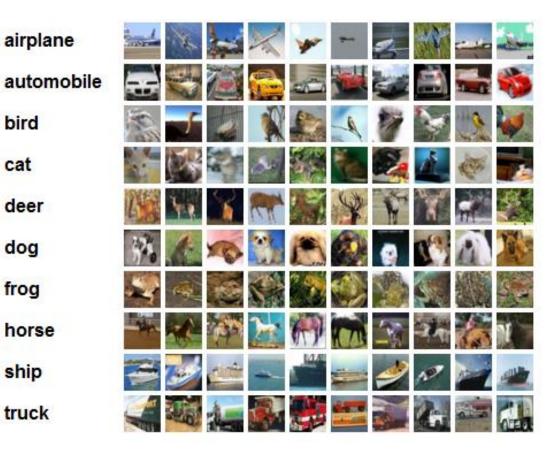
# Assignment #3 : CIFAR-10



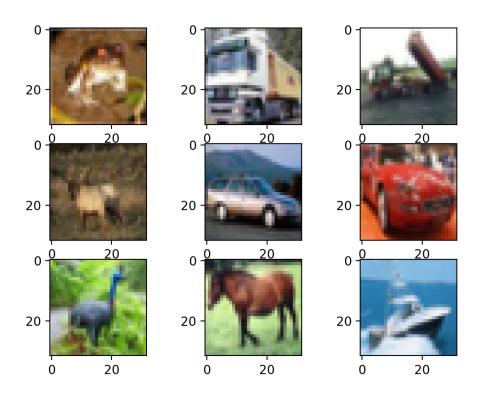
# Assignment #3: CIFAR-10

#### Introduction

- CIFAR-10 : Canadian Institute For Advanced Research
- This is a collection of images that are commonly used to train machine learning and computer vision algorithms.
- The database is also widely used for training and testing in the field of machine learning.
- The database contains 50,000 32\*32 training images, 10,000 validation images, and 10,000 testing images with 10 classes.



# Assignment #3: CIFAR-10



- Shape of each data: [3, 32, 32]

- Range : 0 to 255

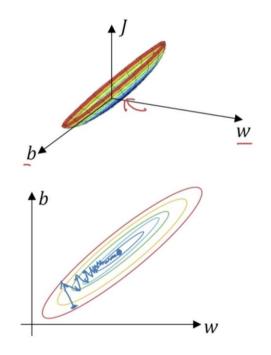
- You can see the image of each data. (available in the assignment code)

## **Standardization**

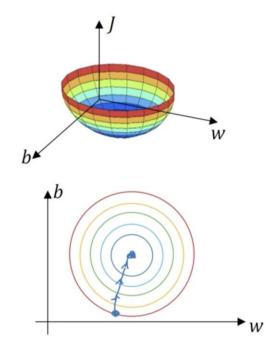
- Standardize the input data.

$$\mu = rac{1}{m} \sum_{i=1}^{m} x^{(i)}$$
 $x := x - \mu$ 
 $\sigma^2 = rac{1}{m} \sum_{i=1}^{m} (x^{(i)} - \mu)^2$ 

Unstandardized



Standardized

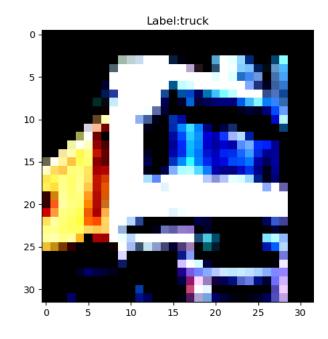


- We use standardization to apply gradient descent algorithm easily.

## **Standardization**

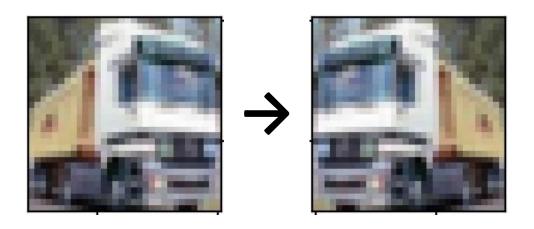


$$\mu = rac{1}{m} \sum_{i=1}^m x^{(i)}$$
 $x := x - \mu$ 
 $\sigma^2 = rac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu)^2$ 



