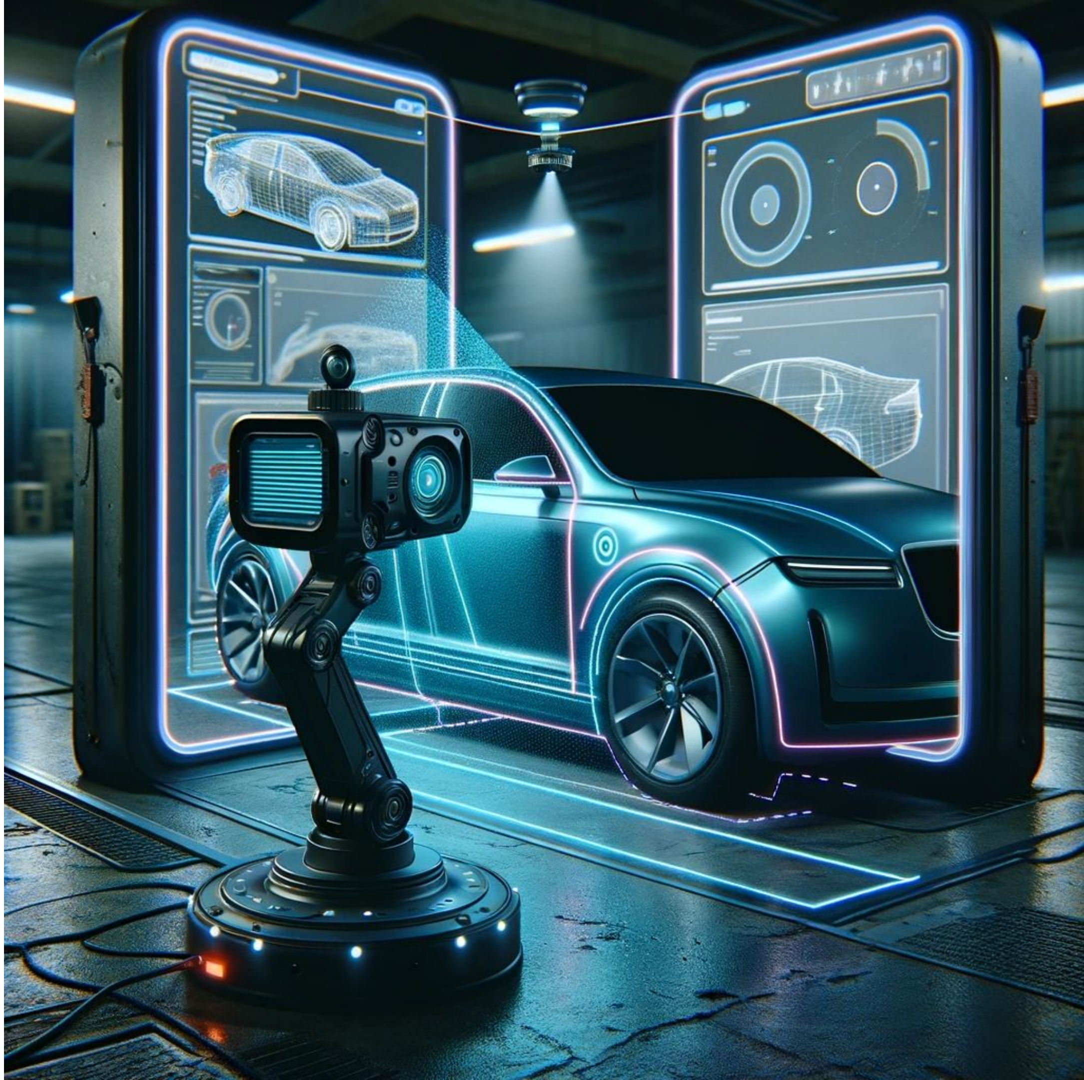
PPGEEC2318

Machine Learning

Computer Vision - Part I



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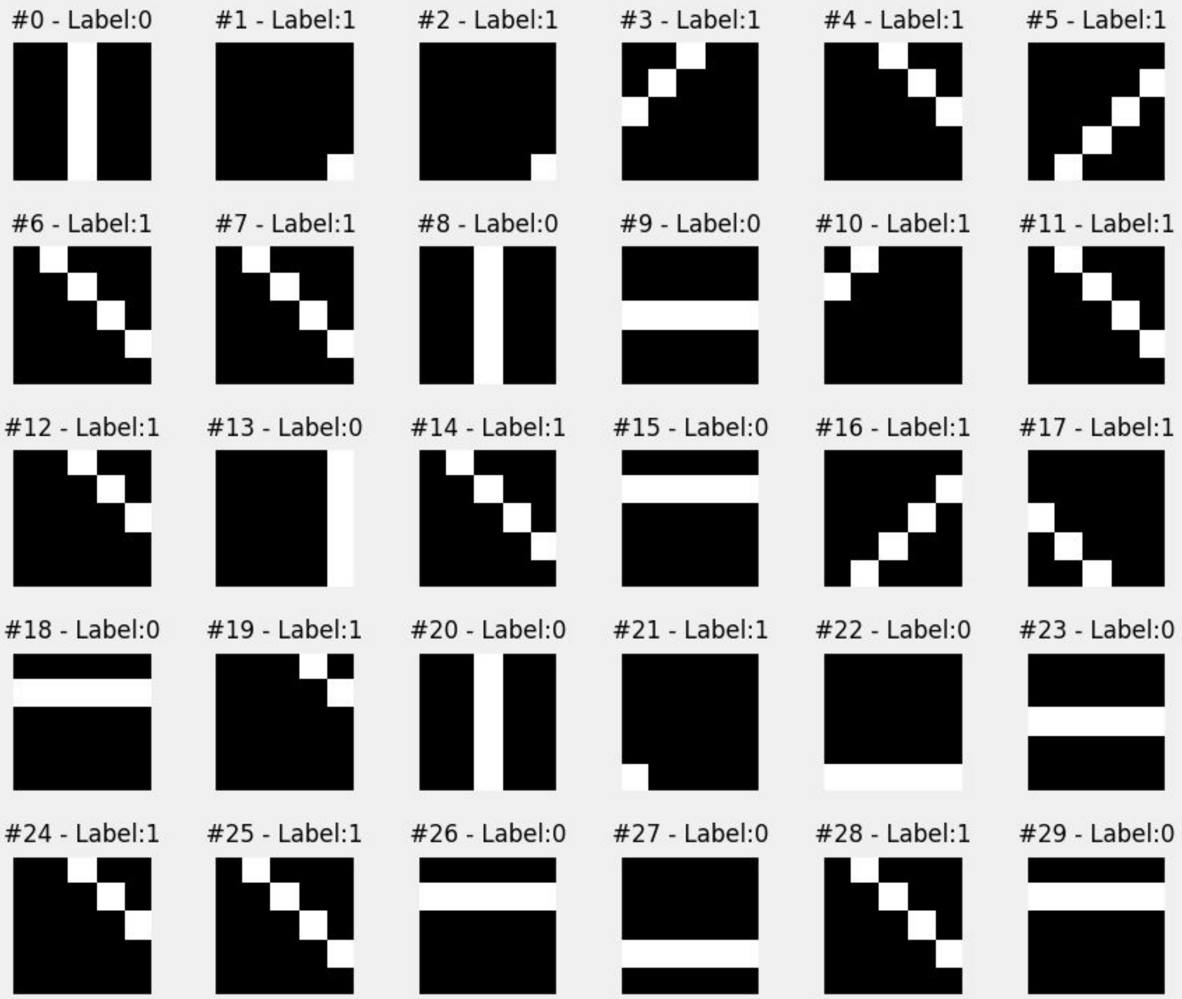
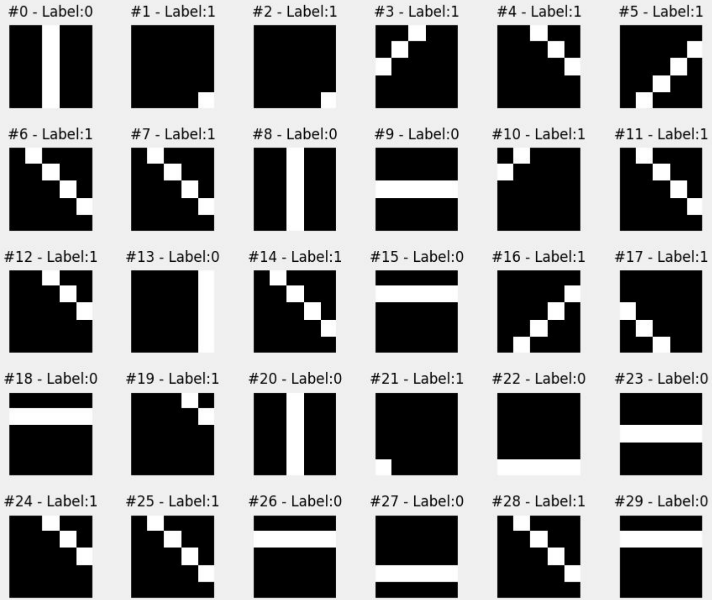
Is the line diagonal?

