March 23rd, 2021

AI+BD ML Lab. Day 2

Training Methodologies with Logistic Regression

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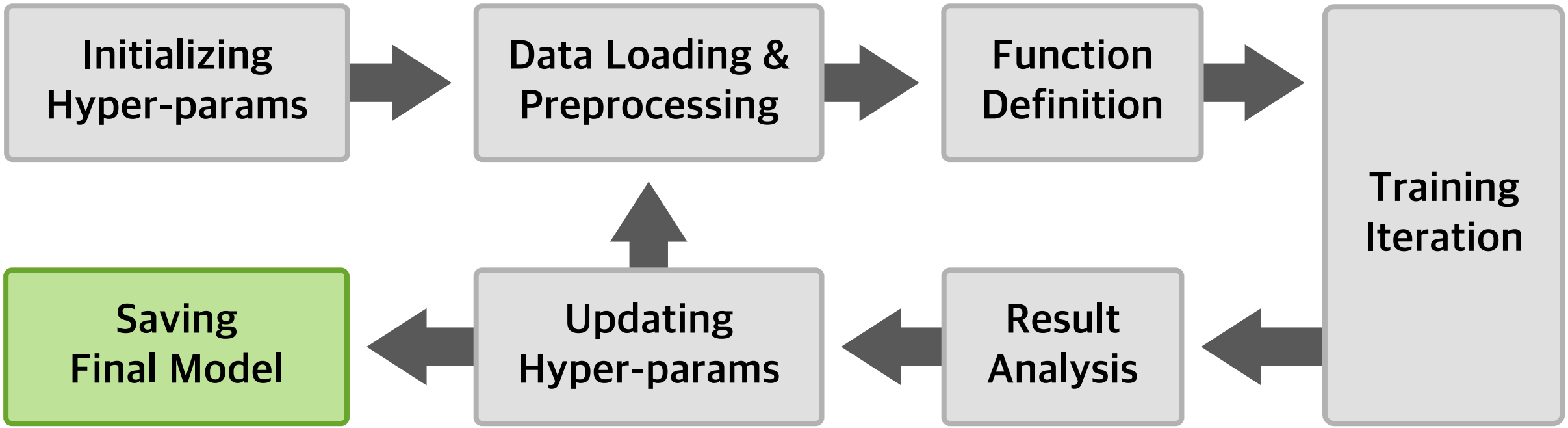
Contents

Goals

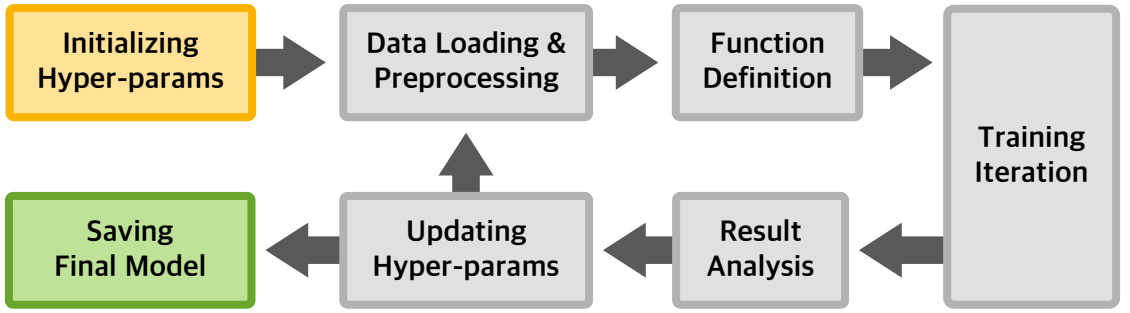
1. Understanding **basic flow of deep learning** & code
2. Applying (1) to the **logistic regression** model with mini-batch SGD
3. Understanding the differences from **weight initialization**
4. Finding proper **hyper-parameters** to get fast convergence speed

Basic Flow of DL



Basic Flow with <code />

Hyper-parameter Initialization




```python
### Common variables
iteration_idx = 0
earlystop_cnt = 0
minimum_loss = 1e+20

### Records upon iterations
iteration_idx_records = []
loss_records = []
gradnorm_records = []
alphanorm_records = []
noisenorm_records = []
time_records = []
earlystop_p_records = []

### Data
s_t_np = s_np.transpose()
s_t = torch.Tensor(s_t_np).to(device)
r = torch.Tensor(r_np).to(device)

### Modules
net = torch.nn.Linear(s_shift_len, 1, bias=False).to(device)
opt = torch.optim.LBFGS(
    net.parameters(), history_size=200, max_iter=30, max_eval=45,
)

### Weight Initialization
torch.nn.init.zeros_(net.weight.data)
```

◀ Initialization code ▶

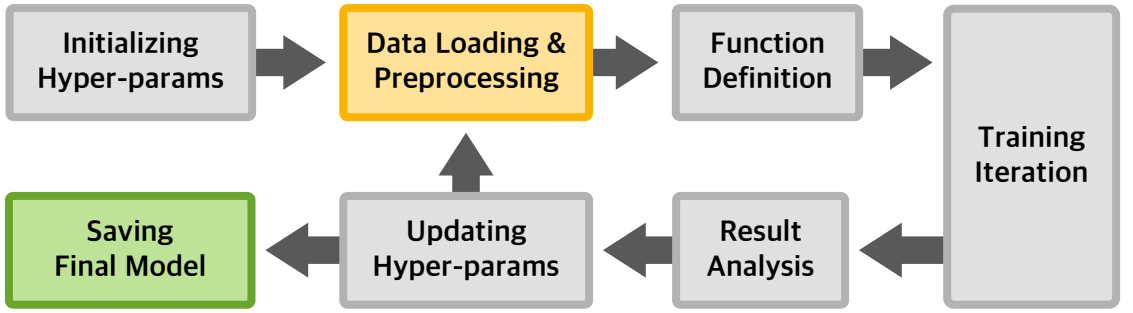
```python
### Torch Device
# * Available options : cpu, cuda:0, cuda:1, and so on
# * Multiple gpus are not supported for now
# * Note that LBFGS is memory-intensive, so cpu may work more efficiently.
device = 'cpu'

### Iteration Settings
iteration_max = 200
log_interval  = 5

### Early Stopping
earlystop_enable     = True
earlystop_patience   = 5
earlystop_log_from   = 4
earlystop_threshold  = 0.0001

### Recording Approximation Procedures
growth_album_enable = False
growth_album_ylim   = [-0.002, 0.020]

### Loss Terms
# * Note that this terms are related to "considering time."
#   That is, as you set terms_weights[0] in large value, the model will search
#   noise-degrading way first, and noise-degrading direction's gradient will
#   pumped in the scale. Then when noise-degrading direction's gradient becomes
#   zero, the second term will be main target of optimum finding.
# * From the experience, I recommend to set first term weight high but not
#   exceeds `s_shift_len`.
terms_weights = [181, 1]
```

Basic Flow with <code />

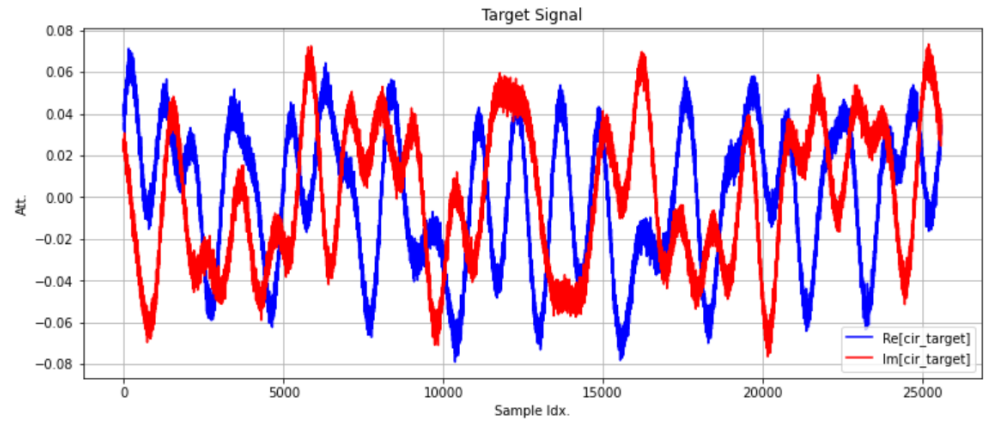
Data Load & Preprocessing

```
[19]: cir_target = hwk.read_mat('../data/gen2-dev/piai_0918.mat', 'cir_4m')[:, 5].squeeze()

      r_np = np.zeros((2 * samp_len, 1))
      tmp_complex = cir_target.reshape([samp_len, 1])
      r_scale = np.sqrt(np.sum(np.power(np.abs(cir_wire), 2)) / np.sum(np.power(np.abs(tmp_complex), 2)))
      tmp_complex = tmp_complex * r_scale / 1000
      print(f'r_scale = {r_scale}')
      r_np[:, 0] = np.vstack([
          np.real(tmp_complex), np.imag(tmp_complex)
      ]).squeeze()



      print(f'R.shape = {r_np.shape}')

r_scale = 0.6657971810705
R.shape = (51200, 1)
```

▲ Loading MATLAB `.mat` file & Automatically scaling data




```
[4]: fig = plt.figure(1998, figsize=(12.5, 5))
     plt.clf()
     plt.plot(np.real(tmp_complex), color='blue')
     plt.plot(np.imag(tmp_complex), color='red')
     plt.legend(['Re[cir_target]', 'Im[cir_target]'])
     plt.xlabel('Sample Idx.')
     plt.ylabel('Att.')
     plt.title('Target Signal')
     plt.grid()
     plt.show()
```

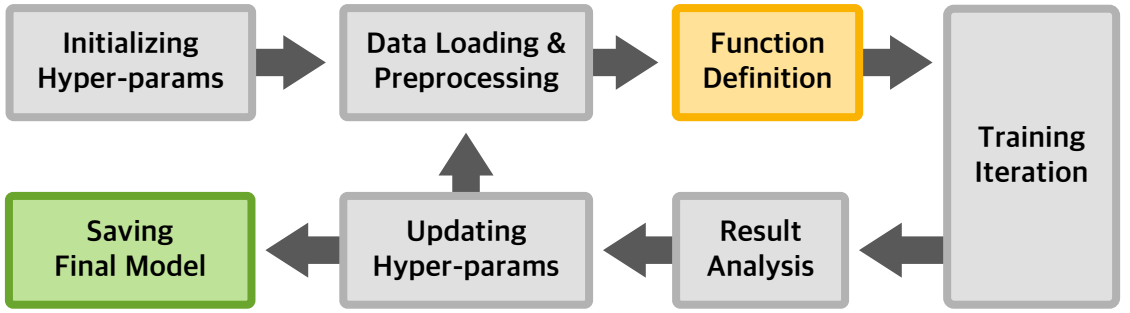


Check your data after preprocessing! ▶

Basic Flow with <code />

Function Definition

```python
class ResNet(nn.Module):
    def __init__(self, num_classes=10):
        super(ResNet, self).__init__()
        self.in_planes = 16

        self.conv1 = nn.Conv2d(3, 16, kernel_size=3,
                               stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(16)
        self.layer1 = self._make_layer(16, 2, stride=1)
        self.layer2 = self._make_layer(32, 2, stride=2)
        self.layer3 = self._make_layer(64, 2, stride=2)
        self.linear = nn.Linear(64, num_classes)

    def _make_layer(self, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(BasicBlock(self.in_planes, planes, stride))
            self.in_planes = planes
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = F.avg_pool2d(out, 8)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out
```



What functions can be defined?