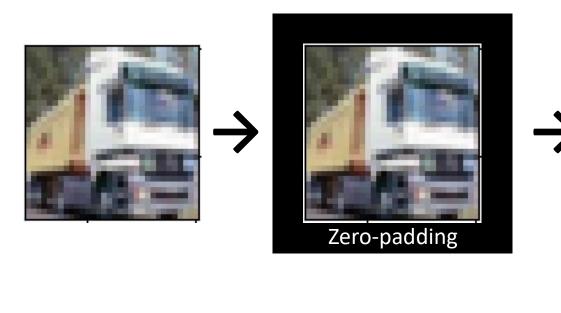
# **Data Augmentation**

1) Flip augmentation



# **Data Augmentation**

2) Crop augmentation



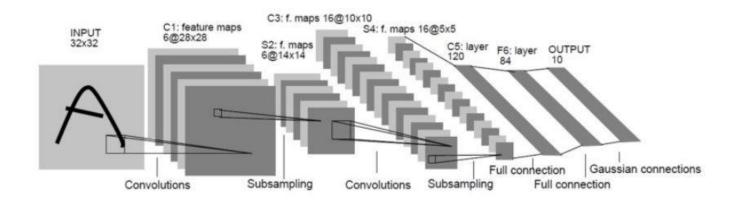


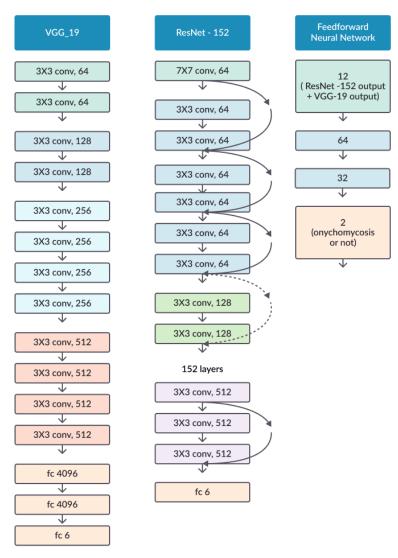




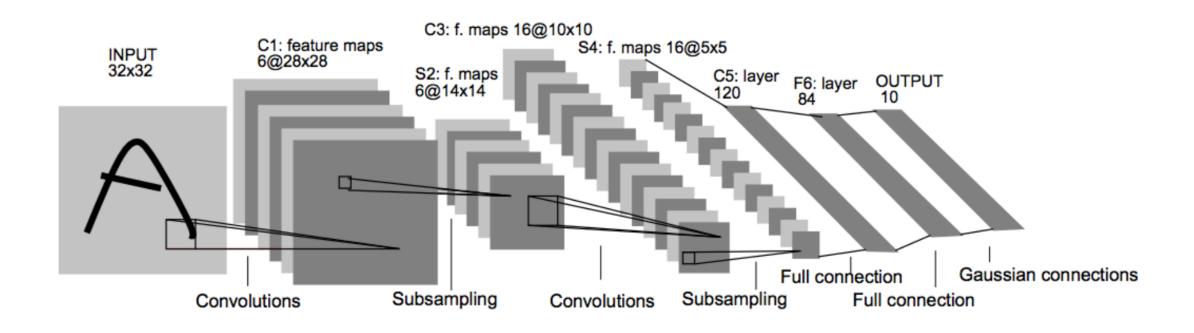


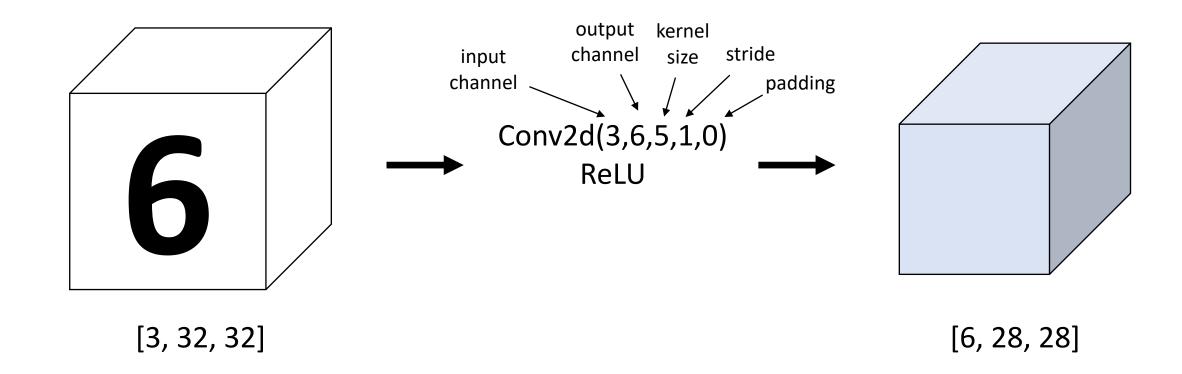
