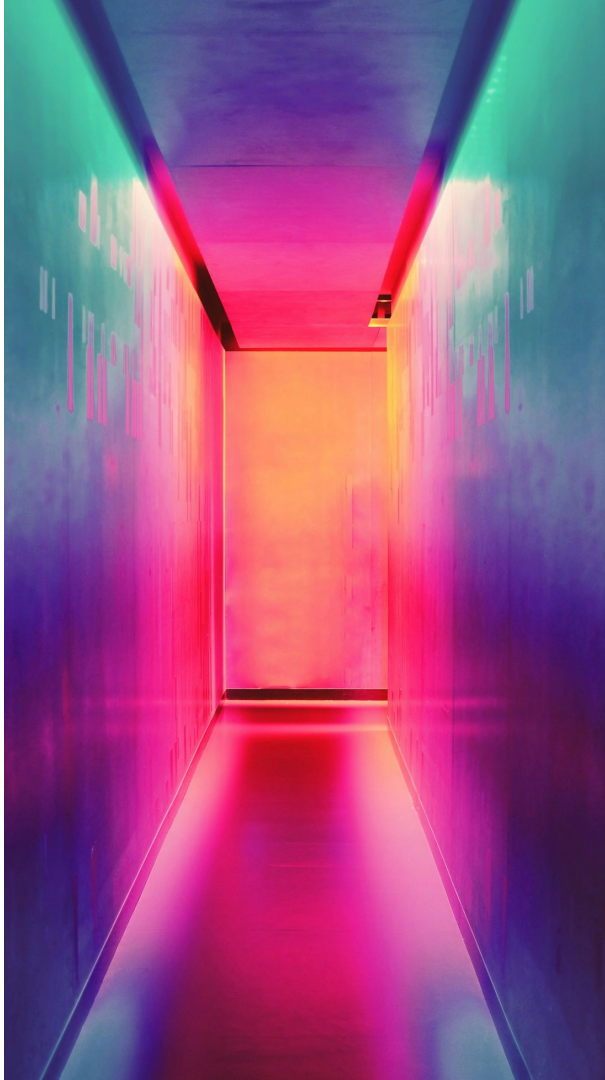
PPGEEC2318

Machine Learning

Computer Vision - Part I

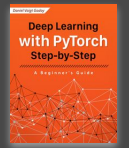


Ivanovitch Silva

- Part I: Fundamentals
- Part II: Computer Vision
  - Chapter 4: Classifying Images
  - Bonus Chapter: Feature Space 345
  - Chapter 5: Convolutions
  - Chapter 6: Rock, Paper, Scissors
  - Chapter 7: Transfer Learning
  - Extra Chapter: Vanishing and Exploding Gradients

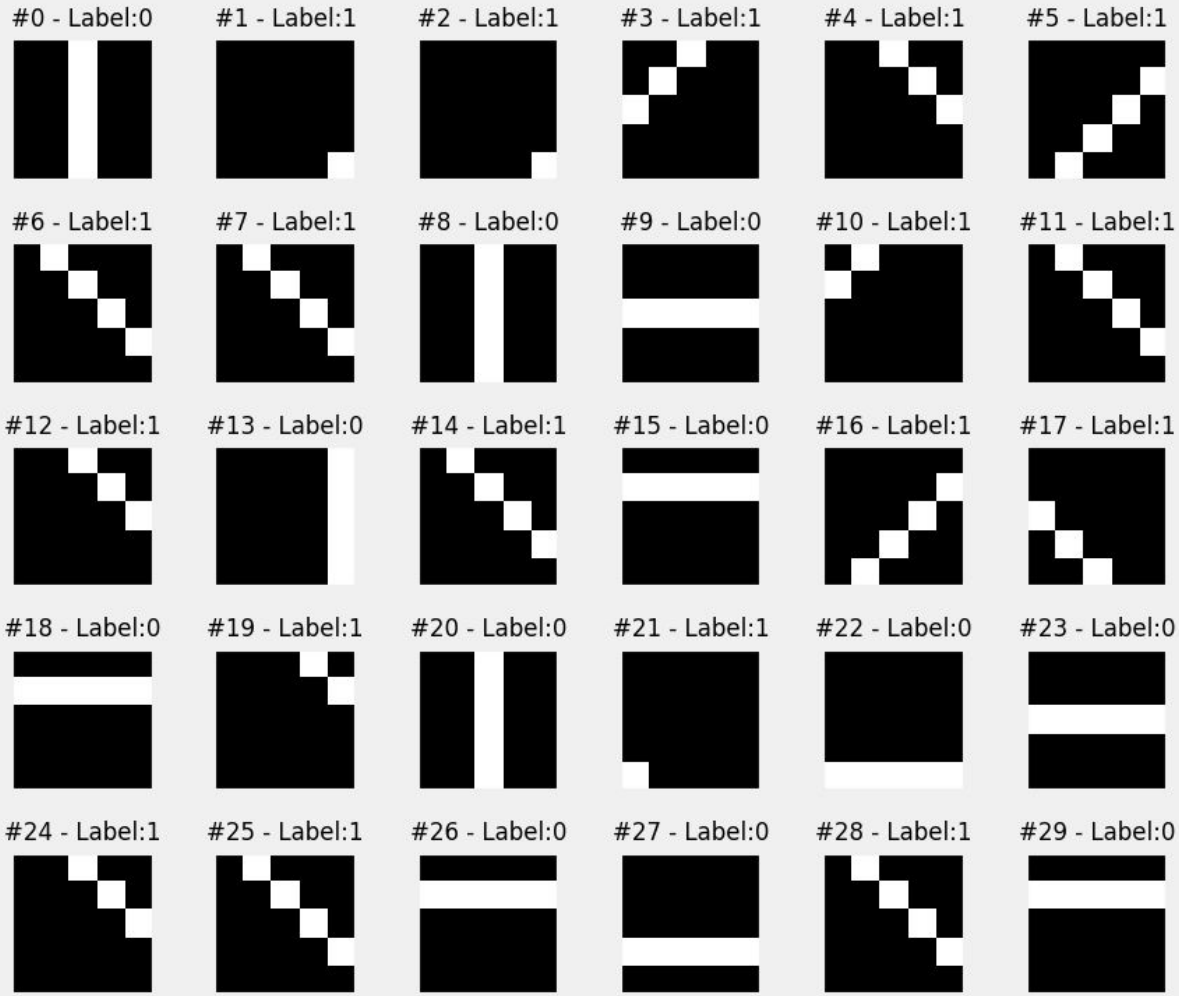
Agenda

1. Data Generation
2. Torchvision: Data Transformation
3. Shallow Model
4. Deep-ish Model
5. Activation Functions
6. Feature Space



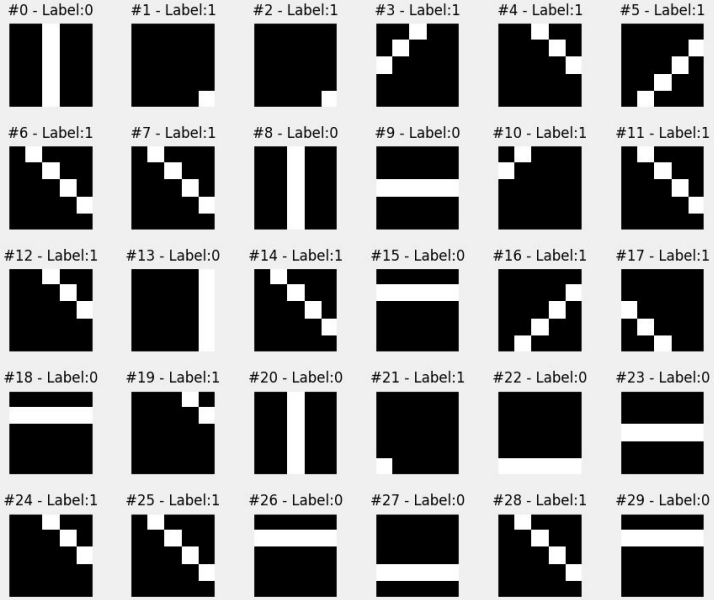
Is the line diagonal?

Data Generation



Classifying Images: Data Generation

If the line **is diagonal**, then we assume it belongs to the **positive class**. If it is not diagonal, it belongs to the negative class.




```
images[0]
array([[[  0,   0, 255,   0,   0],
        [  0,   0, 255,   0,   0],
        [  0,   0, 255,   0,   0],
        [  0,   0, 255,   0,   0],
        [  0,   0, 255,   0,   0]]], dtype=uint8)

labels[0]
0
```

```
images, labels = generate_dataset(img_size=5, n_images=300, binary=True, seed=13)
```

Images and Channels

image_r

```
[[255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]]
```

image_g

```
[[  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]]
```

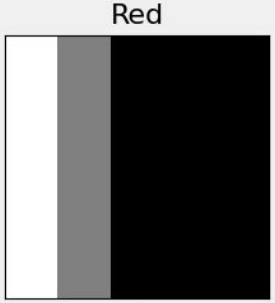
image_b

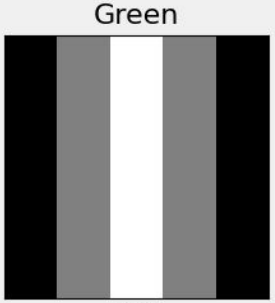
```
[[  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]]
```

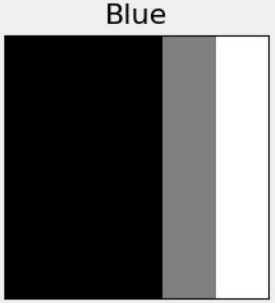
image_gray

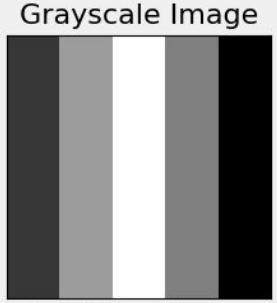
```
[[ 54 118 182 100  18]
 [ 54 118 182 100  18]
 [ 54 118 182 100  18]
 [ 54 118 182 100  18]
 [ 54 118 182 100  18]]
```

Single Channel (grayscale)









The range of pixel values goes from zero (black) to 255 (white), and everything in between is a shade of gray.