- model class

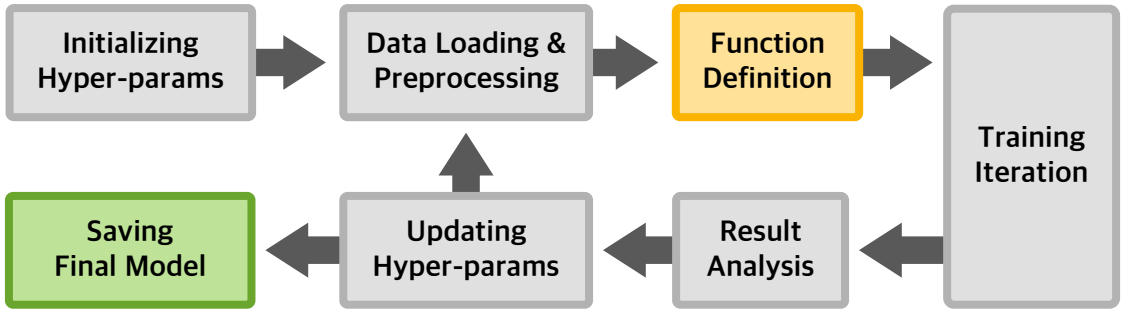
◀ Defined ResNet model class inheriting `torch.nn.Module`

Basic Flow with <code />

Function Definition

```
def epoch():
    def closure():
        ###########################################################################
        ##  loss part start  ######################################################
        ###########################################################################
        noise = r - net(s_t)
        noise_norm = torch.norm(noise)
        alpha_norm = torch.norm(net.weight)

        # objective : minimize noise
        objective = terms_weights[0] * torch.pow(noise_norm, 2) / 2

        # constraint : alpha >= 0
        alpha_maxterm = torch.max(
            torch.zeros(s_shift_len).to(device),
            -net.weight.squeeze(),
        )
        alpha_constraint = terms_weights[1] * torch.sum(alpha_maxterm)

        loss = objective + alpha_constraint
        ###########################################################################
        ###########################################################  end  ##
        ###########################################################################
        opt.zero_grad()
        loss.backward()
        return loss
    loss = opt.step(closure)
    last_loss = loss.item()
    last_grad = net.weight.grad
    last_alpha = get_numpy(net.weight).squeeze().reshape([s_shift_len, 1])
    last_noise = r_np - np.matmul(s_t_np, last_alpha)
    return (last_loss, last_alpha, last_noise, last_grad)
```

◀ Defined epoch function

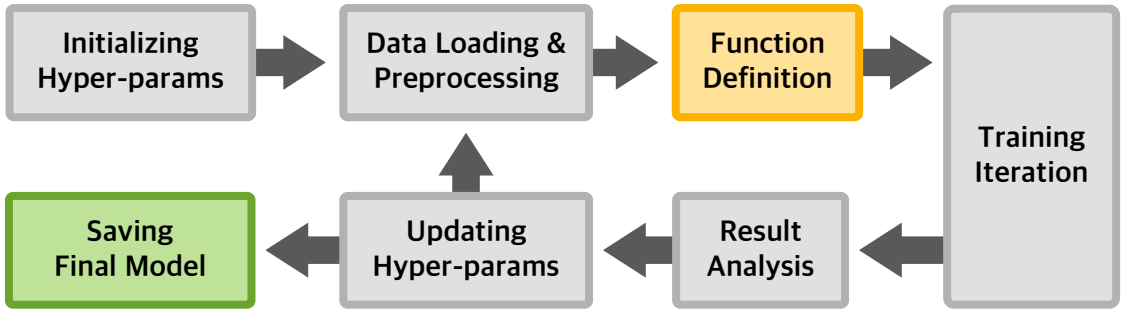


What functions can be defined?

- ➢ model class
- ➢ epoch function

Basic Flow with <code />

Function Definition




```python
def print_log_atomic(_idx, _iter, _loss, _grad, _an, _nn, _time, _p=None):
    tmp_str = f'Iter: {_iter:>5d} >> loss {_loss:<17.10f}   G {_grad:<14.7f}' \
            + f'   ||α|| {_an:<8.5f}   ||N|| {_nn:<8.5f}   🕓 {_time:7.3f}s'
    if _p is not None and _p >= earlystop_log_from:
        tmp_str = tmp_str + f' ¦ p={_p}'
    print(tmp_str)

def print_log(figure=True, alpha=None, noise=None, grad=None):
    if figure:
        plt = draw_figure(None, alpha, noise, grad, False)
        clear_output(wait=True)
        plt.show()
        print('')
    for iii in reversed(range(len(loss_records))):
        print_log_atomic(
            iii,
            iteration_idx_records[iii],
            loss_records[iii],
            gradnorm_records[iii],
            alphanorm_records[iii],
            noisenorm_records[iii],
            time_records[iii],
            earlystop_p_records[iii] if earlystop_enable else None,
        )
    print('')
```

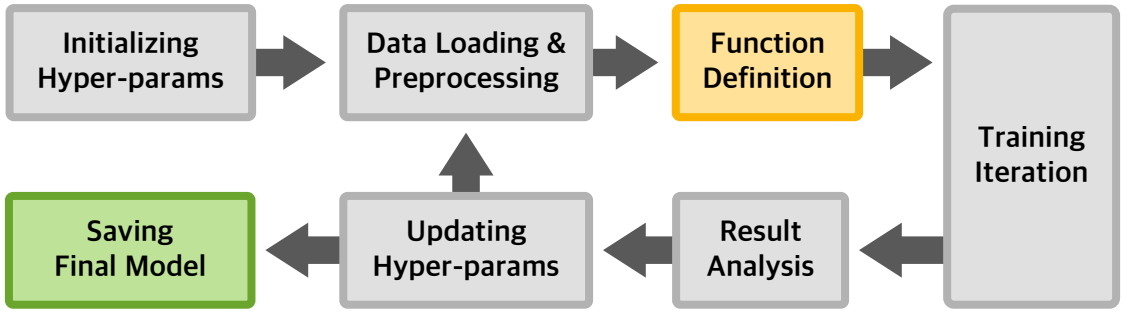
◀ Defined logging function

What functions can be defined?

- model class
- epoch function
- logging function

Basic Flow with <code />

Function Definition




```
def draw_figure(title=None, weights=None, noise=None, grad=None, show=True):
    if weights is None: weights = get_numpy(net.weight).squeeze()
    fig = plt.figure(2000, figsize=(12.5, 5), dpi=240)
    plt.clf()
    fig.patch.set_facecolor('#ffffff')
    ax_noise = fig.add_subplot()
    ax_weight_y = ax_noise.twinx()
    ax_weight = ax_weight_y.twiny()
    ax_grad_y = ax_weight.twinx()
    ax_grad = ax_grad_y.twiny()
    ax_grad_y.axis('off')
    ax_grad.axis('off')
    if noise is not None:
        line_noise1, = ax_noise.plot(
            noise[:samp_len], color='blue', alpha=0.35,
        )
        line_noise2, = ax_noise.plot(
            noise[samp_len:], color='red', alpha=0.35,
        )
        ax_noise_color = np.array([164, 107, 255]) / 255
        ax_noise.axhline(0, color=ax_noise_color)
        ax_noise.set_xlabel('Sample Idx.', color=ax_noise_color)
        ax_noise.set_ylabel('Noise', color=ax_noise_color)
        ax_noise.set_ylim([-0.015, 0.015])
        ax_noise.spines['left'].set_color(ax_noise_color)
        ax_noise.spines['bottom'].set_color(ax_noise_color)
        ax_noise.tick_params(axis='both', colors=ax_noise_color)
```

◀ Defined plotting function

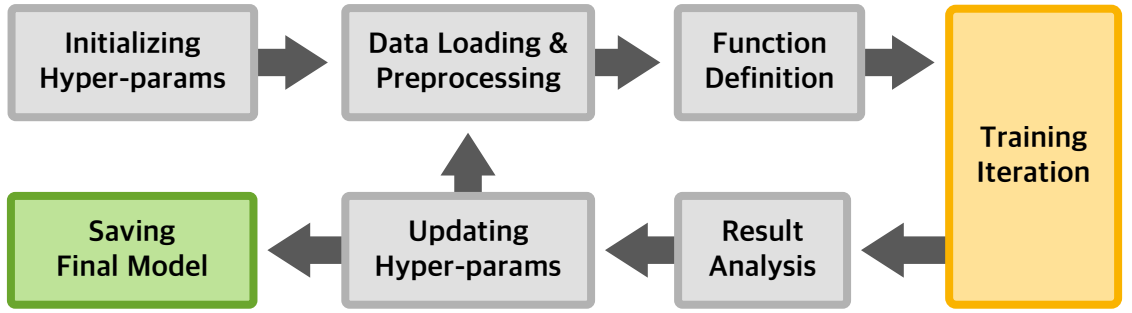
What functions can be defined?

- model class
- epoch function
- logging function
- plotting function

You can make other things into a function, of course~

Basic Flow with <code />

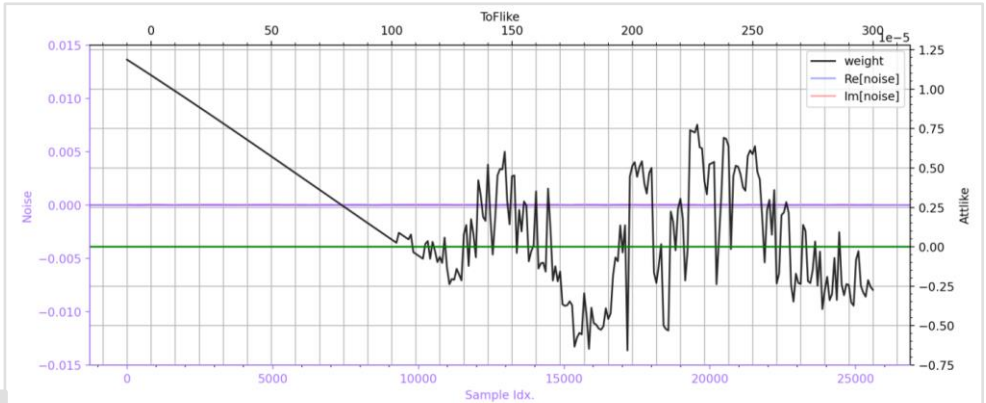
Training Iteration




```
### Iterations
# * Because the loss we get from LBFGS.step is "prev_loss", so using earlystop,
#   we should extract the weight of a previous network from the inflection pt.
#   This is implemented with `last_net2`.
last_loss = float('inf')
last_net, last_net_iter = deepcopy(net), 0
last_net2, last_net2_iter = deepcopy(net), 0
t_all_begin = time.time()
t_begin = time.time()
while True:
    check_exit_result = check_exit()
    if check_exit_result != 'keep going':
        alpha = get_numpy(last_net2.weight).squeeze().reshape([s_shift_len, 1])
        noise = r_np - np.matmul(s_t_np, alpha)
        plot = draw_figure(
            f'Final Model Status [Iteration {last_net2_iter}]\n',
            alpha, noise, None, False,
        )
        clear_output(wait=True)
        t_all_end = time.time()
        plot.show()
        print('')
        print(
            f'Optimized at iteration {last_net2_iter}, ' \
            + f'taken {t_all_end - t_all_begin:.5f}s, ' \
            + f'done with {check_exit_result}.'
        )
        print('')
        print_log(figure=False)
        break

    last_loss, last_alpha, last_noise, last_grad = epoch()
```

◀ Training iteration `while`

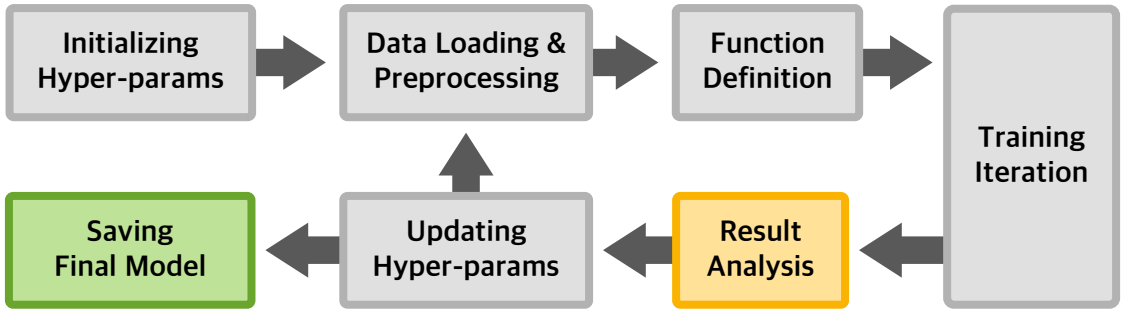
Training output ▶



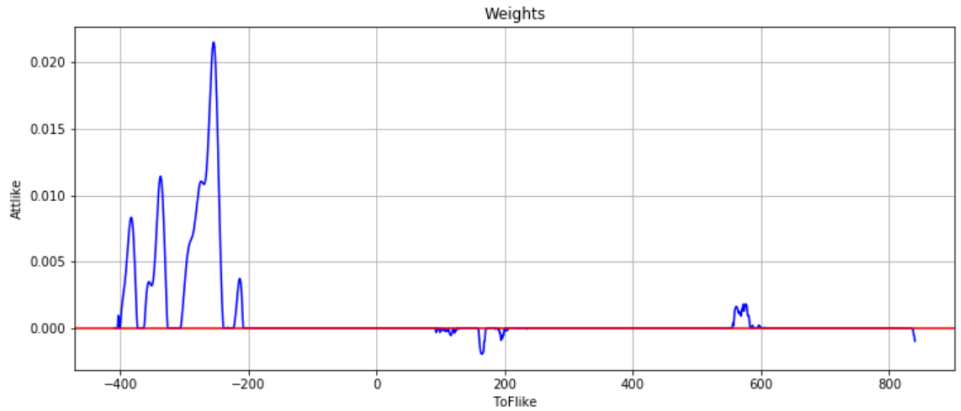

```
Optimized at iteration 0, taken 6.67750s, done with early stopping.

Iter:    6 >> loss 0.0850840732    G 158.7176819    ‖α‖ 0.01193    ‖N‖ 0.02048    0.397s | p=5
Iter:    5 >> loss 0.0610783324    G 141.2044830    ‖α‖ 0.00921    ‖N‖ 0.01740    1.507s | p=4
Iter:    0 >> loss 0.0051941895    G 7.3348756      ‖α‖ 0.00009    ‖N‖ 0.00137    0.225s
```

Basic Flow with <code />

Result Analysis




```
fig = plt.figure(2001, figsize=(12.5, 5))
plt.clf()
plt.plot(s_shift_range, result, color='blue')
plt.axhline(0, color='red')
plt.xlabel('ToFlike')
plt.ylabel('Attlike')
plt.title(f'Weights')
plt.grid()
plt.show()
```



