CS5242 : Neural Networks and Deep Learning

Lecture 5: Multi-Layer Perceptron Inference and Learning

Semester 1 2021/22

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Outline

- Multi-Layer Perceptron
- Loss and gradient descent
- Backpropagation
- PyTorch implementation
- Training with epochs
- Monitoring the loss
- Test set evaluation
- Final code

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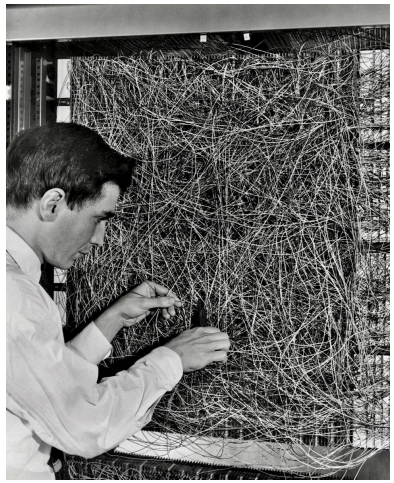
MLP



- Introduced in Frank Rosenblatt in 1957.

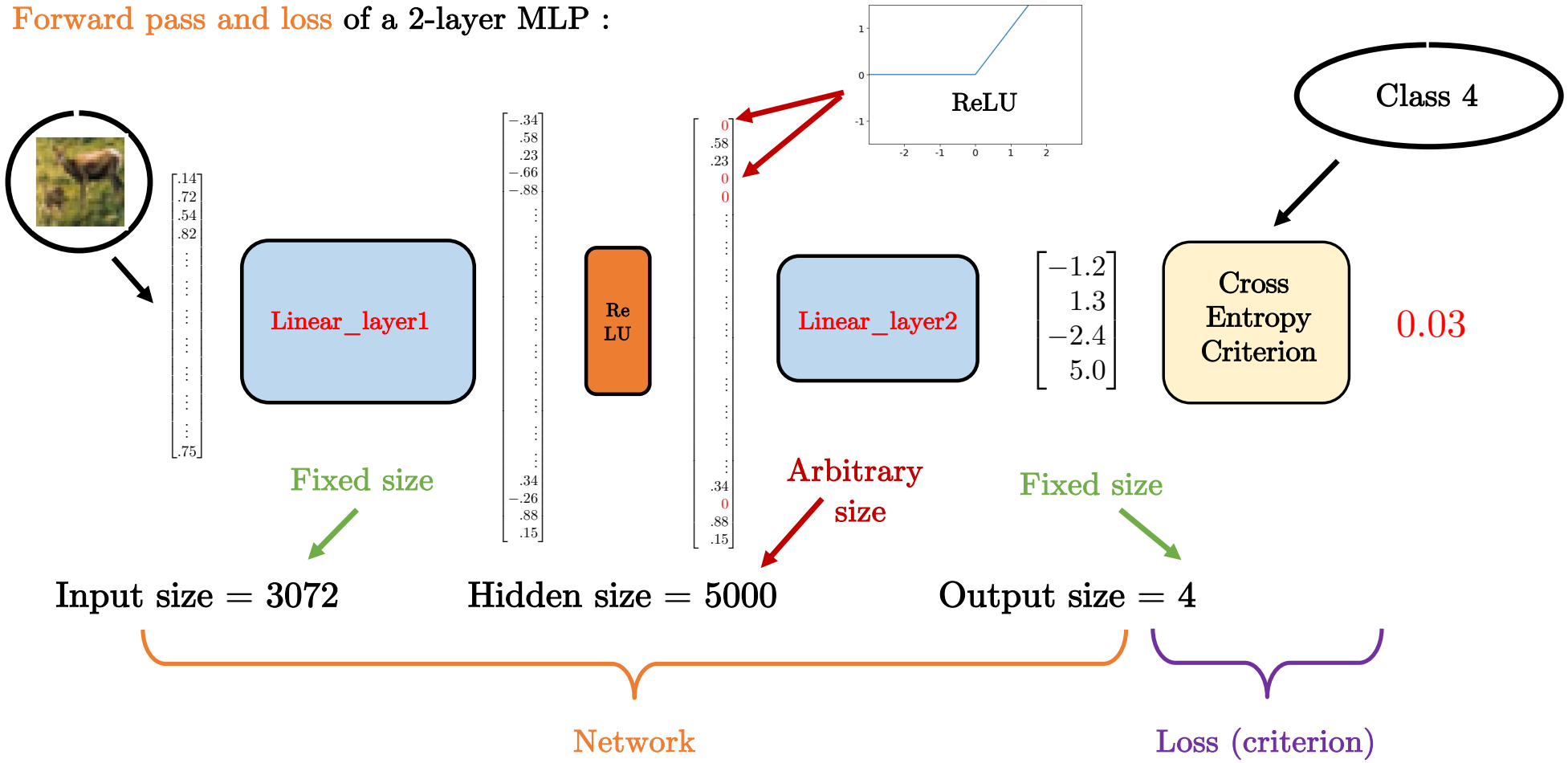
- What is a Multi-Layer Perceptron (MLP)?
  - A MLP is the simplest feedforward neural networks (no cycle connection).
  - A MLP is composed by a series of linear layers + non-linear activations.
  - A MLP is a.k.a. Fully Connected (FC) neural networks.

- Example: Two-layer MLP
  - Consider a two-layer network with only 4 classes:

    Cat, Dog, Horse, Deer

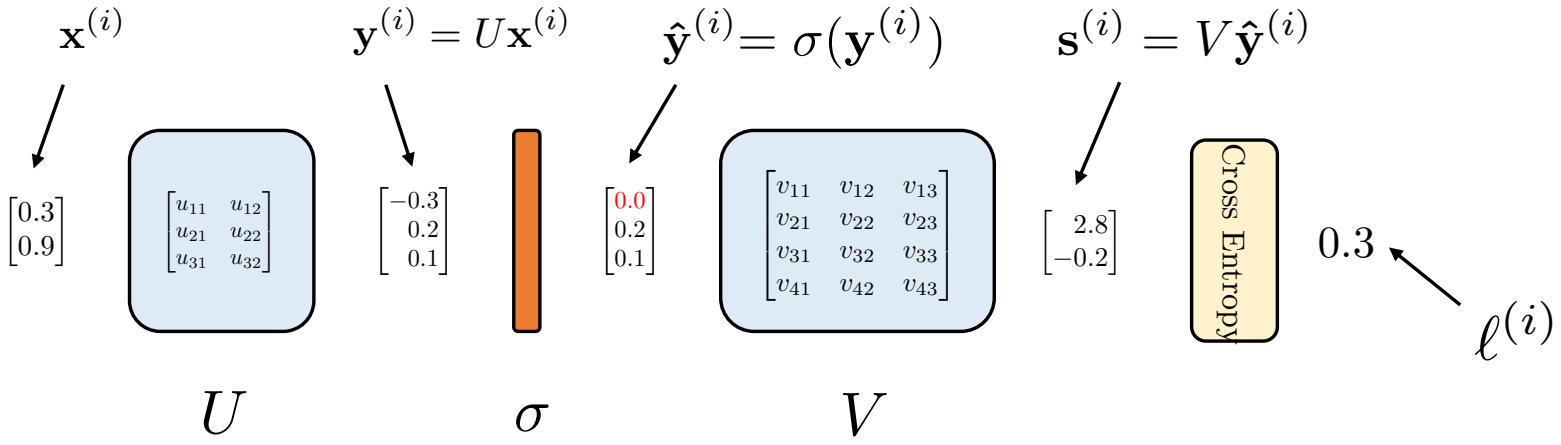
Two-layer MLP

- Forward pass and loss of a 2-layer MLP :