Images and Channels

image_r

```
[[255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]
 [255 128   0   0   0]]
```

image_g

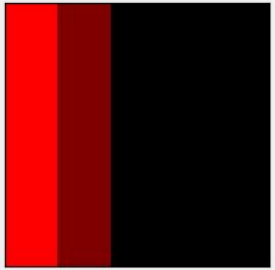
```
[[  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]]
```

image_b

```
[[  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]
 [  0   0   0 128 255]]
```

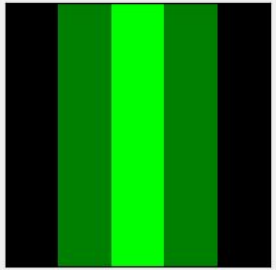
Three Channels (color)

as first channel



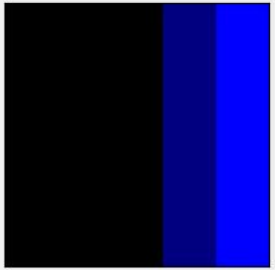
5x5x3 - R only

as second channel



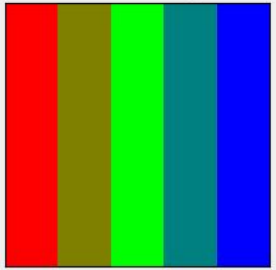
5x5x3 - G only

as third channel



5x5x3 - B only

RGB Image



5x5x3 = (R, G, B) stacked

Shape (NCHW vs NHWC)

- NCHW: (number of images, channels, height, width)
  - Pytorch
- NHWC: (number of images, height, width, channels)
  - Tensorflow
- HWC
  - PIL

```
images.shape
(300, 1, 5, 5)
```

```
example = images[7]
example
array([[[  0, 255,   0,   0,   0],
        [  0,   0, 255,   0,   0],
        [  0,   0,   0, 255,   0],
        [  0,   0,   0,   0, 255],
        [  0,   0,   0,   0,   0]]], dtype=uint8)
```

From dataset to Compose transforms

Torchvision: data transformation

Torchvision is a package containing popular datasets, model architectures, and common image transformations for computer vision.

vision

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NicolasHug Update .git-blame-ignore-revs (#9035) 5f03dc5 · 2 weeks ago 4,050 Commits

.github	Deactivate bc linter (#8999)	2 months ago
android	CXX_STANDARD 14 -> 17 (#7608)	2 years ago
benchmarks	GPU jpeg decoder: add batch support and hardware deco...	9 months ago
cmake	Remove include Python.h (#8413)	last year
docs	Put back docs of decode_png (#9015)	3 weeks ago
examples	Rename cpp example README.rst to README.md (#8467)	11 months ago
gallery	Deprecate video decoding and encoding (#8997)	2 months ago
ios	CXX_STANDARD 14 -> 17 (#7608)	2 years ago
packaging	Revert "[Manylinux_2_28] Modify relocate script for linux ...	2 weeks ago
references	Make v2 transforms authoring public (#8787)	5 months ago
release	Add an OS-independent script for updating the workflow ...	2 months ago
scripts	Update classify_prs notebook (#8383)	last year
test	Upgrade type hint and others to Python 3.9 (#8814)	2 weeks ago
torchvision	Upgrade type hint and others to Python 3.9 (#8814)	2 weeks ago
.clang-format	Add objc clang format (#7677)	2 years ago

About

Datasets, Transforms and Models specific to Computer Vision

pytorch.org/vision

machine-learning computer-vision

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Torchvision 0.22 release Latest
2 weeks ago

+ 46 releases

Packages

No packages published

Torchvision has some common image transformations in its transforms module. It is important to realize there are two main groups of transformations:

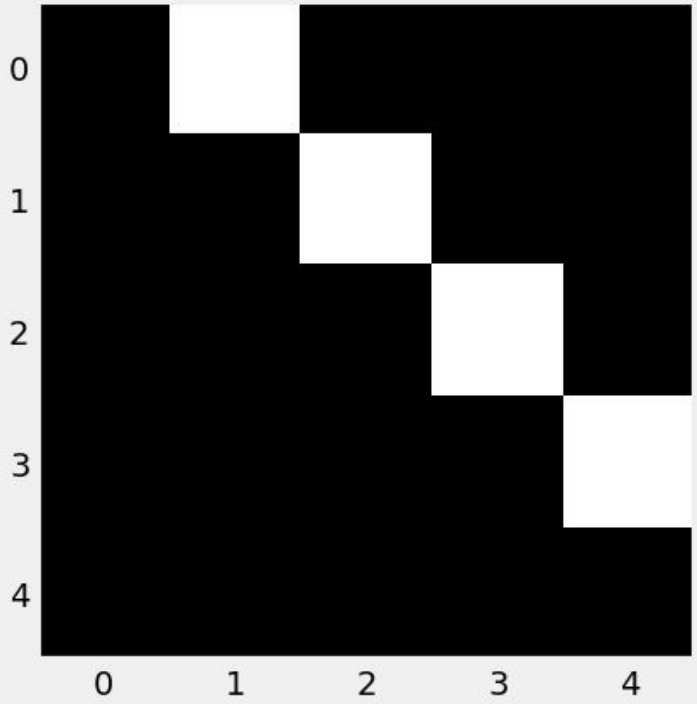
- Transformations for **modifying** the images
- Transformations for **converting** between formats

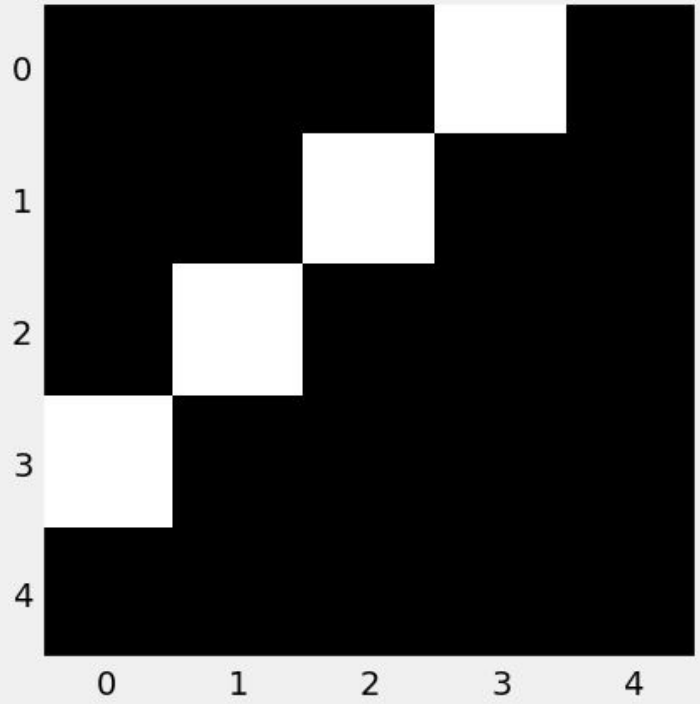
```
# transformation for modifying the images
from torchvision.transforms.v2 import Compose, Normalize, RandomHorizontalFlip, Resize

# Transformation for converting between formats
from torchvision.transforms.v2 import ToImage, ToDtype, ToPILImage
```

```
# preserving the original pixel values and the integer type
image_tensor = ToImage()(example_hwc)
image_tensor, image_tensor.shape

(Image([[[  0, 255,   0,   0,   0],
         [  0,   0, 255,   0,   0],
         [  0,   0,   0, 255,   0],
         [  0,   0,   0,   0, 255],
         [  0,   0,   0,   0,   0]]], dtype=torch.uint8, ),
 torch.Size([1, 5, 5]))

# ToDype scales the values of image_tensor
example_tensor = ToDtype(torch.float32, scale=True)
(image_tensor)
example_tensor

Image([[[0., 1., 0., 0., 0.],
        [0., 0., 1., 0., 0.],
        [0., 0., 0., 1., 0.],
        [0., 0., 0., 0., 1.],
        [0., 0., 0., 0., 0.]]], )
```

```
class Image(torch.Tensor):
    ...
```

```
# The ToTensor() transform has been deprecated since the introduction
# of TorchVision's second version (V2) of transforms in v0.15.
# In the author's book, it is suggested to create a custom ToTensor()
# function to preserve the same behavior as the original transform.

def ToTensor():
    return Compose([ToImage(), ToDtype(torch.float32, scale=True)])

tensorizer = ToTensor()
example_tensor = tensorizer(example_hwc)
example_tensor

Image([[[0., 1., 0., 0., 0.],
        [0., 0., 1., 0., 0.],
        [0., 0., 0., 1., 0.],
        [0., 0., 0., 0., 1.],
        [0., 0., 0., 0., 0.]]], )
```






```
example_img = ToPILImage()(example_tensor)
```

```
flipper = RandomHorizontalFlip(p=1.0)
```

```
normalizer = Normalize(mean=(.5,), std=(.5,))
normalized_tensor = normalizer(img_tensor)
normalized_tensor

Image([[[-1., -1., -1.,  1., -1.],
        [-1., -1.,  1., -1., -1.],
        [-1.,  1., -1., -1., -1.],
        [ 1., -1., -1., -1., -1.],
        [-1., -1., -1., -1., -1.]]], )
```

$$\text{input} = 0 \implies \frac{0 - \text{mean}}{\text{std}} = \frac{0 - 0.5}{0.5} = -1$$

$$\text{input} = 1 \implies \frac{1 - \text{mean}}{\text{std}} = \frac{1 - 0.5}{0.5} = 1$$

Convert, build and transform tensors into useful format

Data Preparation

Splitting the dataset: build a custom splitter

```python
def index_splitter(n, splits, seed=13):
    idx = torch.arange(n)
    # Makes the split argument a tensor
    splits_tensor = torch.as_tensor(splits)
    total = splits_tensor.sum().float()
    # If the total does not add up to one
    # divide every number by the total
    if not total.isclose(torch.ones(1)[0]):
        splits_tensor = splits_tensor / total
    # Uses PyTorch random_split to split the indices
    torch.manual_seed(seed)
    return random_split(idx, splits_tensor)
```

```python
train_idx, val_idx = index_splitter(len(x_tensor), [80, 20])
train_idx, val_idx = index_splitter(len(x_tensor), [0.8, 0.2])
```

Splitting the dataset: build a custom sampler

```
# Builds a loader of each set
train_loader = DataLoader(
   dataset=train_dataset,
   batch_size=16,
   shuffle=True
)
val_loader = DataLoader(
   dataset=val_dataset,
   batch_size=16)
```

Before

```
# Builds a loader of each set
train_loader = DataLoader(
   dataset=dataset,
   batch_size=16,
   sampler=train_sampler)
val_loader = DataLoader(
   dataset=dataset,
   batch_size=16,
   sampler=val_sampler)
```

Option 1

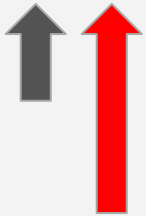
without replacement

```
train_sampler = SubsetRandomSampler(train_idx)
val_sampler =   SubsetRandomSampler(val_idx)
```