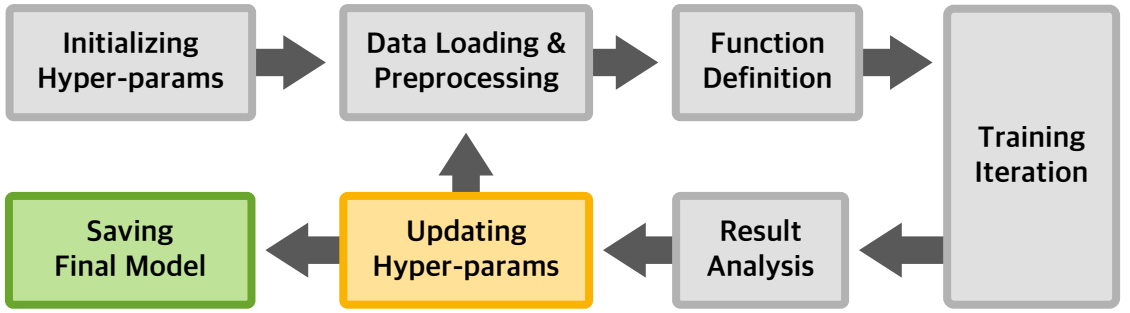
◀ Result analysis ▶

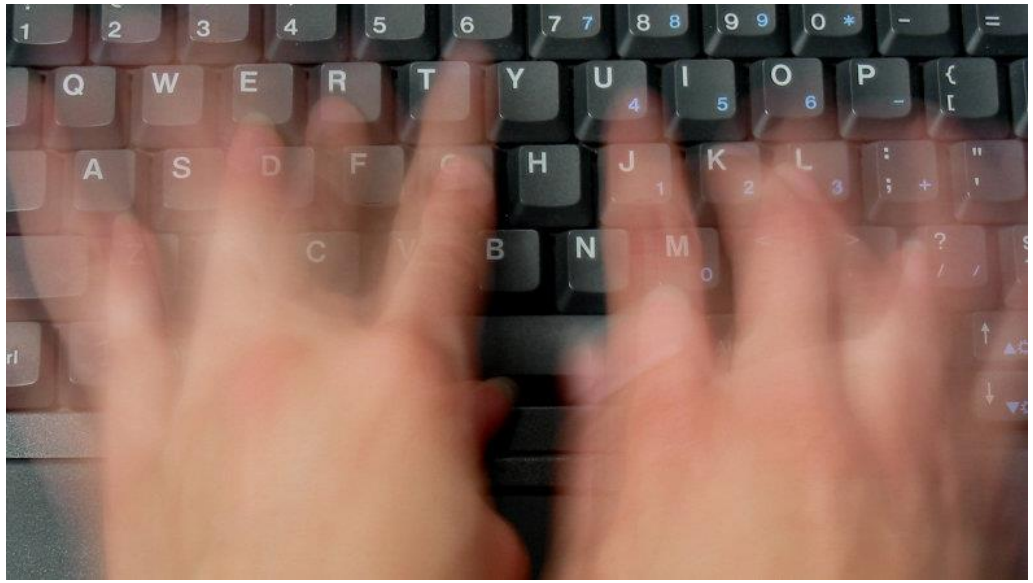
```
target_pow = 0
for idx in range(len(r_np)):
    target_pow += np.power(np.abs(r_np[idx]), 2)
noise_pow = 0
for idx in range(len(noise_complex)):
    noise_pow += np.power(np.abs(noise_complex[idx]), 2)
signal_pow = target_pow - noise_pow
snr_approx = np.log10(signal_pow / noise_pow) * 10
print(f'Target Signal PWR              [R] : {target_pow[0]}')
print(f'Approximated Signal PWR  [A=S^T·a] : {signal_pow[0]}')
print(f'Result Noise PWR           [N=R-A] : {noise_pow[0]}')
print(f'Approximated SNR             [A:N] : {snr_approx[0]}')
```

```
Target Signal PWR              [R] : 44.79031572701082
Approximated Signal PWR  [A=S^T·a] : 44.33525883161393
Result Noise PWR           [N=R-A] : 0.4550568953968937
Approximated SNR             [A:N] : 19.88683548701614
```

Basic Flow with <code />

Updating Hyper-parameters





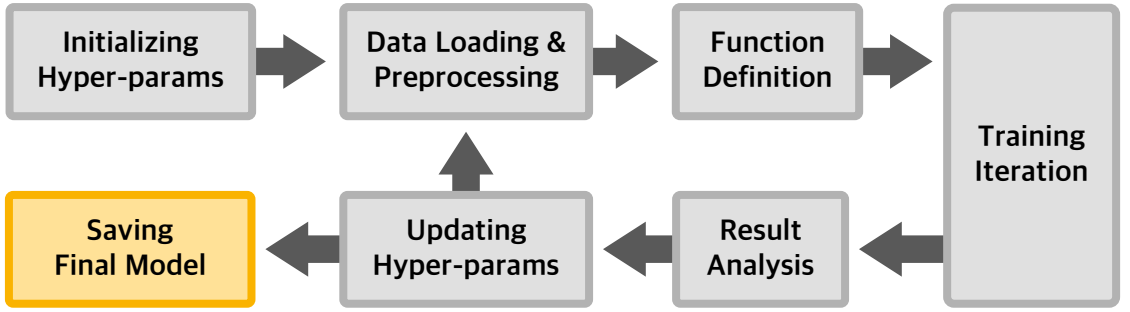
No code, do this by your self.

Basic Flow with <code />

Saving Final Model

```
confdict = {
    'shift_from': s_shift_from,
    'shift_to': s_shift_to,
    'earlystop': earlystop_patience,
    'term_weights': terms_weights,
    'samp_len': samp_len,
}

sav_alpha = result.reshape(s_shift_len, 1)
sav_noise = noise_complex.reshape(samp_len, 1)

hwk.save_mat('./gen2.0.out.mat', 'hwk_03.ipynb', sav_alpha, sav_noise, confdict)
```

▲ Saving model as .mat for further investigation

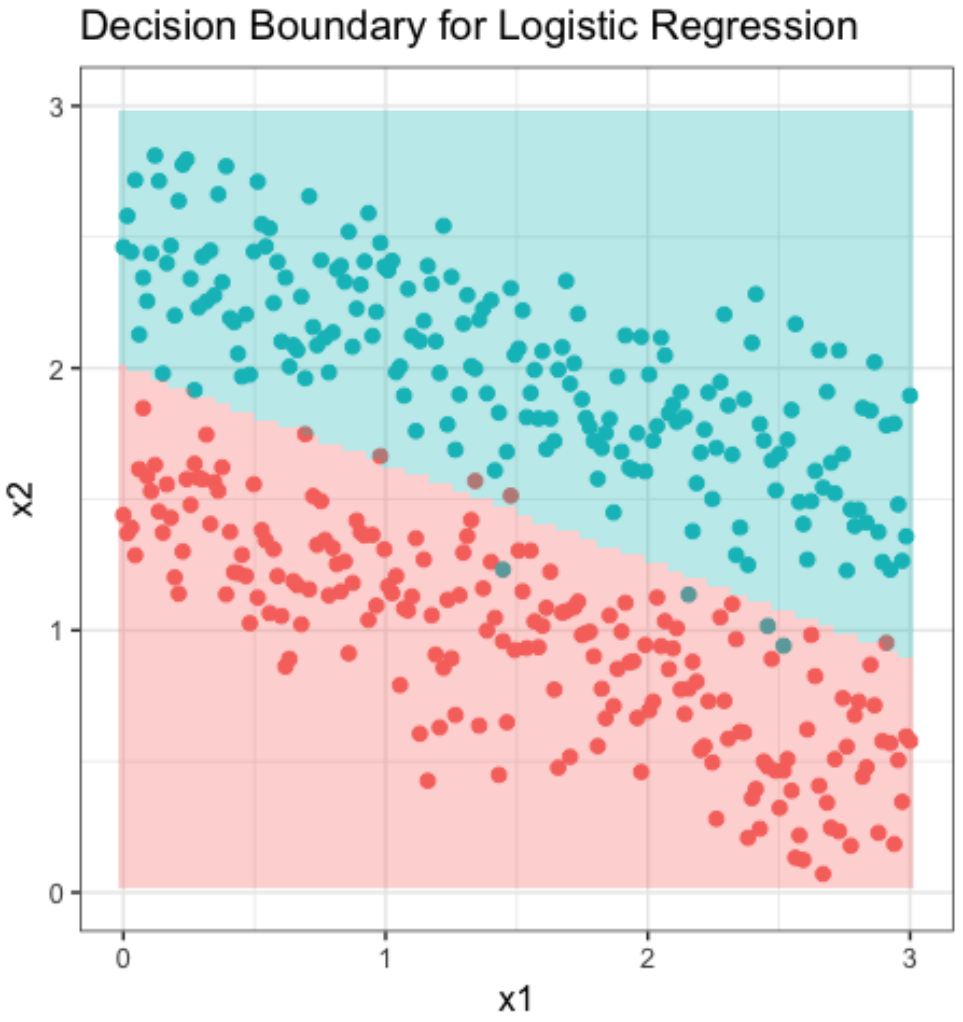


Backgrounds

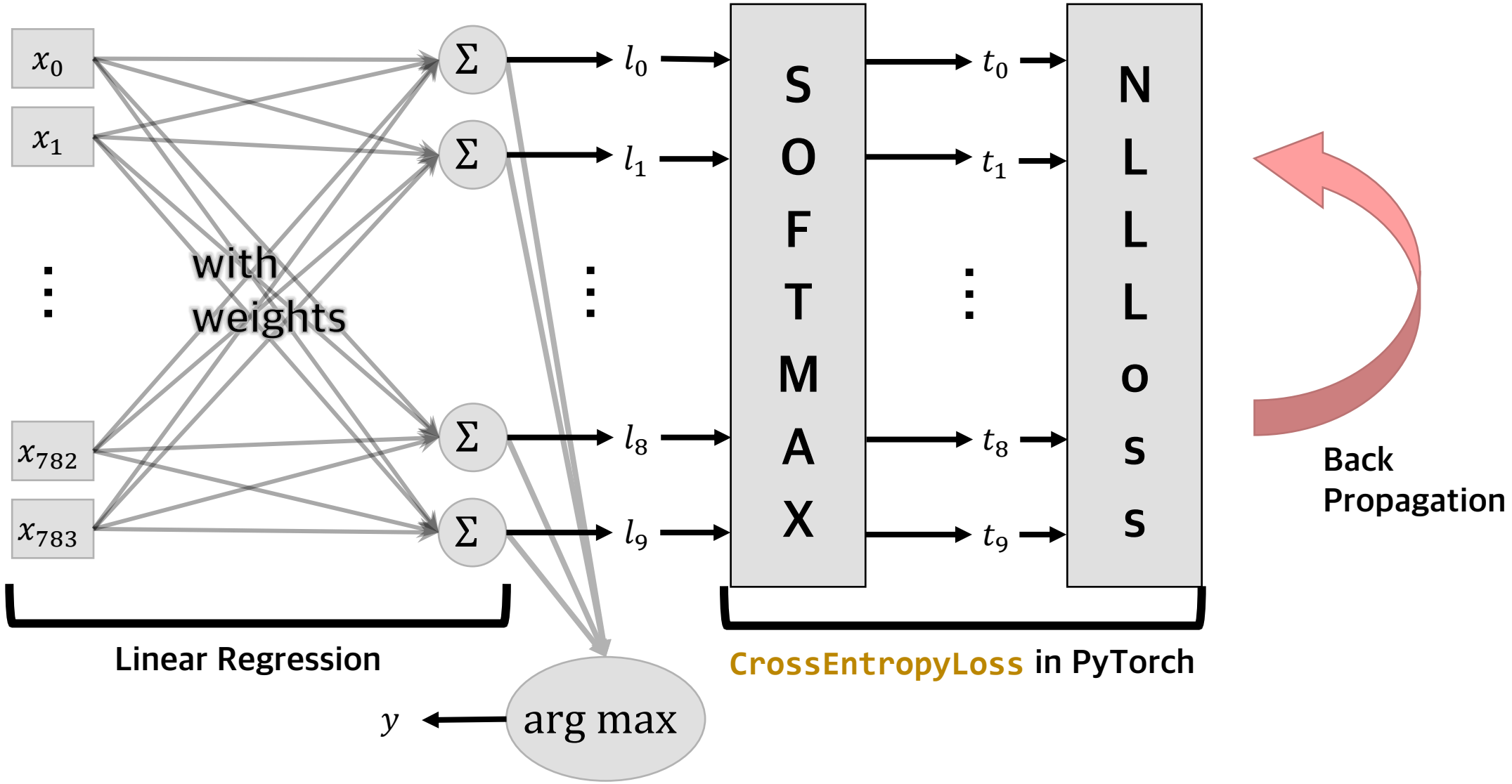
For your information & reminding

Logistic Regression = “Linear Logistic Regression”