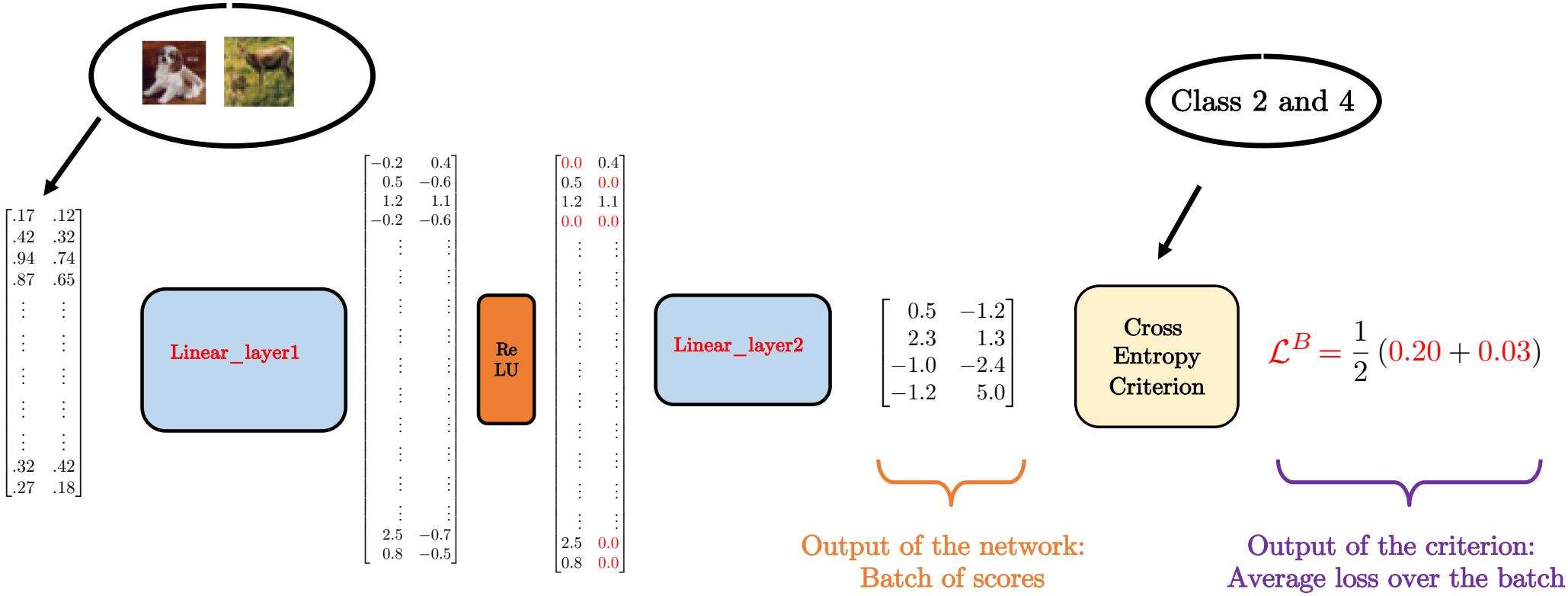
Two-layer MLP

- **Forward pass and loss of a 2-layer MLP with mathematical variables :**



Batch mode

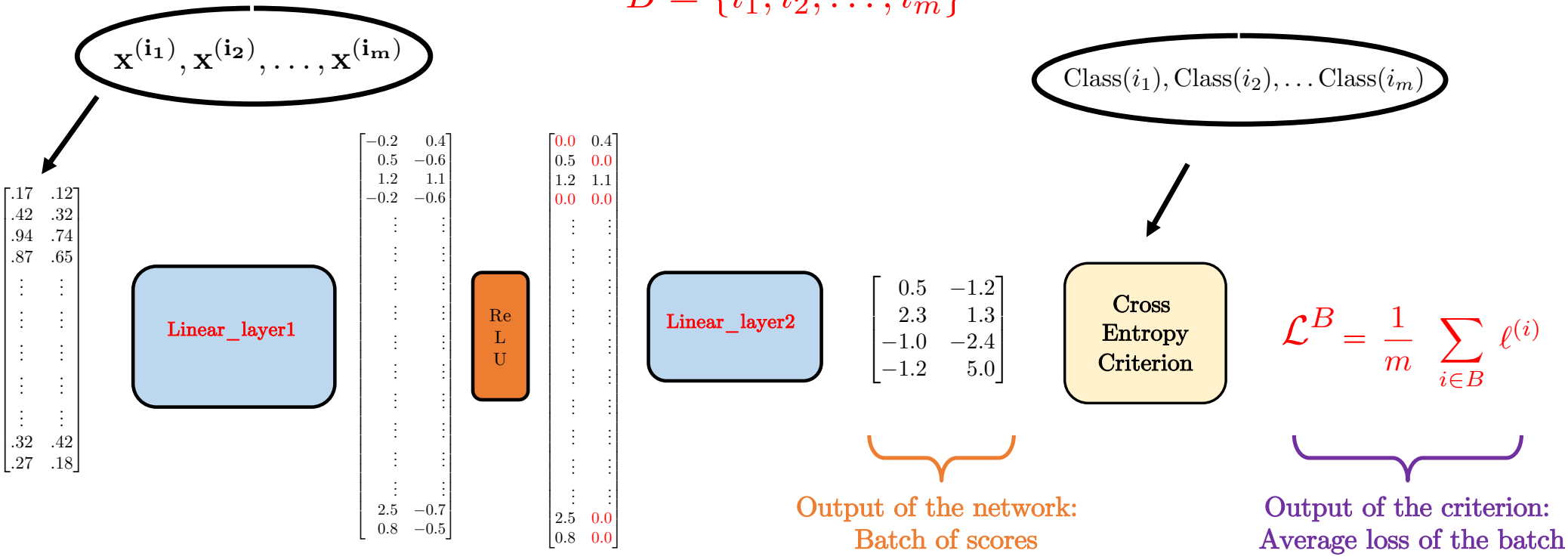
- Forward pass and loss of a 2-layer MLP for two input images :



Batch mode

- Batch size is arbitrary :
  - Sample randomly B indices from the training set :

$$B = \{i_1, i_2, \ldots, i_m\}$$



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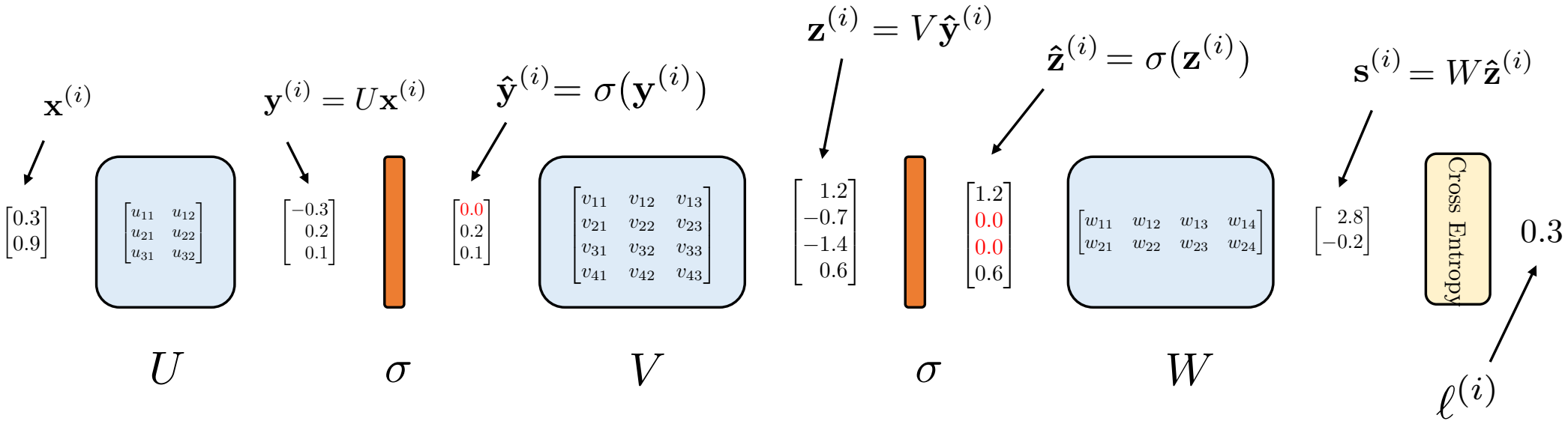
Three-layer MLP

- We consider a three-layer MLP :

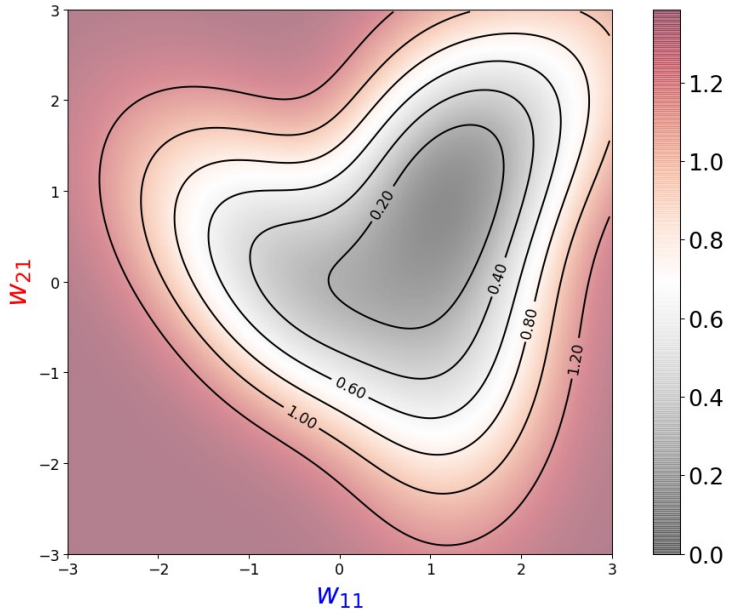


MLP loss

- We want to find the parameters that minimize the cross-entropy loss:

$$\mathcal{L}(u_{11}, u_{12}, \ldots) = \frac{1}{N} \sum_{i=1}^{N} \underbrace{\ell^{(i)}(u_{11}, u_{12}, \ldots)}_{\text{Loss of the } i^{\text{th}} \text{ data point}}$$

Average of the losses over all data points



Mini-batch MLP loss

- Approximated mini-batch loss L^B :
  - Average of the losses of the data points in each batch B :

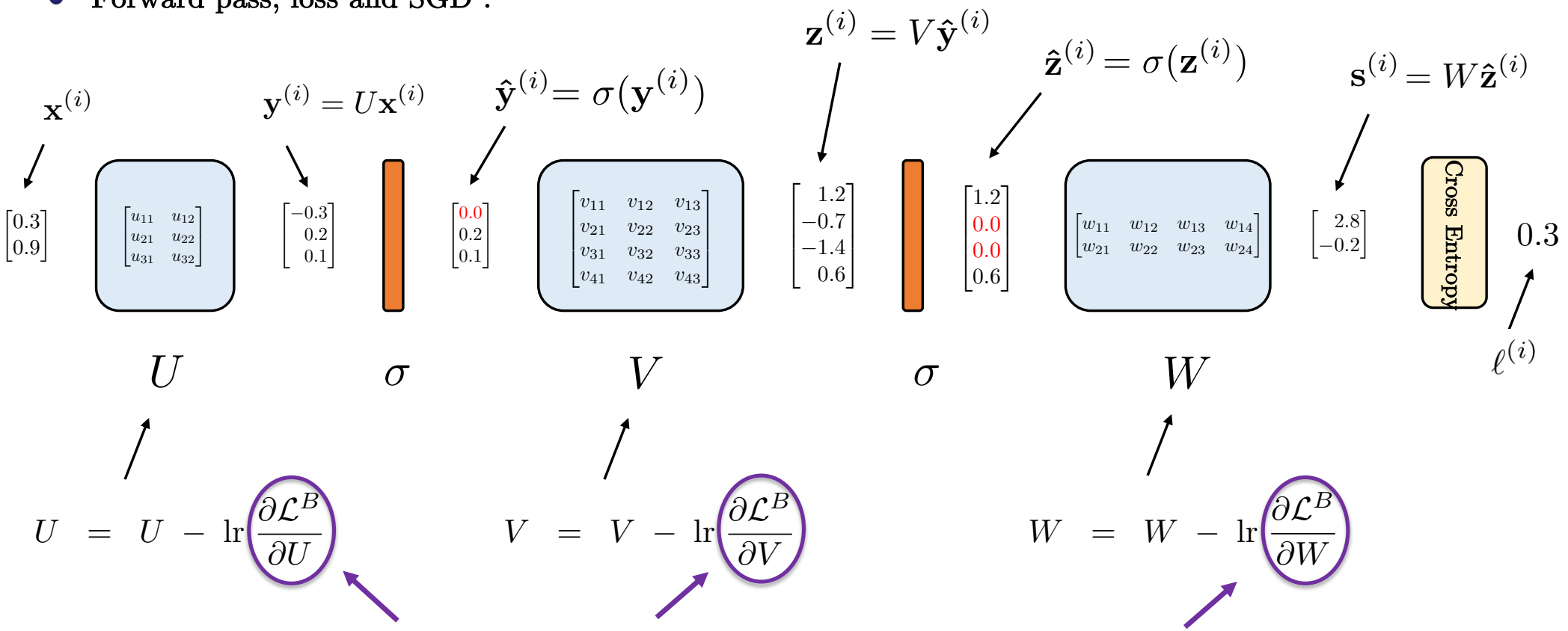
$$\mathcal{L}^B(u_{11}, u_{12}, \ldots) = \frac{1}{m} \sum_{i \in B} \ell^{(i)}(u_{11}, u_{12}, \ldots)$$

$$B = \{i_1, i_2, \ldots, i_m\}$$

Mini-batch B

Stochastic Gradient Descent

- **Forward pass, loss and SGD :**



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Backpropagation

- Backpropagation:
  - Forward pass: Compute the average of the losses $\mathcal{L}^B$ of the data points in the batch by forwarding the batch through the net.
  - Backward pass: Get the derivatives of $\mathcal{L}^B$ w.r.t. the net parameters by back-propagating the loss value (error of prediction) through the net.
  - Update weight: Use the SGD formula to get the new weight values that make the network (a bit) better at prediction:

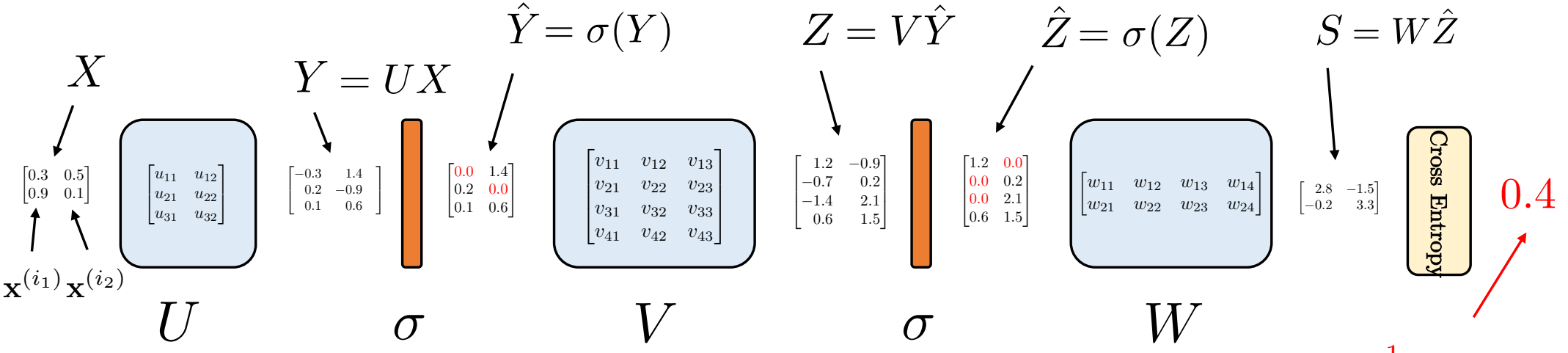
$$U = U - \text{lr} \frac{\partial \mathcal{L}^B}{\partial U}$$

$$V = V - \text{lr} \frac{\partial \mathcal{L}^B}{\partial V}$$

$$W = W - \text{lr} \frac{\partial \mathcal{L}^B}{\partial W}$$

Forward pass

- Forward pass and loss :



$$\mathcal{L}^B = \frac{1}{m} \sum_{i \in B} \ell^{(i)}$$

Average of the losses
of the data points in the batch

Forward pass

Backward pass

- How do we compute the gradients of the loss w.r.t. network parameters?

$$\frac{\partial \mathcal{L}^B}{\partial U} \quad \frac{\partial \mathcal{L}^B}{\partial V} \quad \text{and} \quad \frac{\partial \mathcal{L}^B}{\partial W}$$

- Let us introduce the backpropagation formula for a linear layer (that performs pattern matching).

- Understanding the backpropagation for a linear layer is enough to generalize the backpropagation process to any layer, and any network !

Backpropagation for linear layer – scalar case

- Forward pass:

Input signal x

Weight parameter w

Linear Layer

$y = wx$ Output signal

- Backward pass:

Chain rule on $\mathcal{L}^B(y(w,x))$!

$$\frac{\partial \mathcal{L}^B}{\partial x} = \frac{\partial \mathcal{L}^B}{\partial y} \cdot \frac{\partial y}{\partial x}$$
$$= e.w$$

$$\frac{\partial \mathcal{L}^B}{\partial w} = \frac{\partial \mathcal{L}^B}{\partial y} \cdot \frac{\partial y}{\partial w}$$
$$= e.x$$

Output gradients

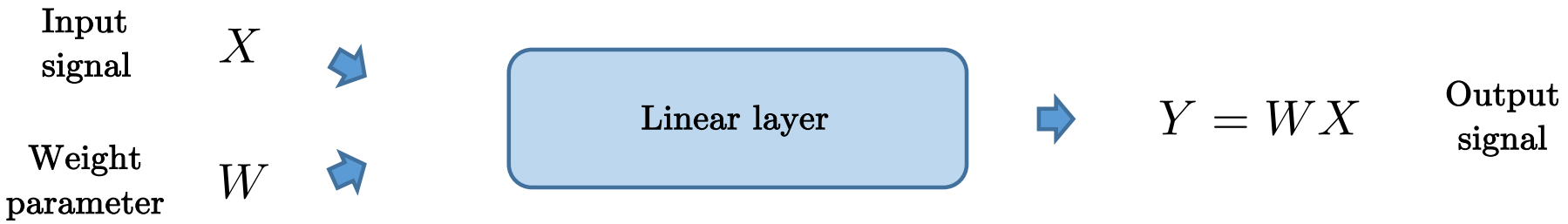
Linear Layer

$e = \frac{\partial \mathcal{L}^B}{\partial y}$ Input gradient

This is the scalar case.

Backpropagation for linear layer - matrix case

- Forward pass:



- Backward pass:

$$\frac{\partial \mathcal{L}^B}{\partial X} = \left(\frac{\partial Y}{\partial X}\right)^T . \frac{\partial \mathcal{L}^B}{\partial Y}$$

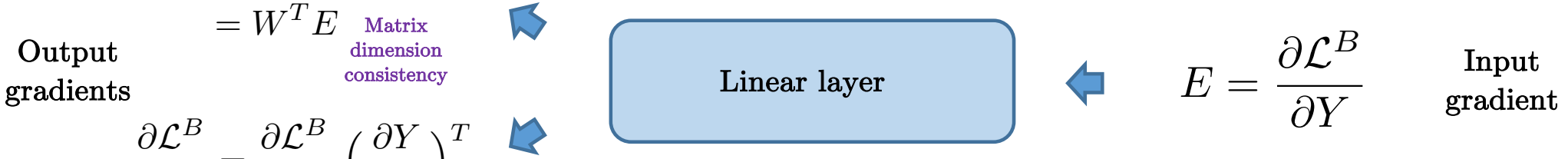
Chain rule on $\mathcal{L}^B(Y(W, X))$!

$$= W^T E$$

Matrix dimension consistency

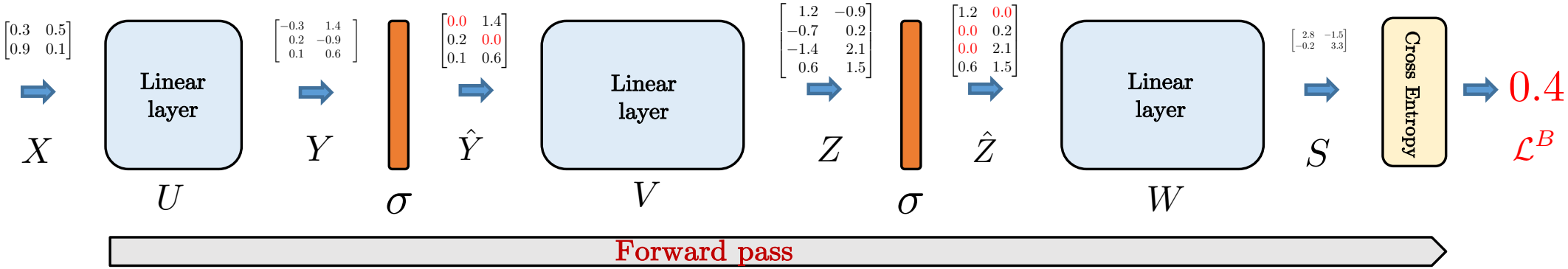
$$\frac{\partial \mathcal{L}^B}{\partial W} = \frac{\partial \mathcal{L}^B}{\partial Y} . \left(\frac{\partial Y}{\partial W}\right)^T$$

$$= E X^T$$

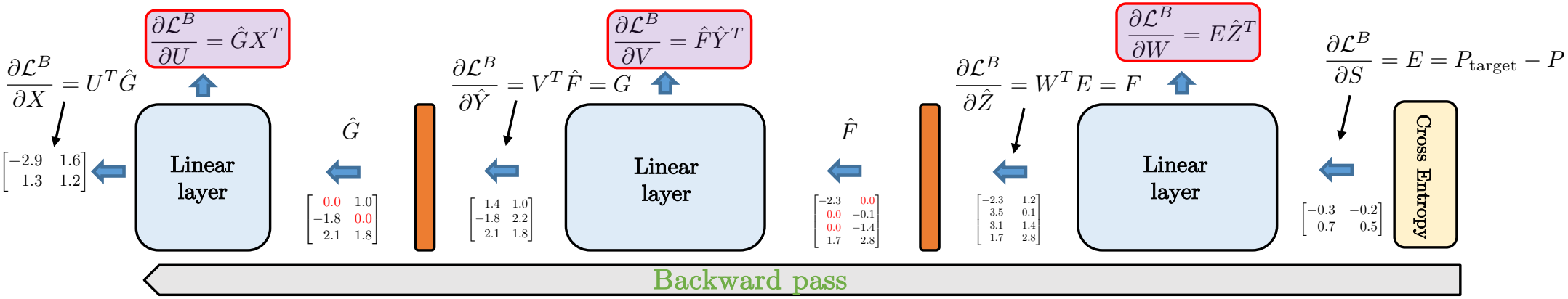


Backpropagation for MLP

- Compute all outputs of the forward pass :

