In [1]:

```python
try:
    import torch as t
    import torch.nn as tnn
except ImportError:
    print("Colab users: pytorch comes preinstalled. Select Change Ru")
    print("Local users: Please install pytorch for your hardware using instr
    print("ACG users: Please follow instructions here: https://vikasdhiman.i

    raise
```

In [2]:

```python
def wget(url, filename):
    """
    Download files using requests package.
    Better than wget command line because this is cross platform.
    """
    try:
        import requests
    except ImportError:
        import subprocess
        subprocess.call("pip install requests".split())
        import requests
    r = requests.get(url)
    with open(filename, 'wb') as fd:
        for chunk in r.iter_content():
            fd.write(chunk)
```

In [3]:

28x29

=

```python
## Doing it the Pytorch way without using our custom feature extraction
DEVICE='cuda:0'
DTYPE=t.float32
import torch
import torch.nn
import torch.optim
import torchvision
from torchvision.transforms import ToTensor
from torch.utils.data import DataLoader

torch.manual_seed(17)
```

These are special classes that are subclassed from DataLoader/Dataset

```python
# Getting the dataset, the Pytorch way
all_training_data = torchvision.datasets.MNIST(
    root="data",
```

where to store data downloaded data

```python
    train=True,
```

train or test

```python
    download=True,
```

complain or download if the dataset is not in the root directory

```python
    transform=ToTensor()
)
```

what to do with data

ToTensor() : intializes your data as tensor object

```python
test_data = torchvision.datasets.MNIST(
    root="data",
    train=False,
```

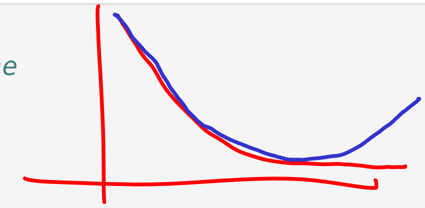
get test data

```python
    download=True,
    transform=ToTensor()
)
```

all the training

~~80%, 20%~~ √90% 10%

```
In [4]: training_data, validation_data = torch.utils.data.random_split(all_training_
```



avoid overfitting →

```
In [8]: # Hyper parameters
        learning_rate = 1e-3 # controls how fast the
        batch_size = 64
        epochs = 5
        momentum = 0.9

        training_dataloader = DataLoader(training_data, shuffle=True, batch_size=bat
        validation_dataloader = DataLoader(validation_data,  batch_size=batch_size)
        test_dataloader = DataLoader(test_data,  batch_size=batch_size)


        loss = torch.nn.CrossEntropyLoss()

        # TODO:
        # Define model = ?
        class MLPNetwork(torch.nn.Module):
            def __init__(self, hidden_size=10, nclasses=10, input_size=28*28):
                super().__init__()
                self._layers = torch.nn.ModuleList([torch.nn.Flatten(),
                    tnn.Linear(input_size, hidden_size),
                    tnn.ReLU(),
                    tnn.Linear(hidden_size, nclasses)])
            def forward(self, x):
                for l in self._layers:
                    xnext = l(x) # call the layers in sequence
                    x = xnext
                return x
        model = MLPNetwork()

        # alternatively you can also
        # hidden_size=10
        # nclasses=10
        # input_size=28*28
        # model = torch.nn.Sequential(torch.nn.Flatten(),
        #              tnn.Linear(input_size, hidden_size),
        #              tnn.ReLU(),
        #              tnn.Linear(hidden_size, nclasses))
        #

        # Define optimizer
        optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate, momentum=m

        def loss_and_accuracy(model, loss, validation_dataloader, device=DEVICE):
            # Validation loop
            validation_size = len(validation_dataloader.dataset)
            num_batches = len(validation_dataloader)
            test_loss, correct = 0, 0

            with torch.no_grad():
                for X, y in validation_dataloader:
                    X = X.to(device)
                    y = y.to(device)
                    pred = model(X)
```

nn = neural network

__setattr__

input

checks for instance of tnn.Module

self.l1 = tnn.Linear

when the weights are initialize

input

900 5

5 10

out

SGD → Stochastic Gradient descent

Linear W_1, b_1

↓

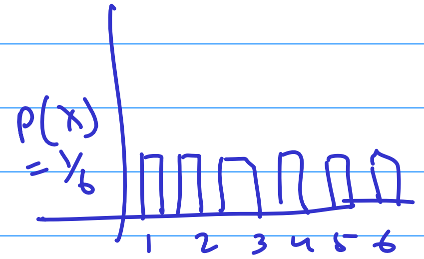
ReLU

Linear W_2, b_2

Entropy (Shanon's): measure of randomness

$$E[X] = \sum_{x \in X} -p(X=x)\log_2\big(p(X=x)\big)$$

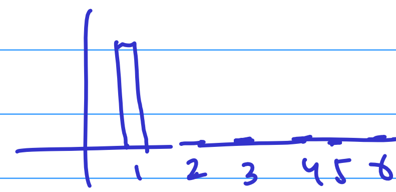
bits ← bits required to capture information in X