## **Convolutional Neural Network**

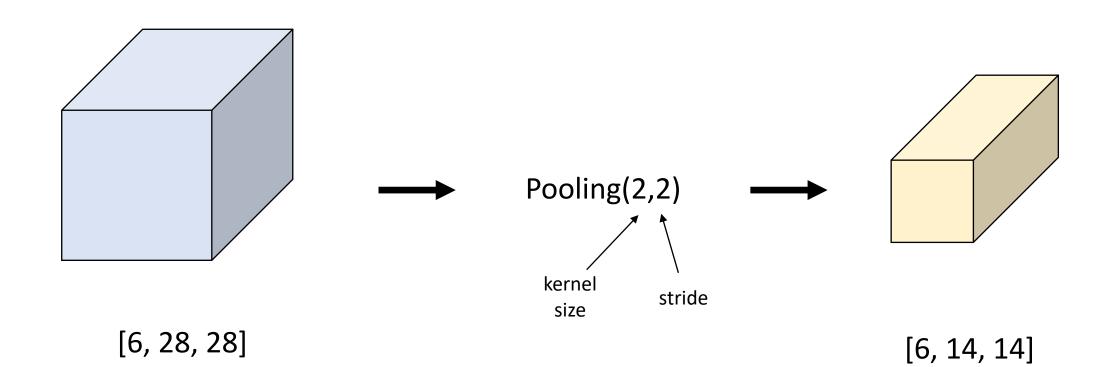


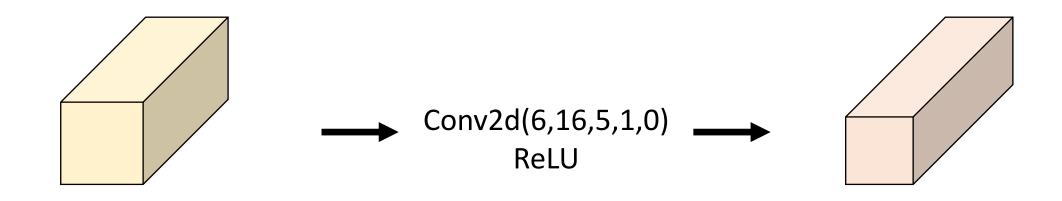


# [1. LeNet-5<sup>1</sup>]

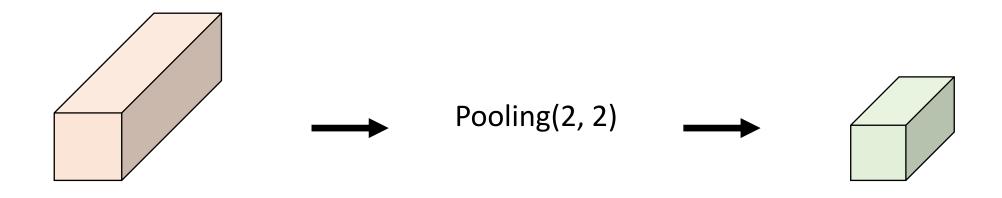




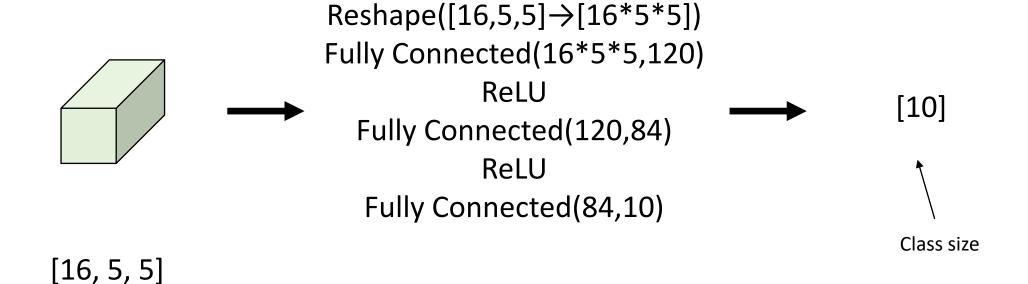


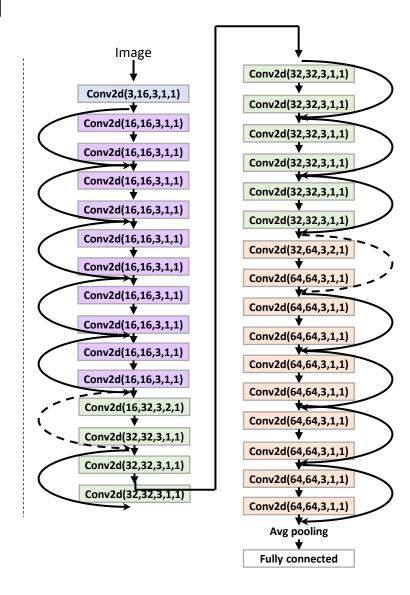


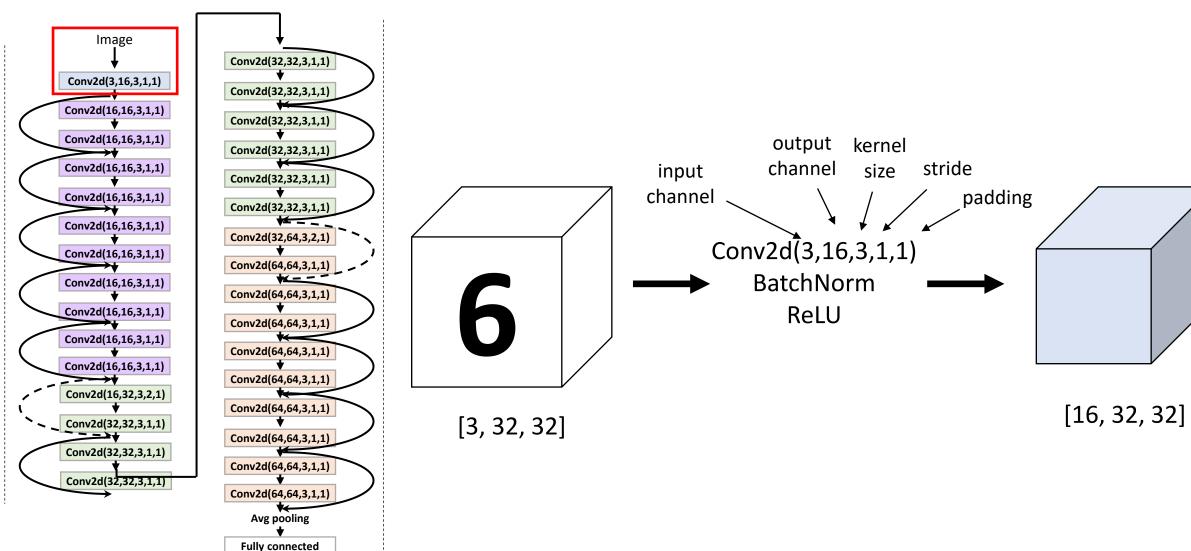
[6, 14, 14] [16, 10, 10]