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]]
```

Red | Green | Blue | Grayscale Image

Single Channel (grayscale)

5x5 | 5x5 | 5x5 | 5x5 = 0.21R + 0.72G + 0.07B

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

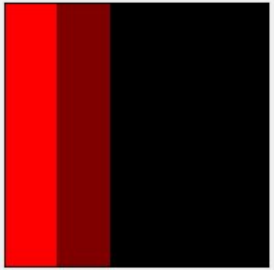
```
[[  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]
 [  0 128 255 128   0]]
```

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]]
```

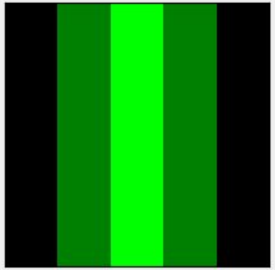
Three Channels (color)

as first channel



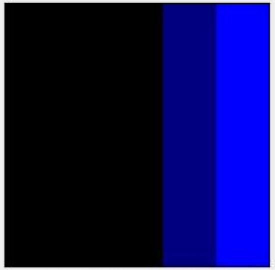
5x5x3 - R only

as second channel



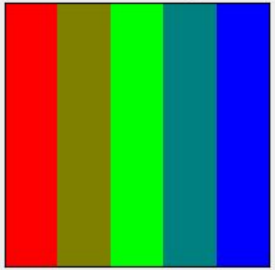
5x5x3 - G only

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

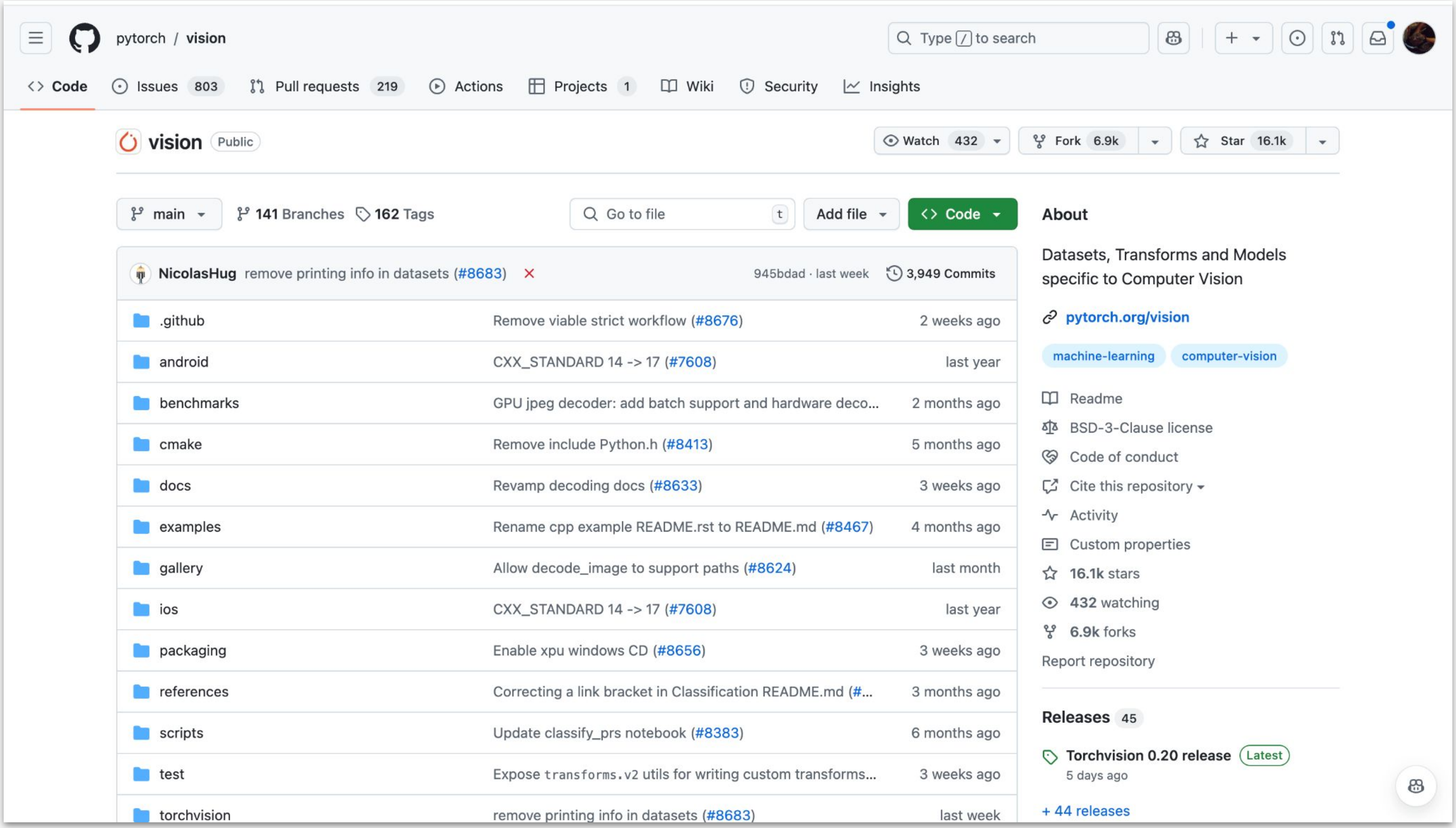
```
images.shape
(300, 1, 5, 5)
```

```
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.


pytorch / vision
Type / to search
Code
Issues 803
Pull requests 219
Actions
Projects 1
Wiki
Security
Insights
vision Public
Watch 432
Fork 6.9k
Star 16.1k
main
141 Branches
162 Tags
Go to file
t
Add file
Code
NicolasHug remove printing info in datasets (#8683)
945bdad · last week
3,949 Commits
.github | Remove viable strict workflow (#8676) | 2 weeks ago
android | CXX_STANDARD 14 -> 17 (#7608) | last year
benchmarks | GPU jpeg decoder: add batch support and hardware deco... | 2 months ago
cmake | Remove include Python.h (#8413) | 5 months ago
docs | Revamp decoding docs (#8633) | 3 weeks ago
examples | Rename cpp example README.rst to README.md (#8467) | 4 months ago
gallery | Allow decode_image to support paths (#8624) | last month
ios | CXX_STANDARD 14 -> 17 (#7608) | last year
packaging | Enable xpu windows CD (#8656) | 3 weeks ago
references | Correcting a link bracket in Classification README.md (#... | 3 months ago
scripts | Update classify_prs notebook (#8383) | 6 months ago
test | Expose transforms.v2 utils for writing custom transforms... | 3 weeks ago
torchvision | remove printing info in datasets (#8683) | last week
About
Datasets, Transforms and Models specific to Computer Vision
pytorch.org/vision
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computer-vision
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Activity
Custom properties
16.1k stars
432 watching
6.9k forks
Report repository
Releases 45
Torchvision 0.20 release
Latest
5 days ago
+ 44 releases

```python
from torchvision.transforms import Compose, ToTensor
from torchvision.transforms import Normalize, ToPILImage
from torchvision.transforms import RandomHorizontalFlip, Resize
```

```python
composer = Compose([RandomHorizontalFlip(p=1.0),
                    Normalize(mean=(.5,), std=(.5,))])
composed_tensor = composer(example_tensor)
```

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

Convert, build and transform tensors into useful format

Data Preparation

Splitting the dataset: build a custom splitter

```
def index_splitter(n, splits, seed=13):
    idx = torch.arange(n)
    # Makes the split argument a tensor
    splits_tensor = torch.as_tensor(splits)
    # Finds the correct multiplier, so we don't have
    # to worry about summing up to N (or one)
    multiplier = n / splits_tensor.sum()
    splits_tensor = (multiplier * splits_tensor).long()
    # If there is a difference, throws at the first split
    # so random_split does not complain
    diff = n - splits_tensor.sum()
    splits_tensor[0] += diff
    # Uses PyTorch random_split to split the indices
    torch.manual_seed(seed)
    return random_split(idx, splits_tensor)
```

```
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

```python
# 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

