Deep Learning Toolkit
(PyTorch & Timm)

Rowel Atienza, PhD

University of the Philippines

github.com/roatienza

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PyTorch

https://pytorch.org/

https://github.com/yunjey/pytorch-tutorial

Why PyTorch?

Easy to build, train, validate and debug models

Available implementation and pre-trained weights of state-of-the-art (SOTA) models

Huge community of users

Production-ready

PyTorch now under Linux Foundation

PyTorch is now 2.0 – better and faster model training and inference

Install and Test

```
pip install torch torchvision torchaudio
```

Activate python3

```
>>> import torch
>>> print(torch.__version__)
2.4.0+cu121
```

Introducing PyTorch for Deep Learning

`torch.Tensor`

Model Inference

Tensor

https://pytorch.org/docs/stable/tensors.html

Tensor – PyTorch Data Structure

Numpy data structure: `ndarray`

```
>>> a = np.ones((1,2))
>>> type(a)
<class 'numpy.ndarray'>
```

PyTorch data structure: `Tensor`

```
>>> b = torch.ones((1,2))
>>> type(b)
<class 'torch.Tensor'>
```

Numpy `ndarray` vs PyTorch `Tensor`

Data Structure	CPU	AI Accelerator		
		GPU	TPU	IPU
Numpy `ndarray`	✓	✗	✗	✗
PyTorch `Tensor`	✓	✓	✓	✓

Tensor operations/attributes

```
Initialize:
a = torch.tensor(
                  [[2., 2.],
                   [4., 4.]])
x = torch.tensor(
                  [[1.], [2.]])
```

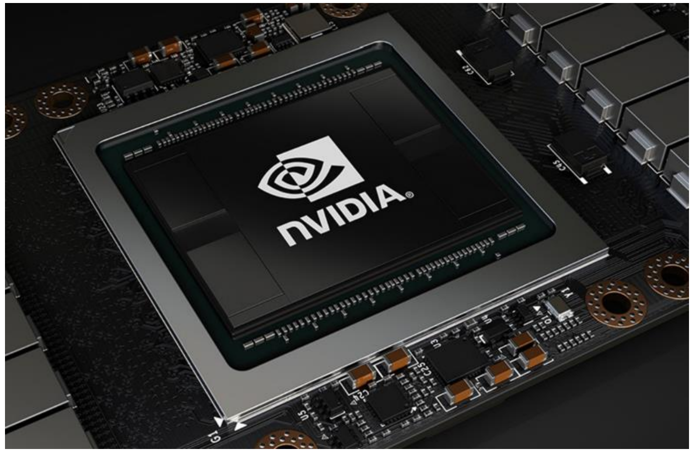
```
Size/shape:
>>> a.size()
torch.Size([2, 2])
>>> a.shape
torch.Size([2, 2])
>>> a.dtype
torch.float32
```

Multiply:

```
>>> a @ x
tensor([[ 6.],
         [12.]])
>>> torch.matmul(a,x)
tensor([[ 6.],
         [12.]])
>>> einsum(
     'i j, j k -> i k’,
      a, x)
tensor([[ 6.],
         [12.]])
```

Available Devices for PyTorch

```
device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Using {device} device")
```

Laptop	GPU server
`Using cpu device`	`Using cuda device`
	

Tensor in GPU

```
a = torch.tensor([[2., 2.], [4., 4.]])
a.device
```

Laptop	GPU server
`device(type='cpu')`	`device(type='cpu')`

```
a = a.to(device)
```

Laptop	GPU server
`device(type='cpu')`	`device(type='cuda', index=0)`

Tensor in GPU and Back to CPU

Laptop	GPU server

`>>> a`
`tensor([[2., 2.],`
`        [4., 4.]])`
	`>>> a`
	`tensor([[2., 2.],`
	`        [4., 4.]], device='cuda:0')`