Splitting the dataset: build a weighted sampler

```
x_train_tensor = x_tensor[train_idx]
y_train_tensor = y_tensor[train_idx]

x_val_tensor = x_tensor[val_idx]
y_val_tensor = y_tensor[val_idx]

classes, counts = y_train_tensor.unique(return_counts=True)
print(classes, counts)
tensor([0., 1.]) tensor([ 80, 160])
```

```
weights = 1.0 / counts.float()
weights
tensor([0.0125, 0.0063])
```



The class with fewer data points (minority class) should get larger weights, while the class with more data points (majority class) should get smaller weights. This way, on average, we'll end up with mini-batches containing roughly the same number of data points in each class: **A balanced dataset.**

Splitting the dataset: build a weighted sampler

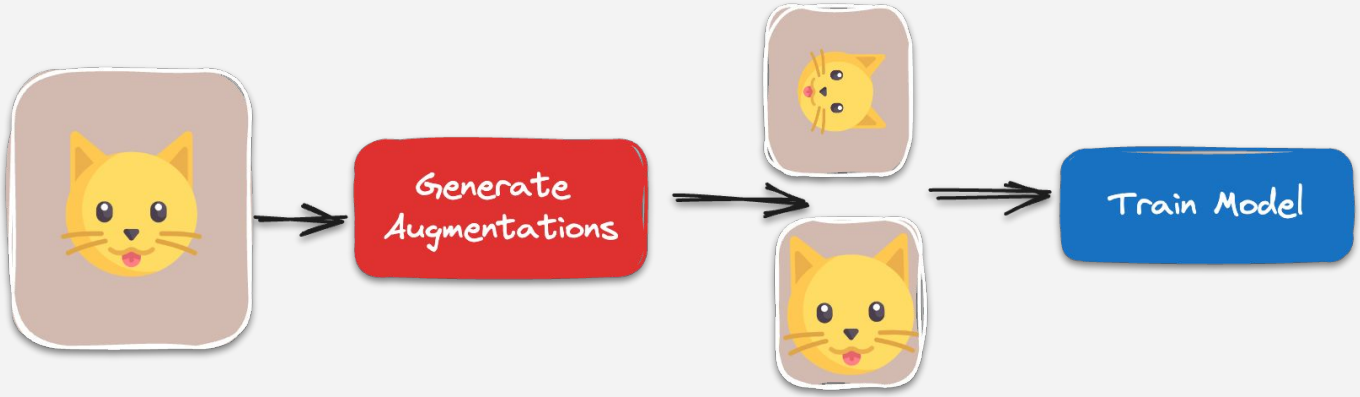
```
weights
tensor([0.0125, 0.0063])

y_train_tensor.squeeze().long()
tensor([1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
        1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1,
        0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1,
        1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1,
        1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
        1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1,
        0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1,
        1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1,
        1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1,
        1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1])
```

```
weights[y_train_tensor.squeeze().long()][:10]
tensor([0.0063, 0.0063, 0.0063, 0.0063, 0.0063, 0.0125, 0.0063, 0.0063, 0.0063,
        0.0063])
```

Splitting the dataset: build a weighted sampler

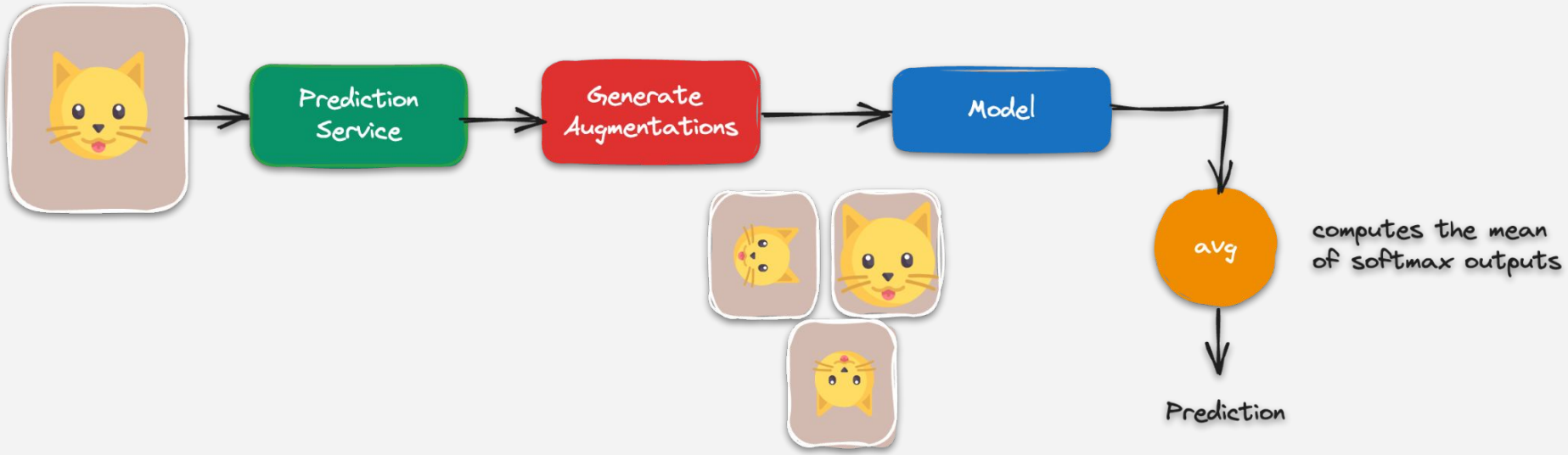
```
# Create an instance of the Generator class from PyTorch
generator = torch.Generator()

# Create a WeightedRandomSampler instance. This sampler will select elements randomly
# based on the specified weights but with a mechanism that allows for replacement,
# meaning the same item can be chosen more than once.
sampler = WeightedRandomSampler(
    weights=sample_weights,       # An array of weights, where each weight corresponds to a sample.
    num_samples=len(sample_weights),  # The total number of samples to draw (equal to the length of weights).
    generator=generator,          # The random number generator object for reproducibility.
    replacement=True              # Allows for the same item to be selected more than once.
)
```

Splitting the dataset: all you need is data augmentation



In general, we want to apply data augmentation to the **training data only**.

Splitting the dataset: all you need is data augmentation



(...) there is also "test-time augmentation", which can be used to improve the performance of a model after it is deployed.

Splitting the dataset: all you need is data augmentation

```
class TransformedTensorDataset(Dataset):
    def __init__(self, x, y, transform=None):
        self.x = x
        self.y = y
        self.transform = transform

    def __getitem__(self, index):
        x = self.x[index]

        if self.transform:
            x = self.transform(x)

        return x, self.y[index]

    def __len__(self):
        return len(self.x)
```

```
train_composer = Compose([RandomHorizontalFlip(p=.5),
                          Normalize(mean=(.5,), std=(.5,))])

val_composer = Compose([Normalize(mean=(.5,), std=(.5,))])
```

```
train_dataset = TransformedTensorDataset(x_train_tensor,
                                         y_train_tensor,
                                       transform=train_composer)
val_dataset = TransformedTensorDataset(x_val_tensor,
                                       y_val_tensor,
                                     transform=val_composer)
```

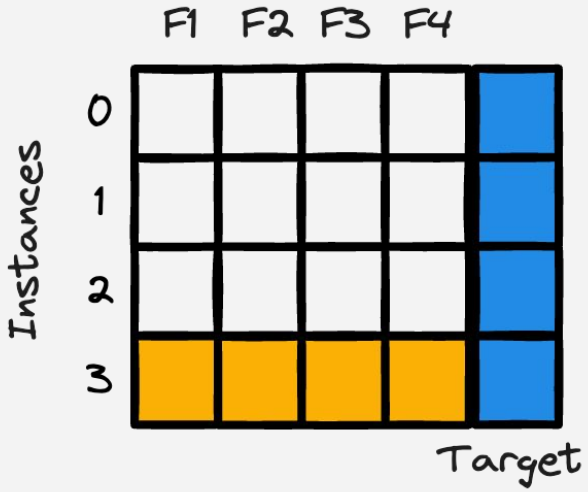
Splitting the dataset: putting it together

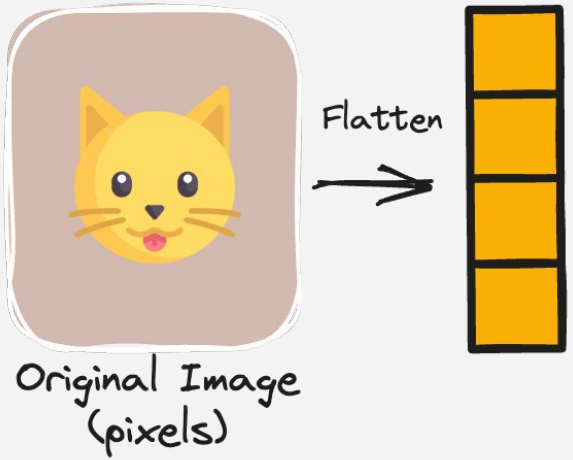
```
# Builds tensors from numpy arrays BEFORE split
# Modifies the scale of pixel values from [0, 255] to [0, 1]
x_tensor = torch.as_tensor(images / 255).float()
y_tensor = torch.as_tensor(labels.reshape(-1, 1)).float()

# Uses index_splitter to generate indices for training and
# validation sets
train_idx, val_idx = index_splitter(len(x_tensor), [80, 20])

# Uses indices to perform the split
x_train_tensor = x_tensor[train_idx]
y_train_tensor = y_tensor[train_idx]
x_val_tensor = x_tensor[val_idx]
y_val_tensor = y_tensor[val_idx]

# Builds different composers because of data augmentation on training set
train_composer = Compose([RandomHorizontalFlip(p=.5),
                          Normalize(mean=(.5,), std=(.5,))])
val_composer = Compose([Normalize(mean=(.5,), std=(.5,))])

# Uses custom dataset to apply composed transforms to each set
train_dataset = TransformedTensorDataset(x_train_tensor,
                                         y_train_tensor,
                                         transform=train_composer)
val_dataset = TransformedTensorDataset(x_val_tensor,
                                       y_val_tensor,
                                       transform=val_composer)
```

Splitting the dataset: putting it together

```
# Builds a weighted random sampler to handle imbalanced classes
sampler = make_balanced_sampler(y_train_tensor)

# Uses sampler in the training set to get a balanced data loader
train_loader = DataLoader(dataset=train_dataset,
                          batch_size=16,
                          sampler=sampler)
val_loader = DataLoader(dataset=val_dataset,
                        batch_size=16)
```