$$E[X] = \left[-\frac{1}{6}\log\left(\frac{1}{6}\right)\right]6$$

Cross entropy

$$H[Y,\hat{Y}] = \sum_{y \in Y} -\overbrace{p(y)}^{\text{true}} \log\big(\overbrace{p(\hat{y})}^{\text{predicted}}\big)$$

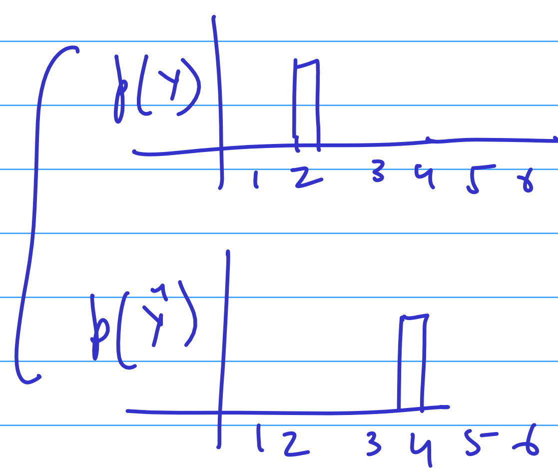


$$E[X] = -1\log(1) + -0\log(0) + -0\log(0) + \dots \text{ 5 times} = 0$$

Cross entropy is a measure of information provided by Y about $\hat{Y}$ and vice versa

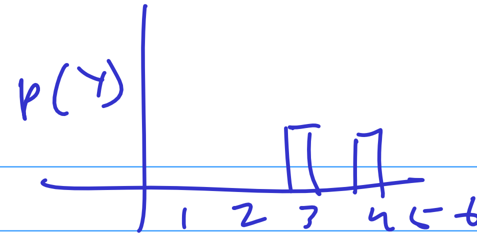
- is maximum when the probabilities mismatch
- is minimum when the prob. match

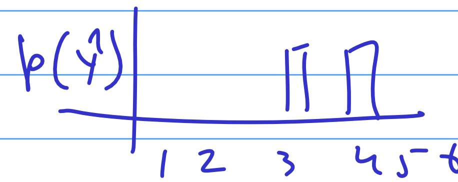
$$H[Y,\hat{Y}] = -0\log 0 + -1\log(0) + -0\log 0 + \dots -0\log 1 + \dots + = \infty$$



$$\log(0^{+}) \to -\infty$$

$$H[Y,\hat{Y}] = -1\log(1) + 0\log(0) + 0\log(0) + \cdots = 0.$$





$$H[Y;\hat{Y}] = -0.5\log(0.5) - 0.5\log(0.5) = -\log(0.5)$$

$\log(1) = 0$

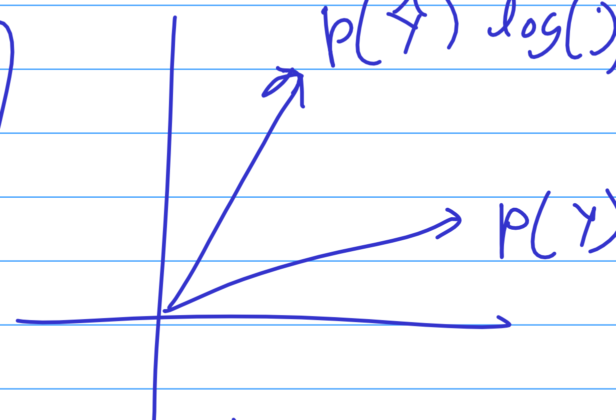
$$\underline{p}(Y) = \begin{bmatrix} p(Y=1) \\ p(Y=2) \\ \vdots \\ p(Y=6) \end{bmatrix}_{6\times 1}$$