```python
# 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

```python
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

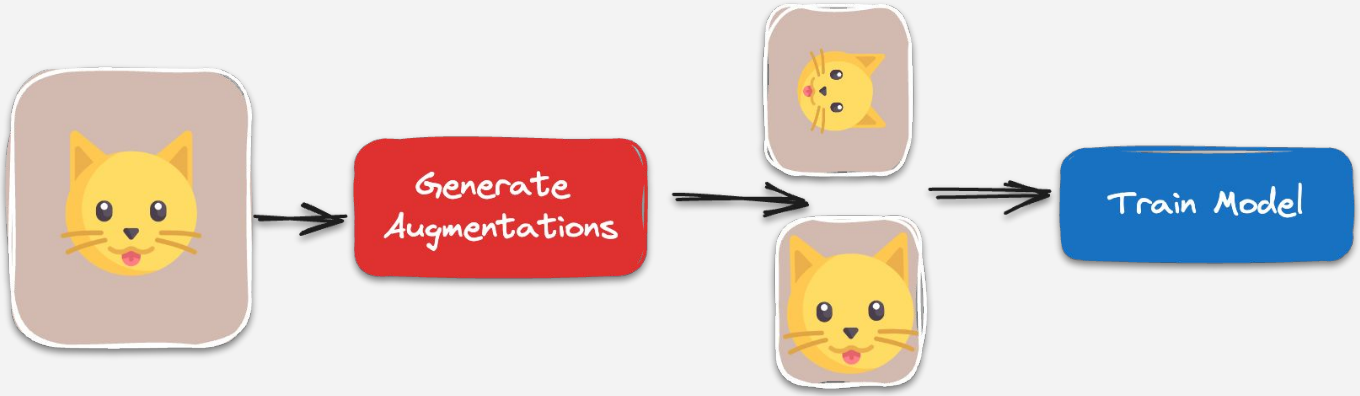
```
weights
tensor([0.0125, 0.0063])

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

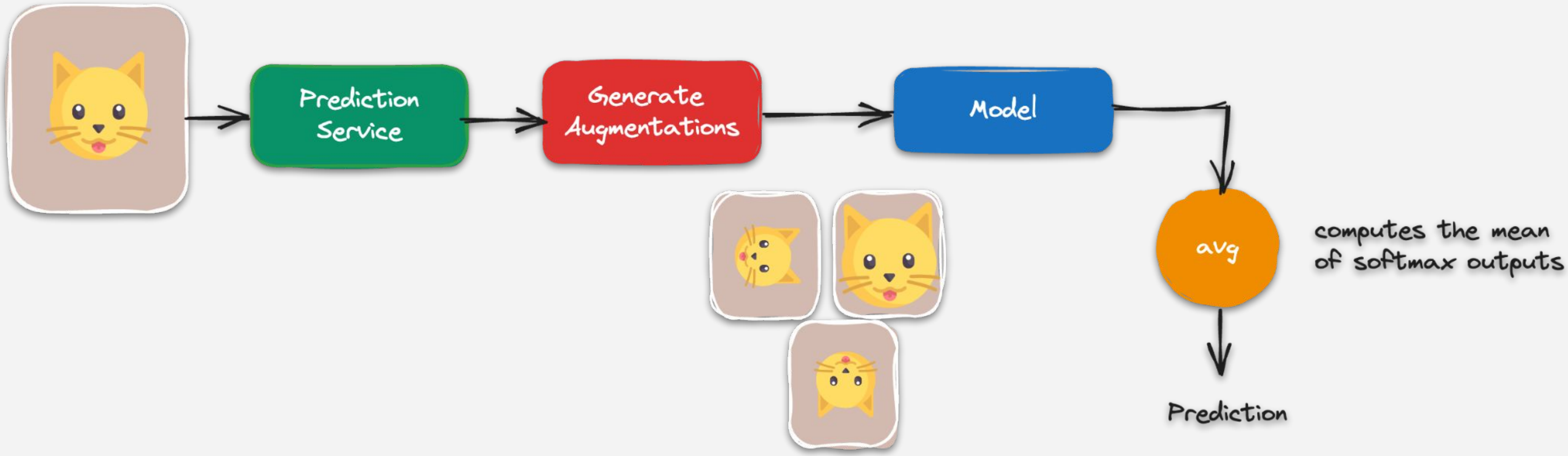
```
# Create an instance of the Generator class from PyTorch
generator = torch.Generator()

# 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

```python
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)
```

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

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

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

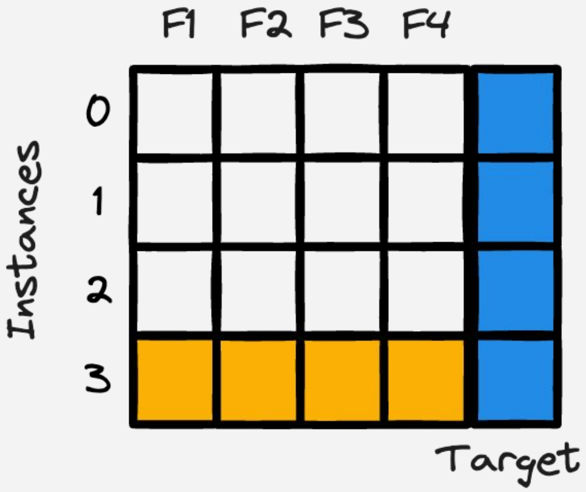
Splitting the dataset: putting it together

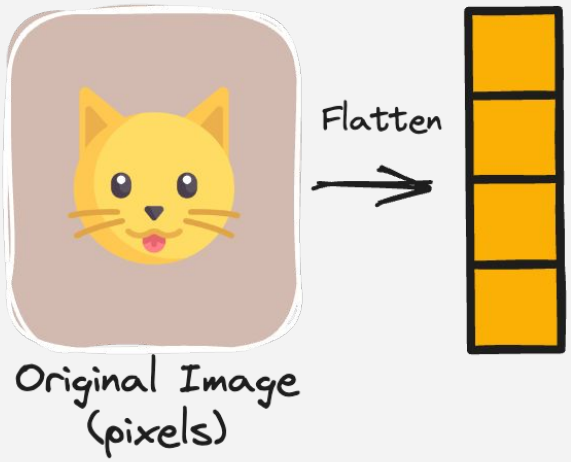
```
# Builds tensors from numpy arrays BEFORE split
# Modifies the scale of pixel values from [0, 255] to [0, 1]
x_tensor = torch.as_tensor(images / 255).float()
y_tensor = torch.as_tensor(labels.reshape(-1, 1)).float()

# 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



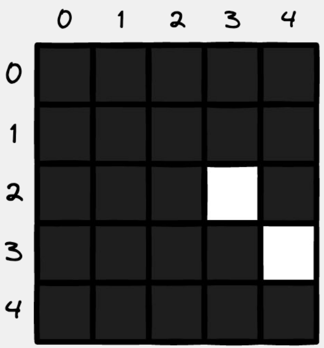


Splitting the dataset: pixels as features

```
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

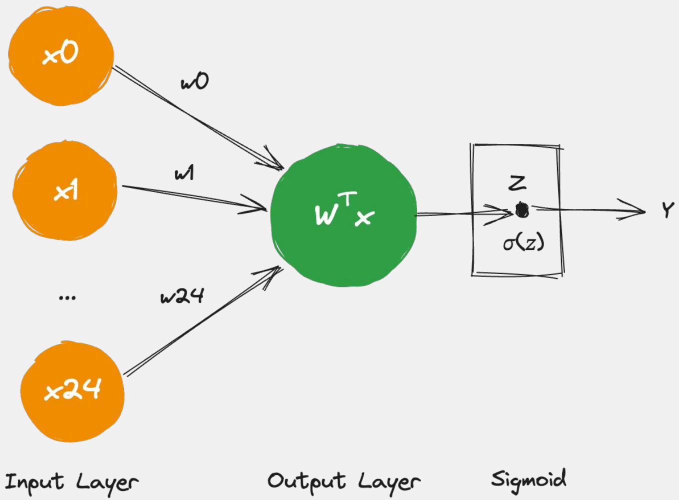
Shallow Model



Original Image

Flatted Image

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

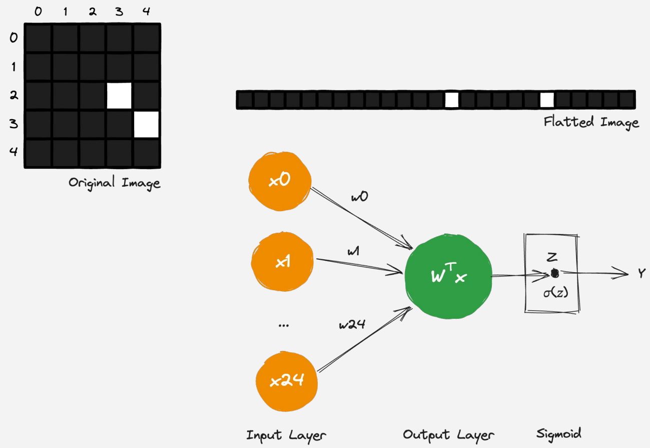


$$W=\underset{(25\times1)}{\begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_{24} \end{bmatrix}};X=\underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{24} \end{bmatrix}}$$

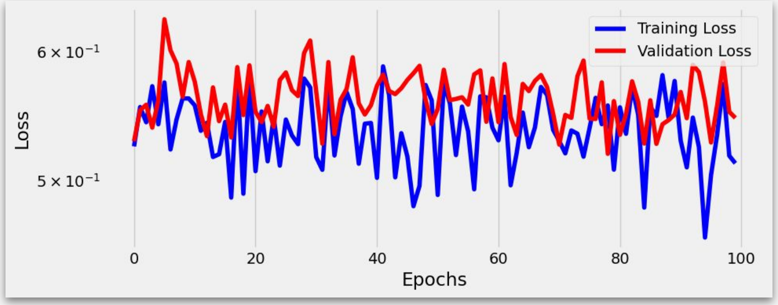
$$z=W^T\cdot X=\underset{(1\times25)}{\begin{bmatrix} - & w^T & - \end{bmatrix}}\underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{24} \end{bmatrix}}=\underset{(1\times25)}{\begin{bmatrix} w_0 & w_1 & \cdots & w_{24} \end{bmatrix}}\underset{(25\times1)}{\begin{bmatrix} x_0 \\ x_1 \\ \vdots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

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

