Introduction to Pytorch

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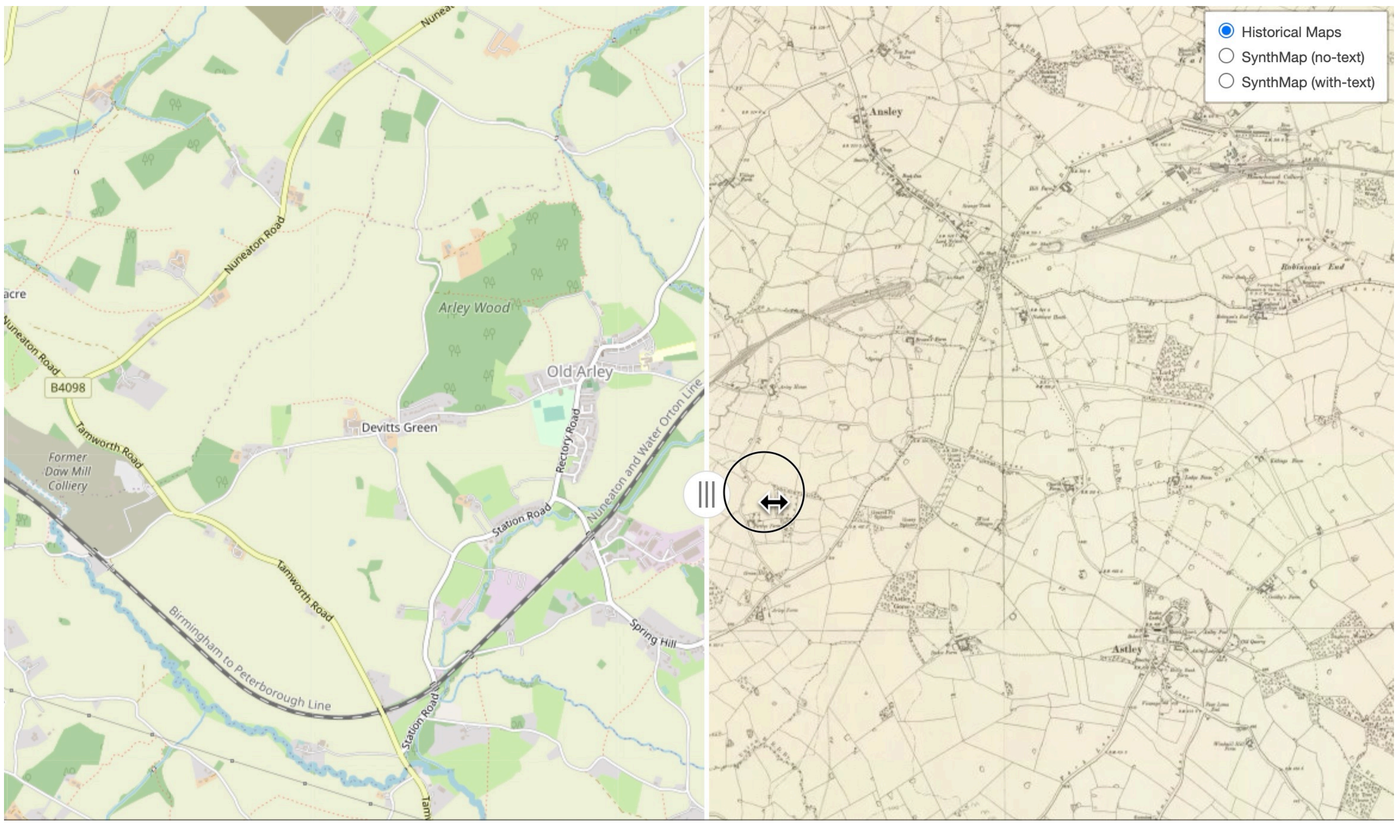
Deep Learning Applications

- Text Detection
- Image Style Transfer
- Face Pose & Gaze Detection
- Video Synthesis