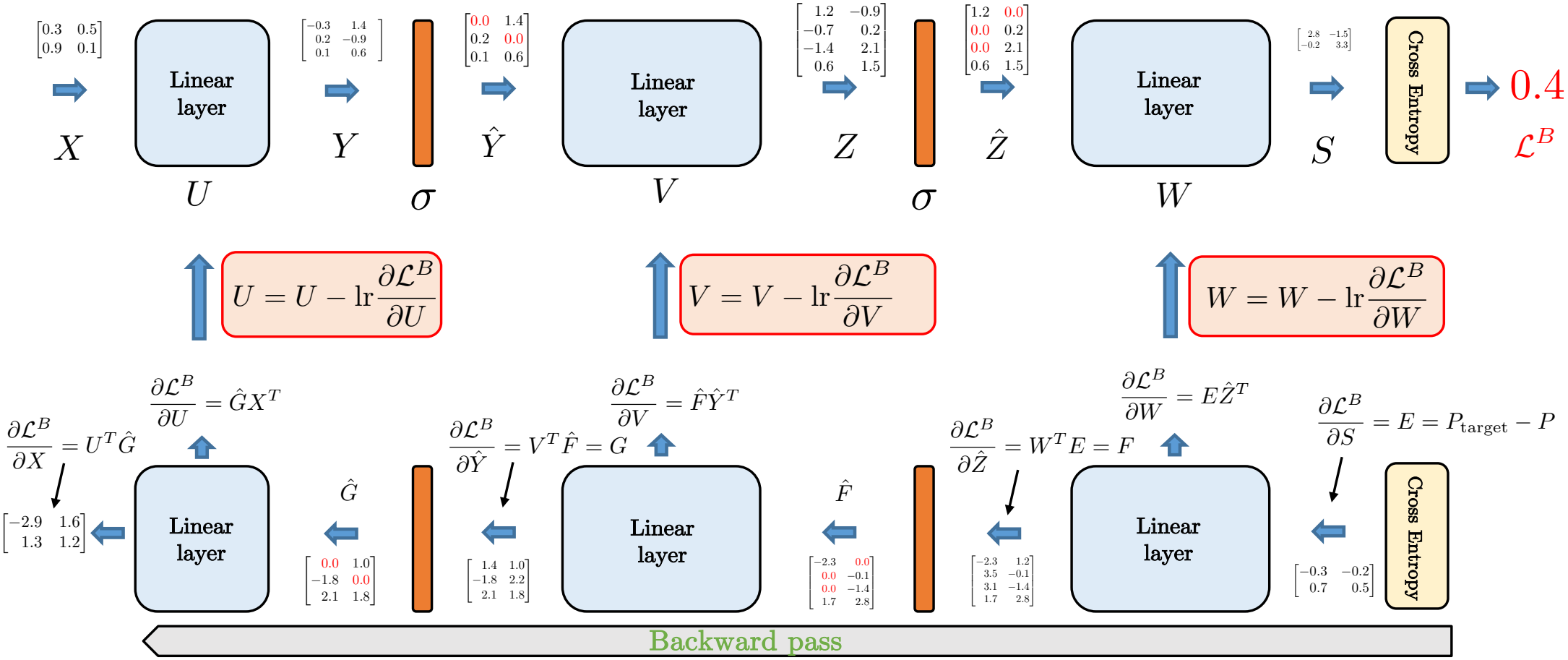


- Compute all gradients of network parameters sequentially in the backward direction :



Backpropagation for MLP

- Update all network parameters with gradient descent sequentially in the backward direction :

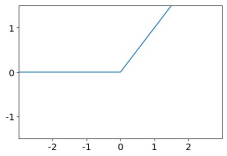


Backpropagation for ReLU layer

- Forward pass:

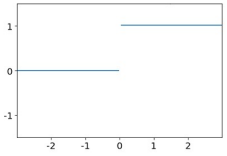
Input signal X → **ReLU layer** → $Y = \max(X, 0)$ Output signal

No weight parameter !



- Backward pass:

$$\frac{\partial Y}{\partial X} = \frac{\partial}{\partial X}\max(X,0) = \begin{cases} 1 & \text{if X value is positive} \\ 0 & \text{otherwise} \end{cases} = \text{step}(X)$$



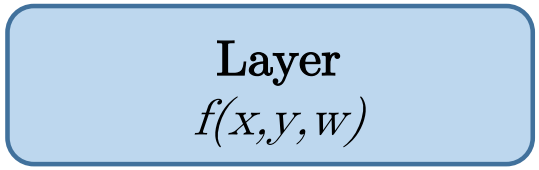
Output gradient $\frac{\partial \mathcal{L}^B}{\partial X} = \left(\frac{\partial Y}{\partial X}\right)^T \cdot \frac{\partial \mathcal{L}^B}{\partial Y} = \text{step}(X)E$ ← **ReLU layer** ← $E = \frac{\partial \mathcal{L}^B}{\partial Y}$ Input gradient

Chain rule on $\mathcal{L}^B(Y(W,X))$!

Generalizing backpropagation for any layer

- **Forward pass:**

Input signals: x, y, w



$$z = f(x, y, w)$$

Output signal

- **Backward pass:**

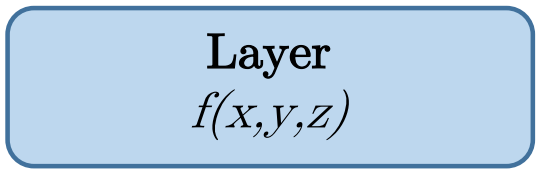
Chain rule on $\mathcal{L}^B(f(x, y, w))$!

Output gradients:

$$\frac{\partial \mathcal{L}^B}{\partial x} = \frac{\partial \mathcal{L}^B}{\partial z} \cdot \frac{\partial z}{\partial x}$$

$$\frac{\partial \mathcal{L}^B}{\partial y} = \frac{\partial \mathcal{L}^B}{\partial z} \cdot \frac{\partial z}{\partial y}$$

$$\frac{\partial \mathcal{L}^B}{\partial w} = \frac{\partial \mathcal{L}^B}{\partial z} \cdot \frac{\partial z}{\partial w}$$



$$e = \frac{\partial \mathcal{L}^B}{\partial z}$$

Input gradient

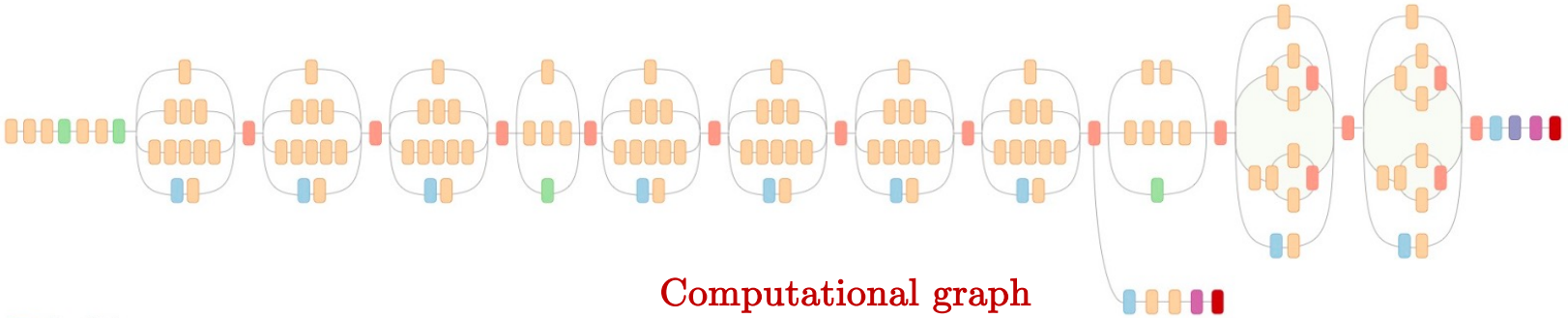
Backpropagation formula: Output gradient = Input gradient . Local gradient !

Backpropagation for any (huge) network

- Backpropagation is a local rule:

$$\text{Output gradient} = \text{Input gradient} \cdot \text{Local gradient}$$

- As such, it can scale up to any number of layers!



Computational graph

Design your own layer

Xavier Bresson @xbresson · 1 Oct 2017

@nitish_gup - I defined a new function torch.mm for sparse pytorch variables

Sparse x Dense -> Dense matrix multiplication

Hi everyone, I am trying to implement graph convolutional layer (as described in Semi-Supervised Classification with Graph Convolutional Networks) in...

discuss.pytorch.org

1 2 6

Show this thread

```python
class my_sparse_mm(torch.autograd.Function):
    """
    Implementation of a new autograd function for sparse variables,
    called "my_sparse_mm", by subclassing torch.autograd.Function
    and implementing the forward and backward passes.
    """

    def forward(self, W, x):  # W is SPARSE
        self.save_for_backward(W, x)
        y = torch.mm(W, x)
        return y

    def backward(self, grad_output):
        W, x = self.saved_tensors
        grad_input = grad_output.clone()
        grad_input_dL_dW = torch.mm(grad_input, x.t())
        grad_input_dL_dx = torch.mm(W.t(), grad_input )
        return grad_input_dL_dW, grad_input_dL_dx
```