```python
# 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()
```

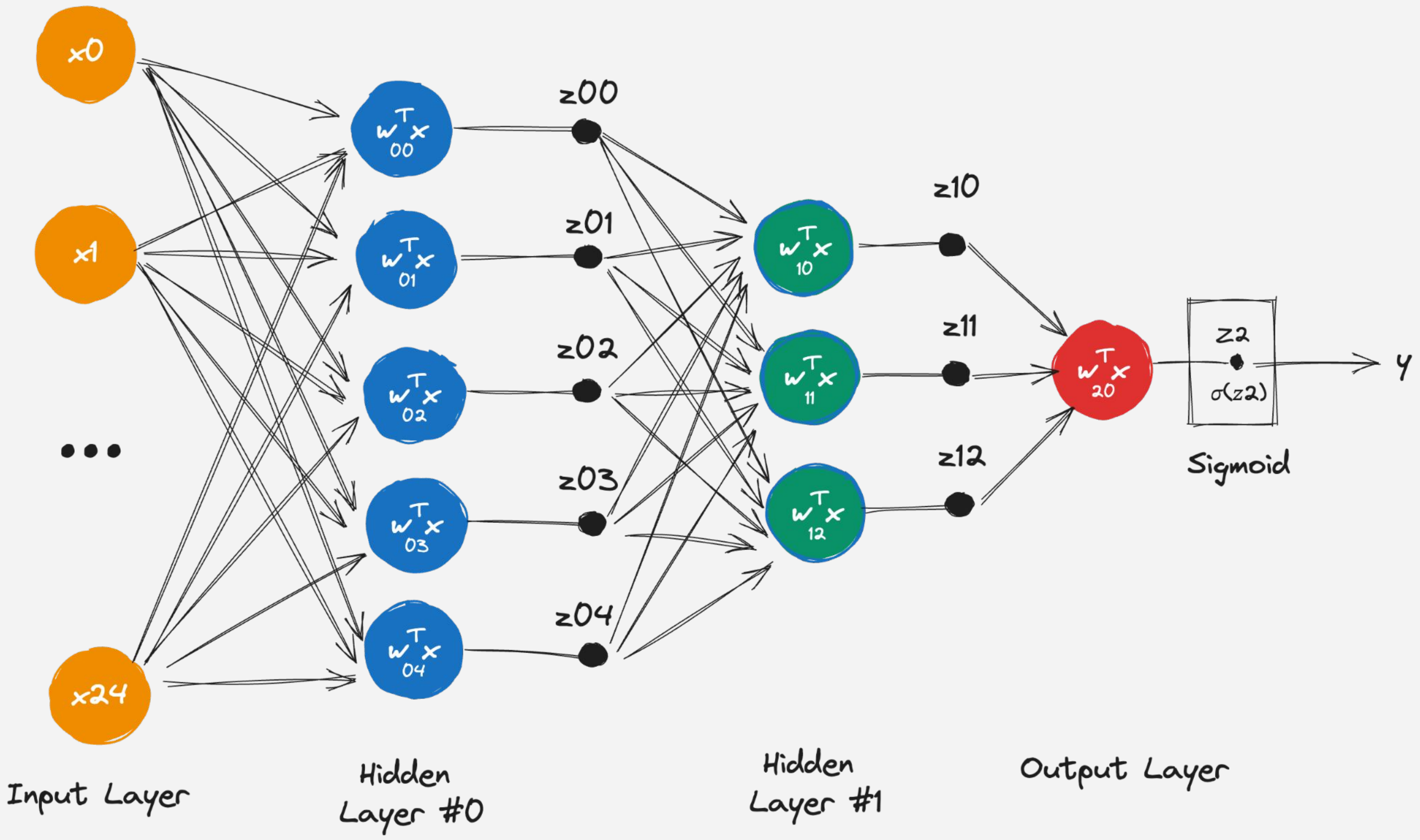