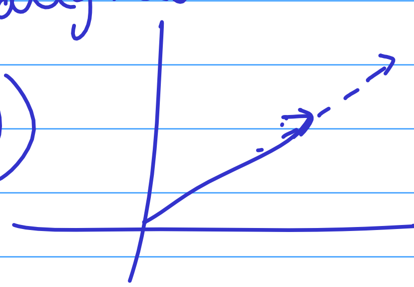
$$\underline{p}(\hat{Y}) = \begin{bmatrix} p(\hat{Y}=1) \\ \vdots \\ p(\hat{Y}=6) \end{bmatrix}_{6\times 1} \longrightarrow \log(p(\hat{Y})) = \begin{bmatrix} \log(\;) \\ \vdots \\ \log(\;) \end{bmatrix}$$

$p(\hat{Y})$ $\log(\cdot)$

$$\underbrace{H[Y,\hat{Y}] = -\underline{p}(Y)^T \left[\underline{\log}(\underline{p}(\hat{Y}))\right]}_{\text{minimum}}$$

minimum when $p(Y)$ is aligned with $\underline{\log}(\underline{p}(\hat{Y}))$





$$\underbrace{\vec{a}\cdot\vec{b} = |a|\cdot|b|\cos\theta}_{\text{max when } \theta = 0}$$

Classification → Binary : (two classes)

Hinge loss

Classification → Multi-class

Cross entropy loss

MNIST – 10 digits

$$\left.\begin{array}{l} Y = 0 \\ Y = 1 \\ Y = 2 \\ \vdots \\ Y = 9 \end{array}\right\} \text{9 possible classes}$$

for every ima

28  28

X

$\longrightarrow \underbrace{\text{label } Y = 3}$

↓ convert label to probability

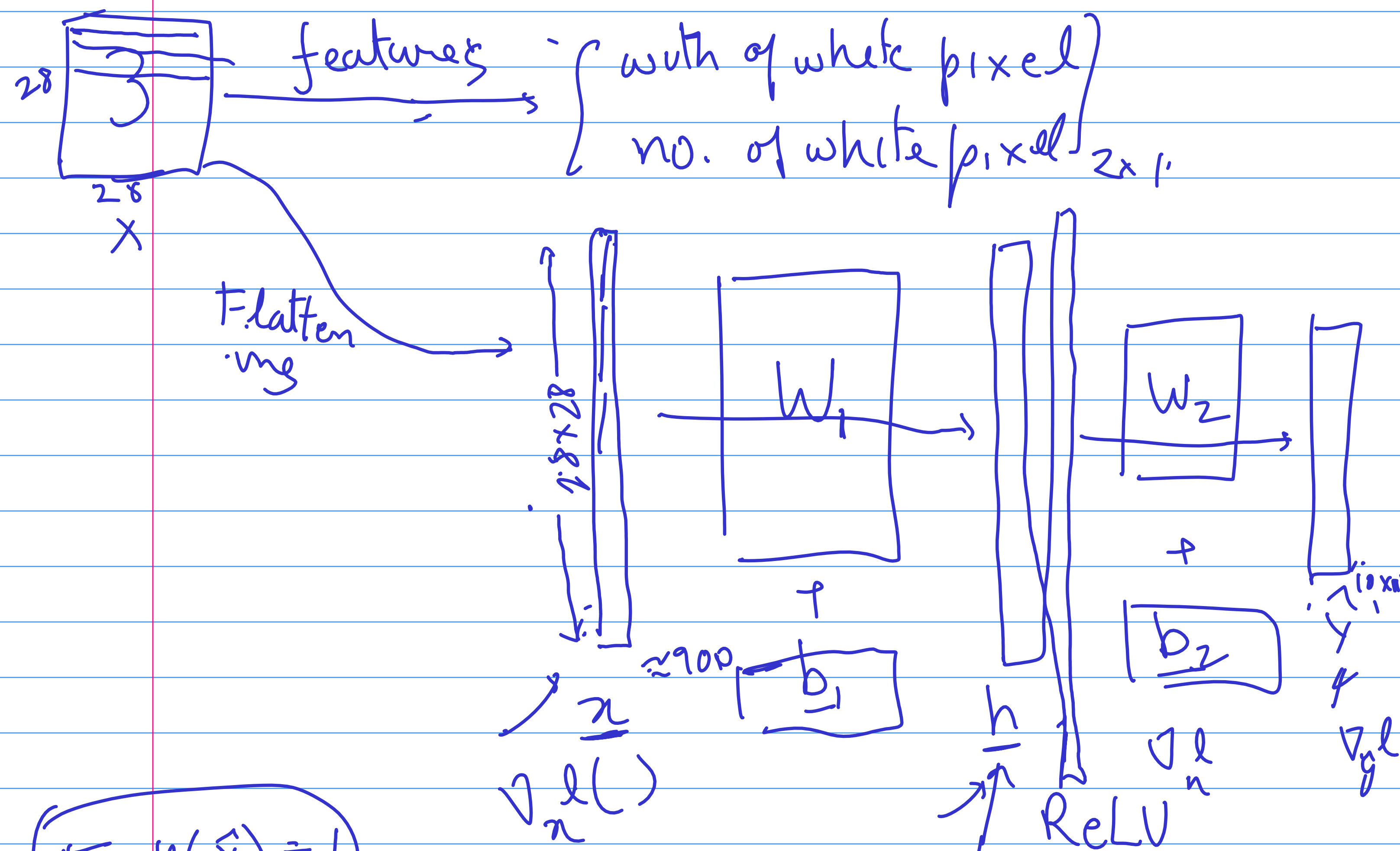
$$\begin{bmatrix} P(Y=0) = 0 \\ \vdots \\ P(Y=3) = 1 \\ \\ P(Y=9) = 0 \end{bmatrix}$$