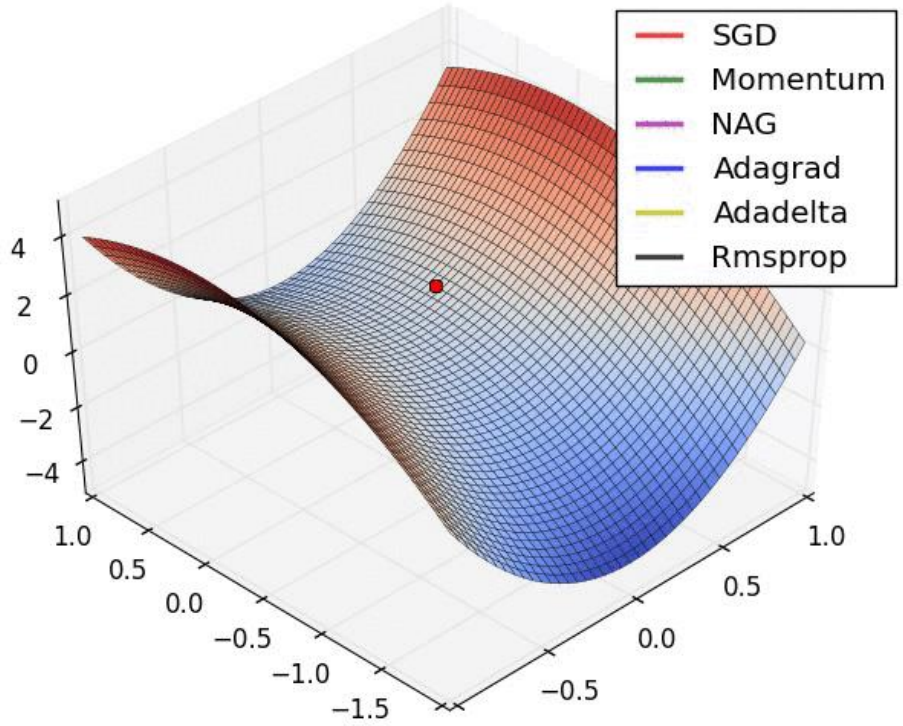
- **Regression = “Fitting”**
- **Logistic = “Linear Logistic”**
  - Decision boundary to be learned is linear
  - But output is not “score”, but logistic probability (softmax)
  - Logistic value is more fit to real world’s probability than linear score
  - Let’s go

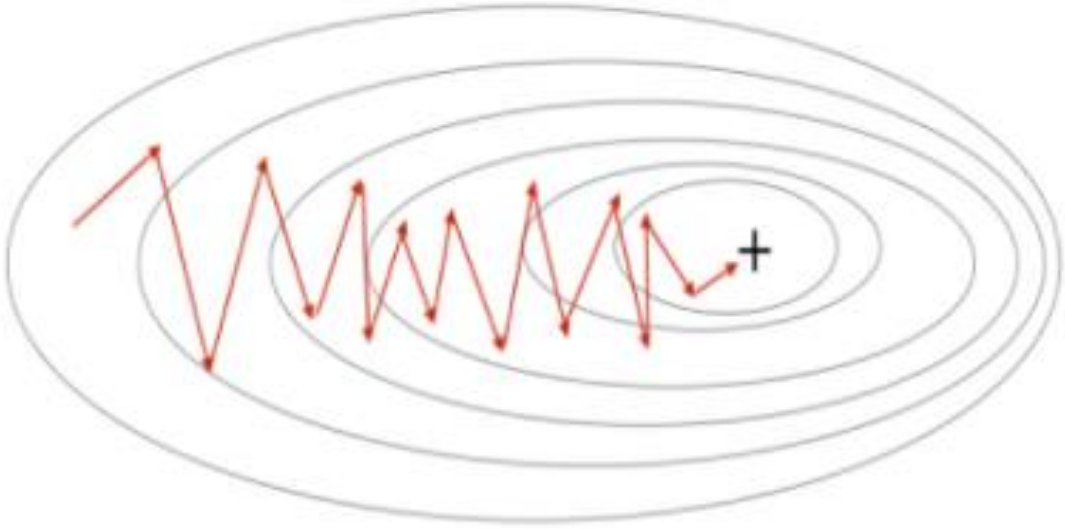


How is LR expressed in learning model?



Stochastic Gradient Descent





Because we randomly pick dataset to train

Gradient Descent

Stochastic Gradient Descent

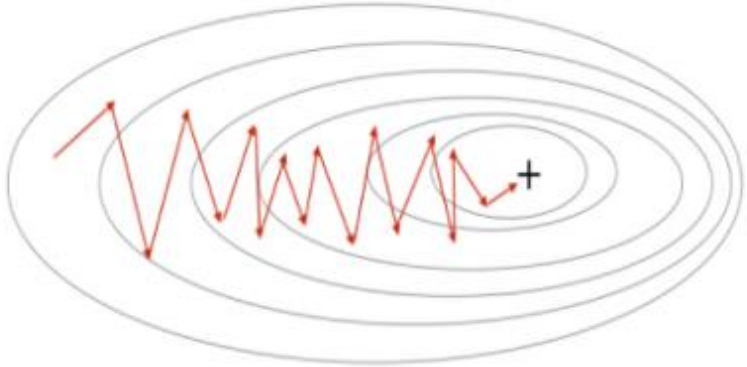
Mini-batch Stochastic Gradient Descent

Why Mini-batch SGD?

SGD samples 1 data from dataset at each iteration

- This one-shot learning makes learning oscillate!
- So put more data pair and accumulate gradients!

Mini-batch SGD samples many data at each iteration

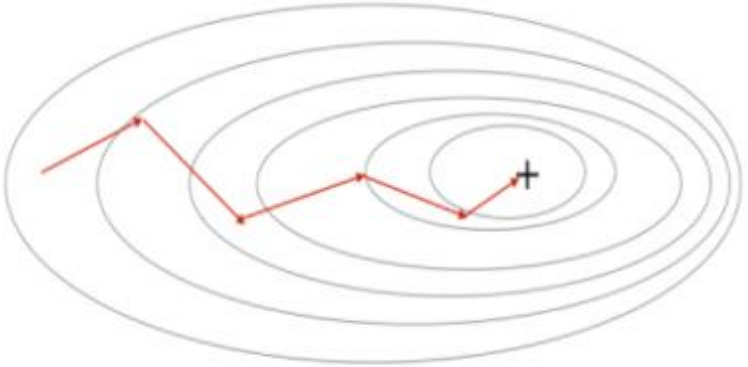


Stochastic Gradient Descent

How about learn all data pair at an iteration?

Good approach, so-called “Batch SGD”! But…

- It takes a lot of time and memory to learn all data pair when dataset becomes larger
- Hard to overcome local optimal



Mini-batch SGD

Summary

- We gonna attach “logistic function” so that the linear regression model can do classification task!

- We gonna give a dataset of specified size (not all !) for better gradient descent performance!

It’s coding time

Let’s fill the I.P.Y.N.B

Preparation

Base .ipynb :

https://git.io/aibd-py-2

Required Python Packages :

- matplotlib numpy scikit-learn
- torch torchvision seaborn

1. Library Importation & Device Preparation

Already prepared for you!

```
# You don't need to edit this section today.
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import time
import torch
import torch.nn as nn

from IPython.display import clear_output
from multiprocessing import cpu_count
from sklearn.metrics import confusion_matrix
from torch.optim import SGD
from torch.utils.data import DataLoader, random_split
from torchvision.datasets import MNIST
from torchvision.transforms import ToTensor

MNIST.resources = [
  (
    'https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz',
    'f68b3c2dcbeaaa9fbdd348bbdeb94873'
  ), (
    'https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz',
    'd53e105ee54ea40749a09fcbcd1e9432'
  ), (
    'https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz',
    '9fb629c4189551a2d022fa330f9573f3'
  ), (
    'https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz',
    'ec29112dd5afa0611ce80d1b7f02629c'
  )
]

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(f'{"CPU" if device == "cpu" else "GPU"} will be used in training/validation.')
```

Dataset URL in `torchvision` package is outdated

- So temporarily replaced source URL
- Future `torchvision` package will contain working URLs

2. Hyper-Parameters

```
# Data Loader
batch_size = 32

# Learning
logging_dispfig = True
maximum_epoch = 25
learning_rate = 0.1
```

Already prepared for you!

This section is generally filled during coding, but let's fill it in advance today.

- `batch_size` : the number of dataset in one mini-batch (generally a multiple of 2)
- `logging_dispfig` : switch for displaying learning graph during training
- `maximum_epoch` : training epoch count
- `learning_rate` : learning rate what you know

3. Data Load & Preprocessing

But no preprocessing today.

Download training dataset

```
# Load dataset into python variable
train_data = MNIST("./", train=True, transform=ToTensor(), target_transform=None, download=True)
train_data, valid_data = random_split(train_data, [54000, 6000])
test_data = MNIST("./", train=False, transform=ToTensor(), target_transform=None, download=True)
```

ToTensor?

Original dataset is in form of “PIL (Python Image Library)” image, so using **`torchvision.transforms.ToTensor()`** we can convert the image into torch Tensor.

3. Data Load & Preprocessing

But no preprocessing today.

Split train dataset to training set & validation set (ratio = 9:1)

```python
# Load dataset into python variable
train_data = MNIST("./", train=True, transform=ToTensor(), target_transform=None, download=True)
train_data, valid_data = random_split(train_data, [54000, 6000])
test_data = MNIST("./", train=False, transform=ToTensor(), target_transform=None, download=True)
```

Download test dataset

Datasets

- `train_data` : dataset used at gradient descent (real training)
- `valid_data` : dataset used to check learning progress
- `test_data` : dataset used to evaluate performance of model

3. Data Load & Preprocessing

But no preprocessing today.

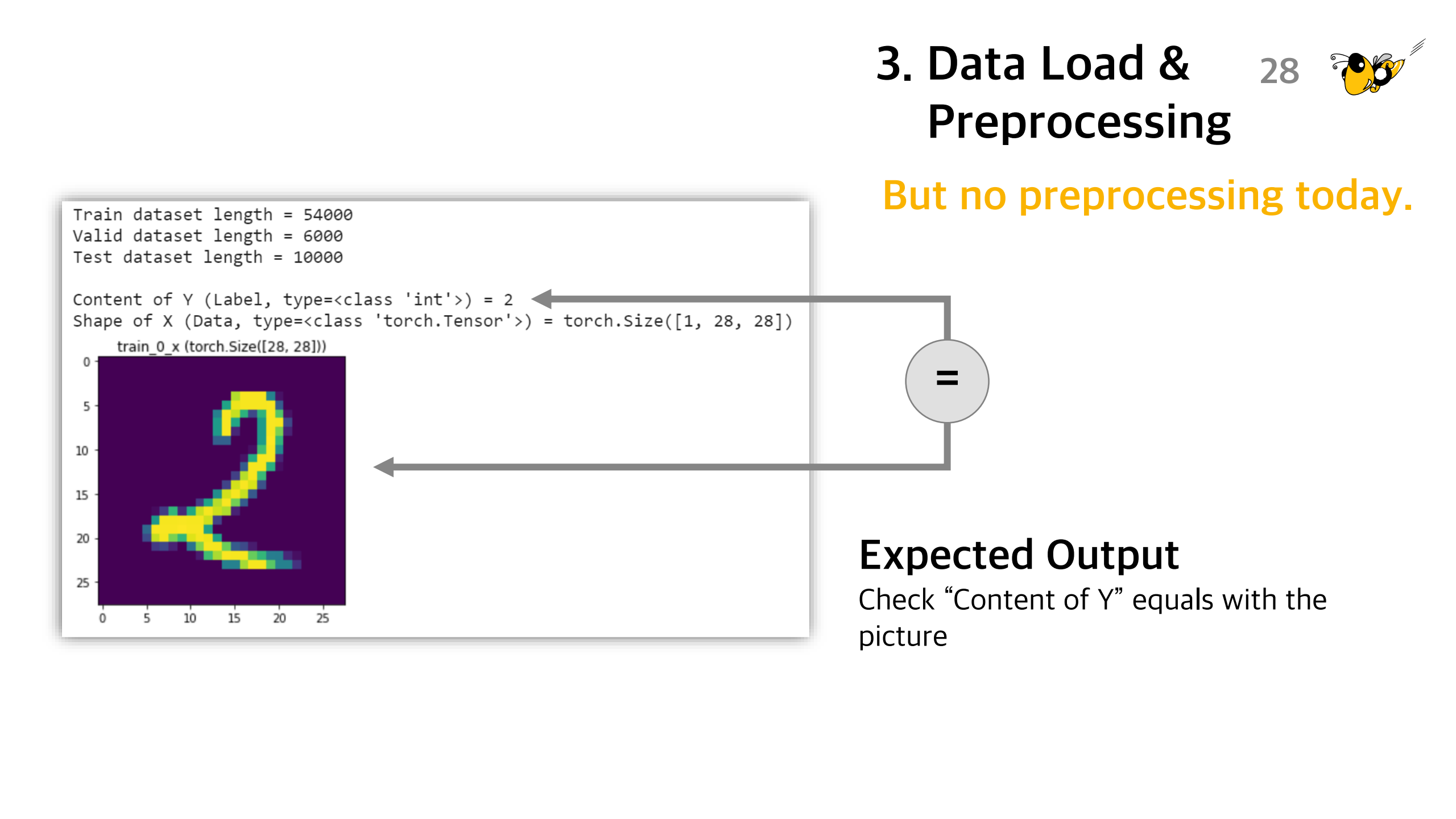
```
# Check the data
print(f'Train dataset length = {len(train_data)}')
print(f'Valid dataset length = {len(valid_data)}')
print(f'Test dataset length = {len(test_data)}\n')

train_0_x, train_0_y = train_data[0]
print(f'Content of Y (Label, type={type(train_0_y)}) = {train_0_y}')
print(f'Shape of X (Data, type={type(train_0_x)}) = {train_0_x.shape}')
plt.figure(1)
plt.imshow(train_0_x.squeeze())
plt.title(f'train_0_x ({train_0_x.squeeze().shape})')
plt.show()
```