```python
n_epochs = 100

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

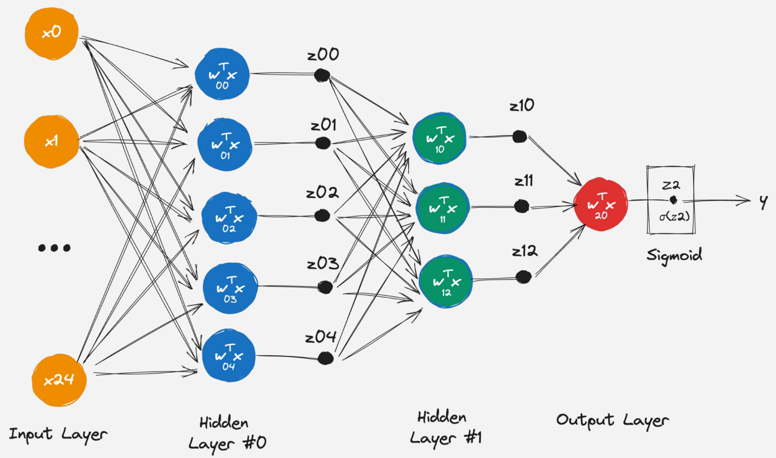


There we go, let's add not one, but two hidden layers

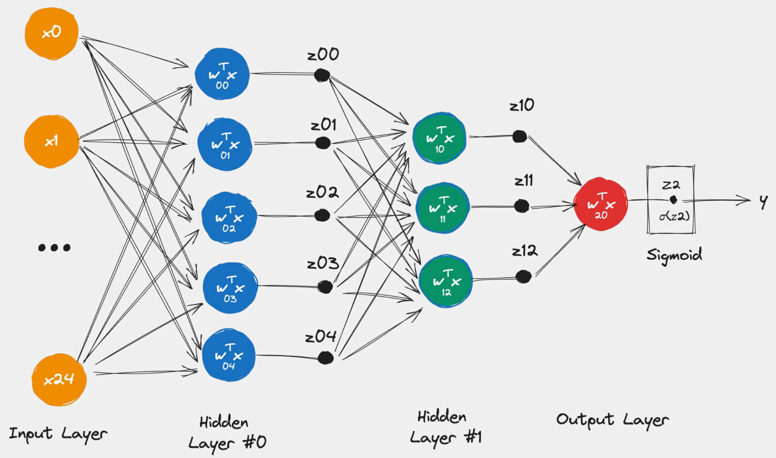
Deep-ish Model



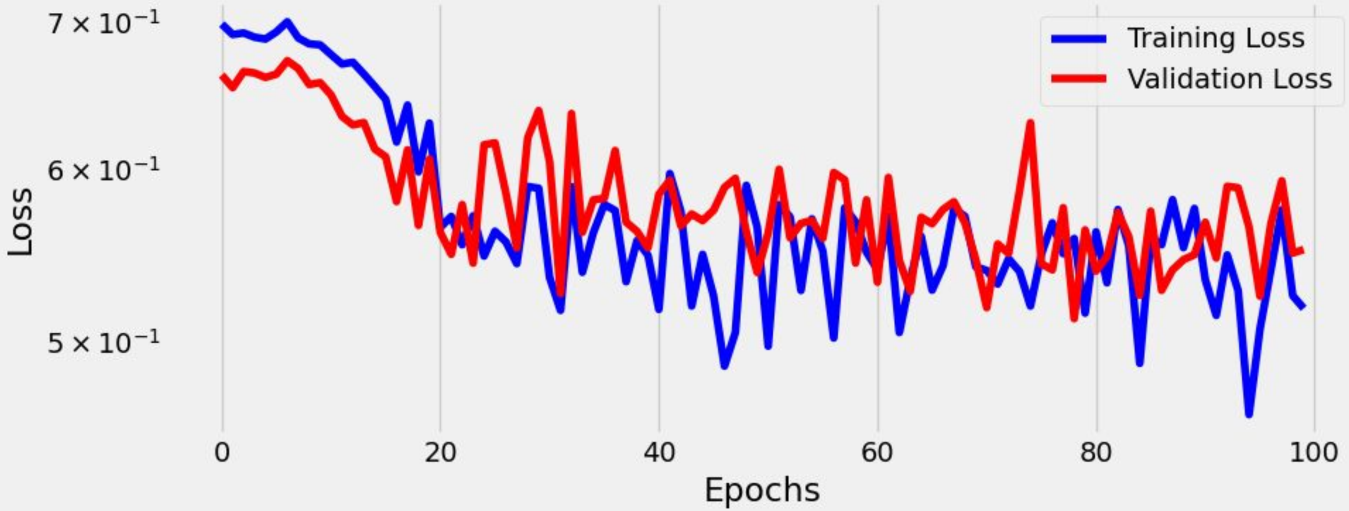
x0
x1
...
x24
z00
z01
z02
z03
z04
z10
z11
z12
Z2
σ(z2)
y
Sigmoid
Input Layer
Hidden Layer #0
Hidden Layer #1
Output Layer



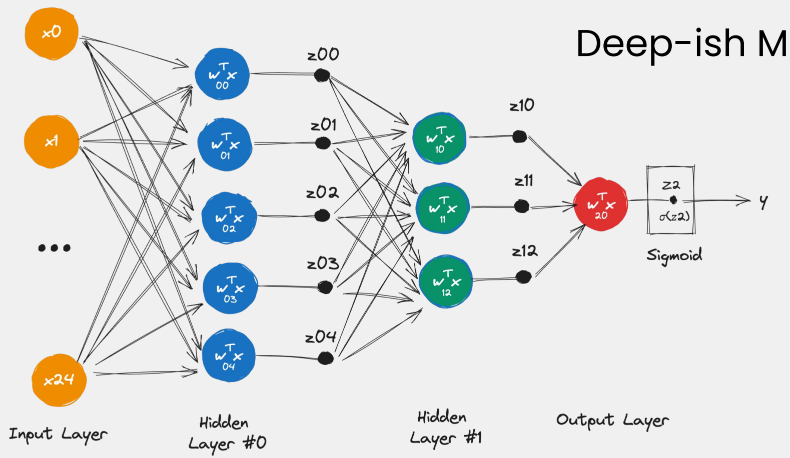

```python
# Sets learning rate - this is "eta" ~ the "n" like Greek letter
lr = 0.1

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()
```



