Lab 2b: Pytorch Operators and Optimizers

University of Washington

ECE 596/AMATH 563

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PyTorch

Outline

- Pytorch operators and layers
  - Activation Functions
  - Normalization
  - Dropout
  - Loss Functions
- Designing Training Procedures: Pytorch Optimizers
- Assignment: Fashion MNIST

PyTorch Operators and Layers

PyTorch Operators/Layers

- Activation Functions
- Normalization
- Dropout
- Loss Functions

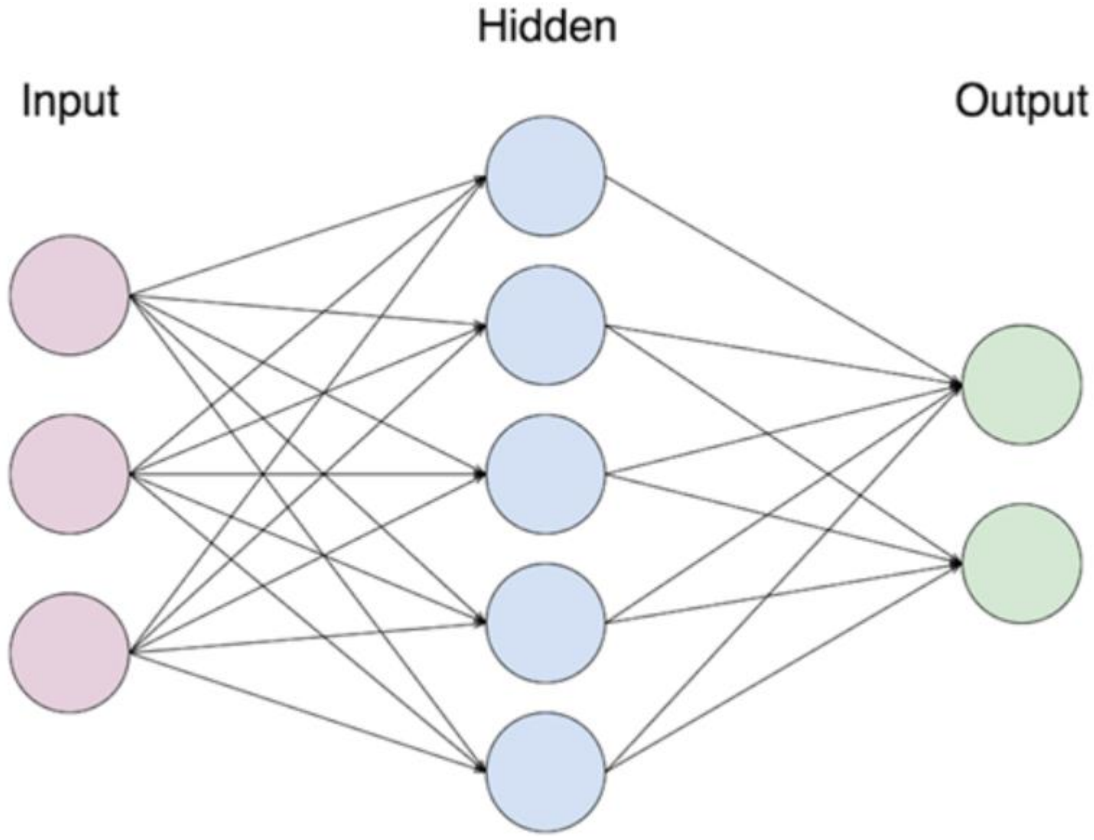
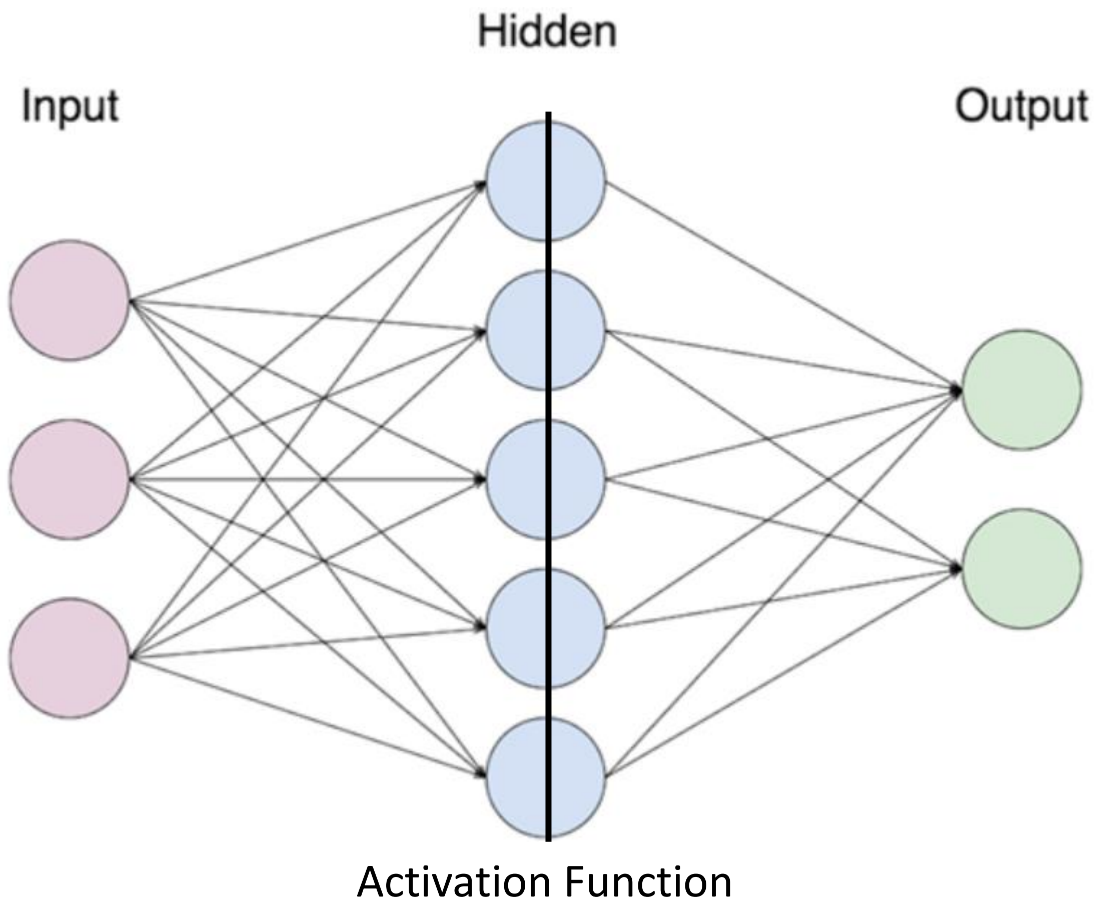