Python Template Literal <f> Basic

From python 3.6, template literal <f> is supported

- Write <f> before opening apostrophe
- In string, use **{variable}** to embed variable

3. Data Load & Preprocessing



But no preprocessing today.

```
Train dataset length = 54000
Valid dataset length = 6000
Test dataset length = 10000

Content of Y (Label, type=<class 'int'>) = 2
Shape of X (Data, type=<class 'torch.Tensor'>) = torch.Size([1, 28, 28])
```


=

Expected Output

Check “Content of Y” equals with the picture

3. Data Load & Preprocessing

`shuffle` option
if `True`, DataLoader will shuffle dataset every epoch

But no preprocessing today.

```
# Create data loader
train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True, pin_memory=True,
                          drop_last=True)
valid_loader = DataLoader(valid_data, batch_size=len(valid_data), pin_memory=True)
test_loader = DataLoader(test_data, batch_size=len(test_data), pin_memory=True)
```

DataLoader (`torch.utils.data.DataLoader`)

Useful wrapper for data feeding

- Cut dataset based on **`batch_size`** → We are implementing mini-batch using this feature
- Make dataset into "Python **`Iterable`** object" → We can call **`enumerate()`**, **`iter()`** on **`DataLoader`**

3. Data Load & Preprocessing

But no preprocessing today.

`drop_last` option

when dataset length is not a multiple of `batch_size`, if `drop_last=True`, it drops last small data.

Example) `len(dataset)=38, batch_size=16`
⇒ 6 data pairs will not be used

```
# Create data loader
train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True, pin_memory=True,
                          drop_last=True)
valid_loader = DataLoader(valid_data, batch_size=len(valid_data), pin_memory=True)
test_loader = DataLoader(test_data, batch_size=len(test_data), pin_memory=True)
```

`pin_memory` option

when use CUDA, if `True`, dataset will be fixed on CUDA memory

3. Data Load & Preprocessing

`enumerate` function

make an enumerator who iterates `Iterable` with index

Enumerator will return `(index, content)` tuple(pair)

But no preprocessing today.

```
# Examine the data loader
train_enumerator = enumerate(train_loader)
ex_batch_idx, (ex_data, ex_label) = next(train_enumerator)
print(f'Idx: {ex_batch_idx} / X.shape = {ex_data.shape} / Y.shape = {ex_label.shape}\n')
print(f'Y[0:{batch_size}] = {ex_label}')

preview_index = 0
plt.figure(2)
plt.imshow(ex_data[preview_index, 0, :, :])
plt.title(f'Batch example data [{preview_index}, label={ex_label[preview_index]}]')
plt.show()
```

3. Data Load & Preprocessing

next function

iterate enumerator and returns `(index, content)` tuple

In this case, `content` is `(data,label)` pair, so unpacked

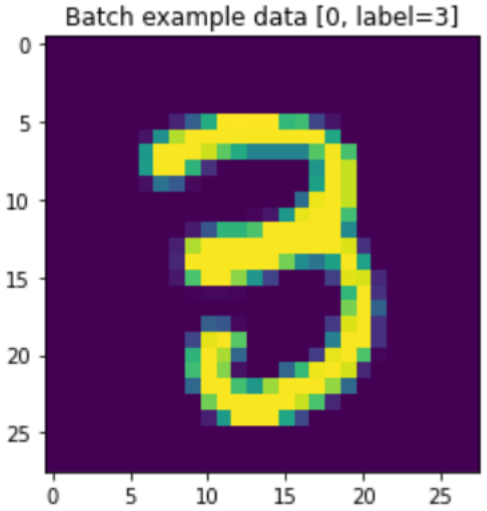
But no preprocessing today.

```
# Examine the data loader
train_enumerator = enumerate(train_loader)
ex_batch_idx, (ex_data, ex_label) = next(train_enumerator)
print(f'Idx: {ex_batch_idx} / X.shape = {ex_data.shape} / Y.shape = {ex_label.shape}\n')
print(f'Y[0:{batch_size}] = {ex_label}')

preview_index = 0
plt.figure(2)
plt.imshow(ex_data[preview_index, 0, :, :])
plt.title(f'Batch example data [{preview_index}, label={ex_label[preview_index]}]')
plt.show()
```

3. Data Load & Preprocessing

But no preprocessing today.

```
Idx: 0 / X.shape = torch.Size([32, 1, 28, 28]) / Y.shape = torch.Size([32])

Y[0:32] = tensor([3, 1, 0, 7, 7, 0, 1, 4, 9, 2, 7, 4, 0, 1, 5, 9, 3, 6, 0, 6, 7, 6, 1, 2,
        3, 1, 0, 4, 1, 0, 8, 7])
```



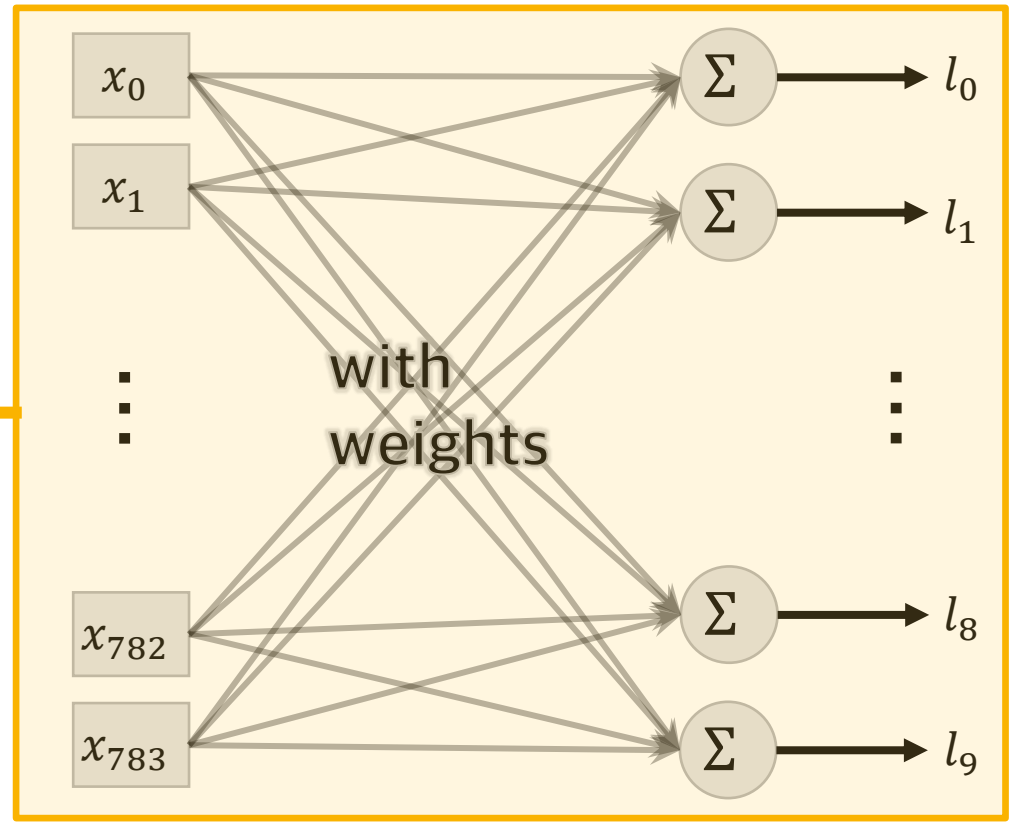
Expected Output

Check label equals with the picture

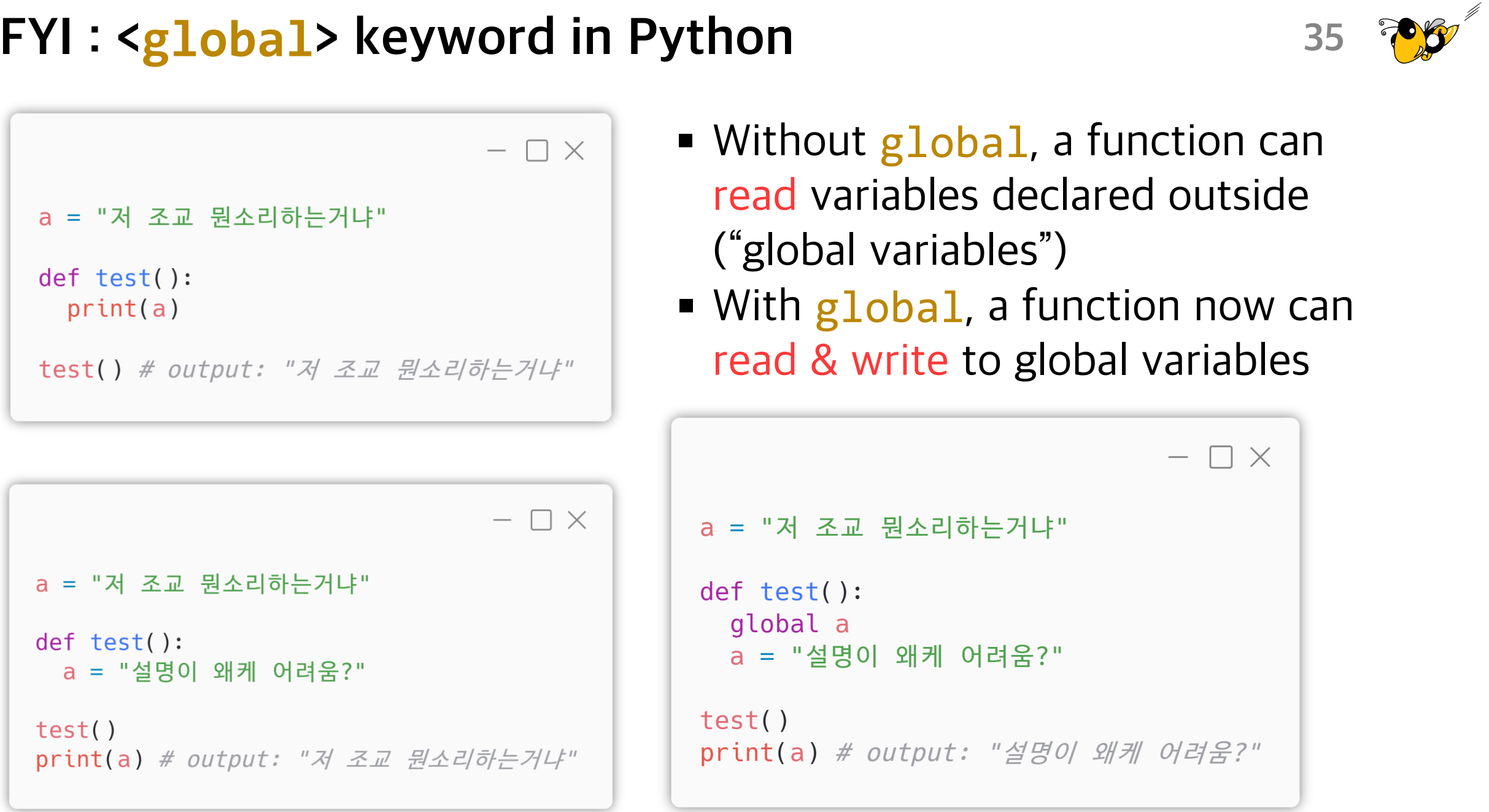
4. Function Definitions

Defining Model

```
# Model
def init_model():
  global net, loss_fn, optim
  net = nn.Linear(len(train_0_x.view([-1])), 10, bias=False).to(device)
  loss_fn = nn.CrossEntropyLoss()
  optim = SGD(net.parameters(), lr=learning_rate)
```



FYI : <global> keyword in Python



```
a = "저 조교 뭔소리하는거냐"

def test():
  print(a)

test() # output: "저 조교 뭔소리하는거냐"
```

- Without `global`, a function can read variables declared outside ("global variables")
- With `global`, a function now can read & write to global variables

```
a = "저 조교 뭔소리하는거냐"

def test():
  a = "설명이 왜케 어려움?"

test()
print(a) # output: "저 조교 뭔소리하는거냐"
```

```
a = "저 조교 뭔소리하는거냐"

def test():
  global a
  a = "설명이 왜케 어려움?"

test()
print(a) # output: "설명이 왜케 어려움?"
```

4. Function Definitions

Defining Epoch Functions

```
# Epoch
def init_epoch():
    global epoch_cnt
    epoch_cnt = 0


def epoch(data_loader):
    # One epoch : gets data_loader as input and returns loss / accuracy, and
    #             last prediction value / its label(truth) value for future use
    global epoch_cnt
    ### Put your script here ###
```

Next Page!

```
def epoch_not_finished():
    # For now, let's repeat training fixed times.
    # We will learn how to determine training stop or continue later.
    return epoch_cnt < maximum_epoch
```

4. Function Definitions

Defining Epoch Functions

```
def epoch(data_loader):
    # One epoch : gets data_loader as input and returns loss / accuracy, and
    #             last prediction value / its label(truth) value for future use
    global epoch_cnt

    iter_loss, iter_acc = [], []

    last_out, last_label = None, None
    last_grad_performed = False

    # Mini-batch iterations
    ### Put your script here ###

    # Up epoch count if backward propagation is done
    if last_grad_performed:
        epoch_cnt += 1

    return np.average(iter_loss), np.average(iter_acc), last_out, last_label
```

Next Page!