Splitting the dataset: pixels as features



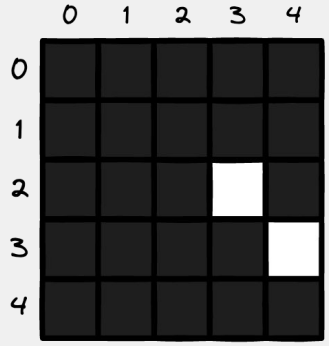


Splitting the dataset: pixels as features

```
import torch.nn as nn

dummy_xs, dummy_ys = next(iter(train_loader))
dummy_xs.shape
torch.Size([16, 1, 5, 5])


flattener = nn.Flatten()
dummy_xs_flat = flattener(dummy_xs)

print(dummy_xs_flat.shape)
print(dummy_xs_flat[0])

torch.Size([16, 25])
tensor([-1., -1., -1.,  1., -1., -1., -1., -1.,  1., -1., -1., -1., -1.,  1.,-1., -1., -1.,
-1.,  1., -1., -1., -1., -1.,  1., -1.])
```

Defining a model to handle a binary classification task

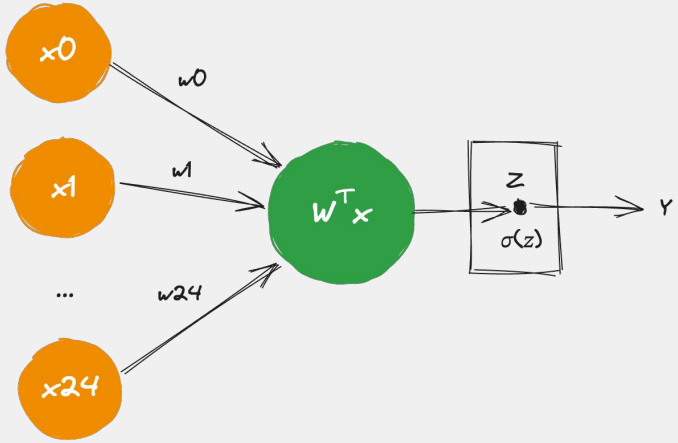
Shallow Model



Original Image

Flatted Image

$$\mathrm{P}(y=1) = \sigma(z) = \sigma(w_0x_0 + w_1x_1 + \cdots + w_{24}x_{24})$$

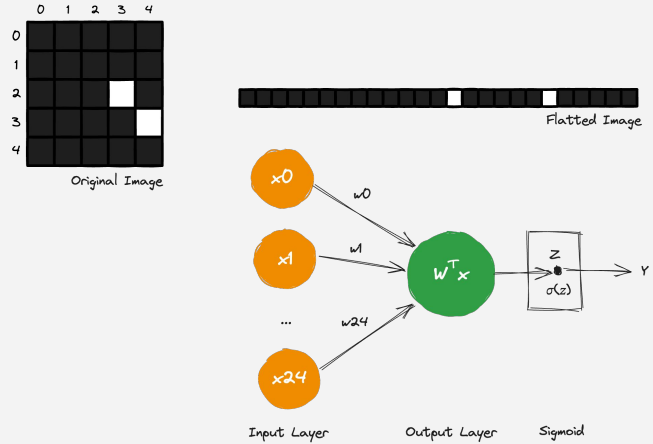


$$W = \underset{(25\times1)}{\begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_{24} \end{bmatrix}}; X = \underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{24} \end{bmatrix}}$$

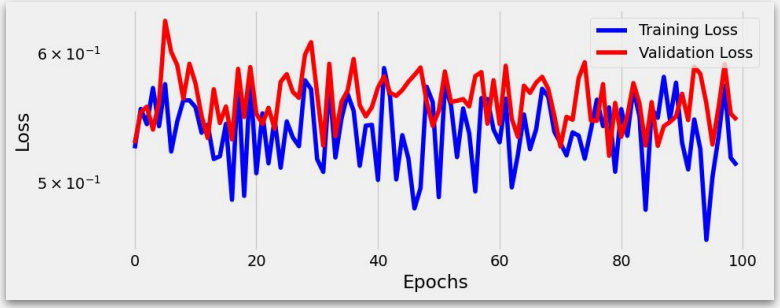
$$z = W^T \cdot X = \underset{(1\times25)}{\begin{bmatrix} - & w^T & - \end{bmatrix}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{24} \end{bmatrix}} = \underset{(1\times25)}{\begin{bmatrix} w_0 & w_1 & \cdots & w_{24} \end{bmatrix}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{24} \end{bmatrix}}$$

$$= w_0x_0 + w_1x_1 + \cdots + w_{24}x_{24}$$

```
# Sets learning rate - this is "eta" ~ the "n" like Greek letter
lr = 0.1

torch.manual_seed(17)
# Now we can create a model
model_logistic = nn.Sequential()
model_logistic.add_module('flatten', nn.Flatten())
model_logistic.add_module('output', nn.Linear(25, 1, bias=False))
model_logistic.add_module('sigmoid', nn.Sigmoid())

# Defines a SGD optimizer to update the parameters
optimizer_logistic = optim.SGD(model_logistic.parameters(), lr=lr)

# Defines a binary cross entropy loss function
binary_loss_fn = nn.BCELoss()
```

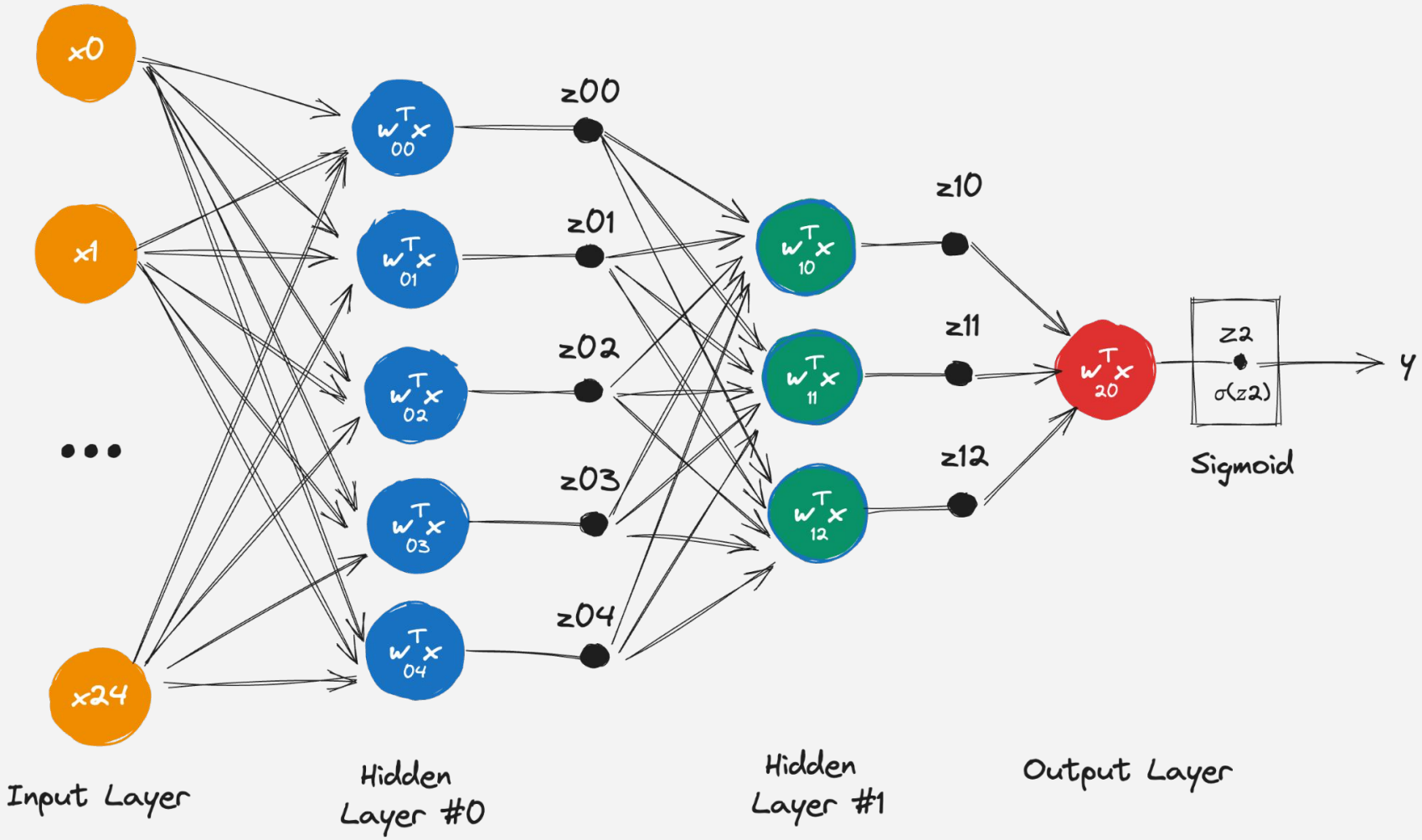


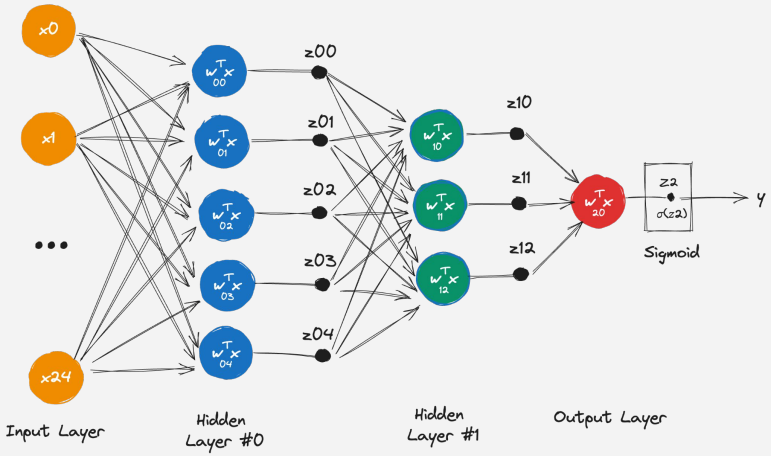

```
n_epochs = 100

reg_logistic = Architecture(model_logistic, binary_loss_fn,
                            optimizer_logistic)
reg_logistic.set_loaders(train_loader,val_loader)
reg_logistic.train(n_epochs)
```