Image source: https://towardsdatascience.com/step-by-step-guide-to-building-your-own-neural-network-from-scratch-df64b1c5ab6e

PyTorch Operators/Layers

- Activation Functions
- Normalization
- Dropout
- Loss Functions



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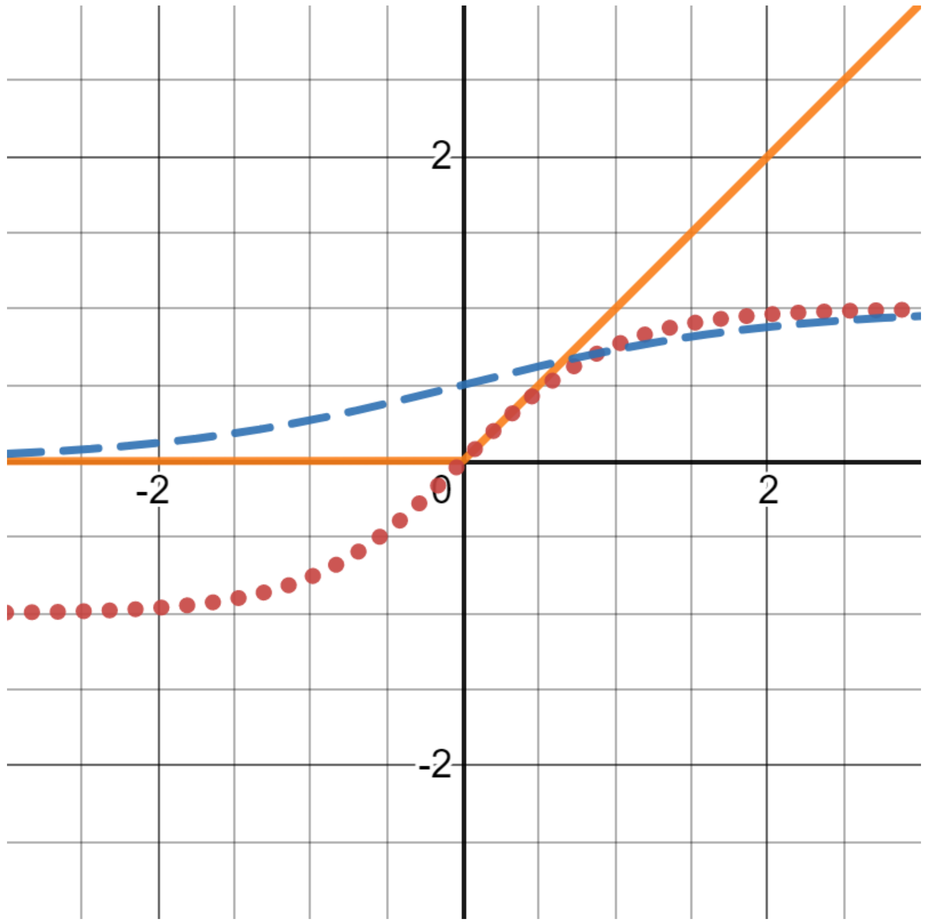
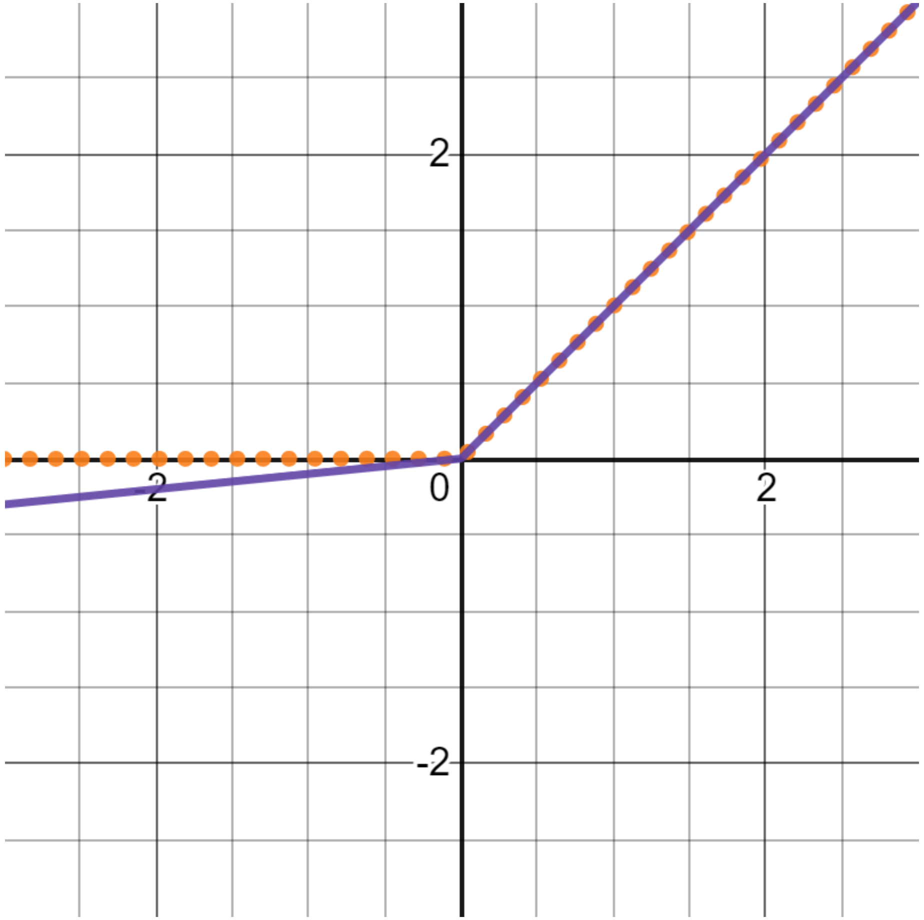
Activation Functions