Laptop – Back to CPU (No Change)	GPU server – Back to CPU

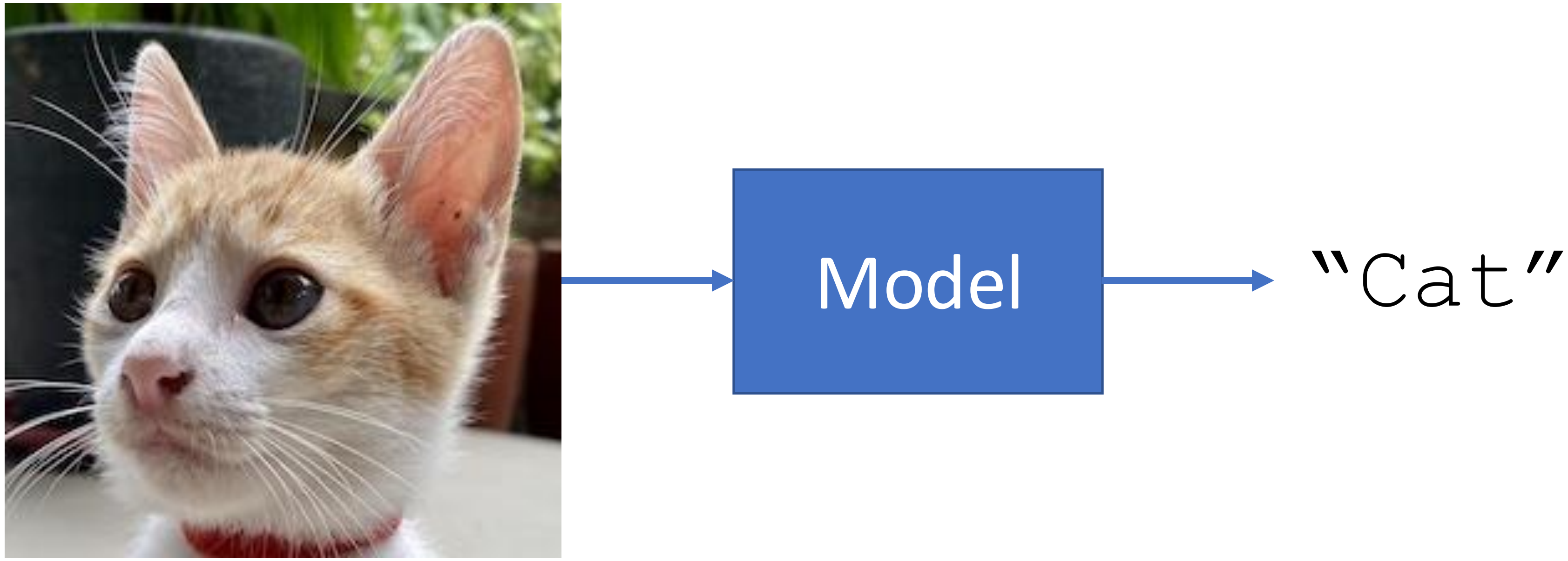
`>>> a = a.cpu()`
`>>> a`
`tensor([[2., 2.],`
`        [4., 4.]])`
	`>>> a = a.cpu()`
	`>>> a`
	`tensor([[2., 2.],`
	`        [4., 4.]])`

Numpy to PyTorch to Numpy

Data Structure	Device	Code
`np.ndarray`	CPU	`a = np.array([ [1., 2.], [2., 4.] ])`