4. Function Definitions

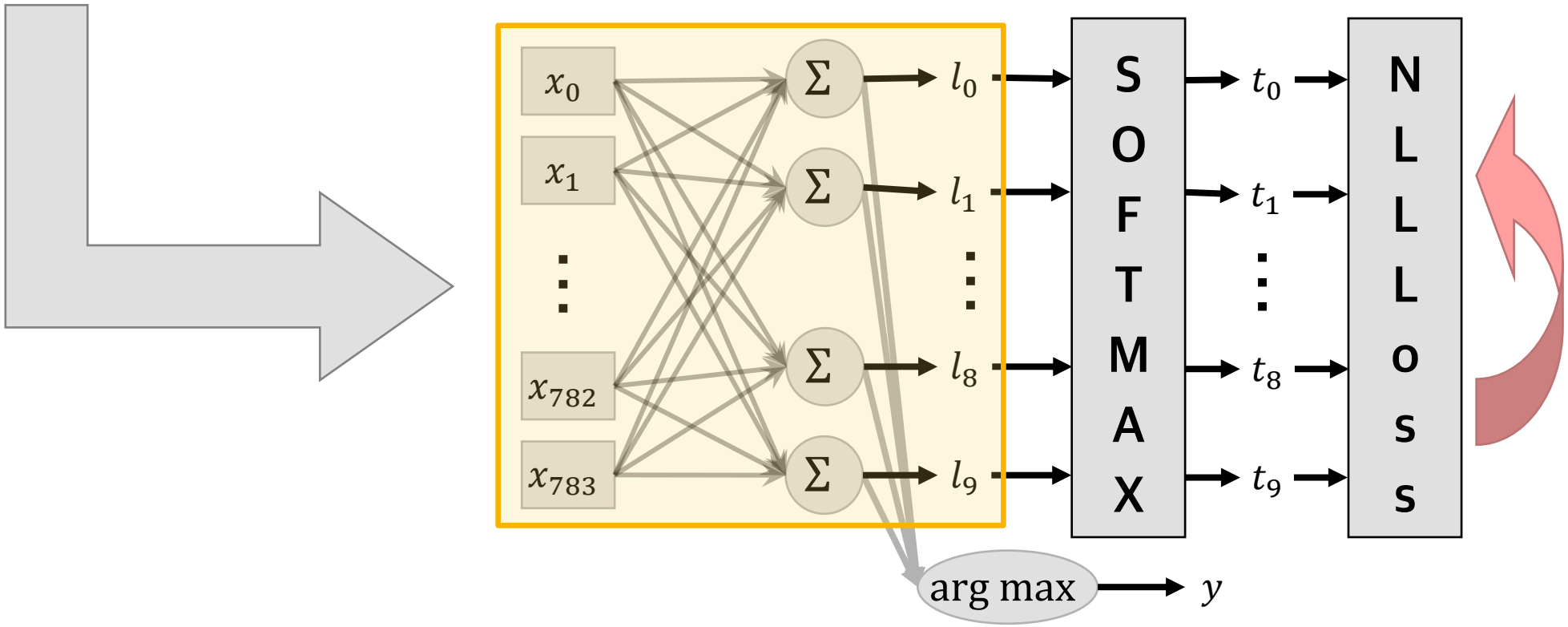
Defining Epoch Functions

```
# Mini-batch iterations
for _data, _label in data_loader:
    data = _data.view([len(_data), -1]).to(device)
    label = _label.to(device)

    # 1. Feed-forward

    # 2. Calculate accuracy

    # 3. Calculate loss

    # 4. Backward propagation if not in `torch.no_grad()`

    # 5. Save current iteration data for future use
```

4. Function Definitions

Defining Epoch Functions

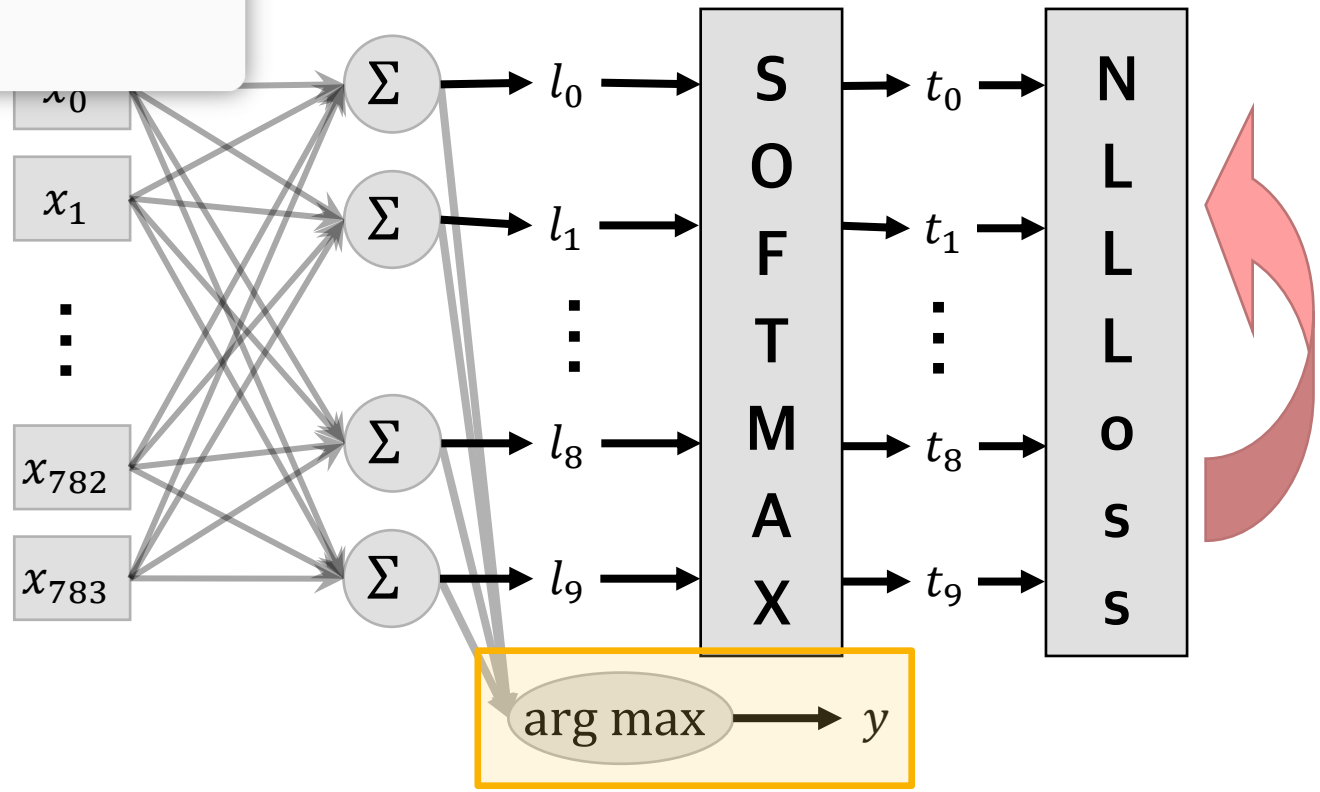
```
# 1. Feed-forward
onehot_out = net(data)
```



4. Function Definitions

Defining Epoch Functions

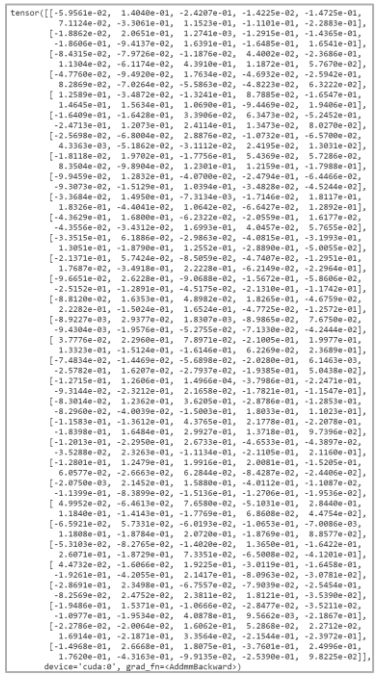
```
# 2. Calculate accuracy
_, out = torch.max(onehot_out, 1)
acc_partial = (out == label).float().sum()
acc_partial = acc_partial / len(label)
iter_acc.append(acc_partial.item())
```



4. Function Definitions

Defining Epoch Functions

```
# 2. Calculate accuracy
_, out = torch.max(onehot_out, 1)
acc_partial = (out == label).float().sum()
acc_partial = acc_partial / len(label)
iter_acc.append(acc_partial.item())
```



arg max in “classes” dimension

1

Compare & Calculate Correct Answer Ratio (Accuracy)

Real Label

2

```
tensor([4, 4, 7, 4, 3, 4, 5, 0, 3, 0, 4, 4, 4, 0, 4, 4, 3, 4, 4, 3, 3, 4, 5, 4,
        0, 4, 5, 5, 4, 4, 7, 5], device='cuda:0')
```

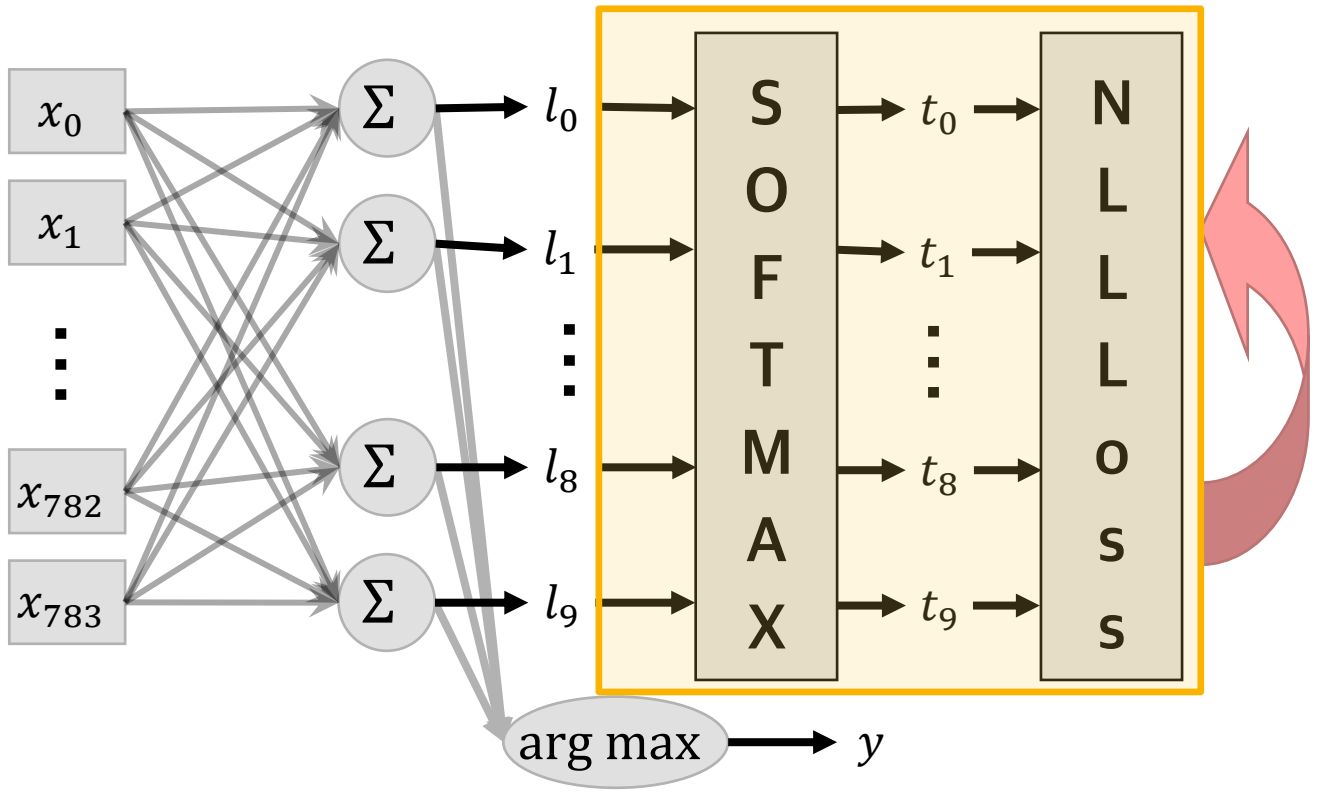
`onehot_out.shape = batch_size*10`
(score for each classes, each data)

`out.shape = batch_size*1`
(predicted label for each data)