- Non-linear functions performed by neurons
- ReLU - Rectified Linear Unit (nn.ReLU)
  - $y \geq 0$
- Tanh (nn.tanh)
  - $-1<y<1$
  - nn.Tanh
- Sigmoid (nn.Sigmoid)
  - $0<y<1$



Activation Functions

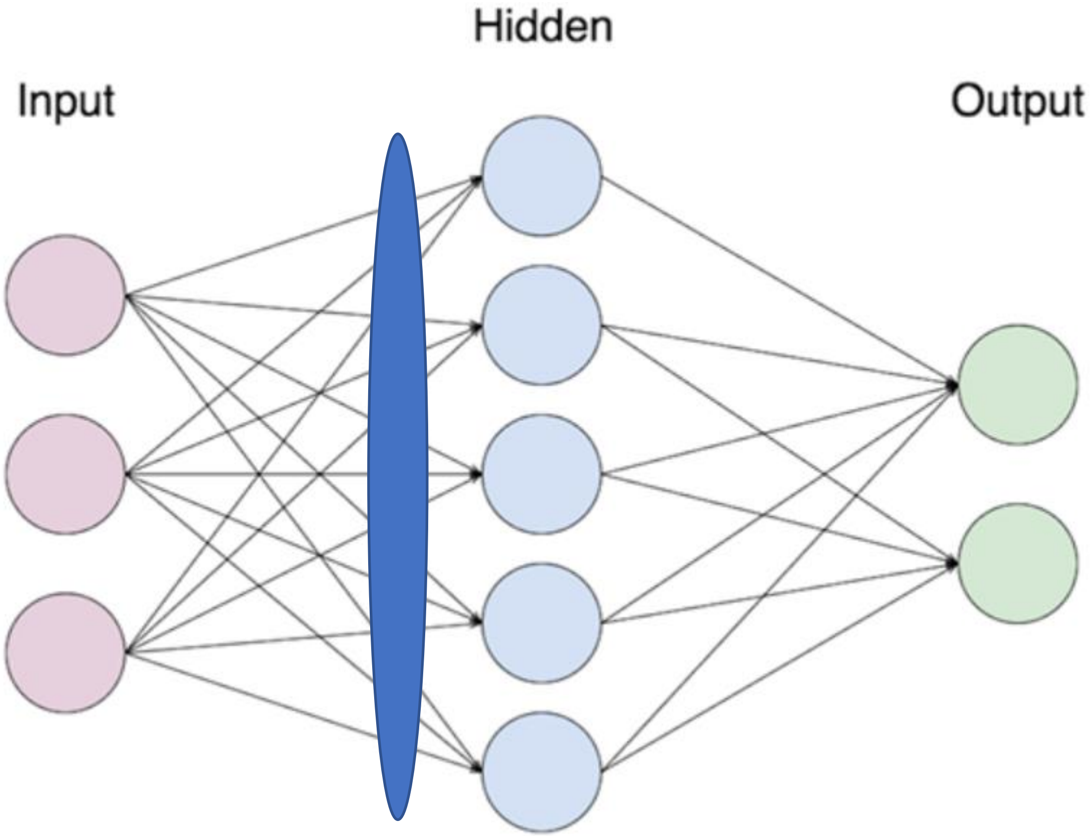
- Leaky ReLU
  - Similar to ReLU, but has non-zero values for negative x
  - Takes argument *negative_slope*, which determines the slope for x<0.
- For full list of activation functions, see: https://pytorch.org/docs/stable/nn.html