Deep Learning Applications – Text Detection

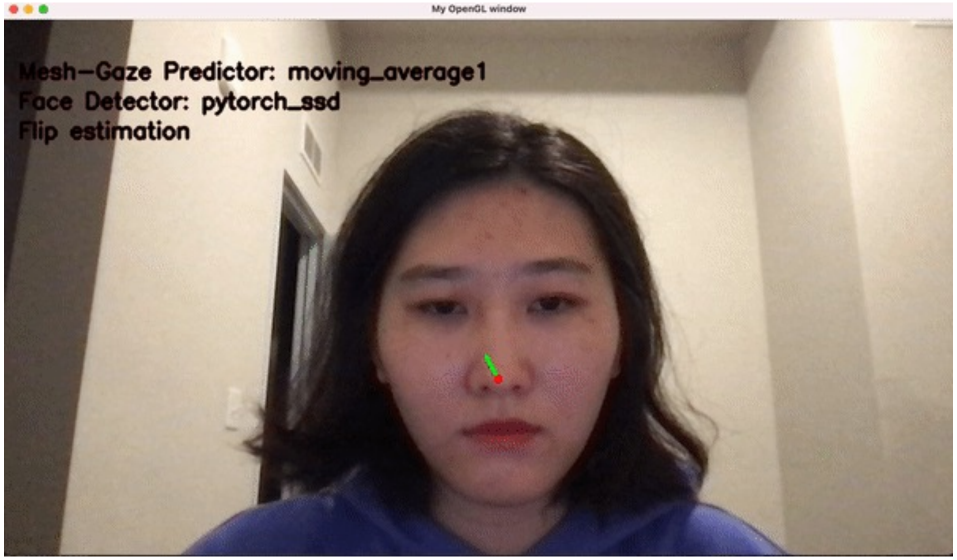
Deep neural network based text detector for historical maps https://github.com/machines-reading-maps/map-kurator

Deep Learning Applications – Map Style Transfer



Convert the OSM map images to the historical style https://zekun-li.github.io/side-by-side/

Deep Learning Applications – Pose & Gaze



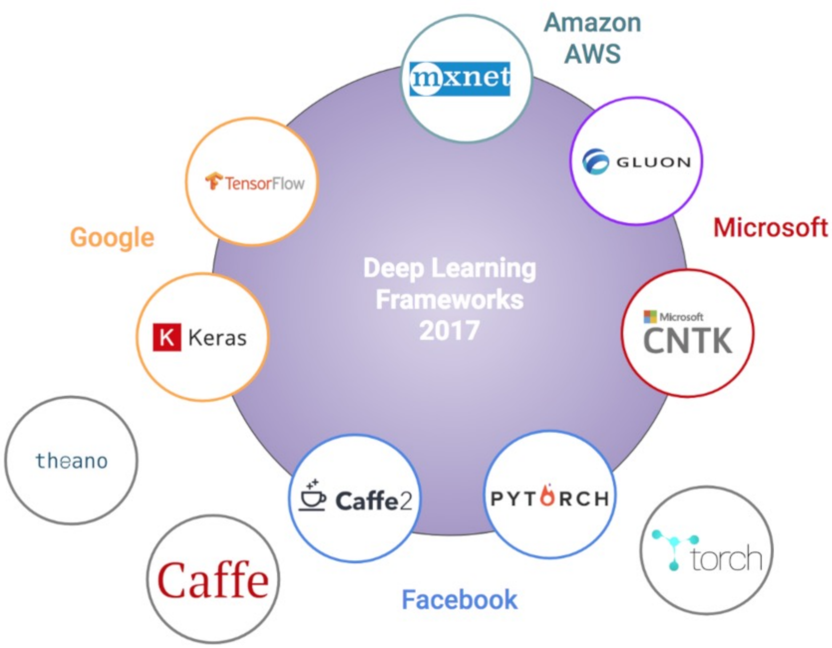
A joint model to predict the gaze and face mesh simultaneously

Deep Learning Applications – Video Synthesis

Wav2Lip: Synthesize lip movement given the audio

Prajwal, K. R., et al. "A lip sync expert is all you need for speech to lip generation in the wild." *Proceedings of the 28th ACM International Conference on Multimedia*. 2020.

Why choose Pytorch?