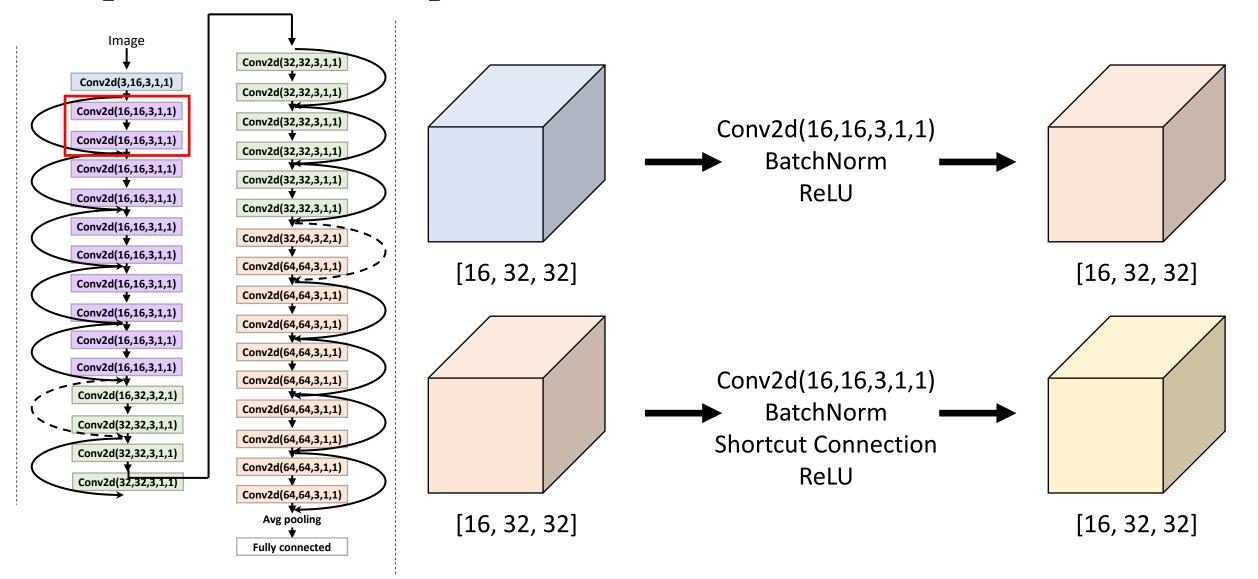


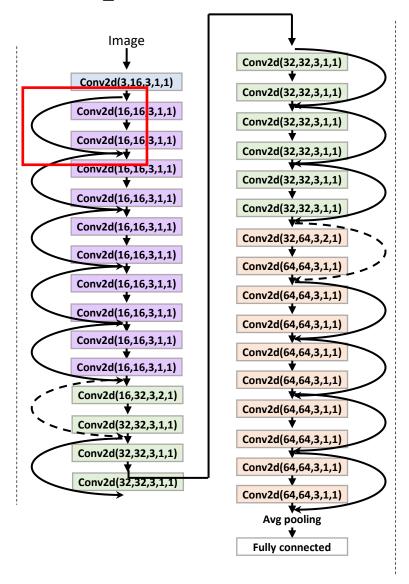
[16, 10, 10]