Leaky ReLU with negative slope = 0.1

Python Operators/Layers

- Activation Functions
- Normalization
- Dropout
- Loss Functions



Normalization

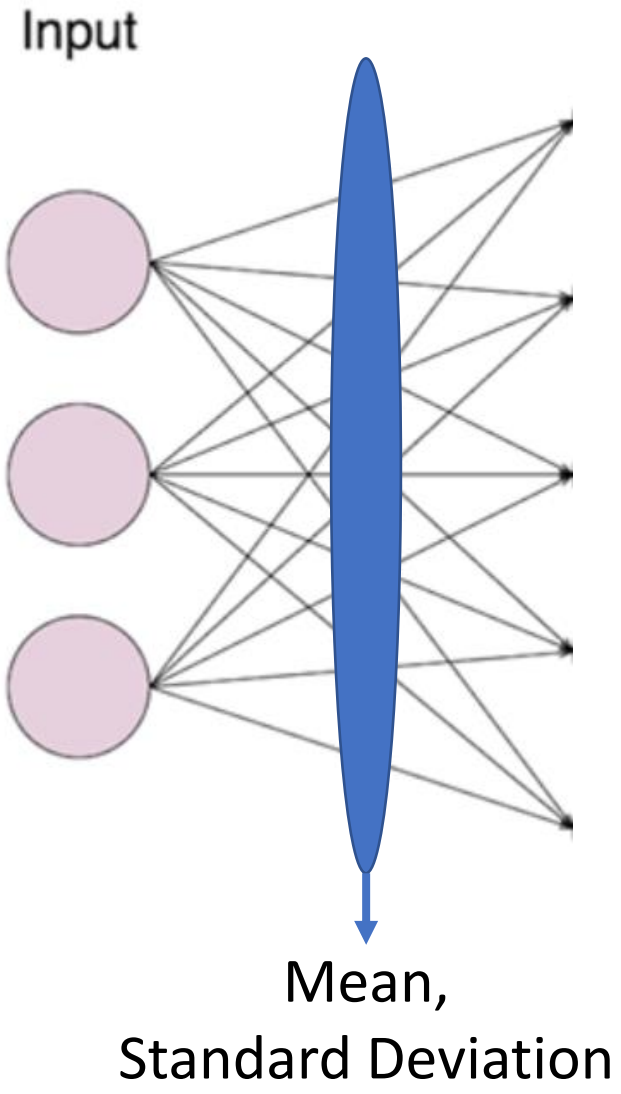
Image source: https://towardsdatascience.com/step-by-step-guide-to-building-your-own-neural-network-from-scratch-df64b1c5ab6e

Input Normalization: Batch Normalization

- Normalizes input into each layer for each training mini-batch
- Addresses issue of shifting input distributions over training
- Inputs:
  - num_features: Number of features in the input vector
  - eps: numerical stability parameter

Example:

```
b = torch.nn.BatchNorm1D(100)
input = torch.rand(50, 100)
output = b(input)
```



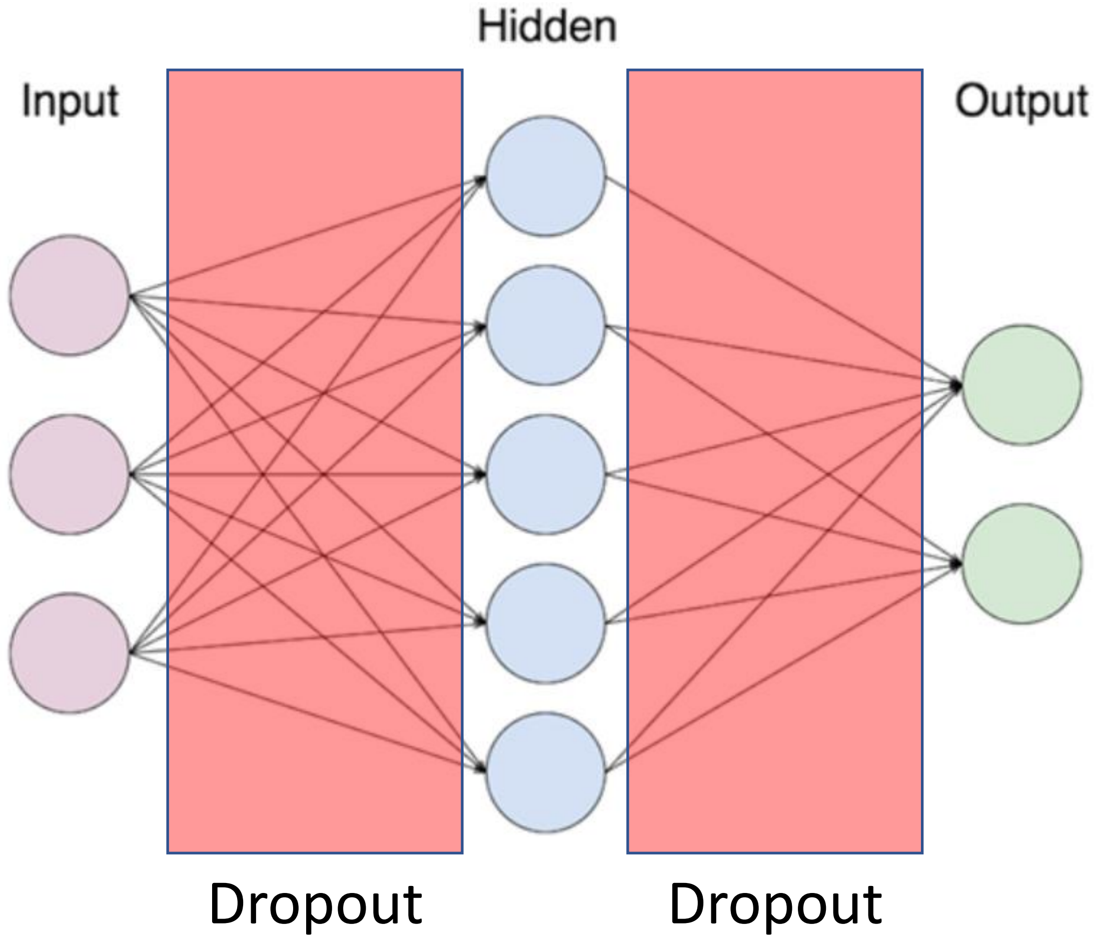
Input Normalization

Other normalization procedures include:

- Layer Norm: Transposes Batch Norm. Normalizes over all summed inputs to a layer
  - https://arxiv.org/abs/1607.06450
- Group Norm: Normalizes by grouped channels instead of batches
  - https://arxiv.org/abs/1803.08494

Python Operators/Layers

- Activation Functions
- Normalization
- **Dropout**
- Loss Functions



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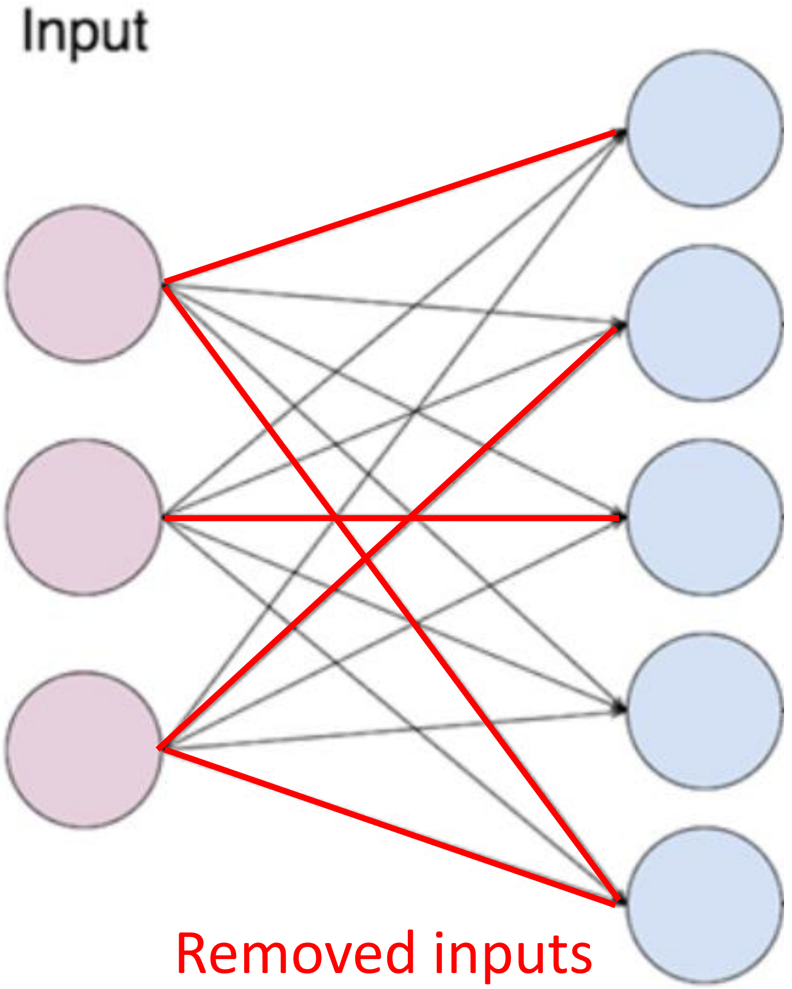
Dropout

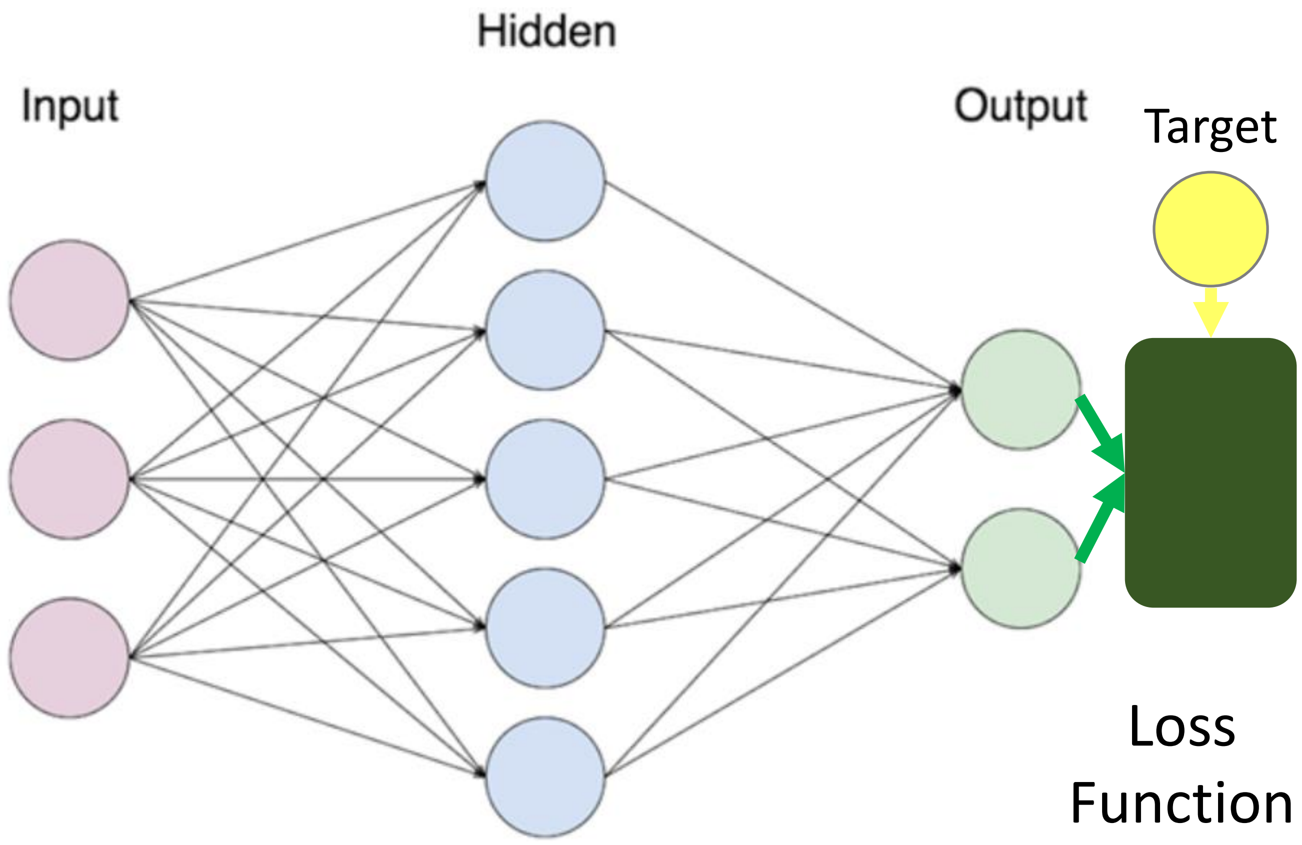
- Randomly zeroes some elements of input tensor with probability *p*
- Effective technique for regularization
- Outputs scaled by 1/1-p
- Treated as identity during evaluation