Model Inference

Model Inference



Input Data → Trained Model → Output Prediction

Input

Can be any type of data

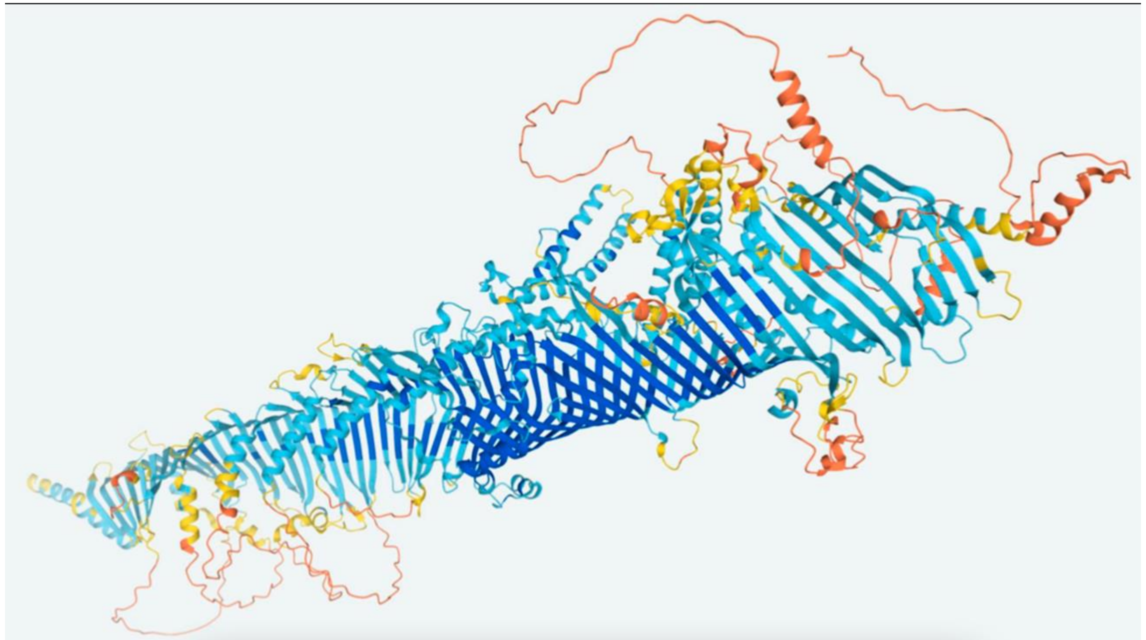
Vision: image, video

Waveforms: speech, music

3D: point cloud

Text: character, word, phoneme

Other forms: radar, multi-spectral, protein structure, etc



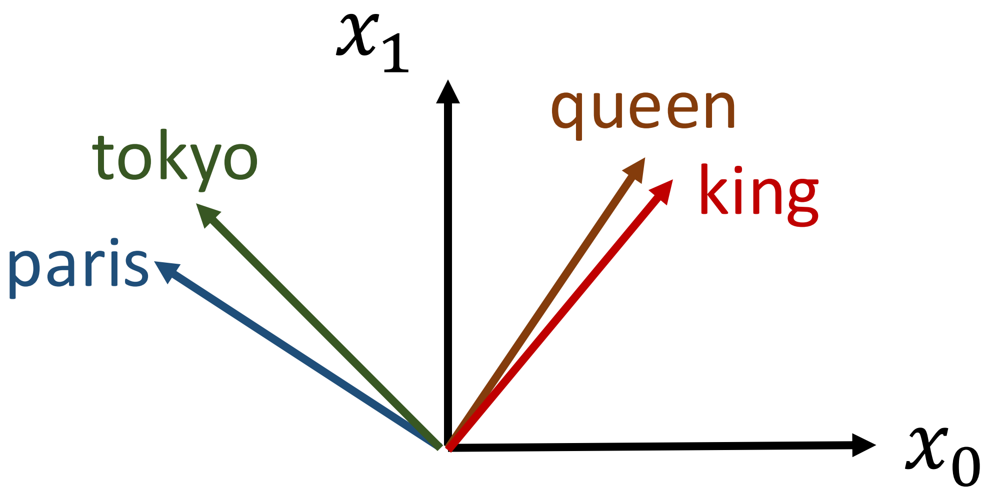
Protein structure of a fruitfly
[Science.org 2021]

Loading Image Data

```
from PIL import Image
img = Image.open(“wonder_cat.jpg”)

# Visualize the data
# in Jupyter
display(img)
```

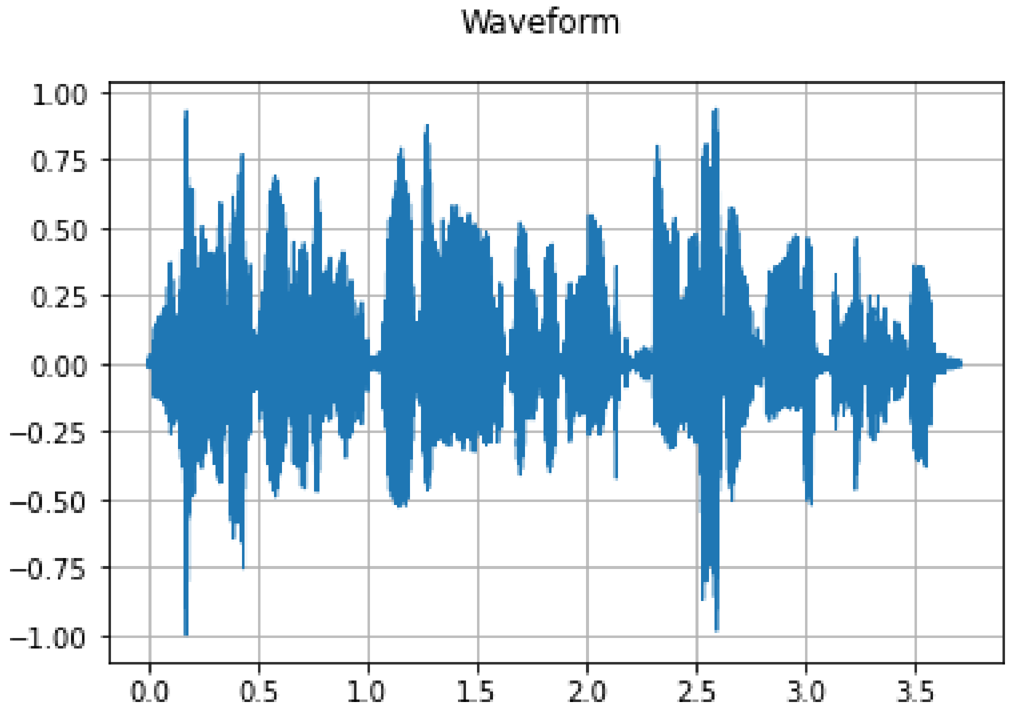
Loading Text Data

```
words = {"hello": 0, "world": 1}
embed_len = len(words)
embed_dim = 4
embed = torch.nn.Embedding(embed_len, embed_dim)
lookup = torch.tensor([words["hello"]], dtype=torch.long)
embed(lookup) # tensor([[-0.3745,  0.1376, -0.3058,  1.0258]])
```