- Python-based framework
- Easy to learn and easy to debug
- Dynamic graph structure
- Supports GPU and CPU computation

Figure from https://devopedia.org/deep-learning-frameworks

Outline

- Pytorch Tensors
- Frequently used layers
  - Linear Layer
  - Convolution Layer
- Activation Functions
- Train neural network with Pytorch

Pytorch Tensor

- Tensor is a **multi-dimensional matrix** containing elements of a single data type
- Tensors can be created directly from a list

```
# Create a tensor directly from a list
a_list = [[0, 1],[2, 3],[4, 5]]
a_tensor = torch.tensor(a_list)
print(a_tensor)
```

- or initialized from Numpy array

```
# Create a tensor from Numpy array
a_array = np.array([[0, 1],[2, 3],[4, 5]])
data = torch.from_numpy(a_array)
print(data)
```

Pytorch Tensor

- Tensor can be created given the size of **existing tensors**
  - Tensor with ones

```
a_ones = torch.ones_like(a_tensor) # same shape as a_tensor, but with ones
print(a_ones)
```

```
tensor([[1, 1],
        [1, 1],
        [1, 1]], dtype=torch.int32)
```

  - Tensor with random values

```
a_rand = torch.rand_like(a_tensor, dtype=torch.float) # same shape as a_tensor, with rand values
print(a_rand)
```

```
tensor([[0.6263, 0.3245],
        [0.4140, 0.2188],
        [0.5598, 0.0729]])
```

Tensor Data Types

- Each tensor has a data type
- You can **specify** the data type **explicitly** when creating tensor
- If **not** specified, the data type will be **inferred** implicitly

```
a_list = [[0, 1],[2, 3],[4, 5]]
a_tensor = torch.tensor(a_list, dtype=torch.float32)
print(a_tensor)
```

```
tensor([[0., 1.],
        [2., 3.],
        [4., 5.]])
```

```
a_list = [[0, 1],[2, 3],[4, 5]]
a_tensor = torch.tensor(a_list, dtype=torch.int)
print(a_tensor)
```

```
tensor([[0, 1],
        [2, 3],
        [4, 5]], dtype=torch.int32)
```

Tensor Attributes

- Frequently used attributes

```
a_list = [[0, 1],[2, 3],[4, 5]]
a_tensor = torch.tensor(a_list, dtype=torch.int)

print(f"Shape of tensor: {a_tensor.shape}")
print(f"Datatype of tensor: {a_tensor.dtype}")
print(f"Device tensor is stored on: {a_tensor.device}")
```

```
Shape of tensor: torch.Size([3, 2])
Datatype of tensor: torch.int32
Device tensor is stored on: cpu
```

- List all attributes and functions with dir()

```
dir(a_tensor)
```

```
'cumprod_',
'cumsum',
'cumsum_',
'data',
'data_ptr',
'deg2rad',
'deg2rad_',
'dense_dim',
'dequantize',
'det',
'detach',
'detach_',
'device',
'diag',
'diag_embed',
'diagflat',
'diagonal',
'diff',
```

Tensor Operations

- Pytorch tensors support indexing and slicing operations

```
a_list = [[0, 1],[2, 3],[4, 5]]
a_tensor = torch.tensor(a_list, dtype=torch.int)
print(a_tensor)
print(a_tensor[2][1])
print(a_tensor[:,0])
```

```
tensor([[0, 1],
        [2, 3],
        [4, 5]], dtype=torch.int32)
tensor(5, dtype=torch.int32)
tensor([0, 2, 4], dtype=torch.int32)
```

Tensor Operations

- Joining tensors

```
t1 = torch.cat([a_tensor, a_tensor, a_tensor], dim=1)
print(t1)
```

```
tensor([[0, 1, 0, 1, 0, 1],
        [2, 3, 2, 3, 2, 3],
        [4, 5, 4, 5, 4, 5]], dtype=torch.int32)
```

```
t2 = torch.cat([a_tensor, a_tensor, a_tensor], dim=0)
print(t2)
```

```
tensor([[0, 1],
        [2, 3],
        [4, 5],
        [0, 1],
        [2, 3],
        [4, 5],
        [0, 1],
        [2, 3],
        [4, 5]], dtype=torch.int32)
```

Tensor Multiplication

- Matrix Multiplication

```
y1 = a_rand @ a_rand.T
y2 = a_rand.matmul(a_rand.T)

y3 = torch.rand(3,3)
torch.matmul(a_rand, a_rand.T, out=y3)

print(y1)
print(y2)
print(y3)
```

```
tensor([[0.4975, 0.3303, 0.3742],
        [0.3303, 0.2193, 0.2477],
        [0.3742, 0.2477, 0.3187]])
tensor([[0.4975, 0.3303, 0.3742],
        [0.3303, 0.2193, 0.2477],
        [0.3742, 0.2477, 0.3187]])
tensor([[0.4975, 0.3303, 0.3742],
        [0.3303, 0.2193, 0.2477],
        [0.3742, 0.2477, 0.3187]])
```