one-hot vector

model

$$f(X;\theta) \longrightarrow \hat{Y} = f(X;\theta)$$

MLP : $\frac{\text{Multi}}{2}$ layer perceptron



$$\sum_{y \in Y} p(\hat{y}) = 1$$

Freedom to choose

$h \in \mathbb{R}^{5\times1}$

$x \in [0,1]$

$$p(\hat{y}) = \mathrm{MLP}(x; W_2, b_2, W_1, b_1) = \underbrace{b_2 + W_2}_{\text{Linear}}\Big(\mathrm{ReLU}\big(\overbrace{\underbrace{W_1 x + b_1}_{h_{5\times1}}}^{\text{Linear}}\big)\Big)$$

$\in \mathbb{R}^{10\times1}$

$\mathbb{R} = \text{float32} =$ 4 bytes

$$\begin{bmatrix} W_1 \in \mathbb{R}^{h\times900\times4} & b_1 \in \mathbb{R}^{h\times1\times4} \\ W_2 \in \mathbb{R}^{10\times h\times4} & b_2 \in \mathbb{R}^{10\times1\times4} \end{bmatrix}$$

$x \in \mathbb{R}^{900\times1}$

Total bytes $= 5\times900\times4 + 5\times4 + 10\times5\times4 + 10\times4$

$$\underbrace{\underline{z} \in (-\infty, \infty)^{n\times 1}}_{\mathbb{R}} \xrightarrow{\boxed{\text{softmax}}} \underbrace{(0,1)^{n\times 1}}_{\underline{p}(\underline{z})} \quad \sum \underline{p}(z) = 1$$

Softmax

$$p(z_i) = \frac{\exp(z_i)}{\sum_{i=1}^{n} \exp(z_i)}$$

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} \xrightarrow{\text{softmax}} \underbrace{\begin{bmatrix} \frac{\exp(z_1)}{\sum \exp(z_i)} \\ \frac{\exp(z_2)}{\sum \exp(z_i)} \\ \vdots \end{bmatrix}}_{p(\underline{z})}$$

$$\exp(\underline{z}) = \begin{bmatrix} \exp(z_1) \\ \vdots \\ \exp(z_n) \end{bmatrix}$$

$$\boxed{\text{softmax}(\underline{z}) = \exp(\underline{z}) / \exp(\underline{z})^T \mathbb{1}_{n\times 1}}$$

$p(\hat{Y}) = \text{Softmax}\left(MLP(\underline{x};)\right) \in \mathbb{R}^{10\times 1}$

$p(Y) =$ one-hot vector

$\text{Loss}(Y, \hat{Y}) = -\sum_{y \in Y} \underbrace{p(Y)} \log(\hat{Y})$

if correct label $=3$

$p(Y=3)=1$

$= -\log(p(\hat{Y}=3))$

$= -\cancel{\log}\left(\dfrac{\cancel{\exp}(\hat{Y}_3)}{\sum_i \exp(\hat{Y}_i)}\right)$

Gradient descent

$D_T = \{(\underline{x}_1, y_1) \ldots$

$l(y_i, \hat{y}_i) \qquad \hat{y}_i = f(\underline{x}_i; \underline{W})$

$L(D, W) = \sum_{i \in D} l(y_i, \hat{y}_i)$] Loss over the entire dataset

1-step

$W_{t+1} = W_t - \alpha \underbrace{\nabla_W \sum_{i \in D} l(y_i, \hat{y}_i)}$ X not feasible for big data sets

$$w_{t+1} = w_t - \alpha \underbrace{\sum_{i \in D} \left[\nabla_w \, l(y_i, \hat{y}_i ; w_{t,0}) \right]}$$ GD