Loading Audio/Speech Data

```
import librosa
wav, sample_rate = librosa.load("data/ljspeech.wav")
plot_waveform(wav, sample_rate)
```



Specialized PyTorch Libraries

`torchvision` - package consists of popular datasets, model architectures, and common image transformations for computer vision.

`torchaudio` - library for audio and signal processing with PyTorch. It provides I/O, signal and data processing functions, datasets, model implementations and application components.

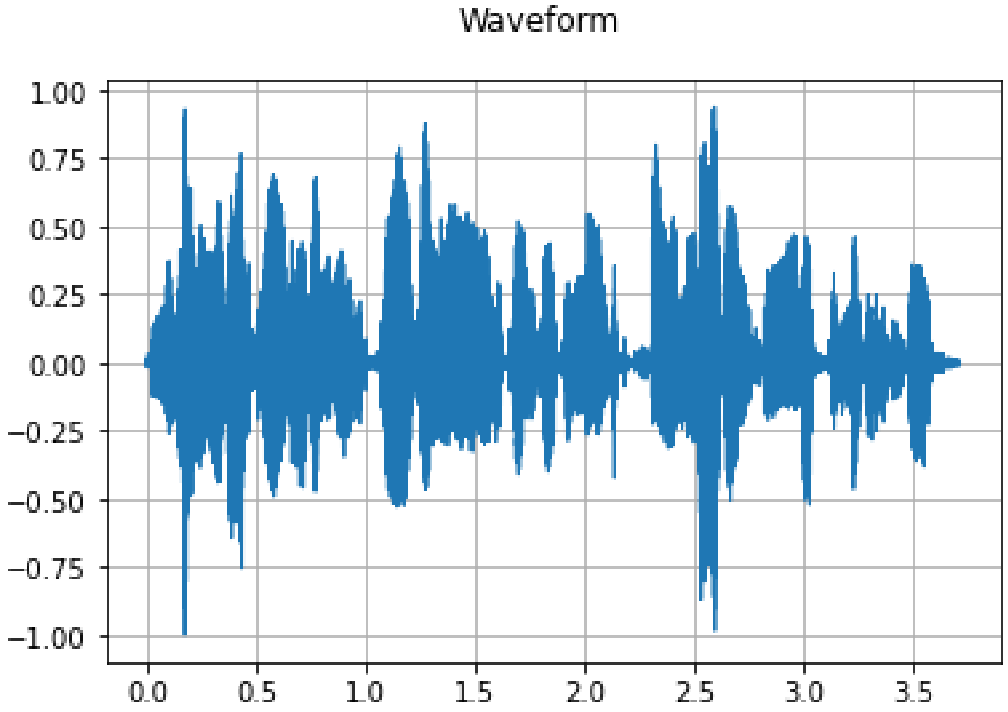
Other libraries – `torchtext`, `torchrec`, `torchmultimodal`, `torchrl`

TorchVision

```
import torchvision
img = torchvision.io.read_image("data/birdie2.jpg")
img = torchvision.transforms.ToPILImage()(img)
display(img)
```

TorchAudio

```
import torchaudio
wav, sample_rate = torchaudio.load ("data/ljspeech.wav")
plot_waveform(wav, sample_rate)
```



Loading Pre-trained Model from `torchvision`

```
resnet = torchvision.models.resnet18(pretrained=True)
```

Other pretrained models available:

AlexNet, SqueezeNet, VGG, EfficientNet, MobileNet, RegNet, ViT, ConvNeXt, etc.