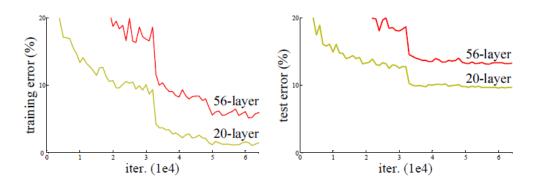




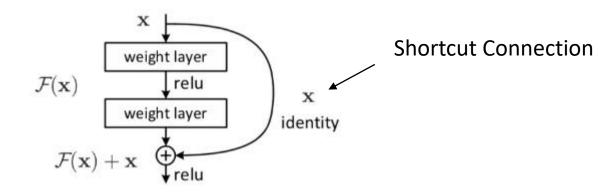


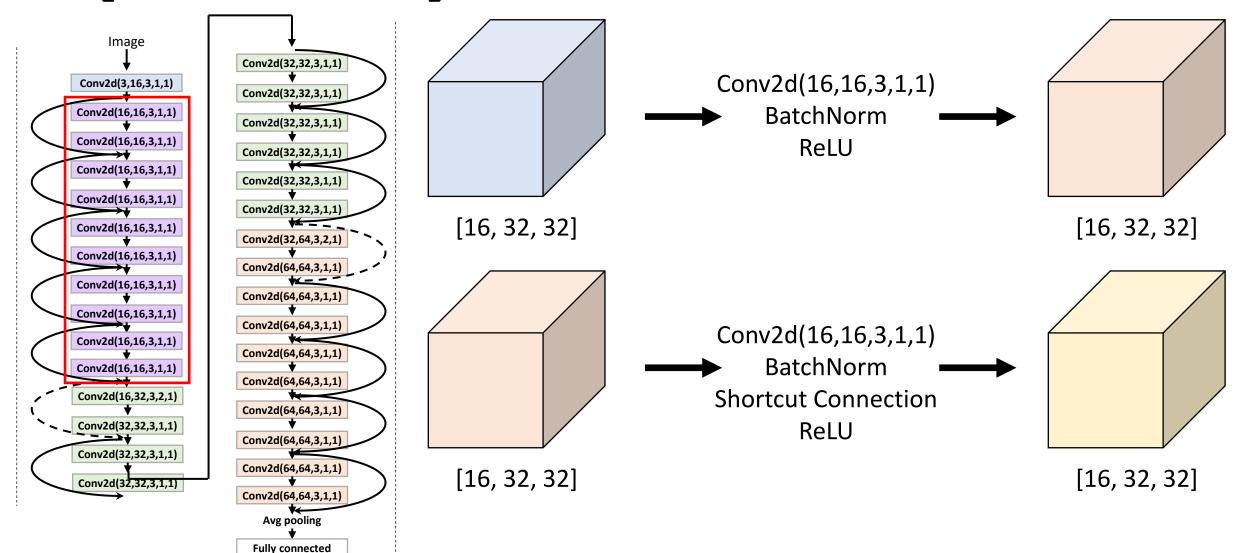


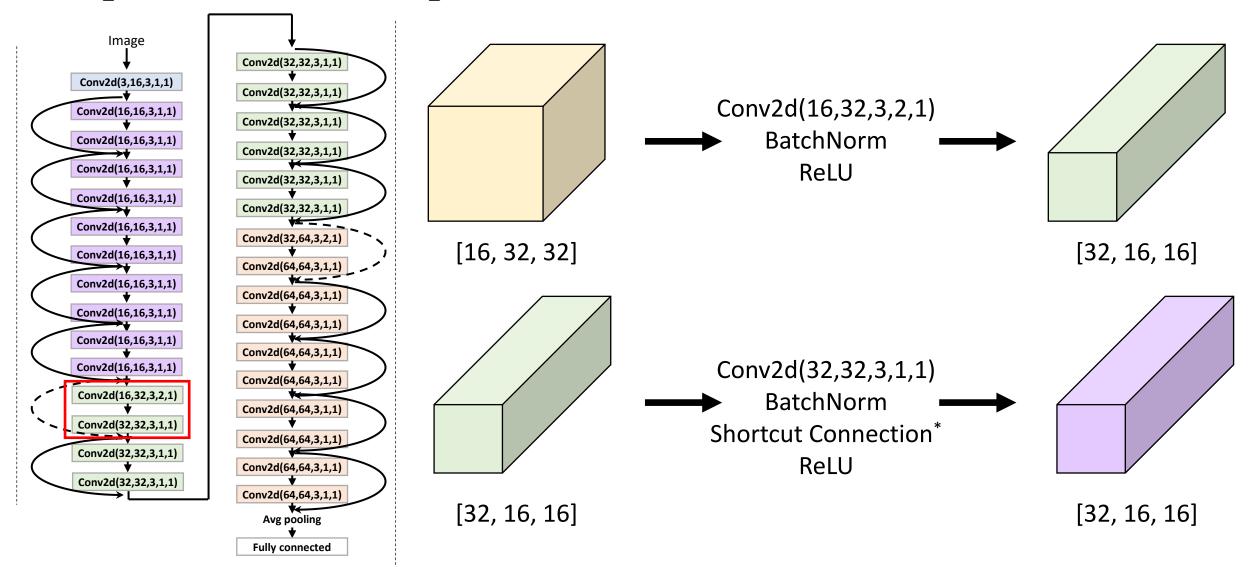
- Deeper network does not gives higher accuracy, Due to Gradient Vanishing and degradation.

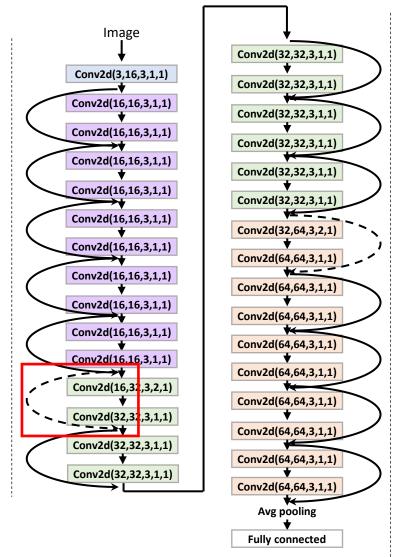


#### [Residual Learning]

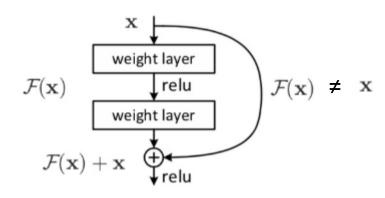


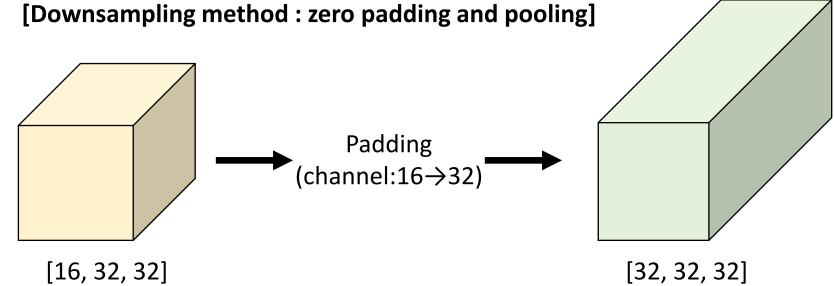


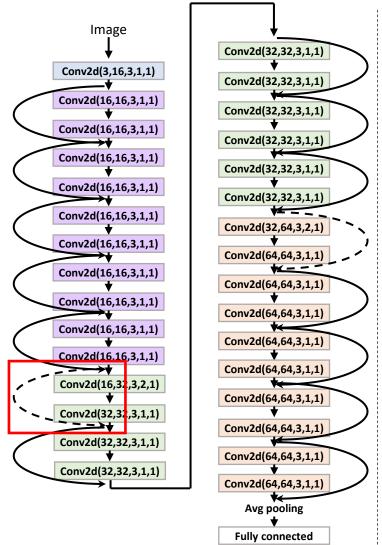




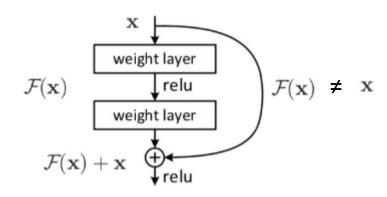
[Shortcut Connection with different shape]