4. Function Definitions

Defining Epoch Functions

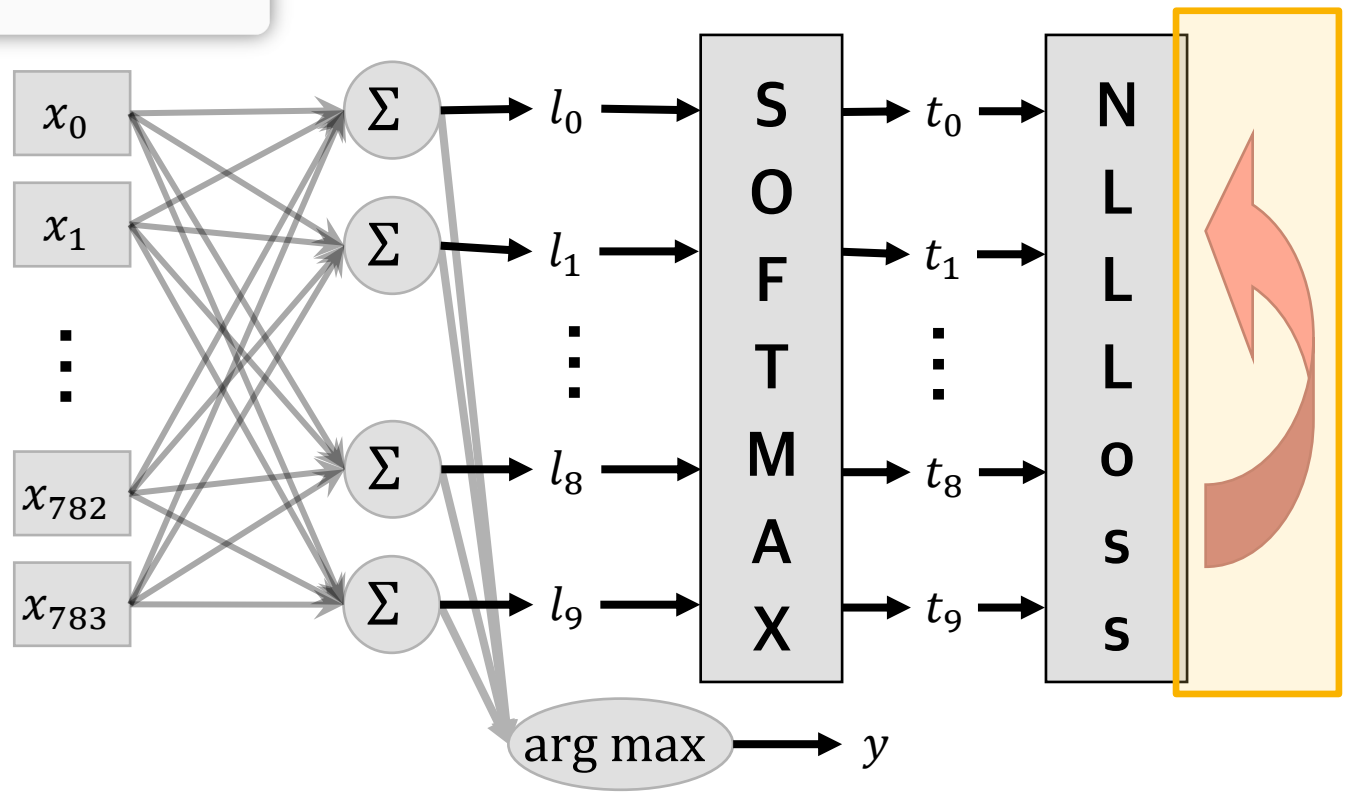
```
# 3. Calculate loss
loss = loss_fn(onehot_out, label)
iter_loss.append(loss.item())
```



4. Function Definitions

Defining Epoch Functions

```python
# 4. Backward propagation if not in `torch.no_grad()`
if onehot_out.requires_grad:
    optim.zero_grad()
    loss.backward()
    optim.step()
    last_grad_performed = True
```



4. Function Definitions

Defining Epoch Functions

```
# 5. Save current iteration data for future use
last_out = out.cpu().detach()
last_label = _label
```

https://i.imgur.com/7kISVTV.png

If you finished, compare your code with above!

4. Function Definitions

Defining Logging Functions

```
def init_log():
    global log_stack, iter_log, tloss_log, tacc_log, vloss_log, vacc_log, time_log
    iter_log, tloss_log, tacc_log, vloss_log, vacc_log = [], [], [], [], []
    time_log, log_stack = [], []


def record_train_log(_tloss, _tacc, _time):
    # Push time, training loss, training accuracy, and epoch count into lists
    time_log.append(_time)
    tloss_log.append(_tloss)
    tacc_log.append(_tacc)
    iter_log.append(epoch_cnt)


def record_valid_log(_vloss, _vacc):
    # Push validation loss and validation accuracy into each list
    vloss_log.append(_vloss)
    vacc_log.append(_vacc)
```

4. Function Definitions

Defining Logging Functions

```
def print_log():
    # Generate log string and put it into log stack
    log_str = f'Iter: {last(iter_log):>4d} >> T_loss {last(tloss_log):<8.5f}   ' \
            + f'T_acc {last(tacc_log):<6.5f}   V_loss {last(vloss_log):<8.5f}   ' \
            + f'V_acc {last(vacc_log):<6.5f}   🕒 {last(time_log):5.3f}s'
    log_stack.append(log_str)

    # Draw figure if want
    if logging_dispfig:
        hist_fig, loss_axis = plt.subplots(figsize=(10, 3), dpi=99)
        hist_fig.patch.set_facecolor('white')

        # Draw loss lines
        loss_t_line = plt.plot(iter_log, tloss_log, label='Train Loss', color='#FF9999', marker='o')
        loss_v_line = plt.plot(iter_log, vloss_log, label='Valid Loss', color='#99B0FF', marker='s')
        loss_axis.set_xlabel('epoch')
        loss_axis.set_ylabel('loss')

        # Draw accuracy lines
        acc_axis = loss_axis.twinx()
        acc_t_line = acc_axis.plot(iter_log, tacc_log, label='Train Acc.', color='#FF0000', marker='+')
        acc_v_line = acc_axis.plot(iter_log, vacc_log, label='Valid Acc.', color='#003AFF', marker='x')
        acc_axis.set_ylabel('accuracy')

        # Append annotations
        hist_lines = loss_t_line + loss_v_line + acc_t_line + acc_v_line
        loss_axis.legend(hist_lines, [l.get_label() for l in hist_lines])
        loss_axis.grid()
        plt.title(f'Learning history until epoch {last(iter_log)}')
        plt.draw()

    # Print log
    clear_output(wait=True)
    if logging_dispfig: plt.show()
    for idx in reversed(range(len(log_stack))):
        print(log_stack[idx])
```

5. Training Iteration

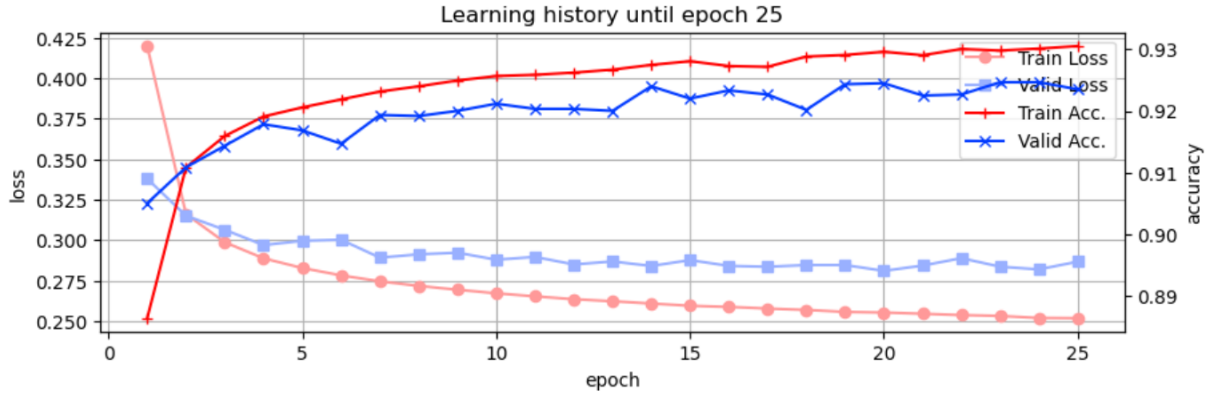
```
# Training Initialization
init_model()
init_epoch()
init_log()

while epoch_not_finished():
  start_time = time.time()
  tloss, tacc, _, _ = epoch(train_loader)
  end_time = time.time()
  time_taken = end_time - start_time
  record_train_log(tloss, tacc, time_taken)
  with torch.no_grad():
    vloss, vacc, _, _ = epoch(valid_loader)
    record_valid_log(vloss, vacc)
  print_log()

print('\n Training completed!')
```

`with torch.no_grad():`

PyTorch code in this section will be operated with autograd to be turned off. So, gradient is not calculated.

- No gradient calculation is needed for validation & test set
- In this section, **`net(data).requires_grad`** will be **`False`**

5. Training Iteration




```
Iter:   25 >> T_loss 0.25175    T_acc 0.93053   V_loss 0.28667    V_acc 0.92350    6.506s
Iter:   24 >> T_loss 0.25190    T_acc 0.93013   V_loss 0.28191    V_acc 0.92467    6.478s
Iter:   23 >> T_loss 0.25312    T_acc 0.92981   V_loss 0.28353    V_acc 0.92467    6.731s
Iter:   22 >> T_loss 0.25365    T_acc 0.93005   V_loss 0.28883    V_acc 0.92267    6.432s
Iter:   21 >> T_loss 0.25447    T_acc 0.92905   V_loss 0.28424    V_acc 0.92250    6.567s
Iter:   20 >> T_loss 0.25521    T_acc 0.92961   V_loss 0.28101    V_acc 0.92450    6.503s
Iter:   19 >> T_loss 0.25562    T_acc 0.92909   V_loss 0.28456    V_acc 0.92433    6.372s
Iter:   18 >> T_loss 0.25684    T_acc 0.92883   V_loss 0.28456    V_acc 0.92017    6.373s
Iter:   17 >> T_loss 0.25771    T_acc 0.92716   V_loss 0.28354    V_acc 0.92267    6.348s
Iter:   16 >> T_loss 0.25870    T_acc 0.92729   V_loss 0.28407    V_acc 0.92333    6.357s
Iter:   15 >> T_loss 0.25941    T_acc 0.92807   V_loss 0.28762    V_acc 0.92200    6.579s
Iter:   14 >> T_loss 0.26079    T_acc 0.92748   V_loss 0.28401    V_acc 0.92400    6.360s
Iter:   13 >> T_loss 0.26221    T_acc 0.92670   V_loss 0.28678    V_acc 0.92000    6.354s
Iter:   12 >> T_loss 0.26347    T_acc 0.92622   V_loss 0.28496    V_acc 0.92033    6.414s
Iter:   11 >> T_loss 0.26523    T_acc 0.92587   V_loss 0.28960    V_acc 0.92033    6.681s
Iter:   10 >> T_loss 0.26711    T_acc 0.92566   V_loss 0.28789    V_acc 0.92117    6.806s
Iter:    9 >> T_loss 0.26933    T_acc 0.92494   V_loss 0.29222    V_acc 0.92000    6.563s
Iter:    8 >> T_loss 0.27169    T_acc 0.92400   V_loss 0.29121    V_acc 0.91917    6.253s
Iter:    7 >> T_loss 0.27453    T_acc 0.92314   V_loss 0.28915    V_acc 0.91933    6.291s
Iter:    6 >> T_loss 0.27820    T_acc 0.92187   V_loss 0.30022    V_acc 0.91467    6.294s
Iter:    5 >> T_loss 0.28274    T_acc 0.92057   V_loss 0.29954    V_acc 0.91683    6.286s
Iter:    4 >> T_loss 0.28874    T_acc 0.91909   V_loss 0.29692    V_acc 0.91783    6.333s
Iter:    3 >> T_loss 0.29866    T_acc 0.91592   V_loss 0.30634    V_acc 0.91433    6.267s
Iter:    2 >> T_loss 0.31605    T_acc 0.91083   V_loss 0.31506    V_acc 0.91083    6.496s
Iter:    1 >> T_loss 0.41990    T_acc 0.88632   V_loss 0.33793    V_acc 0.90500    7.000s

 Training completed!
```

Expected Output

Accuracy Test

```
# Accuracy for test dataset
with torch.no_grad():
    test_loss, test_acc, test_out, test_label = epoch(test_loader)
    print(f'Test accuracy = {test_acc}\nTest loss = {test_loss}')
```

```
Test accuracy = 0.922499954700047
Test loss = 0.2745736539363861
```