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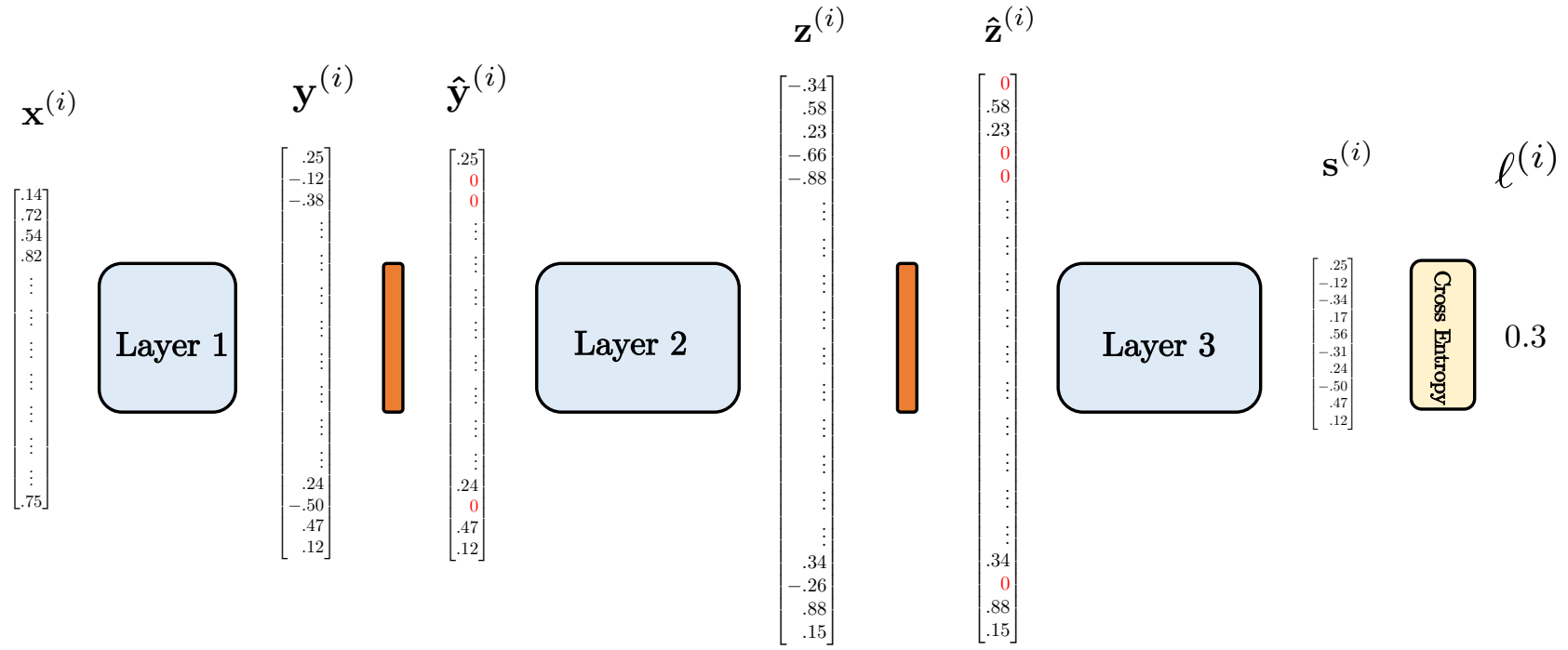
PyTorch implementation

- Let us implement a 3-layer network for MNIST and the cross-entropy loss :



Input size = 784 Hidden size 1 = 1000 Hidden size 2 = 1500 Output size = 10

Network and loss

- Define the network, instantiate it and choose the loss :

Make a class of 3-layer networks

```
class three_layer_net(nn.Module):

    def __init__(self, input_size, hidden_size1, hidden_size2,  output_size):
        super(three_layer_net , self).__init__()

        self.layer1 = nn.Linear( input_size,   hidden_size1 , bias=False)
        self.layer2 = nn.Linear( hidden_size1, hidden_size2 , bias=False)
        self.layer3 = nn.Linear( hidden_size2, output_size  , bias=False)

    def forward(self, x):

        y       = self.layer1(x)
        y_hat   = F.relu(y)
        z       = self.layer2(y_hat)
        z_hat   = F.relu(z)
        scores  = self.layer3(z_hat)

        return scores


net=three_layer_net(784, 1000, 1500, 10)

criterion = nn.CrossEntropyLoss()
```

Create the network →

← Define the loss/criterion

Hyper-parameters:

- Input dim: 784
- 1st hidden layer: 1000
- 2nd hidden layer: 1500
- Output: 10

Stochastic gradient descent

- Create an optimization function :
  - We create an optimizer object (from the **torch.optim** package):

```
optimizer = torch.optim.SGD( net.parameters() , lr=0.01 )
```

We choose our optimizer to be an SGD (there are other SGD-like optimizers)

The optimizer is given access to the parameters of the 3-layer network

We choose the learning rate to be lr = 0.01

Training loop and backpropagation

Create the minibatch

Forward pass: compute the scores

Compute the cross-entropy criterion:

$$\mathcal{L}^B = \frac{1}{m} \sum_{i \in B} \ell^{(i)}$$

Backward pass: compute the gradients

$$\frac{\partial \mathcal{L}^B}{\partial U} \quad \frac{\partial \mathcal{L}^B}{\partial V} \quad \frac{\partial \mathcal{L}^B}{\partial W}$$

Discussed later.

```
for iter in range(5000):

    optimizer.zero_grad()

    indices = torch.LongTensor(bs).random_(0,60000)
    minibatch_data   =  train_data[indices]
    minibatch_label = train_label[indices]

    inputs = minibatch_data.view(bs,784)

    inputs.requires_grad_()

    scores = net( inputs )

    loss = criterion( scores , minibatch_label )

    loss.backward()

    optimizer.step()
```

Discussed later.

Start recording all operations that will be done to the input tensor.

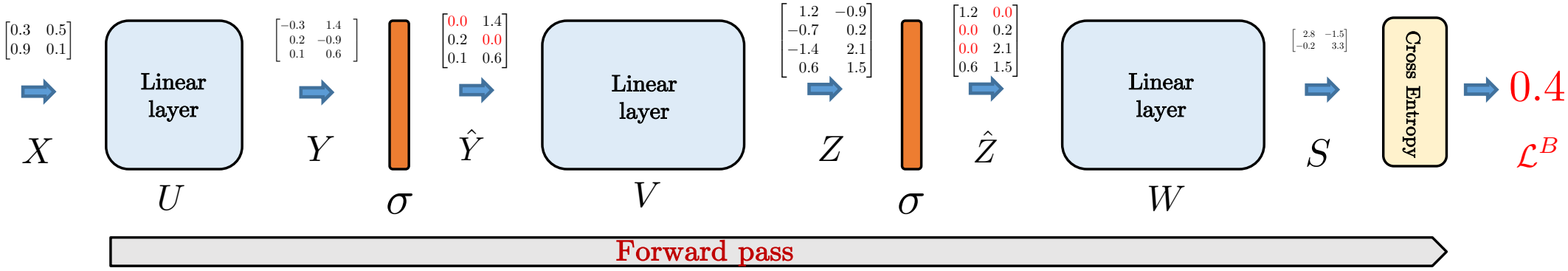
Discussed later.

Do one step of SGD to update the weights

$$U = U - \mathrm{lr} \frac{\partial \mathcal{L}^B}{\partial U} \quad V = V - \mathrm{lr} \frac{\partial \mathcal{L}^B}{\partial V} \quad W = W - \mathrm{lr} \frac{\partial \mathcal{L}^B}{\partial W}$$

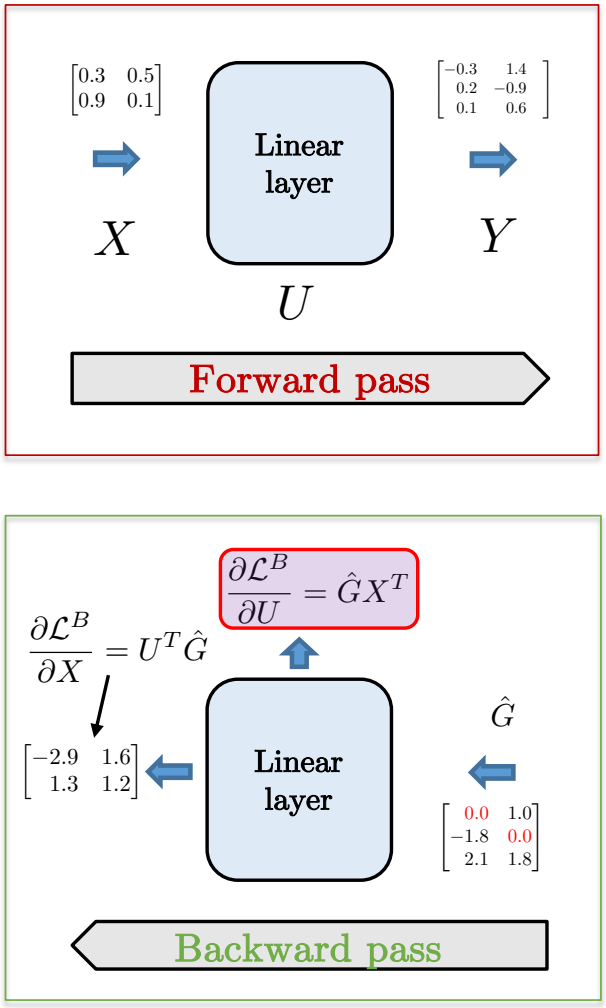
Automatic backpropagation

- **Function requires_grad_() :**
  - It tells Pytorch to start recording all operations that will be done to the input tensor X.
  - PyTorch will create the computational graph by stacking the layers and recording the outputs of all layers in sequential order.
  - It will then compute all gradients automatically (autograd) with the backward pass.