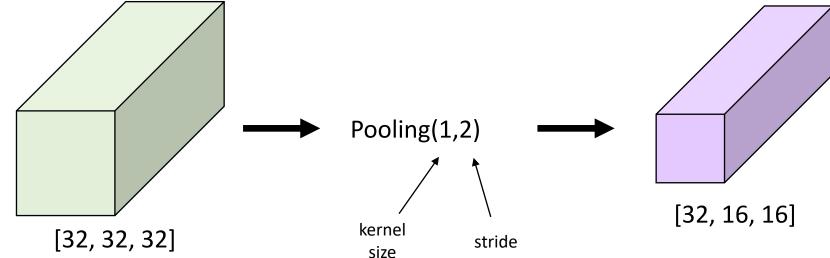


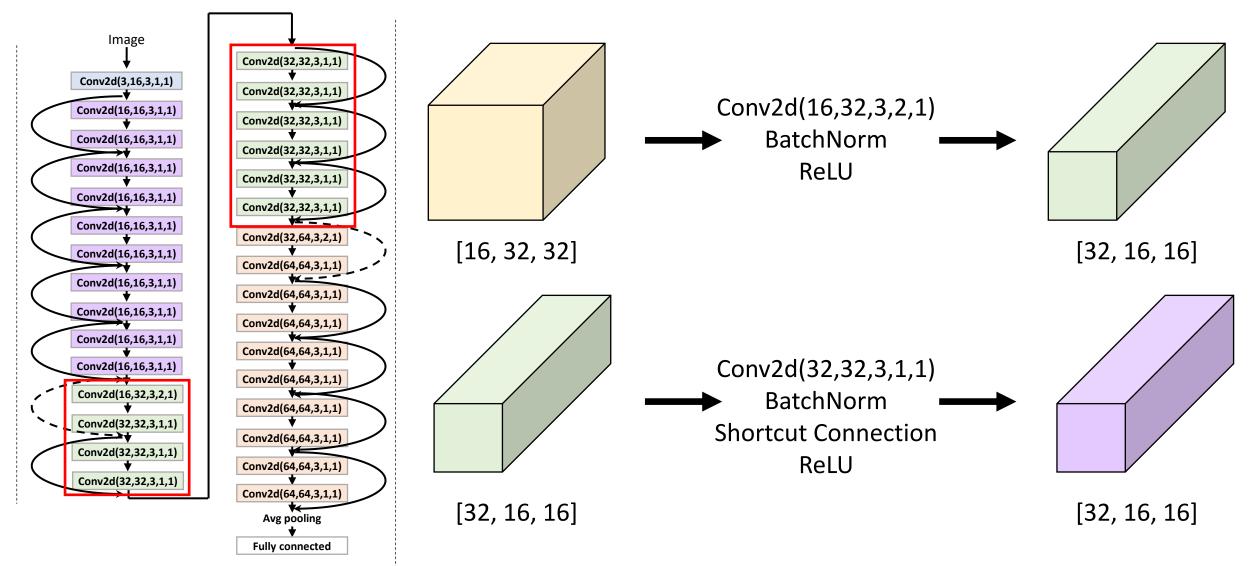


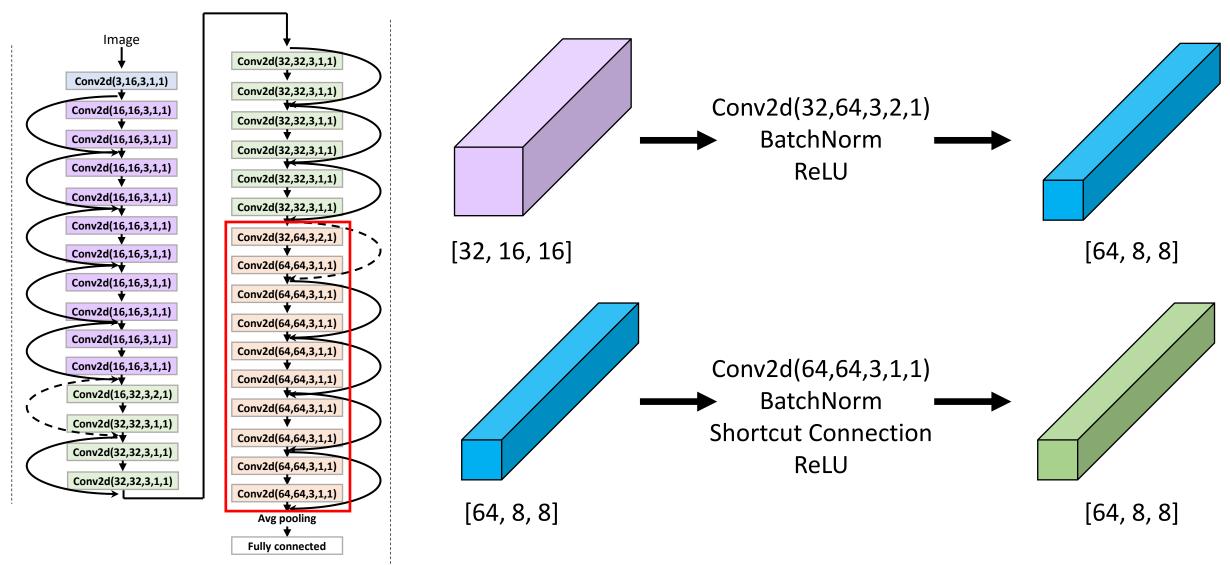
[Shortcut Connection with different shape]