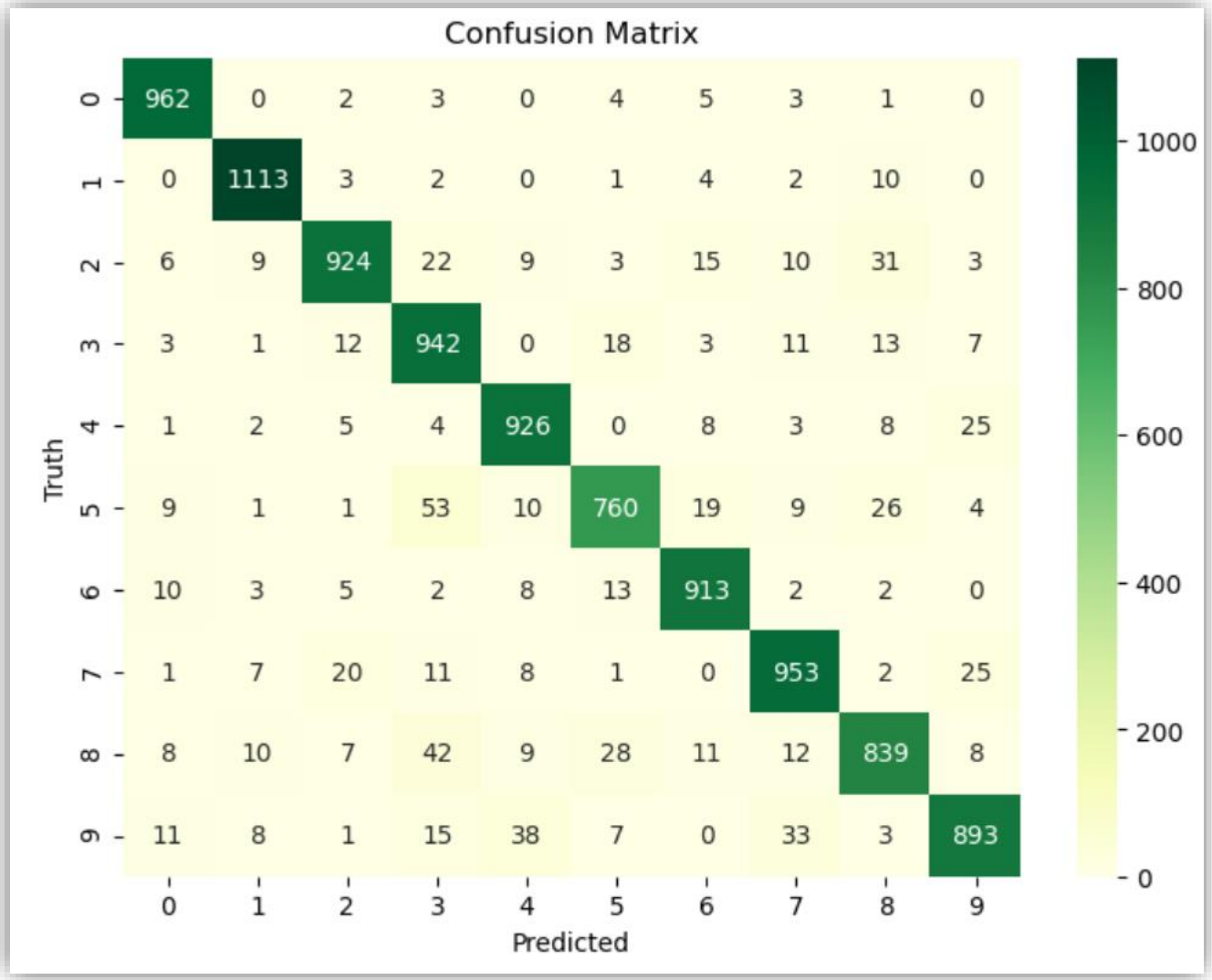
Expected Output

Confusion Matrix

```
# Confusion matrix
our_cmatrix = confusion_matrix(test_label, test_out)
plt.figure(figsize=(8, 6), dpi=99)
sns.heatmap(our_cmatrix, annot=True, fmt='g', cmap='YlGn').set(xlabel='Predicted', ylabel='Truth')
plt.title('Confusion Matrix')
plt.show()
```

6. Result Analysis

Confusion Matrix



Expected Output

7. Saving Model

```
# To save
torch.save(net.state_dict(), './model.pkl')

# To load
net = torch.load('./model.pkl')
```

Weight Initialization

How weight initialization impact the performance?

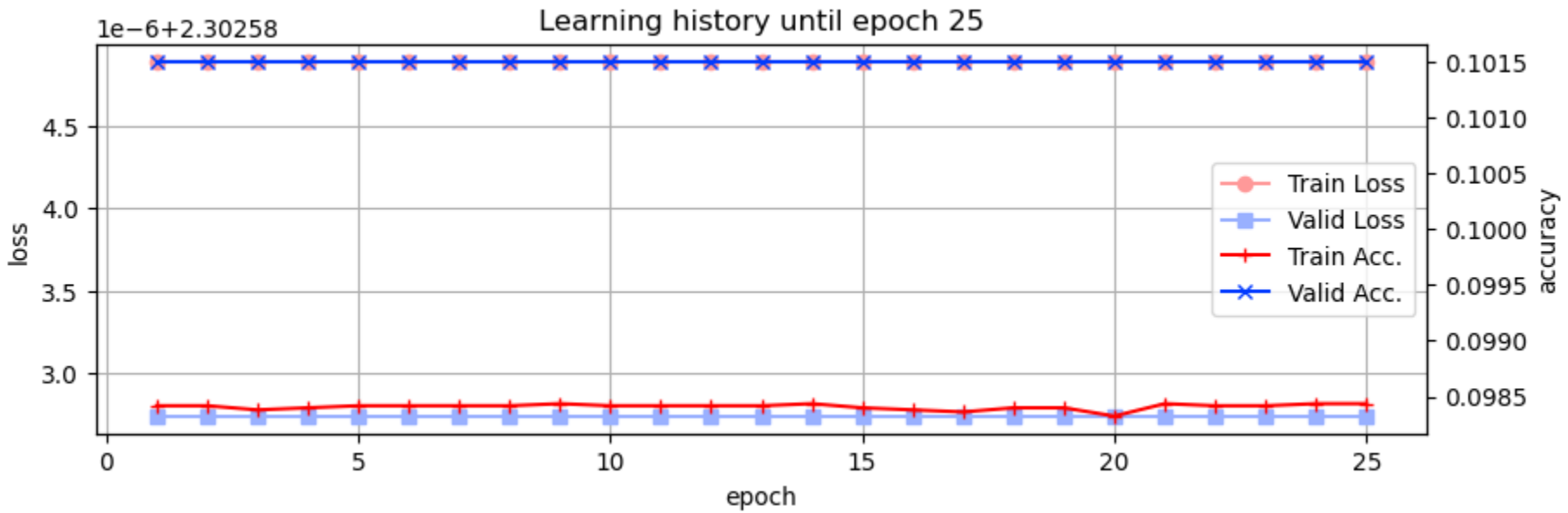
Let’s add some layers …

```
# Data Loader
batch_size = 32

# Model
hidden_layer = 200

# Learning
logging_dispfig = True
maximum_epoch = 25
learning_rate = 0.1
```

```
# Model
def init_model():
  global net, loss_fn, optim
  net = nn.Sequential(
    nn.Linear(len(train_0_x.view([-1])), hidden_layer, bias=False),
    nn.ReLU(),
    nn.Linear(hidden_layer, 10, bias=False)
  ).to(device)
  loss_fn = nn.CrossEntropyLoss()
  optim = SGD(net.parameters(), lr=learning_rate)
  nn.init.zeros_(net[0].weight)
  nn.init.zeros_(net[2].weight)
```

And Try Training.

What's the result?

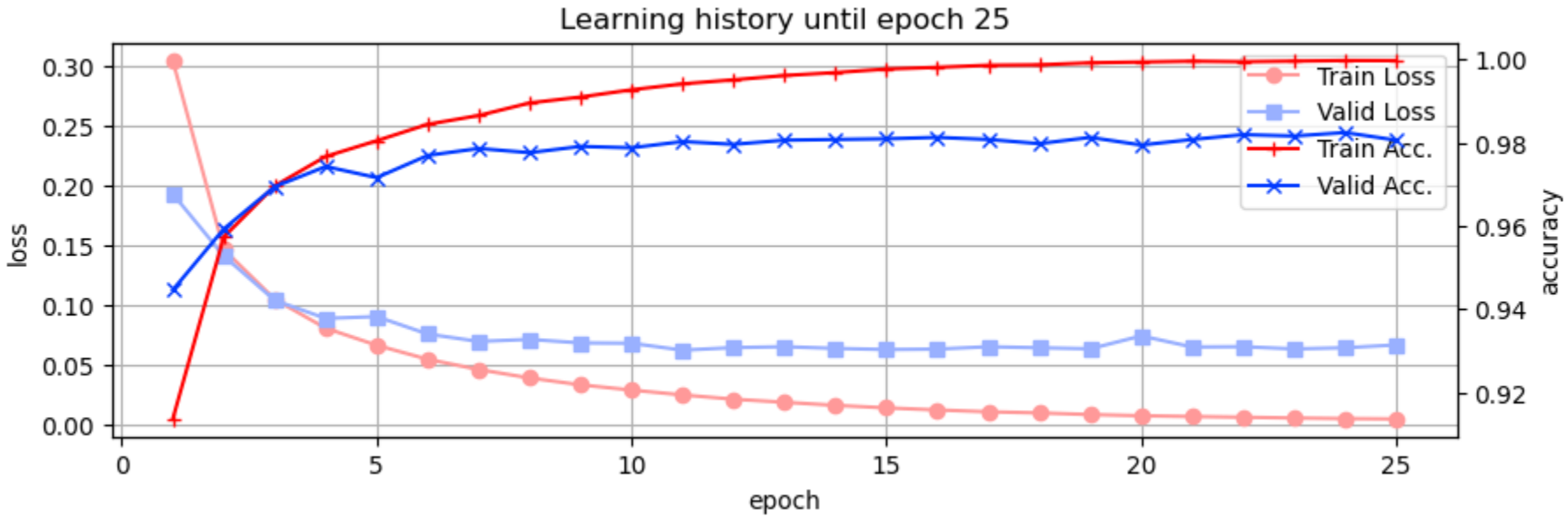


Let’s apply normal distribution to initial weights …

```
# Model
def init_model():
  global net, loss_fn, optim
  net = nn.Sequential(
    nn.Linear(len(train_0_x.view([-1])), hidden_layer, bias=False),
    nn.ReLU(),
    nn.Linear(hidden_layer, 10, bias=False)
  ).to(device)
  loss_fn = nn.CrossEntropyLoss()
  optim = SGD(net.parameters(), lr=learning_rate)
  nn.init.xavier_normal_(net[0].weight)
  nn.init.xavier_normal_(net[2].weight)
```

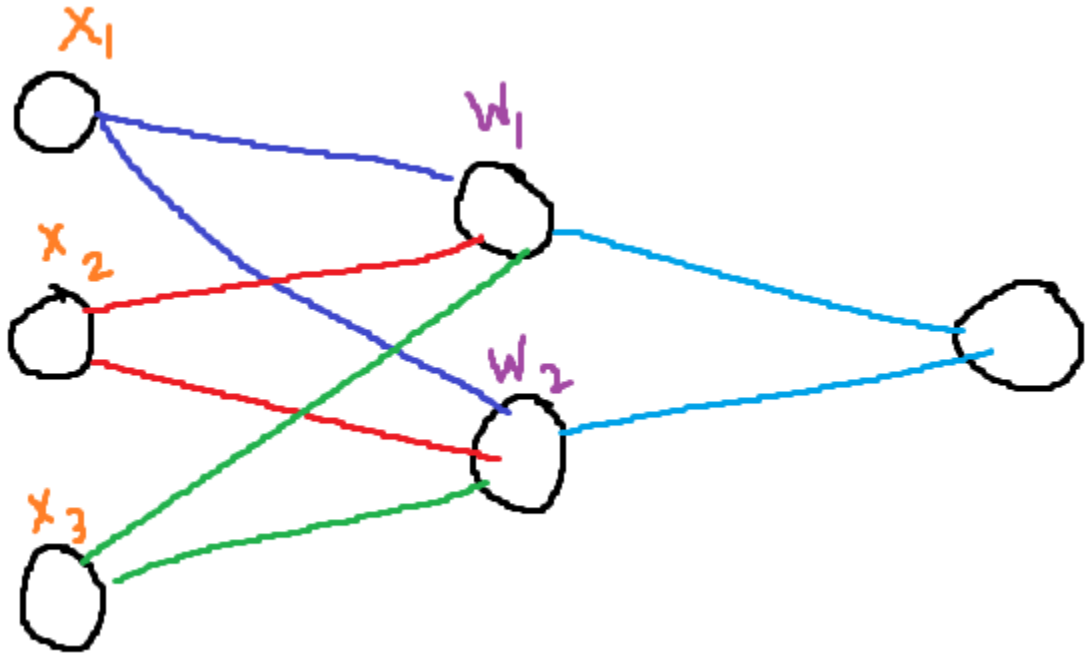
And Try Training Again.

What's the result?



What made this result?

When a model is initialized with zero, they will have same gradient!



So if you want your model work properly, don’t touch to initial value or don’t set it zero!

Finding Proper Hyper-parameters

Is there any way to find best hyper-parameters?

No effective method to find hyper-parameters

Brute-force is the answer!!

You can check the full version of today's .ipynb at

https://git.io/aibd-full-2