$\left[\,\right]_{\times}$

1 epoch

$\{$ for i in D:

$$w_{t+1,i} = w_{t,i} - \alpha \underbrace{\nabla_w \, l(y_i, \hat{y}_i ; w_{t,i})}_{\text{one sample at a time}}$$

Stochastic GD

Batch SGD   batch size

1-epoch

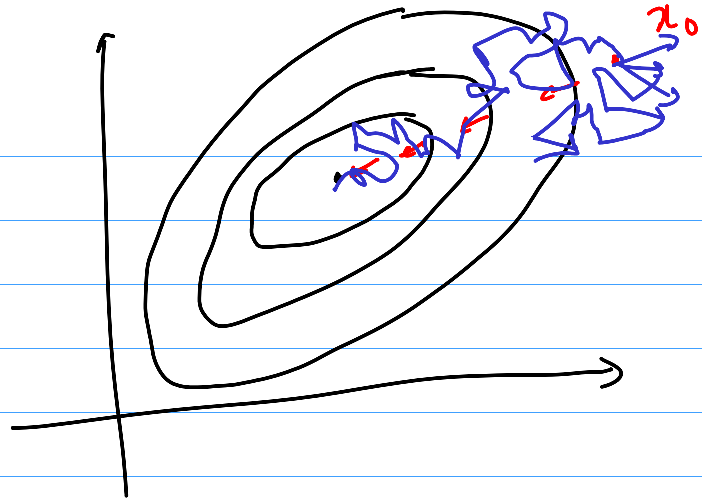
$\{$ for b in range (D/ batch_size)

$$w_{t+1,b} = w_{t,b} - \alpha \underbrace{\nabla_w \sum_{\text{batchsize}} l(y_b, \hat{y}_b)}_{\text{one batch at time}}$$

[SGD with momentum (Next time)

Apr 09,

$L(D, w_t)$



- GD
- SGD

Batch SGD

Use previous directions to move towards minimum faster = SGD with momentum

SGD

for i in range(D):

$$w_{t+1,i} = w_{t,i} - \alpha \nabla_w l(y_i, \hat{y}_i; w_{t,i})$$

SGD with momentum $\lambda \approx 0.9$ $\lambda = 0.99$

for i in range(D):

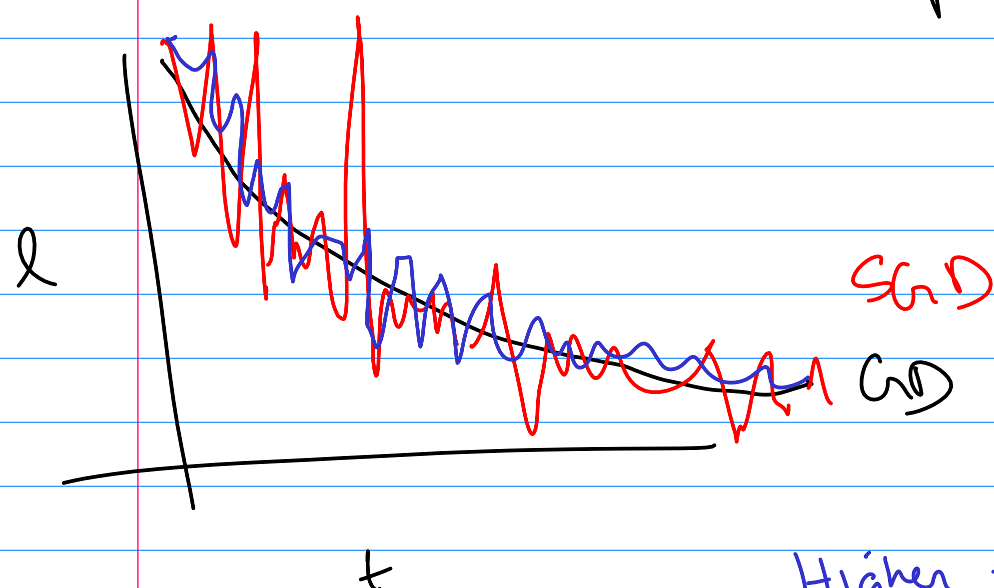
$$v_{t+1,i} = \lambda v_{t,i} + (1-\lambda) \nabla_w l(y_i, \hat{y}_i, w_{t,i})$$