See: https://pytorch.org/vision/master/models.html

Input Data Preparation for Model Ingestion

Simple transform:

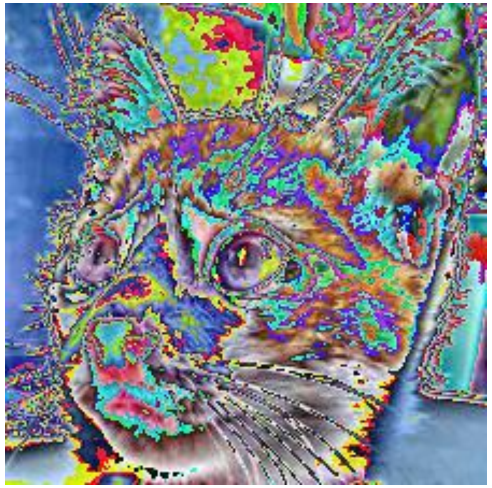
```
from PIL import Image
import torchvision.transforms as transforms

img = Image.open("wonder_cat.jpg")
img = transforms.ToTensor()(img)
```

img

Input Data Preparation for Model Ingestion

Better:

```
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
transform = transforms.Compose([
                      transforms.Resize(256),
                      transforms.CenterCrop(224),
                      transforms.ToTensor(),
                      normalize,])

# PIL image undergoes transforms.
img = transform(img)
```



img

Output: Model Prediction

Model must be in evaluation model: `resnet.eval()`

Ensure that there is a batch dim. If none, add:

```
img = rearrange(img, 'c h w -> 1 c h w')
```

Do the inference in no gradient tracking context:

```
with torch.no_grad():
    pred = resnet(img)
```

Finally, get the index of the maximum probability:

```
pred = torch.argmax(pred, dim=1)
```

What is `argmax()` of `pred` ?

`pred`

Index	Unnormalized Probabilities
0	1.7247
1	2.2064
…	
284	7.4005
285	11.4601
286	6.6287
…	
999	3.2967

`argmax()` → `285`

Human Readable Labels

For ImageNet1k, each index corresponds to a text label:

```
{0: 'tench, Tinca tinca',
 1: 'goldfish, Carassius auratus',
 2: 'great white shark, white shark,
 3: 'tiger shark, Galeocerdo cuvieri',
 …
 998: 'ear, spike, capitulum',
 999: 'toilet tissue, toilet paper}
```

Human Readable Label

For example, `pred` has a value of `285`. This value corresponds to:

```
...
 283: 'Persian cat',
 284: 'Siamese cat, Siamese',
 285: 'Egyptian cat',
 286: 'cougar, puma, catamount, mountain lion, painter, panther, Felis concolor',
 287: 'lynx, catamount',
 288: 'leopard, Panthera pardus',
...
```

TIMM: pyTorch IMage Models

https://rwightman.github.io/pytorch-image-models/

Just announced : Timm is now part of huggingface

https://github.com/huggingface/pytorch-image-models

Why timm?

From the doc:

`timm` is a deep-learning library created by Ross Wightman and is a collection of SOTA computer vision models, layers, utilities, optimizers, schedulers, data-loaders, augmentations and also training/validating scripts with ability to reproduce ImageNet training results.

In short:

`timm` extends PyTorch by implementing many deep learning SOTA models, optimization, regularization and other useful algorithms.

Install and Use

Install:

```
pip install timm
```

Use it like `torchvision`:

```
if use_timm:
  resnet = timm.create_model('resnet18', pretrained=True)
else:
  resnet = torchvision.models.resnet18(pretrained=True)
```

Autograd

`torch.autograd` is PyTorch’s automatic differentiation engine that powers neural network training

Forward and Backward Passes

Forward Pass

Model

θ

$\mathcal{L}(y, \hat{y})$

Compute Loss

Backward Pass

Input Data

Forward Propagation

- In forward prop, the model makes its best guess about the correct output.
- It runs the input data through each of its layers (functions) to make this prediction.

```
prediction = model(data)
```

Backward Propagation

- In backprop, the model adjusts its parameters proportionate to the error in its guess.
- It does this by traversing backwards from the output, collecting the derivatives of the error with respect to the parameters of the functions (gradients), and optimizing the parameters using gradient descent.