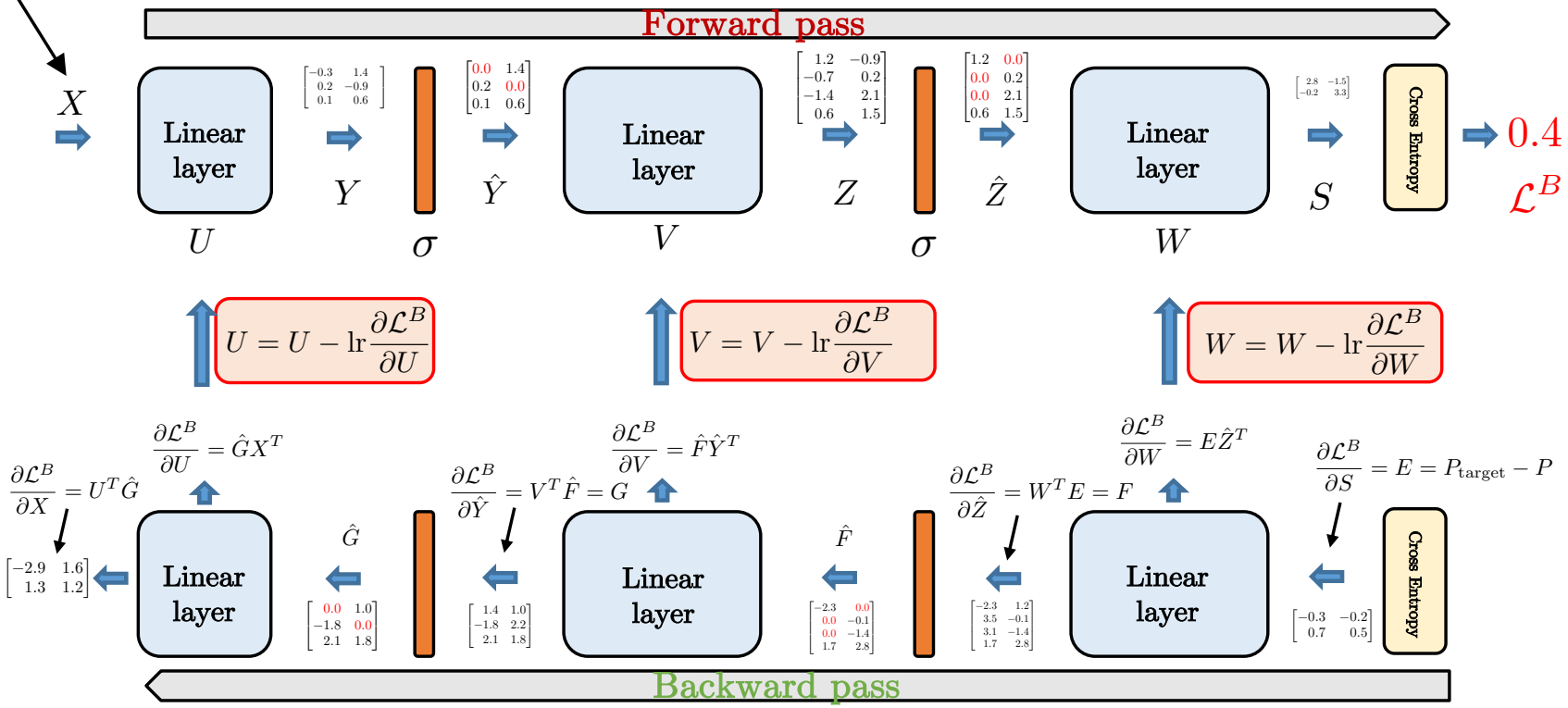
Automatic backpropagation

- Function **requires_grad_() :**
  - In Pytorch, each forward operation that can be performed on a tensor has a backward equivalent (already defined or that can be implemented).
  - In deep learning, most layers are composed of simple operations (sum, multiplication, exp(), convolution, etc) that are efficiently implemented with e.g. MKL on CPU or CUDA on GPU. Python functions are just wrappers.



Automatic backpropagation

Put a requires_grad() flag on this tensor and it will record the history of all the operations it goes through.



Then all these operations are replayed in reverse order with **loss.backward()** (the backward version of these operations)

Gradient accumulation

- If **optimizer.zero_grad()** is NOT used then Pytorch adds the gradient computed on this batch to the total gradient:

$$\frac{\partial \mathcal{L}}{\partial U} = \frac{\partial \mathcal{L}}{\partial U} + \frac{\partial \mathcal{L}^B}{\partial U}\Big|_{\text{computed on this batch}}$$

$$\frac{\partial \mathcal{L}}{\partial W} = \frac{\partial \mathcal{L}}{\partial W} + \frac{\partial \mathcal{L}^B}{\partial W}\Big|_{\text{computed on this batch}}$$

$$\frac{\partial \mathcal{L}}{\partial V} = \frac{\partial \mathcal{L}}{\partial V} + \frac{\partial \mathcal{L}^B}{\partial V}\Big|_{\text{computed on this batch}}$$

- This is only convenient if you want to do a true gradient where you use all the data points to compute the gradient.

```
for iter in range(5000):

    optimizer.zero_grad()

    indices = torch.LongTensor(bs).random_(0,60000)
    minibatch_data  =  train_data[indices]
    minibatch_label = train_label[indices]

    inputs = minibatch_data.view(bs,784)

    inputs.requires_grad_()

    scores = net( inputs )

    loss = criterion( scores , minibatch_label )

    loss.backward()

    optimizer.step()
```

Mini-batch gradient

- But if we want to do a stochastic gradient descent, we need function **optimizer.zero_grad() :**

$$\frac{\partial \mathcal{L}}{\partial U} = 0$$
$$\frac{\partial \mathcal{L}}{\partial V} = 0$$
$$\frac{\partial \mathcal{L}}{\partial W} = 0$$

$$\frac{\partial \mathcal{L}}{\partial U} = 0 + \frac{\partial \mathcal{L}^B}{\partial U}\Big|_{\text{computed on this batch}}$$
$$\frac{\partial \mathcal{L}}{\partial W} = 0 + \frac{\partial \mathcal{L}^B}{\partial W}\Big|_{\text{computed on this batch}}$$
$$\frac{\partial \mathcal{L}}{\partial V} = 0 + \frac{\partial \mathcal{L}^B}{\partial V}\Big|_{\text{computed on this batch}}$$

```
for iter in range(5000):

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    inputs.requires_grad_()

    scores = net( inputs )

    loss = criterion( scores , minibatch_label )

    loss.backward()

    optimizer.step()
```
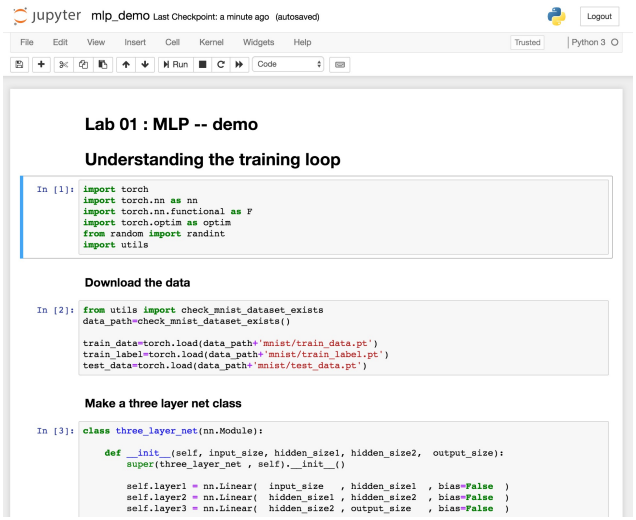

Lab 01

- Understanding the training loop



jupyter mlp_demo Last Checkpoint: a minute ago (autosaved)

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Run Code

Lab 01 : MLP -- demo

Understanding the training loop

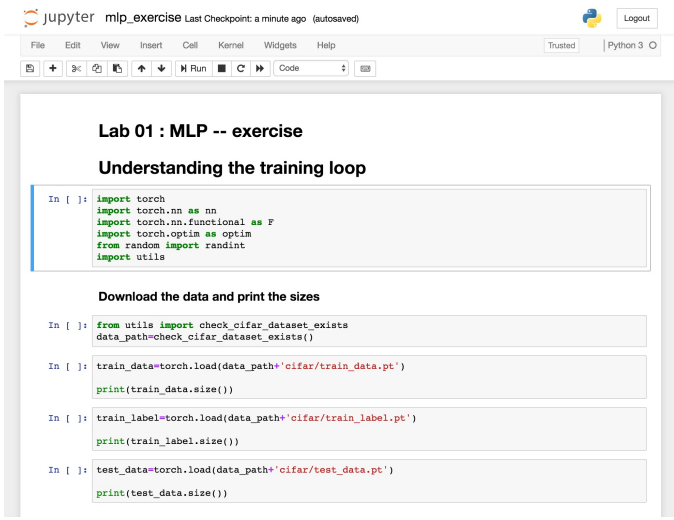
In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the data

In [2]:
```
from utils import check_mnist_dataset_exists
data_path=check_mnist_dataset_exists()

train_data=torch.load(data_path+'mnist/train_data.pt')
train_label=torch.load(data_path+'mnist/train_label.pt')
test_data=torch.load(data_path+'mnist/test_data.pt')
```

Make a three layer net class

In [3]:
```
class three_layer_net(nn.Module):

    def __init__(self, input_size, hidden_size1, hidden_size2,  output_size):
        super(three_layer_net , self).__init__()

        self.layer1 = nn.Linear(  input_size   , hidden_size1  , bias=False  )
        self.layer2 = nn.Linear(  hidden_size1 , hidden_size2  , bias=False  )
        self.layer3 = nn.Linear(  hidden_size2 , output_size   , bias=False  )
```



jupyter mlp_exercise Last Checkpoint: a minute ago (autosaved)

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Run Code

Lab 01 : MLP -- exercise

Understanding the training loop

In [ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the data and print the sizes

In [ ]:
```
from utils import check_cifar_dataset_exists
data_path=check_cifar_dataset_exists()
```

In [ ]:
```
train_data=torch.load(data_path+'cifar/train_data.pt')

print(train_data.size())
```

In [ ]:
```
train_label=torch.load(data_path+'cifar/train_label.pt')

print(train_label.size())
```

In [ ]:
```
test_data=torch.load(data_path+'cifar/test_data.pt')

print(test_data.size())
```

Outline

- Multi-Layer Perceptron
- Loss and gradient descent
- Backpropagation
- PyTorch implementation
- **Training with epochs**
- Monitoring the loss
- Test set evaluation
- Final code

Training with epochs

- Up to now we have been training as follows:
  - Feed 200 randomly selected images to the net (note that the same image can be drawn multiple times).

- An epoch is a full pass through the randomly ordered training set.
  - Training with epochs prevents sampling the same image before seeing all other training images.
  - At the beginning of the epoch, the 60,000 images from the training set are randomly ordered.
    - Then:
      - Feed image 0 - 199 to the net and train.
      - Feed image 200 - 399 to the net and train.
      - ...
      - Feed image 59,800 - 59,999 to the net and train.