Removed inputs
for p = 0.33

Python Operators/Layers

- Activation Functions
- Normalization
- Dropout
- Loss Functions



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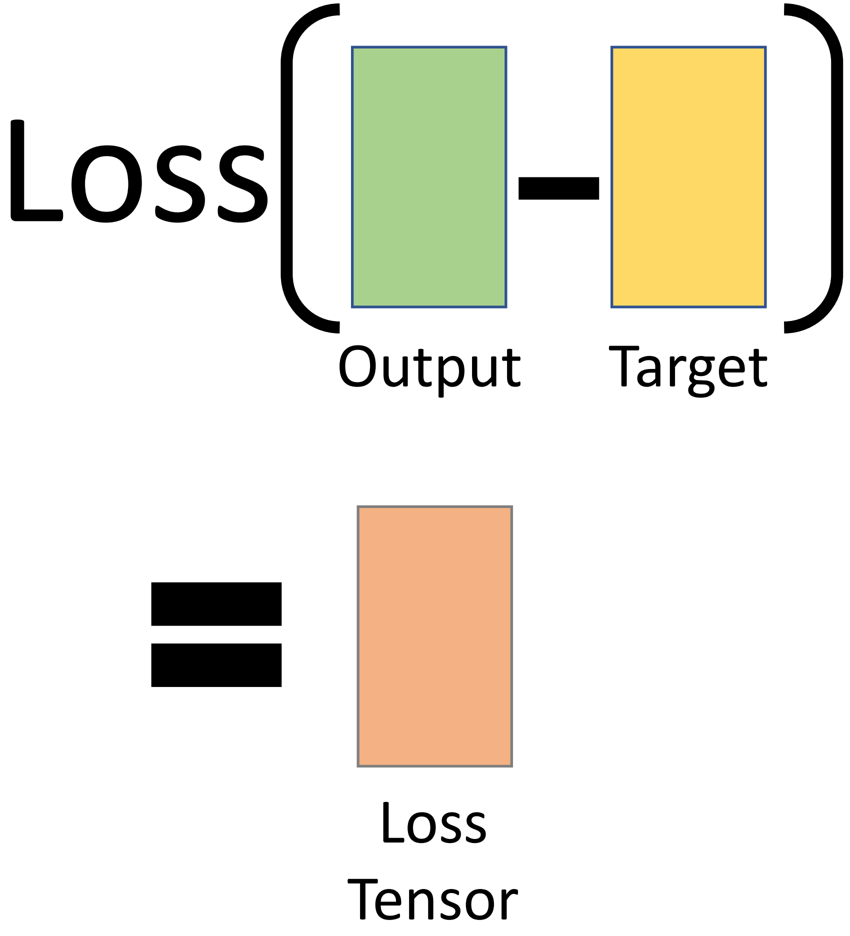
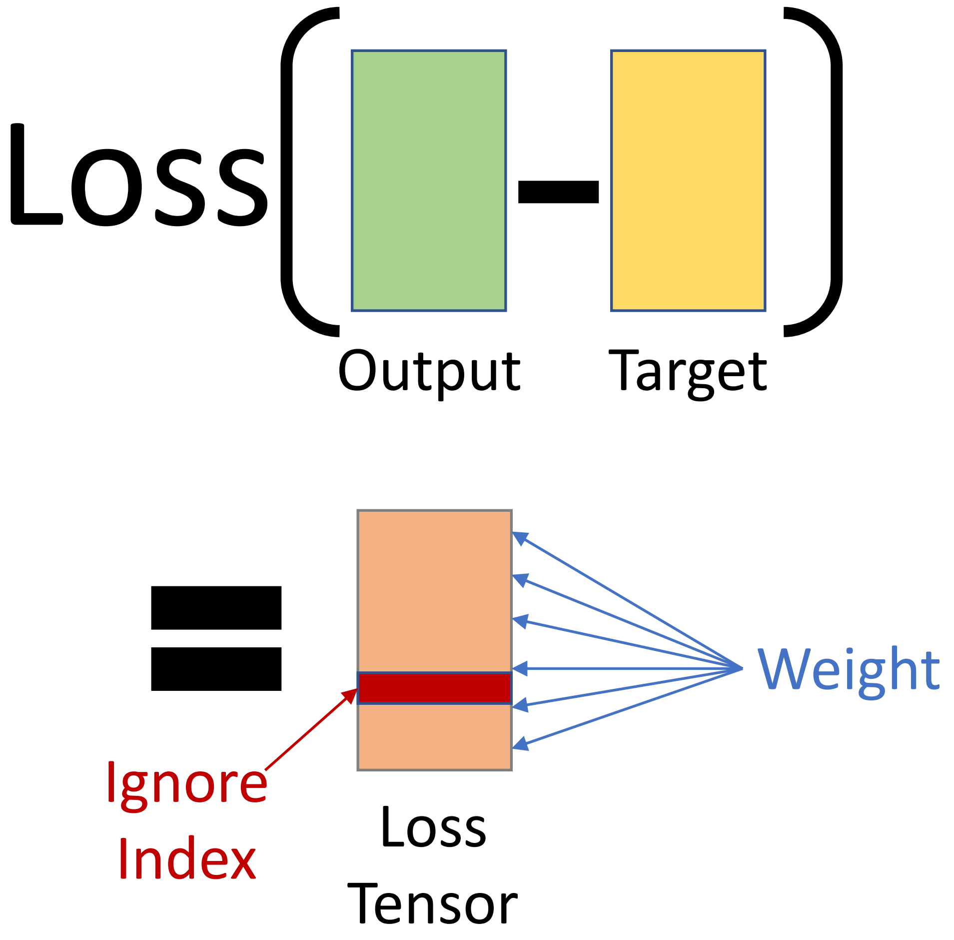
Loss Functions