accele

$$w_{t+1,i} = w_{t,i} - \alpha v_{t+1}$$

position

velocity



SGD with momentum

$\lambda \in (0,1)$

Higher the λ, harder it is to change the velocity

λ is called the momentum factor

```python
            test_loss += loss(pred, y).item()
            correct += (pred.argmax(dim=-1) == y).type(DTYPE).sum().item()

    test_loss /= num_batches
    correct /= validation_size
    return test_loss, correct

def train(model, loss, training_dataloader, validation_dataloader, device=DE
    model.to(device)
    train_losses = []
    valid_losses = []
    for t in range(epochs):
        # Train loop
        training_size = len(training_dataloader.dataset)
        for batch, (X, y) in enumerate(training_dataloader):
            X = X.to(device)
            y = y.to(device)
            # Compute prediction and loss
            pred = model(X)
            loss_t = loss(pred, y)

            # Backpropagation
            optimizer.zero_grad()
            loss_t.backward()
            optimizer.step()

            if batch % 100 == 0:
                loss_t, current = loss_t.item(), (batch + 1) * len(X)
                print(f"loss: {loss_t:>7f}  [{current:>5d}/{training_size:>5
                train_losses.append(loss_t)
                valid_loss, correct = loss_and_accuracy(model, loss, validat
                valid_losses.append(valid_loss)
                print(f"Validation Error: \n Accuracy: {(100*correct):>0.1f}
    return model, train_losses, valid_losses

trained_model, train_losses, valid_losses = train(model, loss, training_data

test_loss, correct = loss_and_accuracy(model, loss, test_dataloader)
print(f"Test Error: \n Accuracy: {(100*correct):>0.1f}%, Avg loss: {test_los
```

Similar to GD

64x28x28

Specific to SGD

One batch at a time

64x1 → one-hot vector 64x10

SGD update

$w_{t+1} = w_t - \alpha v_t$

```
Validation Error:    64/54000]
 Accuracy: 10.9%, Avg loss: 2.325170

Validation Error: 6464/54000]
 Accuracy: 13.6%, Avg loss: 2.183869

Validation Error: 2864/54000]
 Accuracy: 34.1%, Avg loss: 2.001862

Validation Error: 9264/54000]
 Accuracy: 46.8%, Avg loss: 1.787784

Validation Error: 5664/54000]
 Accuracy: 54.8%, Avg loss: 1.580385

Validation Error: 2064/54000]
 Accuracy: 62.2%, Avg loss: 1.389772

Validation Error: 8464/54000]
 Accuracy: 68.5%, Avg loss: 1.216087

Validation Error: 4864/54000]
 Accuracy: 75.8%, Avg loss: 1.061541

Validation Error: 1264/54000]
 Accuracy: 79.9%, Avg loss: 0.935546

Validation Error:    64/54000]
 Accuracy: 80.2%, Avg loss: 0.889401

Validation Error: 6464/54000]
 Accuracy: 82.1%, Avg loss: 0.803695

Validation Error: 2864/54000]
 Accuracy: 82.9%, Avg loss: 0.736784

Validation Error: 9264/54000]
 Accuracy: 83.7%, Avg loss: 0.682686

Validation Error: 5664/54000]
 Accuracy: 84.5%, Avg loss: 0.639954

Validation Error: 2064/54000]
 Accuracy: 85.1%, Avg loss: 0.606284

Validation Error: 8464/54000]
 Accuracy: 85.5%, Avg loss: 0.577947

Validation Error: 4864/54000]
 Accuracy: 86.0%, Avg loss: 0.553612

Validation Error: 1264/54000]
 Accuracy: 86.4%, Avg loss: 0.534344

Validation Error:    64/54000]
 Accuracy: 86.7%, Avg loss: 0.527205
```

```
Validation Error: 6464/54000]
 Accuracy: 86.8%, Avg loss: 0.510988

Validation Error: 2864/54000]
 Accuracy: 87.1%, Avg loss: 0.497435

Validation Error: 9264/54000]
 Accuracy: 87.0%, Avg loss: 0.485881

Validation Error: 5664/54000]
 Accuracy: 87.4%, Avg loss: 0.474297

Validation Error: 2064/54000]
 Accuracy: 87.4%, Avg loss: 0.465911

Validation Error: 8464/54000]
 Accuracy: 87.7%, Avg loss: 0.456387

Validation Error: 4864/54000]
 Accuracy: 87.9%, Avg loss: 0.449242

Validation Error: 1264/54000]
 Accuracy: 87.9%, Avg loss: 0.442204

Validation Error:   64/54000]
 Accuracy: 88.2%, Avg loss: 0.439258

Validation Error: 6464/54000]
 Accuracy: 88.1%, Avg loss: 0.433261

Validation Error: 2864/54000]
 Accuracy: 88.0%, Avg loss: 0.428486

Validation Error: 9264/54000]
 Accuracy: 88.3%, Avg loss: 0.423615

Validation Error: 5664/54000]
 Accuracy: 88.5%, Avg loss: 0.420128

Validation Error: 2064/54000]
 Accuracy: 88.5%, Avg loss: 0.414353

Validation Error: 8464/54000]
 Accuracy: 88.4%, Avg loss: 0.409636

Validation Error: 4864/54000]
 Accuracy: 88.7%, Avg loss: 0.407865

Validation Error: 1264/54000]
 Accuracy: 88.8%, Avg loss: 0.401992

Validation Error:   64/54000]
 Accuracy: 88.9%, Avg loss: 0.401415

Validation Error: 6464/54000]
```