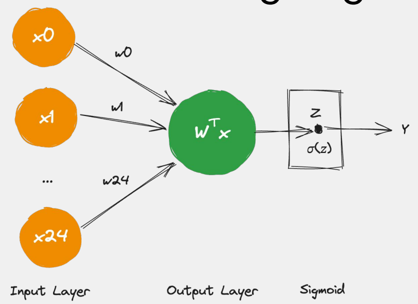

```python
n_epochs = 100

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

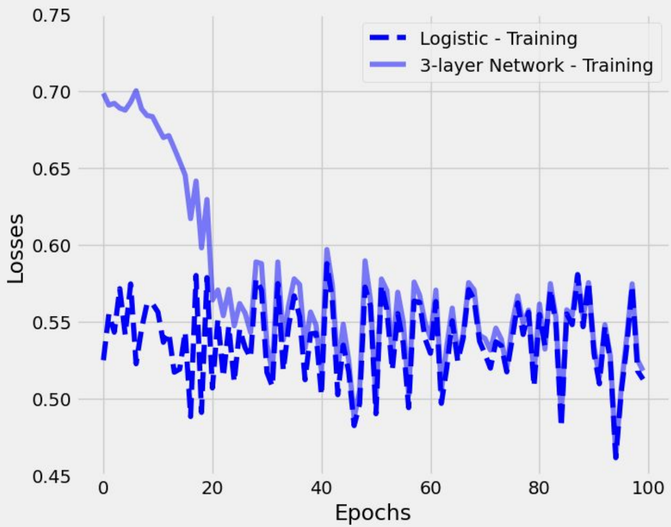


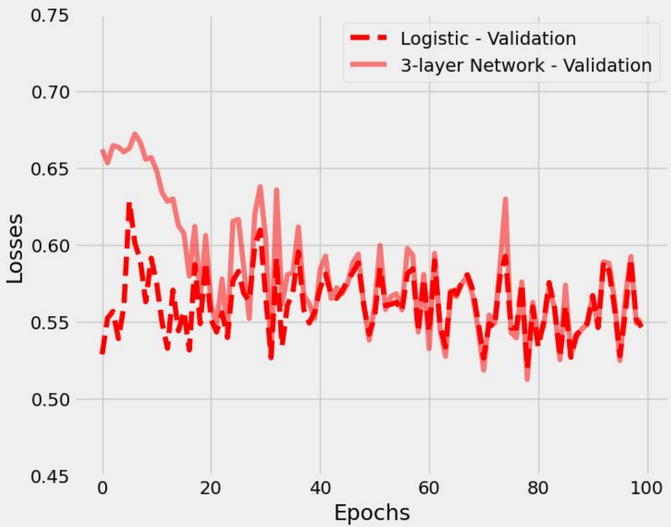
Deep-ish Model

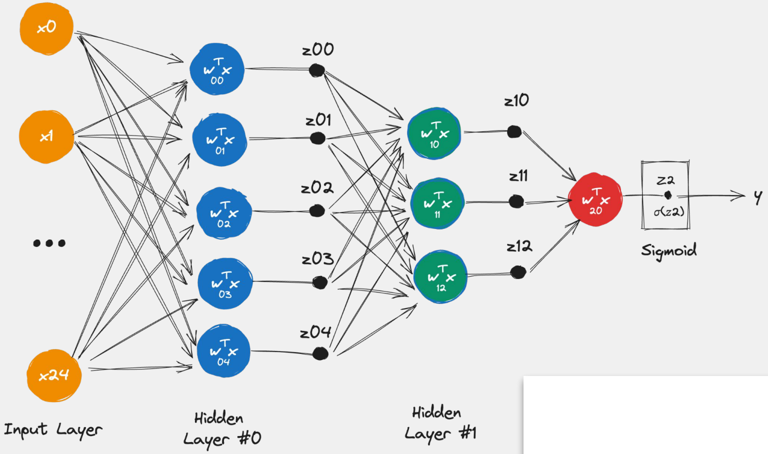


Reg. Logistic Model









Hidden #0

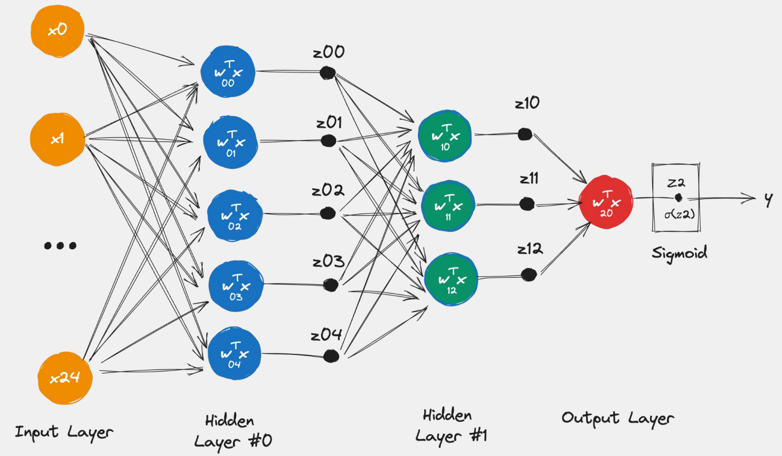
$$\underset{(5\times1)}{\begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}} = \underset{(5\times25)}{\begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\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

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

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

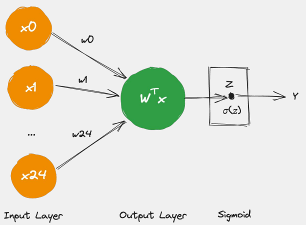


Hidden #0
$$\underset{(5\times1)}{\begin{bmatrix} z_{00} \\ z_{01} \\ z_{02} \\ z_{03} \\ z_{04} \end{bmatrix}} = \underset{(5\times25)}{\begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}}$$

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

This is just the reg. logistic

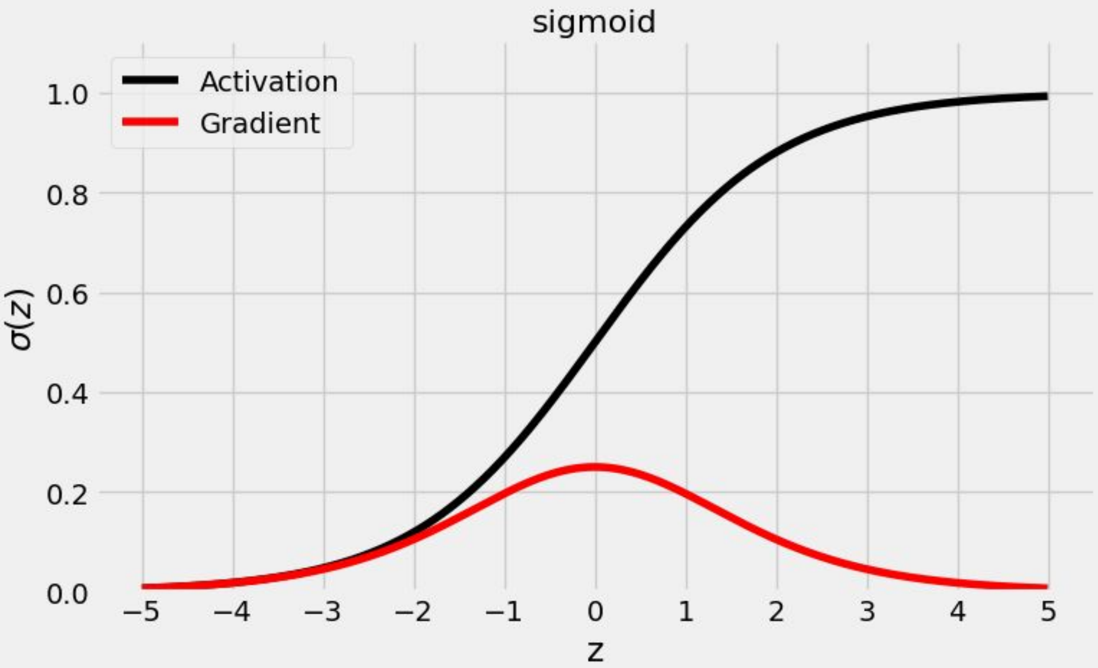


substituting $z's\ldots$