- Loss function parameters:
  - Reduction: how the output will be reduced in dimension:
    - None: Gives entire Loss Tensor with no reduction over batches
    - Sum: Takes sum of the loss tensor across batches, returning a single number
    - Mean: Same as sum, but divides by the number of batches to get the mean



Loss Functions – Cross Entropy Loss

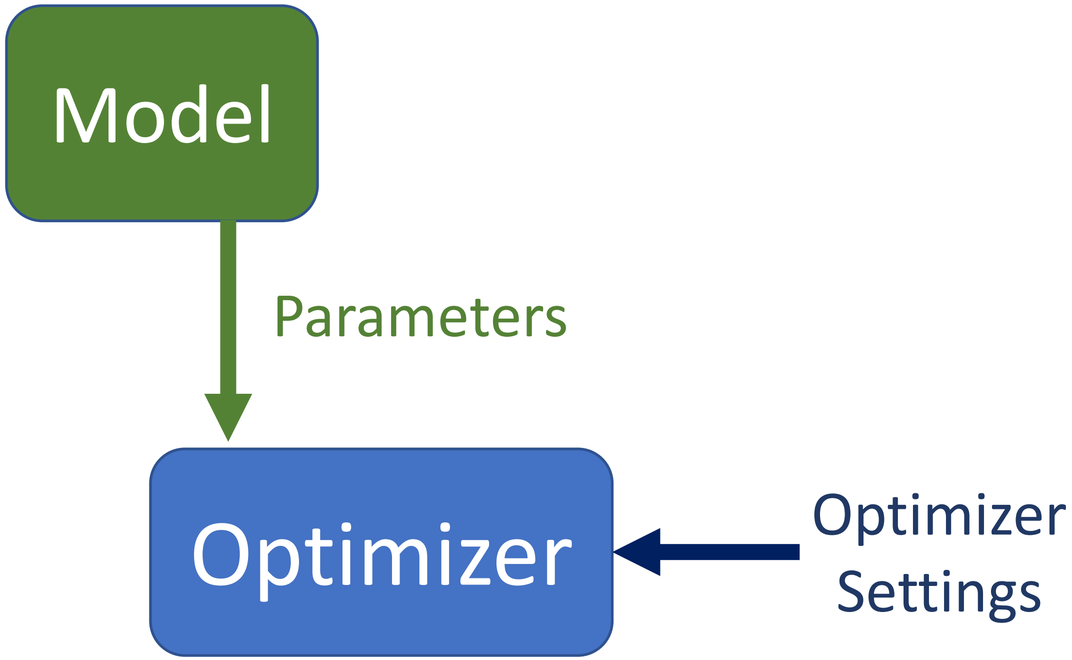
- Cross Entropy Parameters
  - Weight
    - 1D tensor assigning weights to each class, which is helpful if you have an unbalanced training set
  - ignore_index
    - Specifies a target value that is ignored and does not contribute to the input gradient