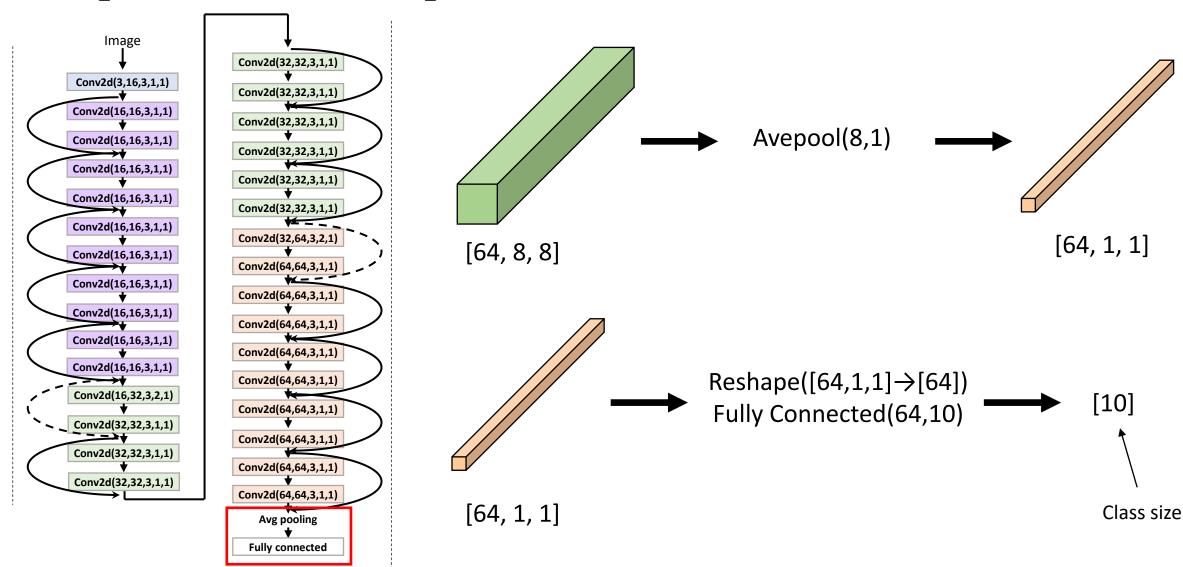


[Downsampling method : zero padding and pooling]









## **Code review**

#### [Objective]

Your model should classifiy of the images into 10 classes.

#### [Classes]

#### [Code structure]

- CIFAR10\_configuration.py
- CIFAR10\_evaluation.py
- CIFAR10\_train.py
- LeNet5\_model.py
- MLP\_model.py
- ResNet\_model.py

#### [CIFAR10\_train.py]

[MLP\_model.py]

```
import torch.nn as nn
class MLP model(nn.Module):
       super().__init__()
                              TODO : MLP 모델 생성 (구조는 실험해 보면서 결과가 좋은 것으로 사용할 것)
                                                  END OF YOUR CODE
   def forward(self, x):
                               TODO : forward path 수행, 결과를 x에 저장
                                                  END OF YOUR CODE
       return x
```

[LeNet5\_model.py]

```
mport torch.nn as nn
:lass LeNet5_model(nn.Module):
      super(). init ()
                               TODO : LeNet5 모델 생성
  def forward(self, x):
                               TODO : forward path 수행, 결과를 x에 저장
                                                    END OF YOUR CODE
      return x
```

[ResNet32\_model.py]

You should find correct number or variable for X1~X10.

```
def forward(self, x):
    x = self.conv1(x)
    x = self.bn1(x)
    x = self.relu(x)
    x = self.layers_2n(x)
    x = self.layers_4n(x)
    x = self.layers_6n(x)
    x = self.pool(x)
    x = x.view(x.size(0), -1)
    x = self.fc_out(x)
    return x
```

```
lass ResNet(nn.Module):
  def __init__(self, num_layers, block, num_classes=10):
      super().__init__()
      self.num_layers = num_layers
      self.bn1 = nn.BatchNorm2d(16)
      self.relu = nn.ReLU(inplace=True)
      self.layers_2n = self.get_layers(block, 16, 16, stride=1)
      self.layers_4n = self.get_layers(block, 16, 32, stride=2)
      self.layers_6n = self.get_layers(block, 32, 64, stride=2)
      self.pool = nn.AvgPool2d(8, stride=1)
      self.fc out = nn.Linear(64, num classes)
      for m in self.modules():
          if isinstance(m, nn.Conv2d):
             nn.init.kaiming normal (m.weight, mode='fan out', nonlinearity='relu')
          if isinstance(m, nn.BatchNorm2d):
             nn.init.constant (m.weight, 1)
             nn.init.constant (m.bias, 0)
  def get_layers(self, block, in_channels, out_channels, stride):
      if stride == 2:
          down sample = True
          down sample = False
      layers_list = nn.ModuleList([block(in_channels, out_channels, stride, down_sample)])
      for _ in range(self.num_layers - 1):
          layers_list.append(block(out_channels, out_channels))
      return nn.Sequential(*layers list)
```