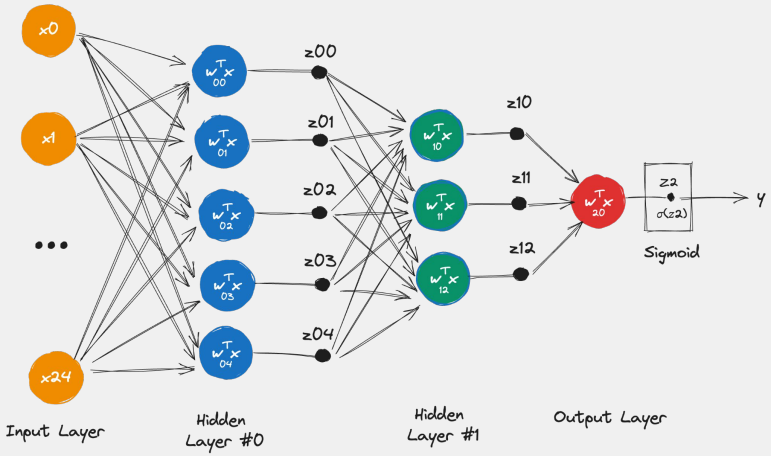
There we go, let's add not one, but two hidden layers

Deep-ish Model

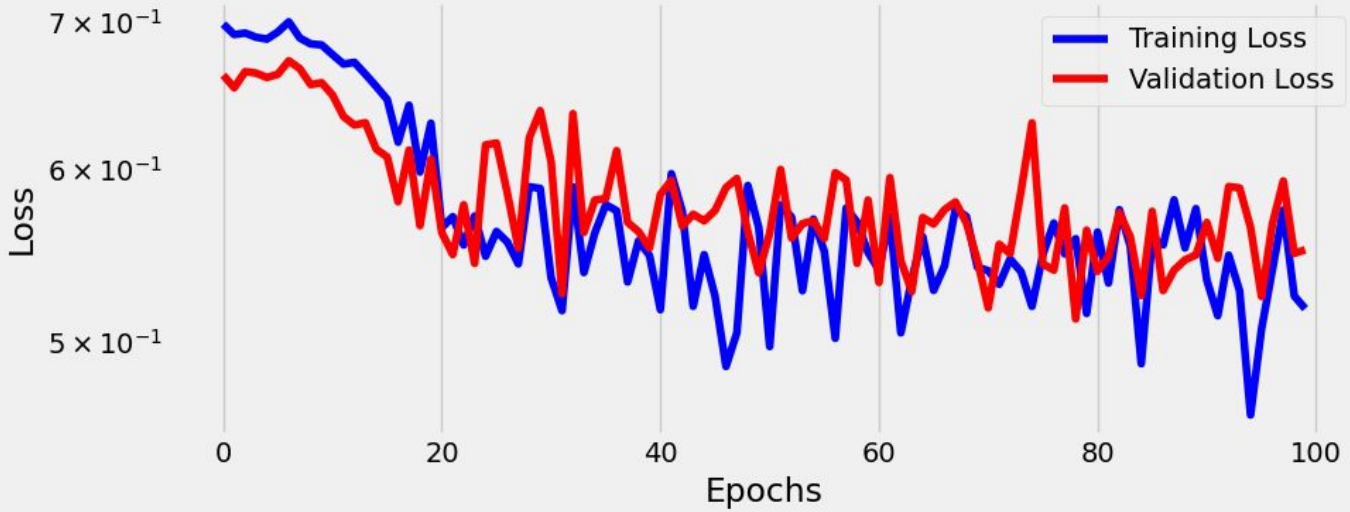

x0
x1
x24
$w_{00}^T x$
$w_{01}^T x$
$w_{02}^T x$
$w_{03}^T x$
$w_{04}^T x$
z00
z01
z02
z03
z04
$w_{10}^T x$
$w_{11}^T x$
$w_{12}^T x$
z10
z11
z12
$w_{20}^T x$
z2
σ(z2)
Sigmoid
y
Input Layer
Hidden Layer #0
Hidden Layer #1
Output Layer



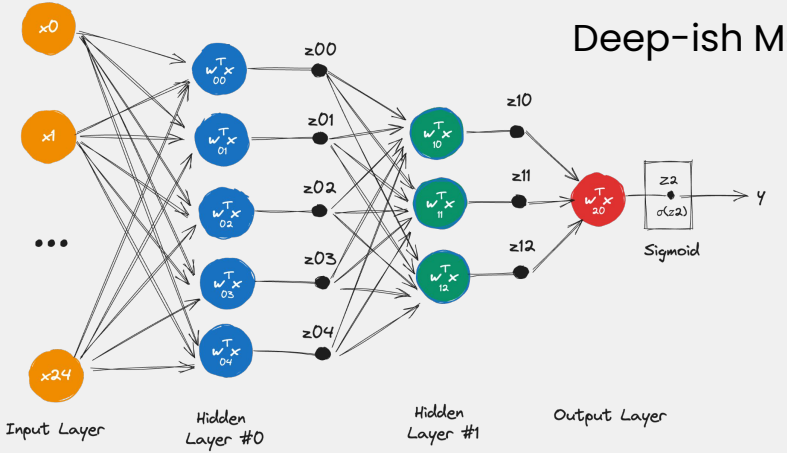

```
# Sets learning rate - this is "eta" ~ the "n" like Greek letter
lr = 0.1

torch.manual_seed(17)
# Now we can create a model
model_nn = nn.Sequential()
model_nn.add_module('flatten', nn.Flatten())
model_nn.add_module('hidden0', nn.Linear(25, 5, bias=False))
model_nn.add_module('hidden1', nn.Linear(5, 3, bias=False))
model_nn.add_module('output', nn.Linear(3, 1, bias=False))
model_nn.add_module('sigmoid', nn.Sigmoid())

# Defines a SGD optimizer to update the parameters
optimizer_nn = optim.SGD(model_nn.parameters(), lr=lr)

# Defines a binary cross entropy loss function
binary_loss_fn = nn.BCELoss()
```



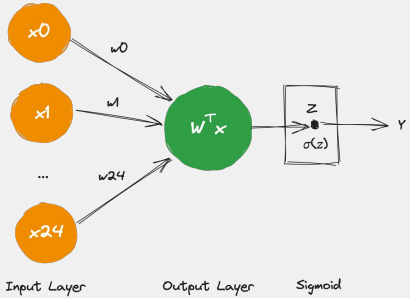

```
n_epochs = 100

arch_nn = Architecture(model_nn, binary_loss_fn, optimizer_nn)
arch_nn.set_loaders(train_loader, val_loader)
arch_nn.train(n_epochs)
```

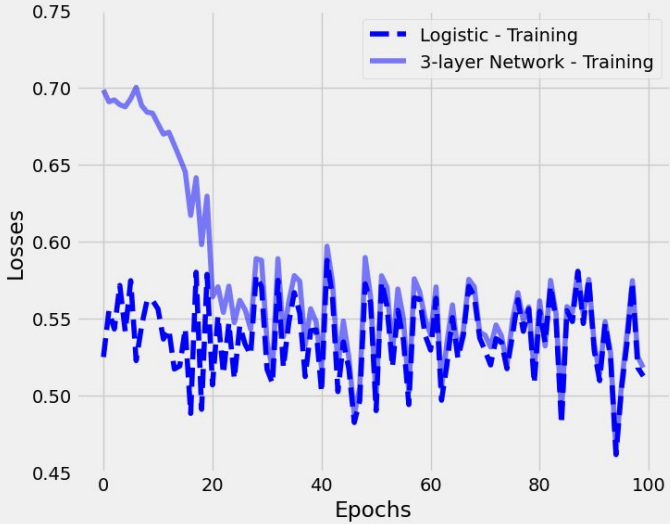


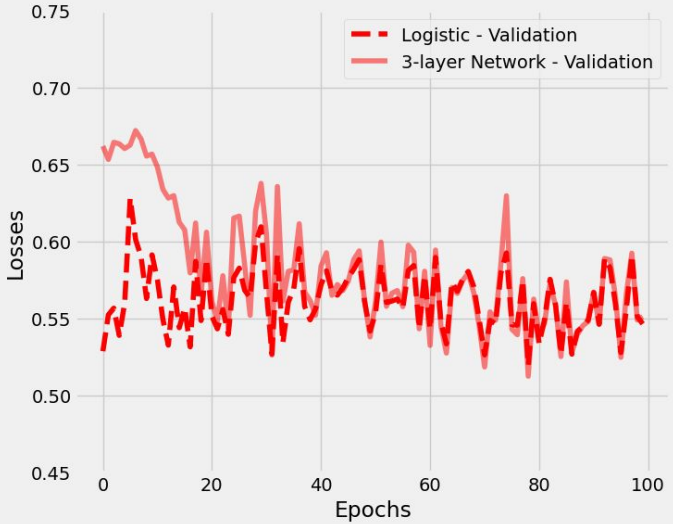
Deep-ish Model

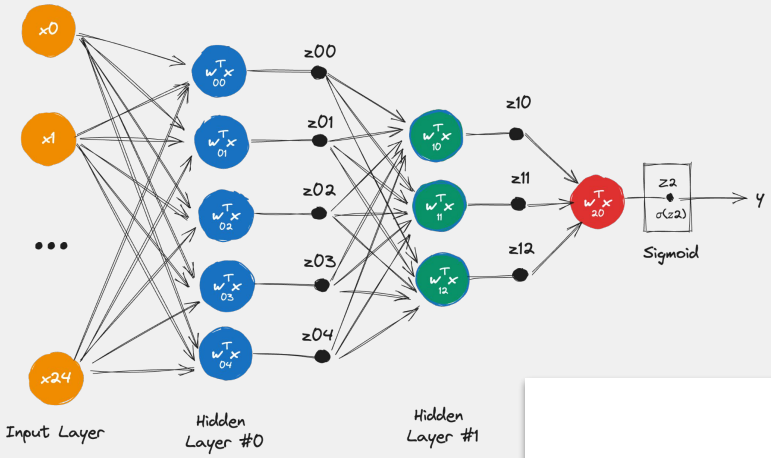


Reg. Logistic Model









Hidden #0

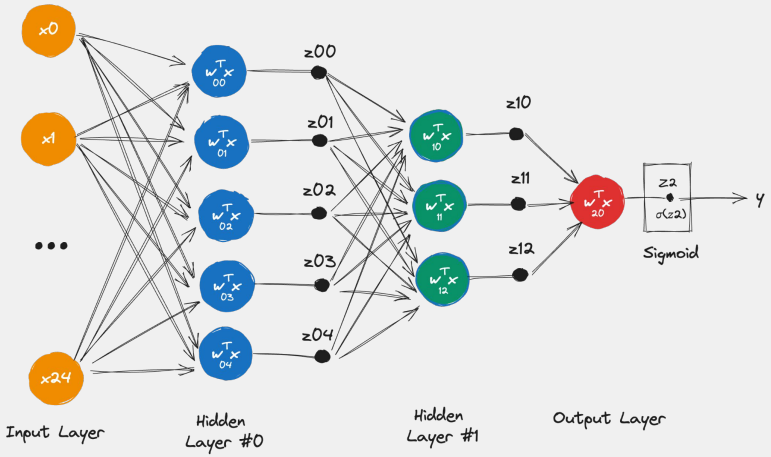
$$\underset{(5\times1)}{\begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}} = \underset{(5\times25)}{\begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}} \begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}_{(25\times1)}$$