$$\underset{(1\times1)}{\begin{bmatrix} z_2 \end{bmatrix}} = \underbrace{\underset{(1\times3)}{\begin{bmatrix} - & w_{20}^T & - \end{bmatrix}}}_{\text{Output Layer}} \underbrace{\underset{(3\times5)}{\begin{bmatrix} - & w_{10}^T & - \\ - & w_{11}^T & - \\ - & w_{12}^T & - \end{bmatrix}}}_{\text{Hidden Layer \#1}} \underbrace{\underset{(5\times25)}{\begin{bmatrix} - & w_{00}^T & - \\ - & w_{01}^T & - \\ - & w_{02}^T & - \\ - & w_{03}^T & - \\ - & w_{04}^T & - \end{bmatrix}}}_{\text{Hidden Layer \#0}} \underset{(25\times1)}{\begin{bmatrix} x_0 \\ \vdots \\ x_{11} \\ \vdots \\ x_{24} \end{bmatrix}}$$

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

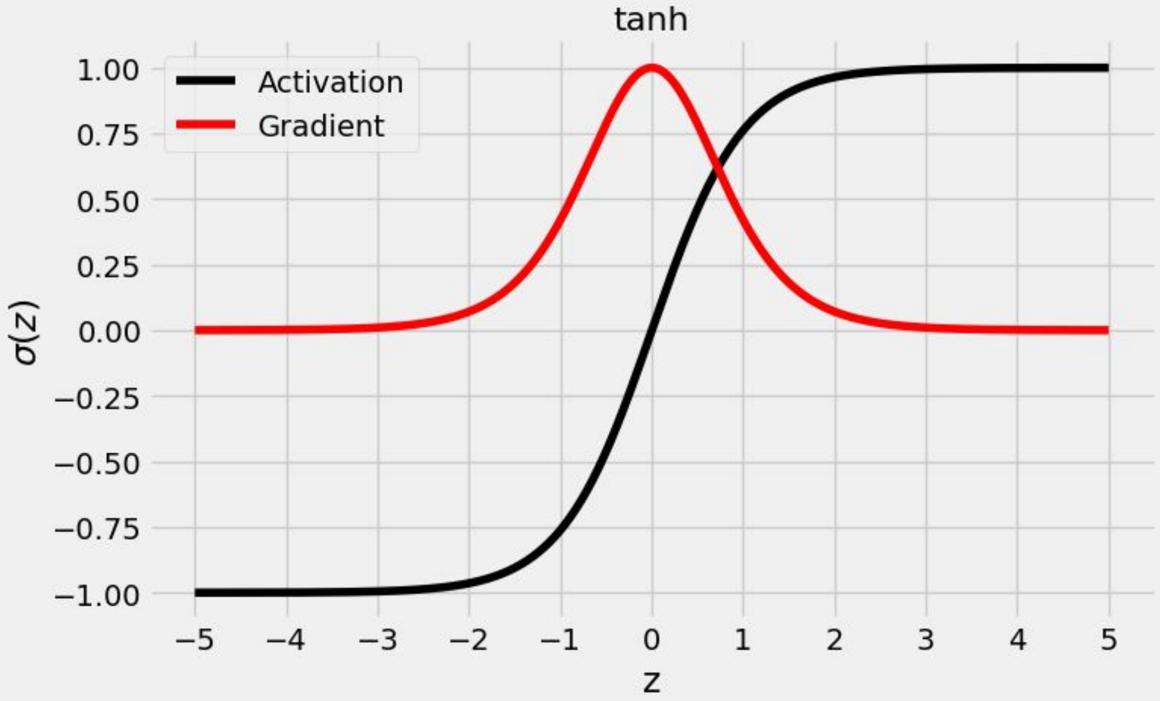
Nonlinear functions either squash or bend straight lines

Activation Functions



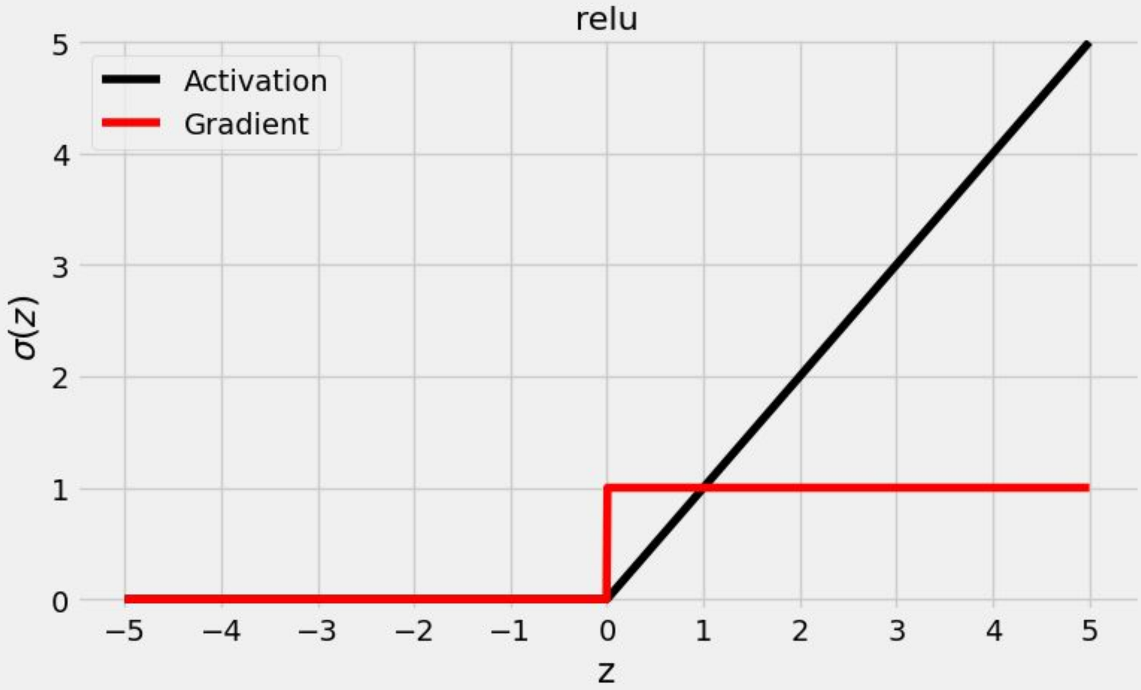
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- 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**.

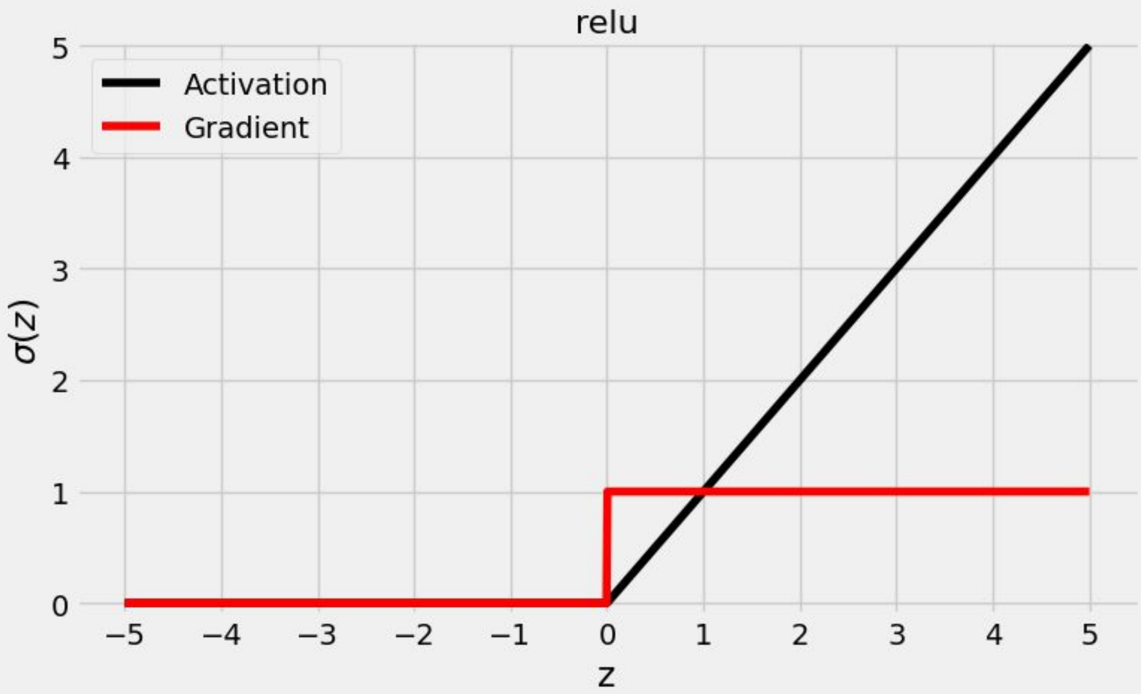


$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}$$

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**.

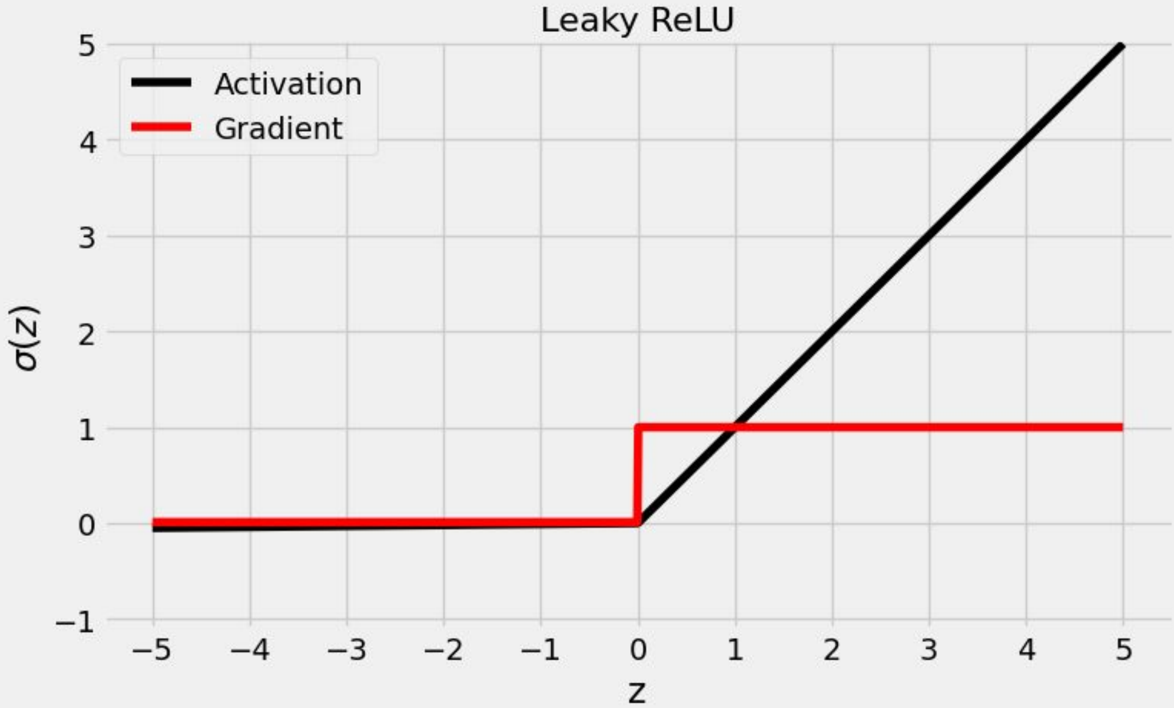


$$\sigma(z) = \begin{cases} z, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}$$

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).**

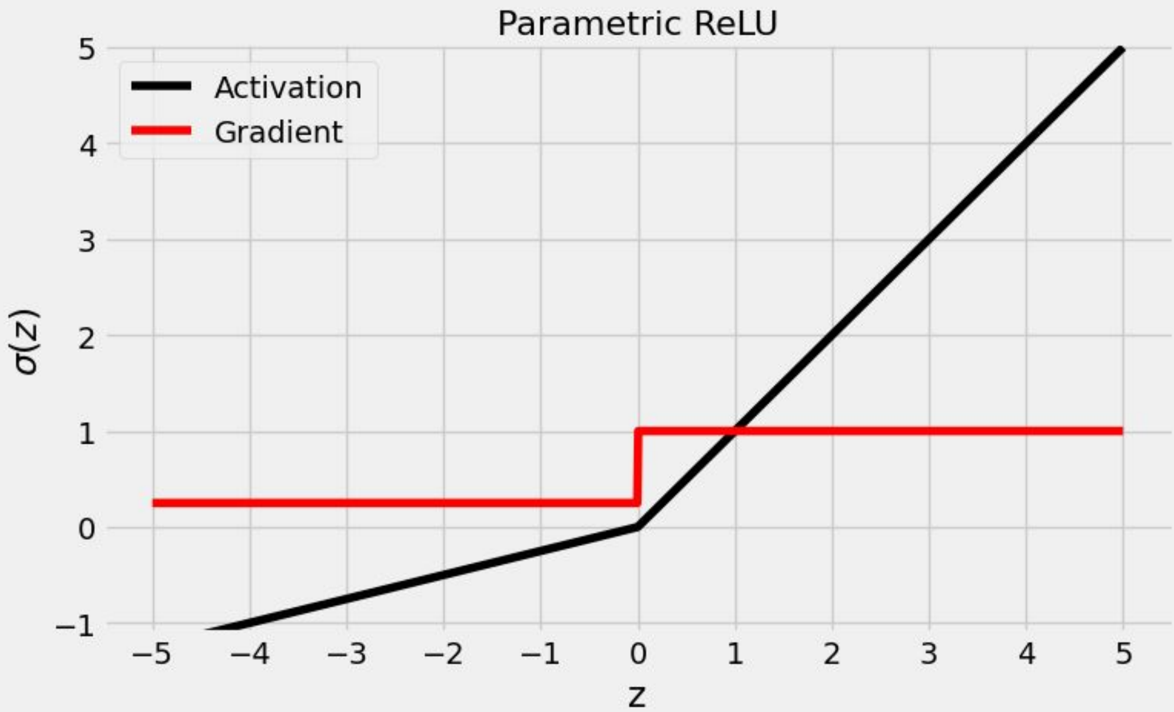


$$\sigma(z) = \begin{cases} z, \text{ if } z \geq 0 \\ 0.01z, \text{ if } z < 0 \end{cases}$$