[ResNet32\_model.py]

You should find correct number or variable for X1~X10.

```
class IdentityPadding(nn.Module):
    def __init__(self, in_channels, out_channels, stride):
        super().__init__()
        self.pooling = nn.MaxPool2d(kernel_size=1, stride=stride)
        self.add_channels = out_channels - in_channels

def forward(self, x):
    x = F.pad(x, [0, 0, 0, 0, 0, self.add_channels])
    x = self.pooling(x)
    return x
```

```
class ResidualBlock(nn.Module):
   def __init__(self, in_channels, out_channels, stride=1, down sample=False):
       super().__init__()
       self.conv1 = nn.Conv2d(in channels, out channels
                                ernel size=X1, stride=X2
                                   ding=X3, bias=False)
       self.bn1 = nn.BatchNorm2d(out channels)
       self.relu = nn.ReLU(inplace=True)
       self.conv2 = nn.Conv2d(out_channels, out_channels
                                     g=X6, bias=False)
       self.bn2 = nn.BatchNorm2d(out channels)
       self.stride = stride
       if down_sample:
           self.down_sample = IdentityPadding(in_channels, out_channels, stride)
           self.down_sample = None
   def forward(self, x):
       shortcut = x
       x = self.conv1(x)
       x = self.bn1(x)
       x = self.relu(x)
       x = self.conv2(x)
       x = self.bn2(x)
       if self.down_sample is not None:
           shortcut = self.down_sample(shortcut)
       x += shortcut
       x = self.relu(x)
       return x
```

	Model	GPU(O/X)	Batch_size	Activation function	Weight initialization	Optimizer	Learning rate	Momentum	Weight decay	LR decay	training time (m)	Early stopping epoch	Accuracy
Setting #1	MLP				_						_		
Setting #2	Lenet5												
Setting #3	ResNet32		128	ReLU	He_normal	SGD	0.1	0.9	0	0			
	Validat	tion dataset a	ccuracy plot										
	Setting	g #1		Se	etting #2			Setting #3					
결과 정리]													
결과 정리]													

Fill in these cells.

							aluatior					<b>↓</b>	
	Model	GPU(O/X)	Batch_size	Activation function	Weight initialization	Optimizer	Learning rate	Momentum	Weight decay	LR decay	training time (m)	Early stopping epoch	Accurac
Setting #1	MLP												
Setting #2	Lenet5		128	ReLU	He manual	SGD	0.1	0.9					
etting #3	ResNet32		128	ReLU	He_normal	SGD	0.1	0.9	0	0			
	Validat	tion dataset a	ccuracy plot										
	Setting	g #1		Se	etting #2			Setting #3					
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Plot an accuracy plot of the validation dataset for each setting.

	Model	GPU(O/X)	Batch size	Activation function	Weight initialization	Optimizer	Learning rate	Momentum	Weight decay	LR decay	training time (m)	Early stopping epoch	Accuracy
Setting #1	MLP		_				3			,			
Setting #2	Lenet5												
Setting #3	ResNet32		128	ReLU	He_normal	SGD	0.1	0.9	0	0			
	Validat	tion dataset a	ccuracy plot										
	Setting	g #1		Se	etting #2			Setting #3			<b>↓</b>		
		<b>5</b> —		-									
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	CIFAR-10 Evaluation Report												
	Model	GPU(O/X)	Batch_size	Activation function	Weight initialization	Optimizer	Learning rate	Momentum	Weight decay	LR decay	training time (m)	Early stopping epoch	Accuracy
Setting #1	MLP												
Setting #2	Lenet5												
Setting #3	ResNet32		128	ReLU	He_normal	SGD	0.1	0.9	0	0			
	Valida	tion dataset a	ccuracy plot	i									

Setting #1 Setting #2 Setting #3

Summarize the report of each experimental setting.

[결과 정리]

### Assignment #3 : CIFAR-10

#### Objective

Your model should classifiy of the images into 10 classes.

#### Requirements

1. Implement multi-layer perceptron with Pytorch or Tensorflow.

(Basic Pytorch code is provided)

(Find the best hyperparameters condition)

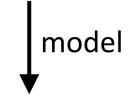
2. Implement LeNet5 model.

(Find the best hyperparameters condition)

- 3. Find the correct X1~X10 values in ResNet32 model and complete the code.
- 4. Implement with 3 settings stated in the evaluation report, and report the result of each settings.
- 5. You should attach the plot of the validation dataset accuracy plot. (implemented in pytorch code)
- 6. You should report the experimental results.

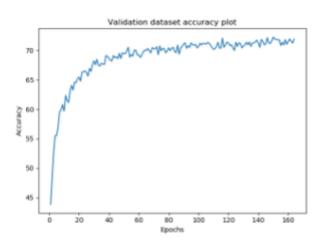
(all kinds of additional experiments are recommended)







# [Validation dataset accuracy plot]



#### • Evaluation Criteria

Simplicity	How concisely did you write the code?
Performance	How well did the results of the code perform?
<b>Brevity and Clarity</b>	How concisely and clearly did you explain the results?

## Assignment #3 : CIFAR-10

- Due to : ~ 5.3(Sun)
- Submission: Online submission on blackboard
- Your submission should contain
  - 1) The whole code of your implementation
  - 2) The evaluation report
- You must implement the components yourself!
- File name : StudentID\_Name.zip

# Q&A

조교 김도현: dhkim1028@korea.ac.kr