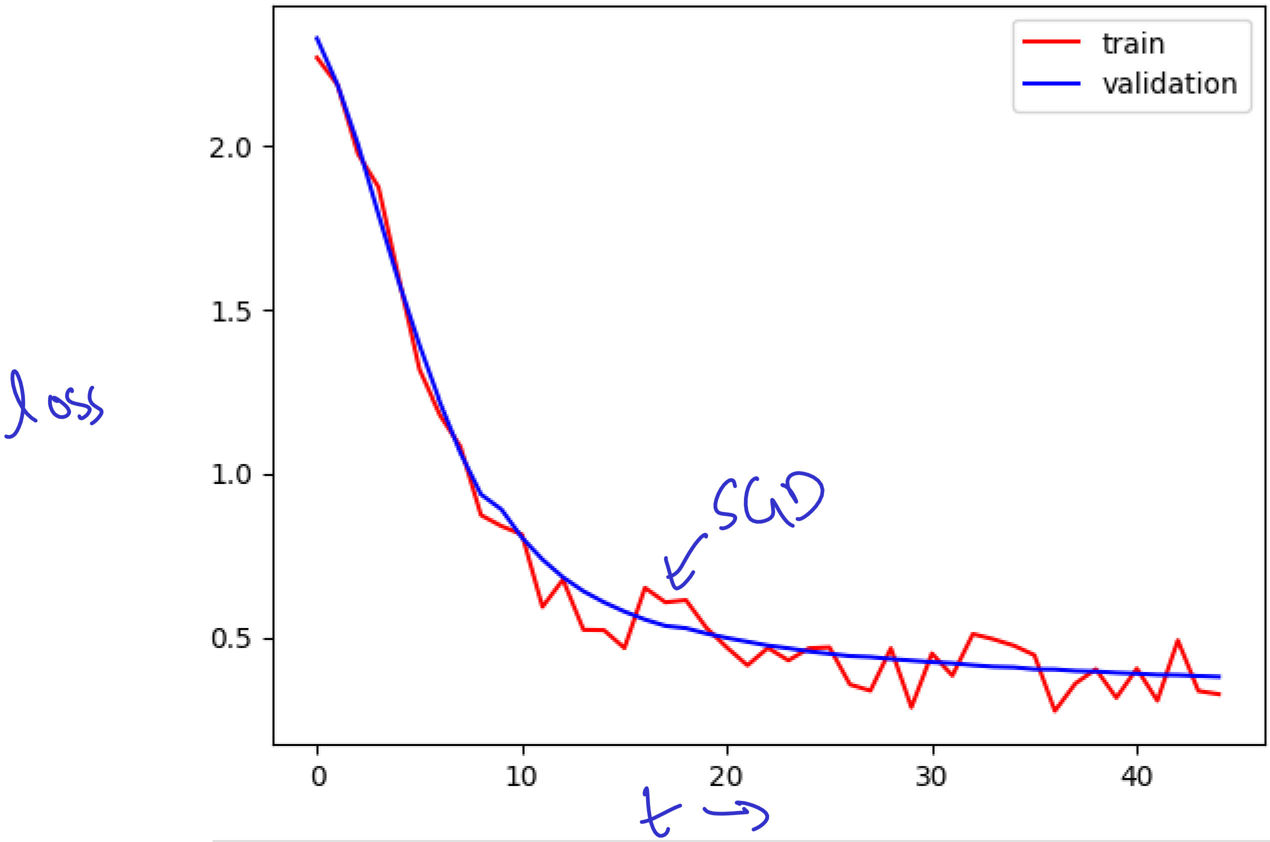
```
 Accuracy: 88.9%, Avg loss: 0.396768

Validation Error: 2864/54000]
 Accuracy: 88.9%, Avg loss: 0.395058

Validation Error: 9264/54000]
 Accuracy: 89.0%, Avg loss: 0.391086

Validation Error: 5664/54000]
 Accuracy: 88.9%, Avg loss: 0.388569

Validation Error: 2064/54000]
 Accuracy: 89.0%, Avg loss: 0.385012

Validation Error: 8464/54000]
 Accuracy: 89.0%, Avg loss: 0.384191

Validation Error: 4864/54000]
 Accuracy: 89.3%, Avg loss: 0.381349

Validation Error: 1264/54000]
 Accuracy: 89.3%, Avg loss: 0.378932

Test Error:
 Accuracy: 90.0%, Avg loss: 0.351287
```