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**.



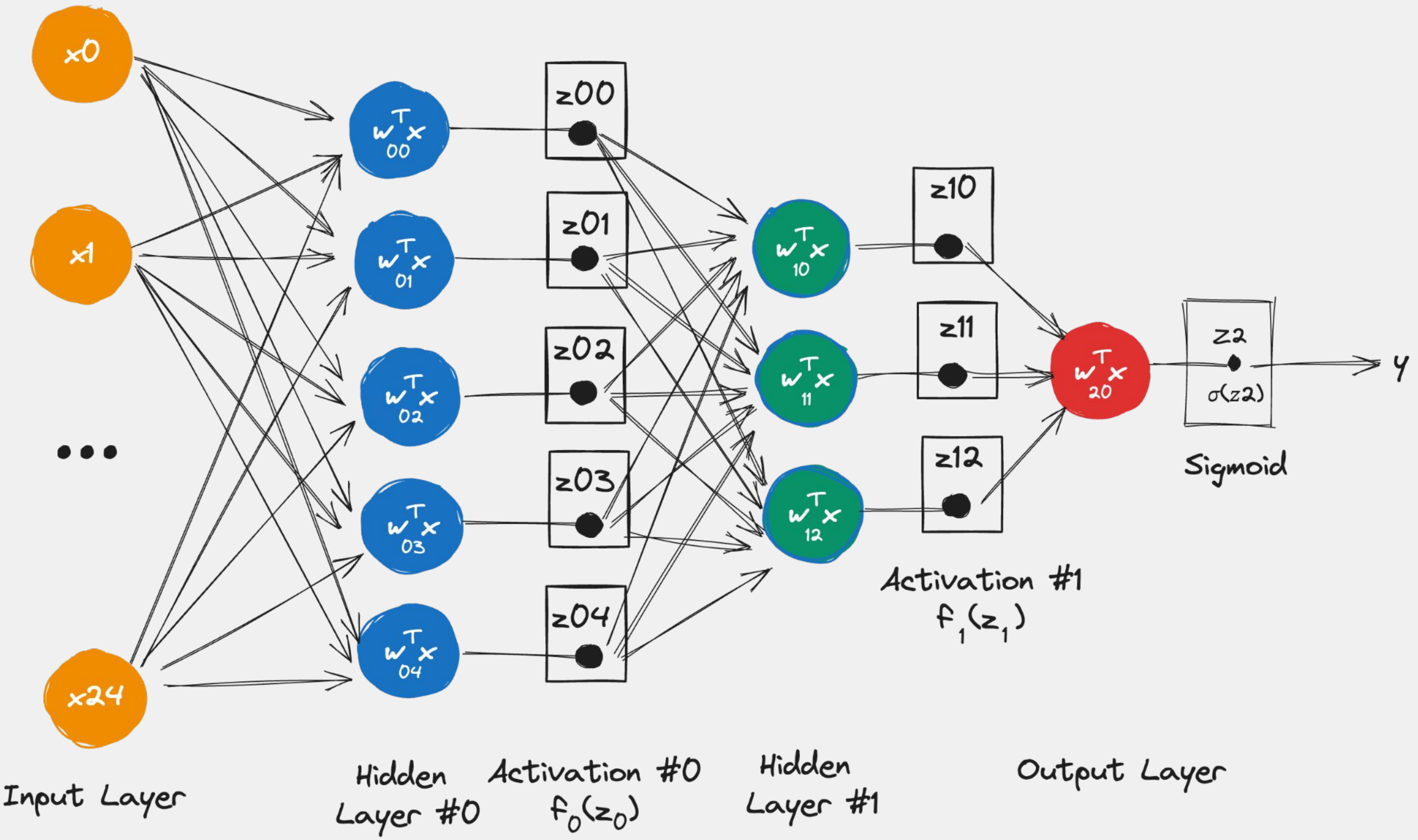
$$\sigma(z) = \begin{cases} z, \ \text{if } z \geq 0 \\ az, \ \text{if } z < 0 \end{cases}$$

or

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

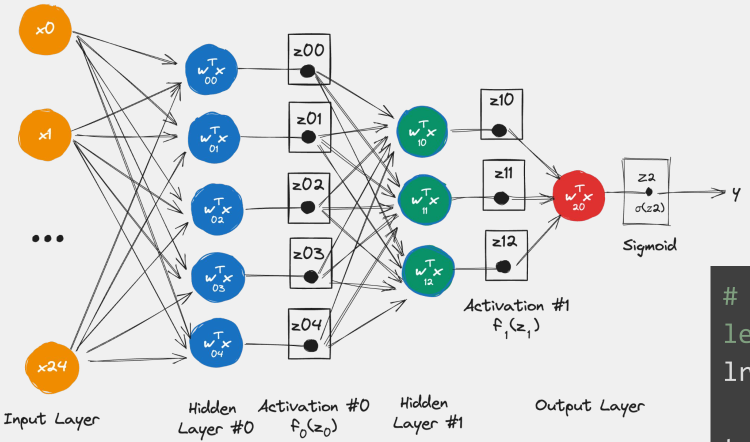
- The Parametric ReLU is the natural evolution of the Leaky ReLU: Instead of arbitrarily choosing a coefficient of leakage (such as 0.01), let's make it a parameter (a).
- We can set the initial value for a despite it is going to be learned.

Deep Model



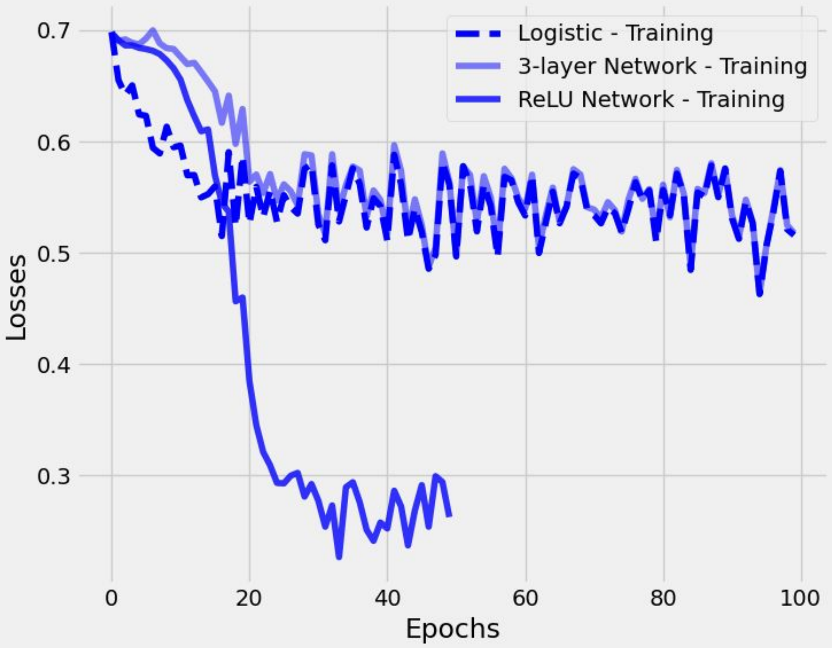
x0
x1
...
x24
Input Layer
$w^T_{00}x$
$w^T_{01}x$
$w^T_{02}x$
$w^T_{03}x$
$w^T_{04}x$
Hidden Layer #0
z00
z01
z02
z03
z04
Activation #0
$f_0(z_0)$
$w^T_{10}x$
$w^T_{11}x$
$w^T_{12}x$
Hidden Layer #1
z10
z11
z12
Activation #1
$f_1(z_1)$
$w^T_{20}x$
Output Layer
z2
σ(z2)
Sigmoid
y

Deep Model

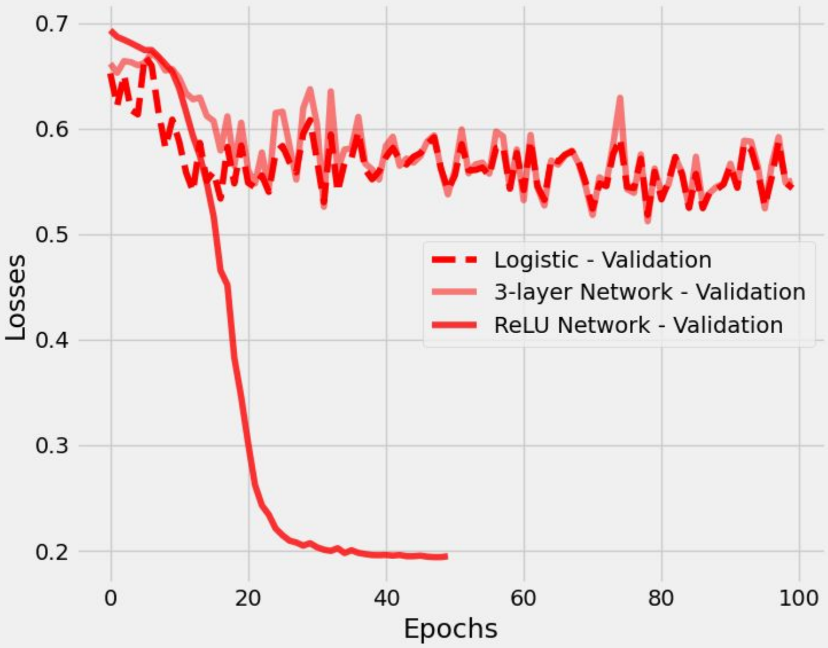



```python
# Sets learning rate - this is "eta" ~ the "n" like Greek letter
lr = 0.1

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



Logistic - Validation
3-layer Network - Validation
ReLU Network - Validation
Losses
Epochs

Bonus Chapter: feature space