Hidden #1

$$\underset{(3\times1)}{\begin{bmatrix} z_{10} \\ z_{11} \\ z_{12} \end{bmatrix}} = \underset{(3\times5)}{\begin{bmatrix} - & w_{10}^T & - \\ - & w_{11}^T & - \\ - & w_{12}^T & - \end{bmatrix}} \underset{(5\times1)}{\begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}}$$

Output

$$\underset{(1\times1)}{\begin{bmatrix} z_2 \end{bmatrix}} = \underset{(1\times3)}{\begin{bmatrix} - & w_{20}^T & - \end{bmatrix}} \underset{(3\times1)}{\begin{bmatrix} z_{10} \\ z_{11} \\ z_{12} \end{bmatrix}}$$



Hidden #0

$$\begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}_{(5\times1)} = \begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}_{(5\times25)} \begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}_{(25\times1)}$$

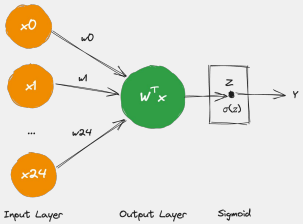
Hidden #1

$$\begin{bmatrix} z_{10} \\ z_{11} \\ z_{12} \end{bmatrix}_{(3\times1)} = \begin{bmatrix} - & w_{10}^T & - \\ - & w_{11}^T & - \\ - & w_{12}^T & - \end{bmatrix}_{(3\times5)} \begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}_{(5\times1)}$$

Output

$$\underset{(1\times1)}{[z_2]} = \underset{(1\times3)}{\begin{bmatrix} - & w_{20}^T & - \end{bmatrix}} \begin{bmatrix} z_{10} \\ z_{11} \\ z_{12} \end{bmatrix}_{(3\times1)}$$

This is just the reg. logistic



substituting $z's\ldots$

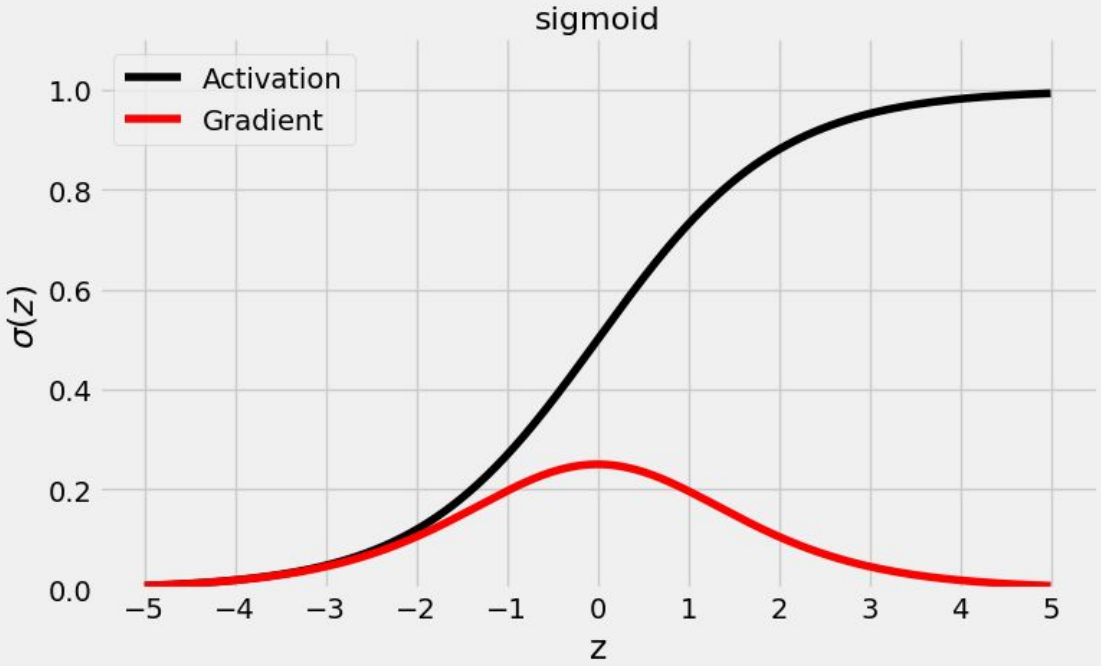
$$\underset{(1\times1)}{[z_2]} = \underbrace{\underset{(1\times3)}{\begin{bmatrix} - & w_{20}^T & - \end{bmatrix}}}_{\text{Output Layer}} \underbrace{\underset{(3\times5)}{\begin{bmatrix} - & w_{10}^T & - \\ - & w_{11}^T & - \\ - & w_{12}^T & - \end{bmatrix}}}_{\text{Hidden Layer \#1}} \underbrace{\underset{(5\times25)}{\begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}}}_{\text{Hidden Layer \#0}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}}$$

multiplying...

$$= \underbrace{\underset{(1\times25)}{\begin{bmatrix} - & w^T & - \end{bmatrix}}}_{\text{Matrices Multiplied}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}}$$

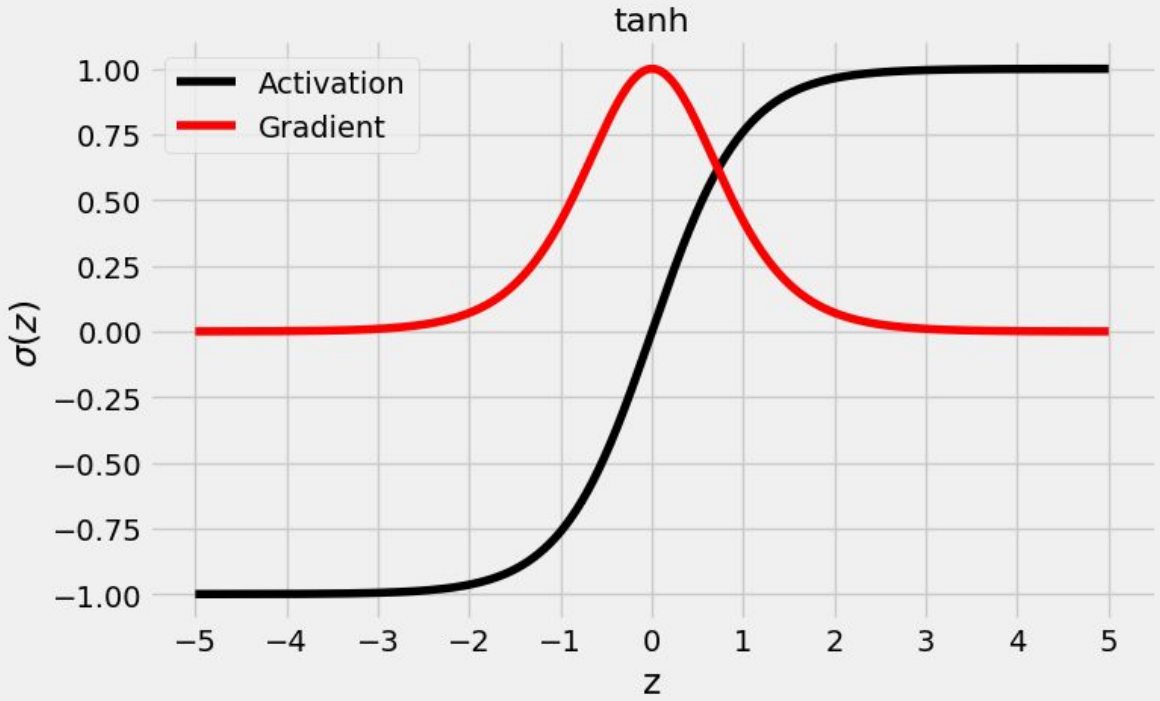
Nonlinear functions either squash or bend straight lines

Activation Functions



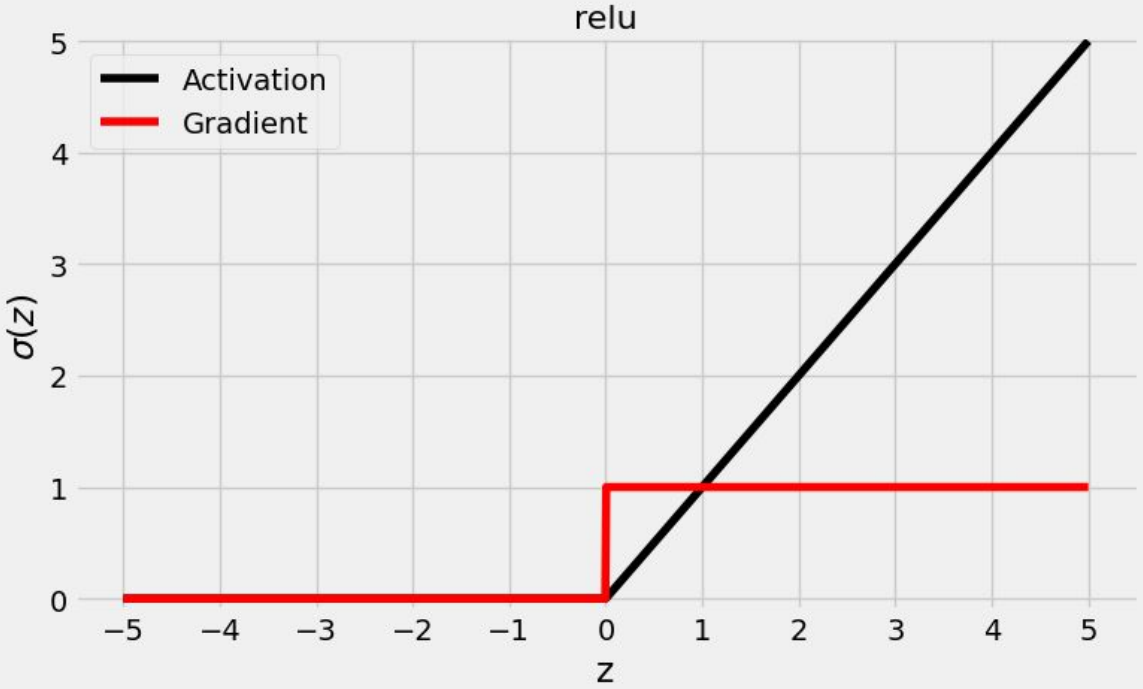
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- Range (0,1) same range probabilities can take, which is why it is used in the output layer for binary classification tasks.
- Gradient peak value is only 0.25 (for z=0).
- Gradient gets close to zero as the absolute value of z reaches a value of -5 or 5.
- The activation values are going to be centered around 0.5, instead of zero. This means that, even if we normalize our inputs to feed the first layer, it will not be the case anymore for the other layers.