In [10]:

```
import matplotlib.pyplot as plt
plt.plot(train_losses, 'r', label='train')
plt.plot(valid_losses, 'b', label='validation')
plt.legend()
```

Out[10]:

```
<matplotlib.legend.Legend at 0x7f92d52b5900>
```



In [11]:
```
torch.nn.__file__
```

Out[11]:
```
'/home/vdhiman/.local/share/virtualenvs/nbgrader-notebooks-_16a_jDm/lib/pyt
hon3.10/site-packages/torch/nn/__init__.py'
```

In [12]:
```
X, _ = next(iter(test_dataloader))
X.shape
```

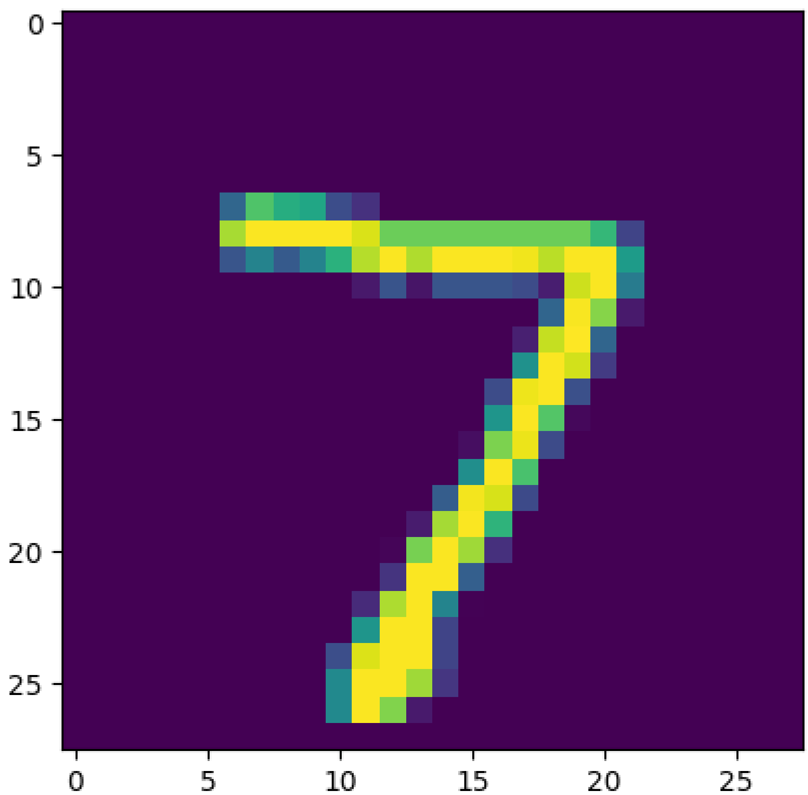
Channels

Out[12]:
```
torch.Size([64, 1, 28, 28])
```

Batch

In [13]:
```
import matplotlib.pyplot as plt
plt.imshow(X[0, 0])
```

Out[13]:
```
<matplotlib.image.AxesImage at 0x7f92d02888b0>
```



In [14]:
```python
print("The predicted image label is ", model(X.to(DEVICE)).argmax(dim=-1)[0])
```

```
The predicted image label is  7
```

In [ ]:

L.R.

Perceptron

Decision Theory

$$\left.\frac{\partial L}{\partial \theta}\right|_{\theta=?} = 0$$

GD

$$\theta_{t+1} = \theta_t - \alpha \frac{\partial L}{\partial \theta}$$

Autograd

Forward mod

Reverse mode / Back propagati

microtorch.py

+

microtorch_nn.py

+

microtorch_mlp.ipynb

Pytorch + SGD with momentum