Compute Loss and gradients

- Compute loss

```
loss = (prediction - labels).sum()
```

- Backpropagate the error

```
loss.backward()
```

  - Autograd then calculates and stores the gradients for each model parameter `.grad` attribute.

Instantiate an optimizer to compute gradients

- Stochastic Gradient Descent (SGD) applied on model parameters with learning rate of 0.01 and momentum of 0.9

```
optim = torch.optim.SGD(model.parameters(),
                        lr=1e-2,
                        momentum=0.9)
```

Zero the optimizer gradients before re-computing gradients

- Compute loss

```
loss = (prediction - labels).sum()
```

- Zero the parameter gradients

```
optim.zero_grad()
```

- Backpropagate the error

```
loss.backward()
```

  - Autograd then calculates and stores the gradients for each model parameter `.grad` attribute.

Initiate gradient descent

```
optim.step()
```

- This is the end of 1 training step

colesbury Sam Gross PyTorch Developer Nov 2017

`loss.backward()` computes `dloss/dx` for every parameter `x` which has `requires_grad=True`. These are accumulated into `x.grad` for every parameter `x`. In pseudo-code:

```
x.grad += dloss/dx
```

`optimizer.step` updates the value of `x` using the gradient `x.grad`. For example, the SGD optimizer performs:

```
x += -lr * x.grad
```

`optimizer.zero_grad()` clears `x.grad` for every parameter `x` in the optimizer. It's important to call this before `loss.backward()`, otherwise you'll accumulate the gradients from multiple passes.

If you have multiple losses (loss1, loss2) you can sum them and then call backwards once:

```
loss3 = loss1 + loss2
loss3.backward()
```

Model

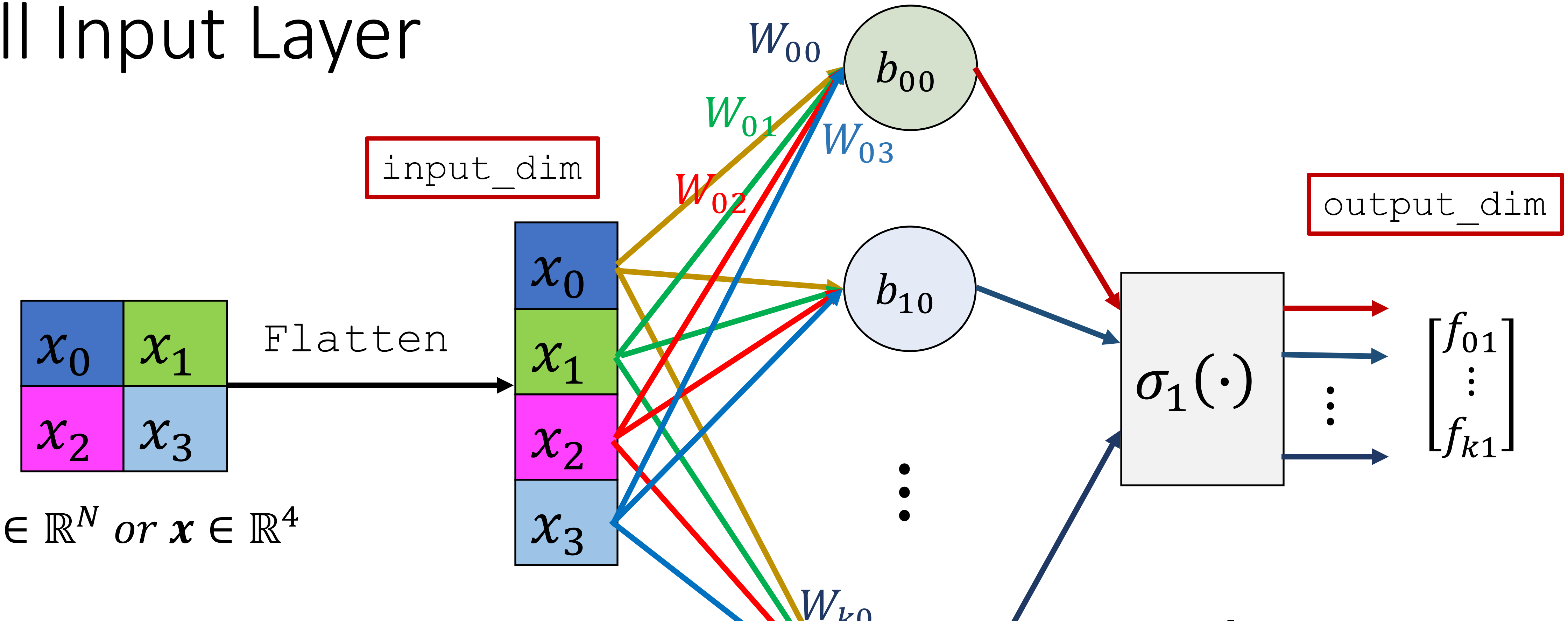
3-layer MLP for Imagenet1k Classification

```
class MLP(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(MLP, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.fc3 = nn.Linear(hidden_size, output_size)
        self.relu = nn.ReLU()

    def forward(self, x):
        x = x.view(x.size(0), -1)  # Flatten the input tensor
        x = self.relu(self.fc1(x))
        x = self.relu(self.fc2(x))
        x = self.fc3(x)

        return x
```