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

- TanH activation function "squashes" the input values into the range (-1, 1).
- Being centered at zero, the activation values are already (somewhat) normalized inputs for the next layer, making the hyperbolic tangent a better activation function than the sigmoid.
- Gradient has a much larger peak value of 1.0 (again, for z = 0), but it's decrease is even faster, approaching zero to absolute values of z as low as three. This is the underlying cause of what is referred to as the problem of **vanishing gradients**.

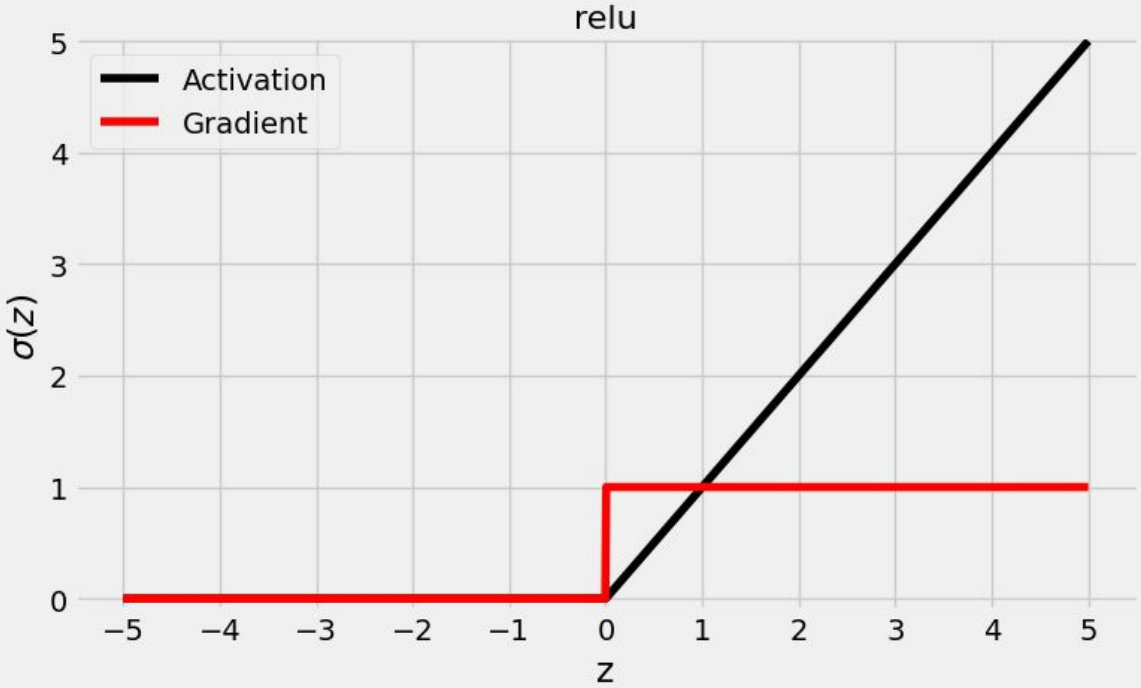


$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}$$

or

$$\sigma(z) = \max(0, z)$$

- RELU addresses the problem of vanishing gradients found with its two predecessors, while also being the fastest to compute gradients for. It does not "squash" the values into a range—it simply preserves positive values and turns all negative values into zero. This pattern leads for a faster convergence.
- This behavior can also lead to what is called a "**dead neuron**"; that is, a neuron whose inputs are consistently negative and, therefore, always has an activation value of zero.
- Worse yet, the gradient is also zero for negative inputs, meaning the weights are not updated. It's like the **neuron got stuck**.

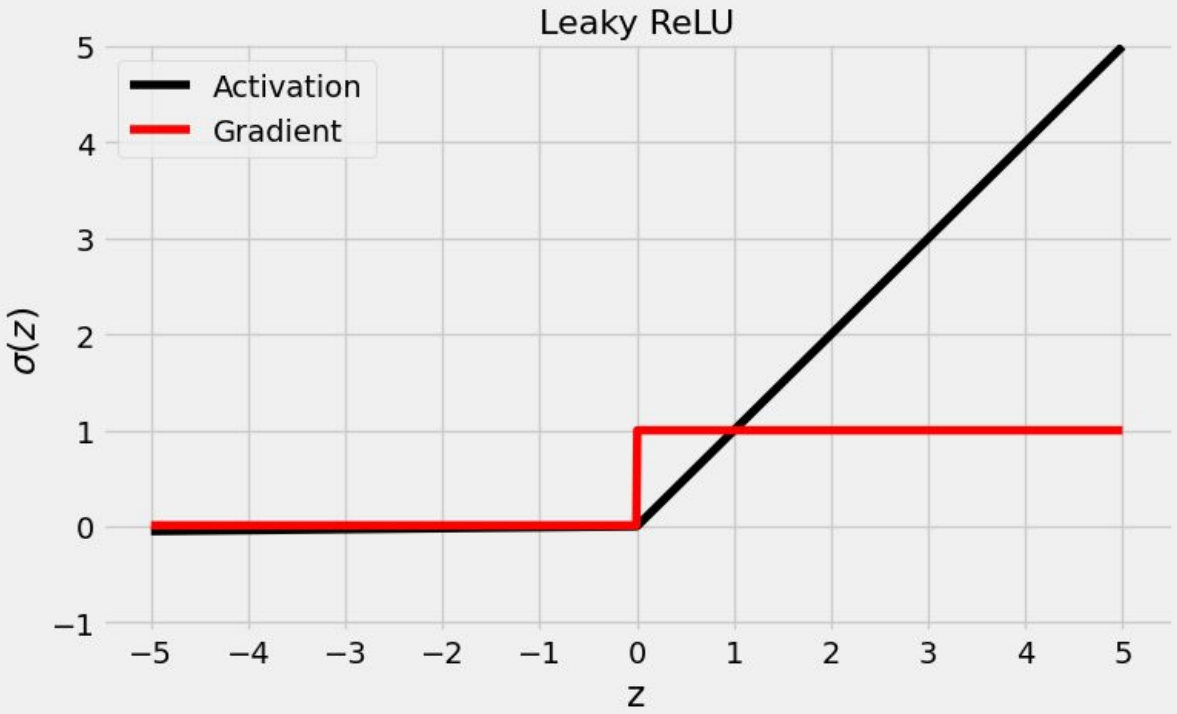


$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}$$

or

$$\sigma(z) = \max(0, z)$$

- The activation values of the ReLU are obviously not centered at zero.
- For deeper and more complex models, this may become an issue commonly called "**internal covariate shift**," which is just fancy for there being different distributions of activation values in different layers.
- In general, **we would like to have all layers producing activation values with similar distributions**, ideally zero centered and with unit standard deviation. **To address this issue, you can use normalization layers (batch normalization).**

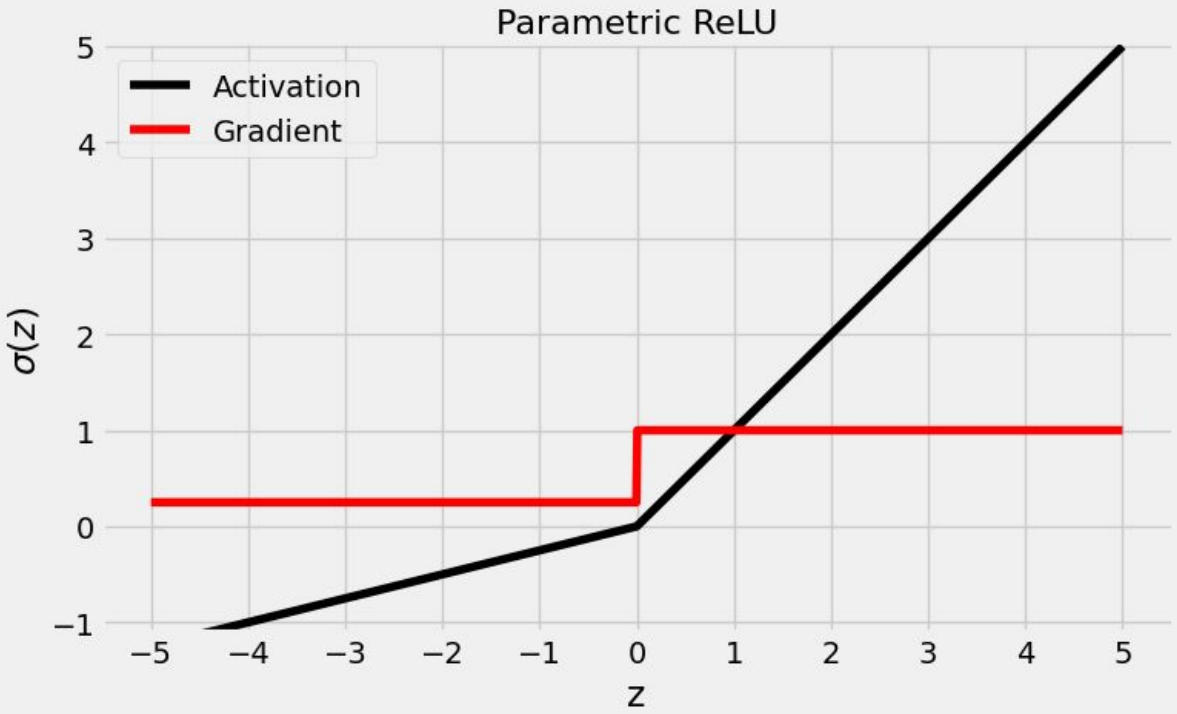


$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0.01z, & \text{if } z < 0 \end{cases}$$

or

$$\sigma(z) = \max(0, z) + 0.01 \min(0, z)$$

- For negative inputs, it returns a tiny activation value and yields a tiny gradient, instead of a fixed zero for both. It may not be much, but **it gives the neuron a chance to get unstuck**.
- The multiplier for negative values, 0.01, is called the **coefficient of leakage**.