Training with epochs

- We have been training as follows:

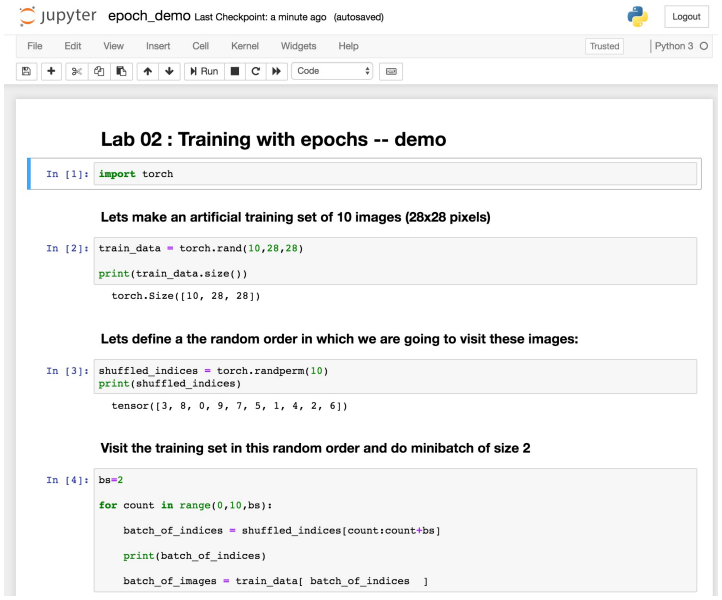
```
for iter in range(5000):

    optimizer.zero_grad()

    indices = torch.LongTensor(bs).random_(0,60000)
    minibatch_data   =  train_data[indices]
    minibatch_label = train_label[indices]

    inputs = minibatch_data.view(bs,784)

    inputs.requires_grad_()

    scores = net( inputs )

    loss = criterion( scores , minibatch_label )

    loss.backward()

    optimizer.step()
```

- Training with epochs :
  - Here we do 8 complete passes through the training set.

```
for epoch in range(8):

    shuffled_indices=torch.randperm(60000)

    for count in range(0,60000,bs):

        optimizer.zero_grad()

        indices=shuffled_indices[count:count+bs]
        minibatch_data =  train_data[indices]
        minibatch_label= train_label[indices]

        inputs = minibatch_data.view(bs,784)

        inputs.requires_grad_()

        scores=net( inputs )

        loss = criterion( scores , minibatch_label)

        loss.backward()

        optimizer.step()
```

Lab 02

- Training with epochs



jupyter epoch_demo Last Checkpoint: a minute ago (autosaved)

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Run Code

Lab 02 : Training with epochs -- demo

```
In [1]: import torch
```

Lets make an artificial training set of 10 images (28x28 pixels)

```
In [2]: train_data = torch.rand(10,28,28)

        print(train_data.size())
```

```
torch.Size([10, 28, 28])
```

Lets define a the random order in which we are going to visit these images:

```
In [3]: shuffled_indices = torch.randperm(10)
        print(shuffled_indices)
```

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

Visit the training set in this random order and do minibatch of size 2

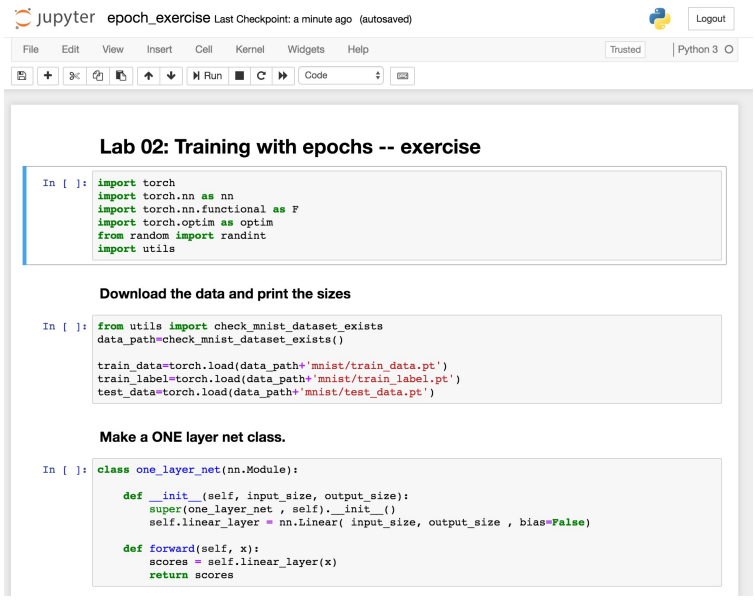
```
In [4]: bs=2

        for count in range(0,10,bs):

            batch_of_indices = shuffled_indices[count:count+bs]

            print(batch_of_indices)

            batch_of_images = train_data[ batch_of_indices  ]
```



jupyter epoch_exercise Last Checkpoint: a minute ago (autosaved)

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Run Code

Lab 02: Training with epochs -- exercise

```
In [ ]: import torch
        import torch.nn as nn
        import torch.nn.functional as F
        import torch.optim as optim
        from random import randint
        import utils
```

Download the data and print the sizes

```
In [ ]: from utils import check_mnist_dataset_exists
        data_path=check_mnist_dataset_exists()

        train_data=torch.load(data_path+'mnist/train_data.pt')
        train_label=torch.load(data_path+'mnist/train_label.pt')
        test_data=torch.load(data_path+'mnist/test_data.pt')
```

Make a ONE layer net class.

```
In [ ]: class one_layer_net(nn.Module):

            def __init__(self, input_size, output_size):
                super(one_layer_net , self).__init__()
                self.linear_layer = nn.Linear( input_size, output_size , bias=False)

            def forward(self, x):
                scores = self.linear_layer(x)
                return scores
```

Outline

- Multi-Layer Perceptron
- Loss and gradient descent
- Backpropagation
- PyTorch implementation
- Training with epochs
- **Monitoring the loss**
- Test set evaluation
- Final code

Monitoring the loss

- Monitoring the loss and the classification error :

Reset to zero at the beginning of a new epoch

running loss += average loss of current mini-batch

running error += average error on current mini-batch

```
for epoch in range(30):

    running_loss=0
    running_error=0
    num_batches=0

    shuffled_indices=torch.randperm(60000)

    for count in range(0,60000,bs):

        optimizer.zero_grad()

        indices=shuffled_indices[count:count+bs]
        minibatch_data =  train_data[indices]
        minibatch_label= train_label[indices]

        inputs = minibatch_data.view(bs,784)

        inputs.requires_grad_()

        scores=net( inputs )

        loss =  criterion( scores , minibatch_label)

        loss.backward()

        optimizer.step()


        # compute and accumulate stats

        running_loss += loss.detach().item()

        error = utils.get_error( scores.detach() , minibatch_label)
        running_error += error.item()

        num_batches+=1


    # compute stats for the full training set
    total_loss = running_loss/num_batches
    total_error = running_error/num_batches

    print('epoch=',epoch, '\t loss=', total_loss , '\t error=', total_error*100 ,'percent')
```

Monitoring loss and error

- Running error $= 10\% + 15\% + 12\% + \ldots\ldots\ldots\ldots\ldots\ldots + 15\%$

Error rate on the 1st batch of 200 images

Error rate on the last batch of 200 images

Error rate on the full training set $= \dfrac{\text{running error}}{\text{number of batches}}$

- Same for the running loss

PyTorch

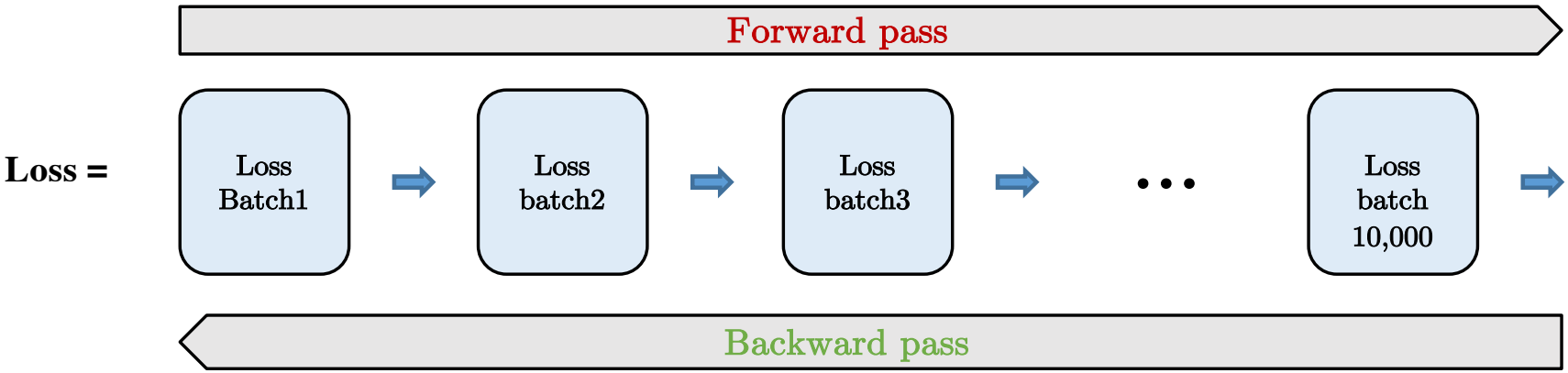
- Understand the code line:
  - **running_loss += loss.detach().item()**

- Function **item()** :
  - Get a Python number from a tensor containing a single value.

- Function **detach()** :
  - This function extracts the value of the node in the computational graph.
  - This function is essential to avoid building a big computational graph for the **running_loss**.
  - If it is not used, then the graph will be big and the backward pass (autograd) will take a long time, but for nothing as the **running_loss** value does not need the gradient!

PyTorch

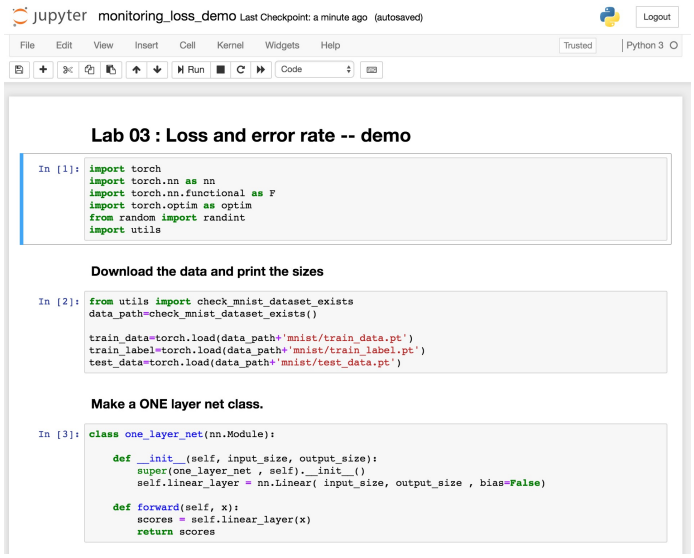
- Without **detach()** :
  - **running_loss += loss**
  - **loss.backward()**



10,000 batches !