`nn.Linear(input_dim, output_dim)`

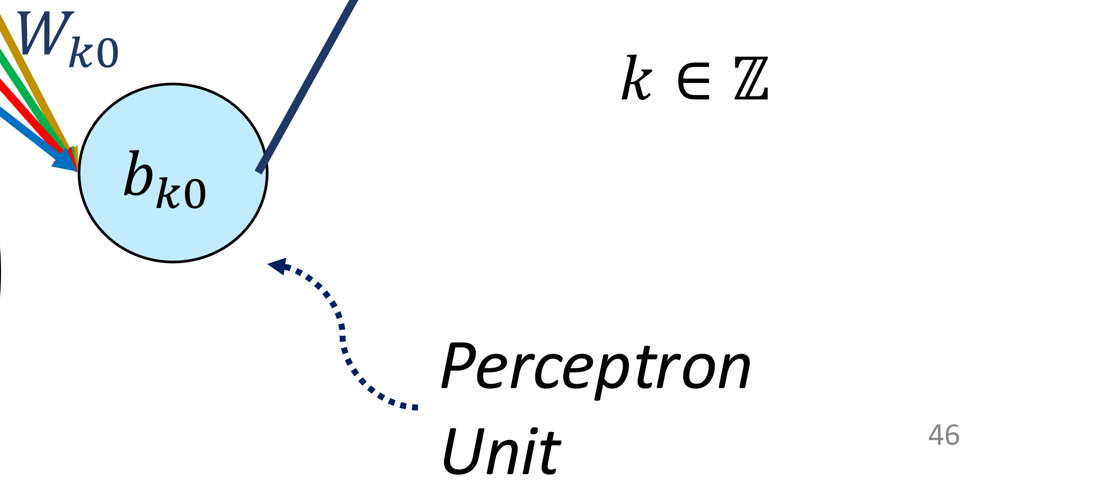
- `input_dim` = input dimensions
- `output_dim` = output dimensions

Recall Input Layer



$$\boldsymbol{f}_1(\boldsymbol{x};\ \boldsymbol{\theta}_0) = \sigma_1(\boldsymbol{W}_0\boldsymbol{x} + \boldsymbol{b}_0)$$