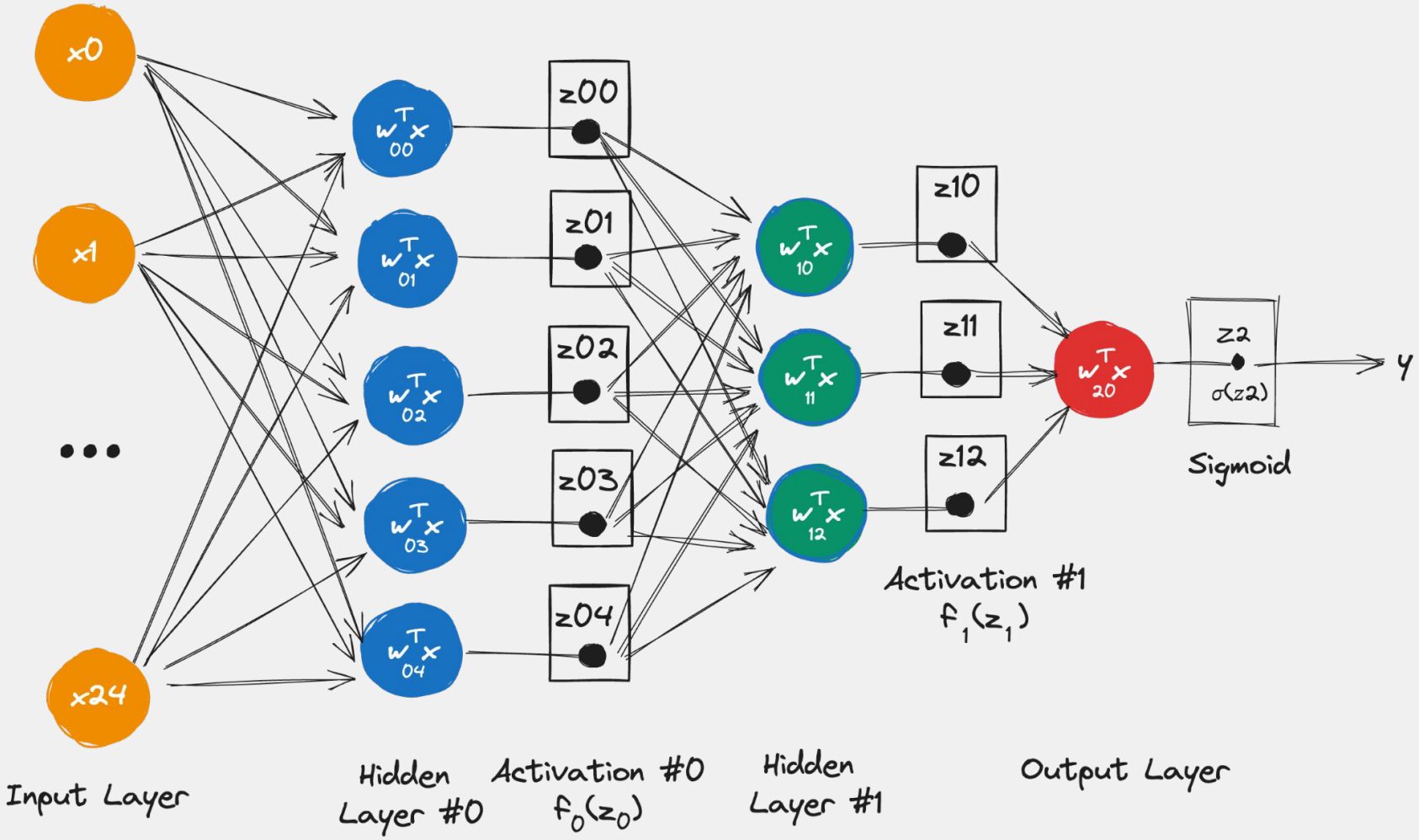
$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ az, & \text{if } z < 0 \end{cases}$$

or

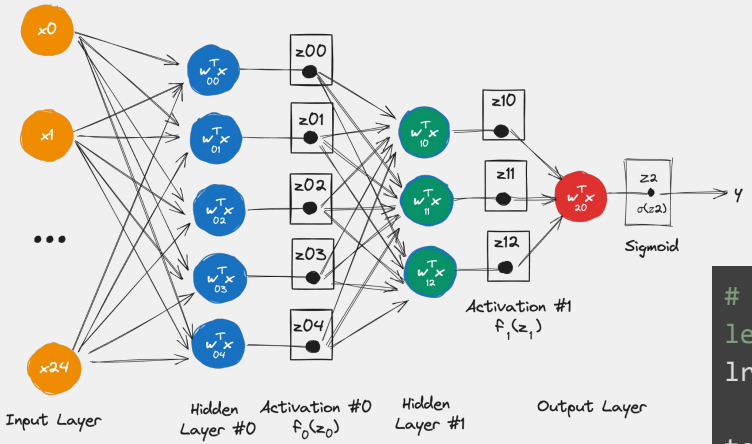
$$\sigma(z) = \max(0, z) + a \min(0, z)$$

- The Parametric ReLU is the natural evolution of the Leaky ReLU: Instead of arbitrarily choosing a coefficient of leakage (such as 0.01), let's make it a parameter (a).
- We can set the initial value for a despite it is going to be learned.

Deep Model

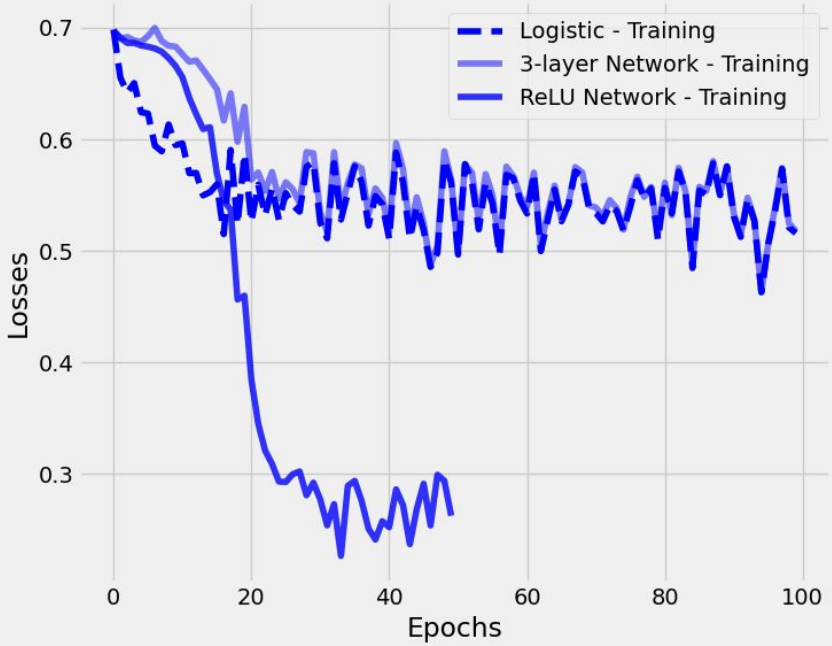

x0
x1
...
x24
$w_{00}^T x$
$w_{01}^T x$
$w_{02}^T x$
$w_{03}^T x$
$w_{04}^T x$
z00
z01
z02
z03
z04
$w_{10}^T x$
$w_{11}^T x$
$w_{12}^T x$
z10
z11
z12
$w_{20}^T x$
z2
σ(z2)
Sigmoid
y
Activation #1
$f_1(z_1)$
Input Layer
Hidden Layer #0
Activation #0
$f_0(z_0)$
Hidden Layer #1
Output Layer

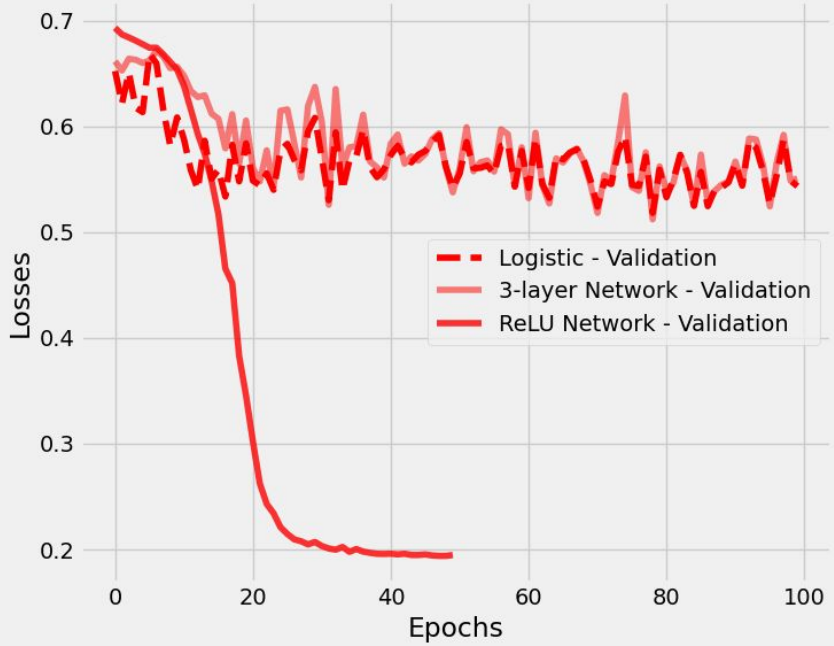
Deep Model




```
# Sets learning rate - this is "eta" ~ the "n" like Greek
letter
lr = 0.1

torch.manual_seed(17)
# Now we can create a model
model_relu = nn.Sequential()
model_relu.add_module('flatten', nn.Flatten())
model_relu.add_module('hidden0', nn.Linear(25, 5, bias=False))
model_relu.add_module('activation0', nn.ReLU())
model_relu.add_module('hidden1', nn.Linear(5, 3, bias=False))
model_relu.add_module('activation1', nn.ReLU())
model_relu.add_module('output', nn.Linear(3, 1, bias=False))
model_relu.add_module('sigmoid', nn.Sigmoid())

# Defines a SGD optimizer to update the parameters
optimizer_relu = optim.SGD(model_relu.parameters(), lr=lr)

# Defines a binary cross entropy loss function
binary_loss_fn = nn.BCELoss()
```

Deep Model


Logistic - Training
3-layer Network - Training
ReLU Network - Training
Losses
Epochs
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100


Logistic - Validation
3-layer Network - Validation
ReLU Network - Validation
Losses
Epochs
0.7
0.6
0.5
0.4
0.3
0.2
0
20
40
60
80
100

Bonus Chapter: feature space