Designing Training Procedures

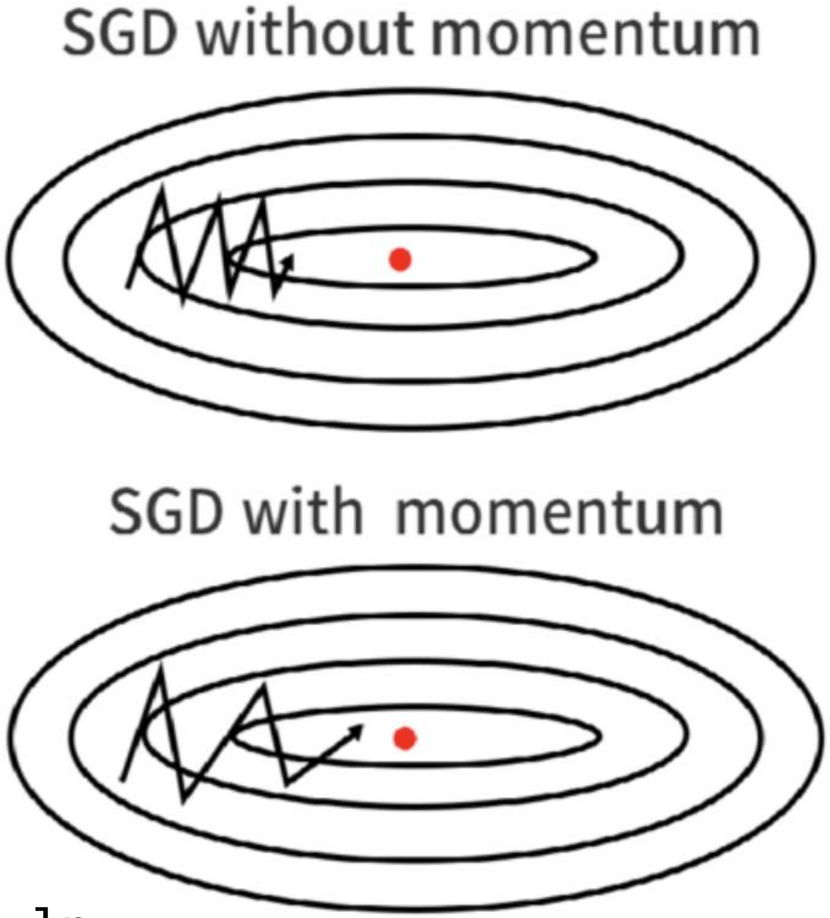
Optimizer Initialization

- Parameters:
    - Should be iterable containing parameters to optimize
    - E.g., model.parameters() or [var1, var2]
    - Parameters must be defined BEFORE the optimizer
- Optimizer Settings
    - Learning rate, weight decay, etc.



Optimizers

- Stochastic Gradient Descent (`torch.optim.SGD`)
  - params: Model parameters
  - lr: Learning rate (required)
  - momentum: momentum factor (default: 0)
  - weight_decay: (default: 0)



Example: `torch.optim.SGD(model.parameters(), lr = 0.001, momentum = 0.2, weight_decay = 0.1)`

Optimizers

- Adam (`torch.optim.Adam`)
  - params: Model parameters
  - lr: Learning rate (default: 0.001)
  - betas: coefficients (tuple) used for computing running averages of gradient and its square (default: (0.9, 0.999))
  - eps: term added to denominator to improve numerical stability (default: 1e-8)
  - weight_decay: (default: 0)

Example:

```
torch.optim.Adam(model.parameters(),
lr = 0.01, betas = (0.95, 0.998),
eps = 1e-7)
```

Other Common Optimizers

- AdaDelta (`torch.optim.Adadelta`)
  - Precursor to Adam which uses first-order estimates to adapt learning rate
- Adamax (`torch.optim.Adamax`)
  - Variant on Adam based on infinity norm
- RMSProp (`torch.optim.RMSprop`)
  - Take the square root of the gradient average before adding epsilon to normalization of LR

Network Hyperparameters

- Architecture choice
  - Fully connected/Linear layer
  - Convolutional Layer
  - Recurrent layer

Lab Assignment: Fashion MNIST Classification

The Fashion MNIST Dataset

- Labels 0–9 (Dress, shirt, coat, etc.)
- Data consists of grayscale images of fixed size (28x28) – flattens to 784
- Drop-in replacement for the original MNIST, but more complicated

Fashion MNIST Classification Task

- Load the Fashion MNIST dataset using torchvision.datasets
- A fully-connected network for classification
- Try different optimizers, regularization, initialization and batch normalization and form a table of the results.
- Report your loss as ”loss curve” and accuracy for different settings and draw conclusions

```python
import torch
import torchvision


train_batch_size =  # Define train batch size
test_batch_size  =  # Define test batch size (can be larger than train batch size)


# Use the following code to load and normalize the dataset
train_loader = torch.utils.data.DataLoader(
  torchvision.datasets.FashionMNIST('/files/', train=True, download=True,
                             transform=torchvision.transforms.Compose([
                               torchvision.transforms.ToTensor(),
                               torchvision.transforms.Normalize(
                                 (0.1307,), (0.3081,))
                             ])),
  batch_size=train_batch_size, shuffle=True)

test_loader = torch.utils.data.DataLoader(
  torchvision.datasets.FashionMNIST('/files/', train=False, download=True,
                             transform=torchvision.transforms.Compose([
                               torchvision.transforms.ToTensor(),
                               torchvision.transforms.Normalize(
                                 (0.1307,), (0.3081,))
                             ])),
  batch_size=test_batch_size, shuffle=True)
```

Optimizers to consider

- RMSProp
- Adam
- SGD

Which optimizer works well and in which aspects, such as convergence time, accuracy, training and testing loss why? Try to explain it.

Regularization to consider

- L1 / L2
- Dropout layers

  (torch.nn.Dropout)

Apply regularization after check for over-fitting or under-fitting?

Consider how to balance regularization and loss optimization?

torch.optim.Adam parameter:

Parameters

- **params** (*iterable*) – iterable of parameters to optimize or dicts defining parameter groups
- **lr** (*float*, *optional*) – learning rate (default: 1e-3)
- **betas** (*Tuple*[*float*, *float*], *optional*) – coefficients used for computing running averages of gradient and its square (default: (0.9, 0.999))
- **eps** (*float*, *optional*) – term added to the denominator to improve numerical stability (default: 1e-8)
- **weight_decay** (*float*, *optional*) – weight decay (L2 penalty) (default: 0)
- **amsgrad** (*boolean*, *optional*) – whether to use the AMSGrad variant of this algorithm from the paper On the Convergence of Adam and Beyond (default: False)
- **maximize** (*bool*, *optional*) – maximize the params based on the objective, instead of minimizing (default: False)

Initialization & Normalization to consider

- Random normal
- Xavier
- He (Kaiming)

- Batch Normalization
- Layer Normalization

Check Torch.nn.init:
https://pytorch.org/docs/stable/nn.init.html

How do they work?

Hyperparameters to consider

- Number of layers
- Neurons in each layer
- Training Batch Size
- Learning Rate
- Activation function (ReLU vs tanh vs sigmoid)
- Number of training epochs