Lab 03

- Computing the loss and the error rate



jupyter monitoring_loss_demo Last Checkpoint: a minute ago (autosaved)

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Run Code

Lab 03 : Loss and error rate -- demo

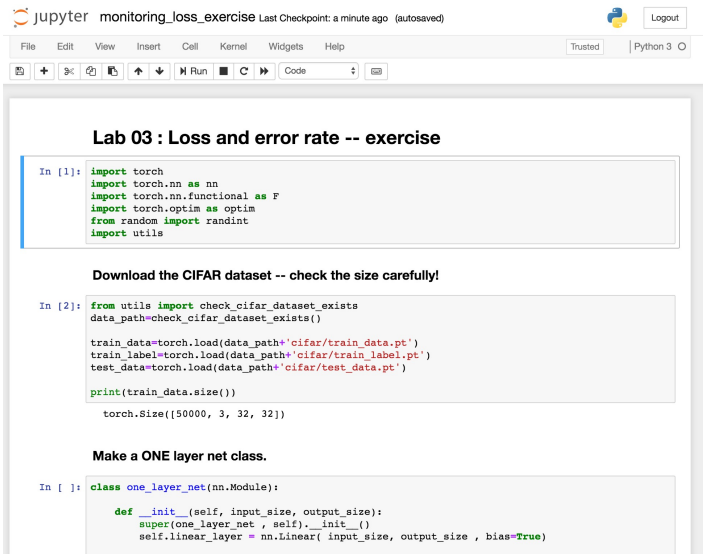
In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the data and print the sizes

In [2]:
```
from utils import check_mnist_dataset_exists
data_path=check_mnist_dataset_exists()

train_data=torch.load(data_path+'mnist/train_data.pt')
train_label=torch.load(data_path+'mnist/train_label.pt')
test_data=torch.load(data_path+'mnist/test_data.pt')
```

Make a ONE layer net class.

In [3]:
```
class one_layer_net(nn.Module):

    def __init__(self, input_size, output_size):
        super(one_layer_net , self).__init__()
        self.linear_layer = nn.Linear( input_size, output_size , bias=False)

    def forward(self, x):
        scores = self.linear_layer(x)
        return scores
```



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Run Code

Lab 03 : Loss and error rate -- exercise

In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the CIFAR dataset -- check the size carefully!

In [2]:
```
from utils import check_cifar_dataset_exists
data_path=check_cifar_dataset_exists()

train_data=torch.load(data_path+'cifar/train_data.pt')
train_label=torch.load(data_path+'cifar/train_label.pt')
test_data=torch.load(data_path+'cifar/test_data.pt')

print(train_data.size())
```

```
torch.Size([50000, 3, 32, 32])
```

Make a ONE layer net class.

In [ ]:
```
class one_layer_net(nn.Module):

    def __init__(self, input_size, output_size):
        super(one_layer_net , self).__init__()
        self.linear_layer = nn.Linear( input_size, output_size , bias=True)
```

Outline

- Multi-Layer Perceptron
- Loss and gradient descent
- Backpropagation
- PyTorch implementation
- Training with epochs
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- **Test set evaluation**
- Final code

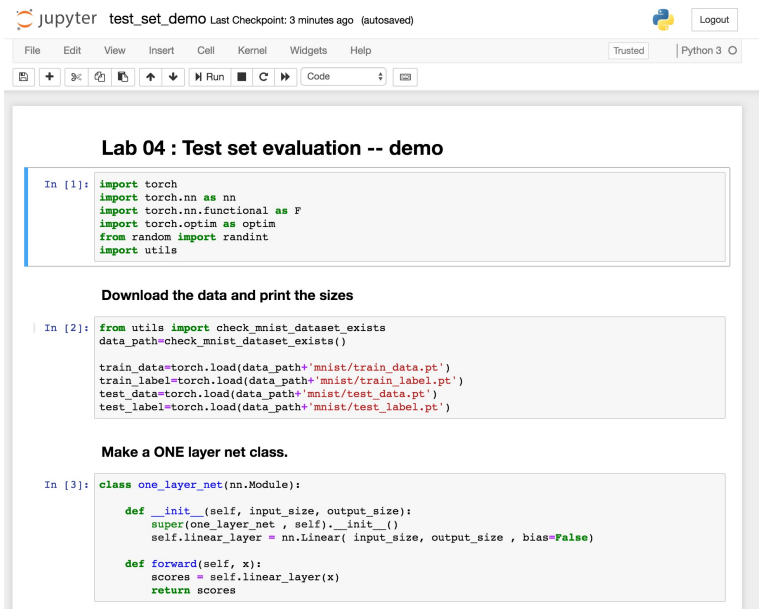
Generalization performance

- Evaluation on the test set :
  - No need to shuffle the test set.
  - Just make a pass through the full test set in the original order.

```
running_error=0
num_batches=0


for i in range(0,10000,bs):

    minibatch_data =  test_data[i:i+bs]
    minibatch_label= test_label[i:i+bs]

    inputs = minibatch_data.view(bs,784)

    scores = net( inputs )

    error = utils.get_error( scores , minibatch_label)

    running_error += error.item()

    num_batches+=1



total_error = running_error/num_batches

print( 'error rate on test set =', total_error*100 ,'percent')
```

Lab 04

- Test set evaluation



jupyter test_set_demo Last Checkpoint: 3 minutes ago (autosaved)

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Run Code

Lab 04 : Test set evaluation -- demo

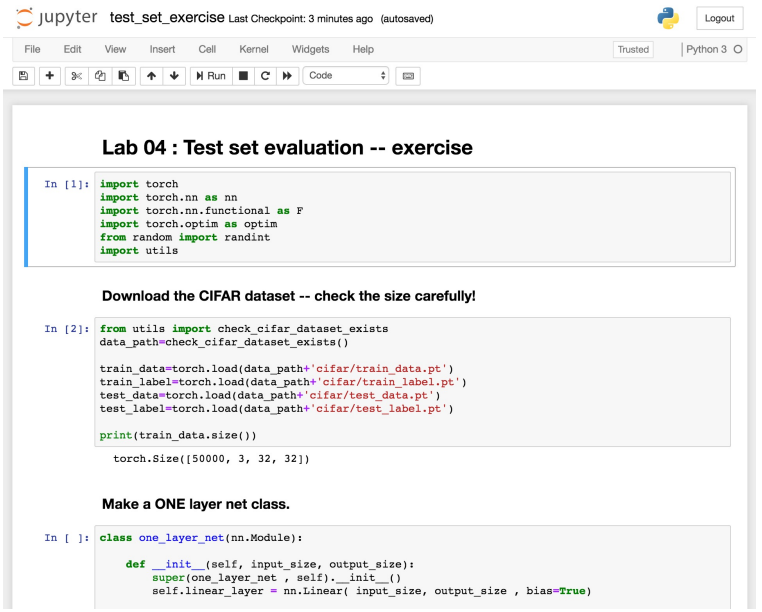
In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the data and print the sizes

In [2]:
```
from utils import check_mnist_dataset_exists
data_path=check_mnist_dataset_exists()

train_data=torch.load(data_path+'mnist/train_data.pt')
train_label=torch.load(data_path+'mnist/train_label.pt')
test_data=torch.load(data_path+'mnist/test_data.pt')
test_label=torch.load(data_path+'mnist/test_label.pt')
```

Make a ONE layer net class.

In [3]:
```
class one_layer_net(nn.Module):

    def __init__(self, input_size, output_size):
        super(one_layer_net , self).__init__()
        self.linear_layer = nn.Linear( input_size, output_size , bias=False)

    def forward(self, x):
        scores = self.linear_layer(x)
        return scores
```



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Run Code

Lab 04 : Test set evaluation -- exercise

In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from random import randint
import utils
```

Download the CIFAR dataset -- check the size carefully!

In [2]:
```
from utils import check_cifar_dataset_exists
data_path=check_cifar_dataset_exists()

train_data=torch.load(data_path+'cifar/train_data.pt')
train_label=torch.load(data_path+'cifar/train_label.pt')
test_data=torch.load(data_path+'cifar/test_data.pt')
test_label=torch.load(data_path+'cifar/test_label.pt')

print(train_data.size())
```

```
torch.Size([50000, 3, 32, 32])
```

Make a ONE layer net class.

In [ ]:
```
class one_layer_net(nn.Module):

    def __init__(self, input_size, output_size):
        super(one_layer_net , self).__init__()
        self.linear_layer = nn.Linear( input_size, output_size , bias=True)
```

Outline

- Multi-Layer Perceptron
- Loss and gradient descent
- Backpropagation
- PyTorch implementation
- Training with epochs
- Monitoring the loss
- Test set evaluation
- **Final code**

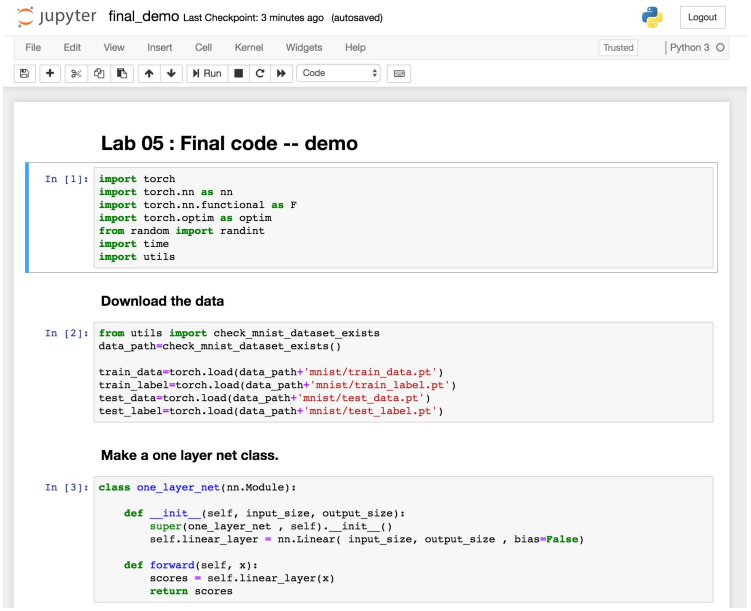
Final code

- We just make the following improvements to our code:
  - Add a learning rate schedule.
  - Evaluate on test set every 10 epochs (rather than waiting for the end of the training).
  - Provide some timing information.
  - Count number of parameters in network.

- This final code is a prototype for any deep learning project:
  - What changes for a new project:
    - New data (collect, prepare, access to batch of training data)
    - New architecture
    - New learning rate schedule

Lab 05

- Demo of the final code :



Questions?