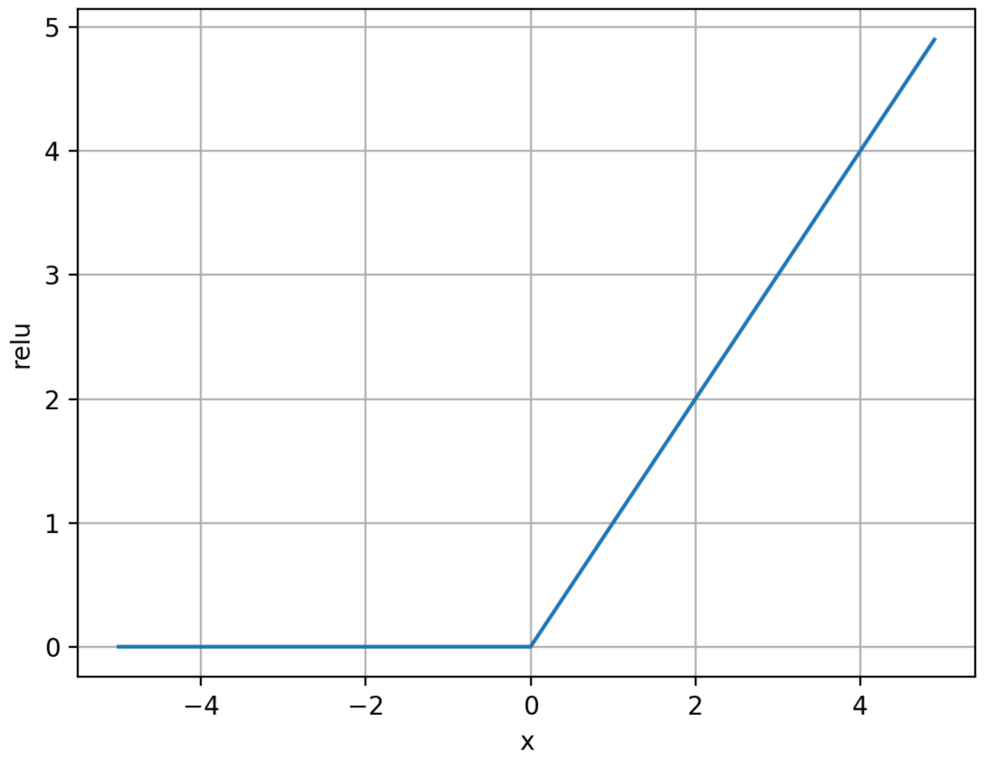
$$\boldsymbol{f}_1(\boldsymbol{x};\ \boldsymbol{\theta}_0) = \sigma_1\left(\begin{bmatrix} W_{00} & \cdots & W_{03} \\ \vdots & \ddots & \vdots \\ W_{k0} & \cdots & W_{k3} \end{bmatrix}\begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_{00} \\ \vdots \\ b_{k0} \end{bmatrix}\right)$$



`nn.relu()`

Rectified Linear Unit:

$$\sigma(x) = ReLU(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$



Where is the softmax?

Softmax:

$$\sigma(x_i) = \frac{e^{x_i}}{\sum_{k=0}^{C} e^{x_k}}$$

Recall Cross Entropy

For discrete distribution, Categorical Cross-Entropy is:

$$CE = H(P, Q) = -\sum_i P(x_i) \log Q(x_i)$$

If CE is used, no need for softmax

```
loss = nn.CrossEntropyLoss()
```

Model Training

Model Training

- Data Pre-processing Transform
- Dataset and Dataloader
- Model Training
  - Identify the loss function and optimizer
  - Model in train mode
  - Train for N epochs

Data Transform

```python
# Define the transforms to be applied to the images
transform = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
```

Dataset and Dataloader

```python
# Load the ImageNet dataset
imagenet_dataset = datasets.ImageNet(root="/raid/imagenet/dataset/",
                                     split="train",
                                     transform=transform)

# Create a DataLoader to load the images in batches
dataloader = DataLoader(imagenet_dataset, batch_size=32, shuffle=True)
```

Device, Loss and Optimizer

```python
import torch.optim as optim
import torch

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
# Define the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(mlp.parameters(), lr=0.001)
```

Model Training

```
# Define the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(mlp.parameters(), lr=0.001)

mlp.train()
# Train the model for 10 epochs
for epoch in range(10):
    running_loss = 0.0
    for i, data in enumerate(dataloader, 0):
        # Get the inputs and labels from the dataloader
        inputs, labels = data
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward + backward + optimize
        outputs = mlp(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
```

Model Inference

Model Inference

- Data Pre-processing Transform
- Dataset and Dataloader
- Model Evaluation
  - Model in eval mode
  - Compute performance on evaluation split

Data Pre-processing Transform

```
# Define the transforms to be applied to the images
transform = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
```

Dataset and Dataloader

```
# create a test dataloader
imagenet_dataset = datasets.ImageNet(root="/raid/imagenet/dataset/",
                                     split="val",
                                     transform=transform)

dataloader = DataLoader(imagenet_dataset, batch_size=32, shuffle=False)
```

Performance Evaluation

```
# evaluate the model on the validation set
correct = 0
total = 0
with torch.no_grad():
    for data in dataloader:
        # Get the inputs and labels from the dataloader
        inputs, labels = data
        inputs, labels = inputs.to(device), labels.to(device)

        # Forward pass
        outputs = mlp(inputs)
        _, predicted = torch.max(outputs.data, 1)

        # Compute accuracy
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print(f"Accuracy: {100 * correct / total:.2f}%")
```

End