- Element-wise Multiplication

```
z1 = a_rand * a_rand
z2 = a_rand.mul(a_rand)

z3 = torch.rand(3,2)
torch.mul(a_rand, a_rand, out=z3)
print(z1)
print(z2)
print(z3)
```

```
tensor([[0.3922, 0.1053],
        [0.1714, 0.0479],
        [0.3133, 0.0053]])
tensor([[0.3922, 0.1053],
        [0.1714, 0.0479],
        [0.3133, 0.0053]])
tensor([[0.3922, 0.1053],
        [0.1714, 0.0479],
        [0.3133, 0.0053]])
```

Tensor Gradient

- Pytorch could automatically calculate the gradient of a tensor

```
# requires_grad=True tells PyTorch to store the gradient
x = torch.tensor([3.], requires_grad=True)

# Currently None since x is not connected to other tensors
print(x.grad)
```

```
None
```

```
# Calculating the gradient of y with respect to x
y = x * x  # y=x^2
y.backward()
print(x.grad) # d(y)/d(x) = d(x^2)/d(x) = 2x = 6
```

```
tensor([6.])
```

Tensor Gradient

- Gradients will be summed up before making an update

```
z = x * x * 5 # 5x^2
z.backward()
print(x.grad) #d(y)/d(x) + d(z)/d(x) = 2x + 10x = 36
```

```
tensor([36.])
```

- Reset gradient with `.grad.zero_()` or `optimizer.zero_grad()` during training

```
x.grad.zero_() # zero out the gradient
z = x * x * 5 # 5x^2
z.backward()
print(x.grad) #d(z)/d(x) = 10x = 30
```

```
tensor([30.])
```

Linear Layer

- Create a Linear Layer
  - Linear Layer performs the operation y=Ax+b
  - A and b are network parameters (weights) initialized randomly
  - If we do not need b, set the `bias=False`

```
input = torch.ones(32, 200)
# N,H_in -> N,H_out

# Make a linear layers transforming N, H_in dimensinal inputs to N, H_out
# dimensional outputs
linear = nn.Linear(200, 100)
linear_output = linear(input)
linear_output.shape
```

```
torch.Size([32, 100])
```

Linear Layer

- Create a Linear Layer
  - Linear Layer can also take 3D tensor as input

```
# Create the inputs
input = torch.ones(32,3,200)
# N, *, H_in -> N, *, H_out


# Take N,*,H_in dimensinal inputs and output N,*,H_out tensor
linear = nn.Linear(200, 100)
linear_output = linear(input)
linear_output.shape
```

Question: what is the shape of linear_output?

Linear Layer

- Create a Linear Layer
  - Linear Layer can also take 3D tensor as input

```
# Create the inputs
input = torch.ones(32,3,200)
# N, *, H_in -> N, *, H_out


# Take N,*,H_in dimensinal inputs and output N,*,H_out tensor
linear = nn.Linear(200, 100)
linear_output = linear(input)
linear_output.shape
```

```
torch.Size([32, 3, 100])
```

Linear Layer

- Shape of the network parameters A and b

```
linear = nn.Linear(200, 100)
A, b = list(linear.parameters())
print(A.shape)
print(b.shape)
```

Question: what is the shape of A and b?

Linear Layer

- Shape of the network parameters A and b

```
linear = nn.Linear(200, 100)
A, b = list(linear.parameters())
print(A.shape)
print(b.shape)
```

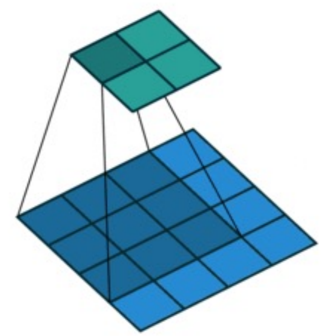
```
torch.Size([100, 200])
torch.Size([100])
```

Convolution Layer

- Convolution Layer
  - nn.Conv2d

```
input = torch.ones(32,3,100,100) # batch_size, channel, height, width
# Conv2d(in_channels, out_channels, kernel_size, stride, padding, kwargs)
# With square kernels and equal stride
m = nn.Conv2d(3, 16, 3, stride=2)
output = m(input)
print(output.shape)
```

```
torch.Size([32, 16, 49, 49])
```



blue map is input
green map is output

Figure from https://github.com/vdumoulin/conv_arithmetic

Activation Functions

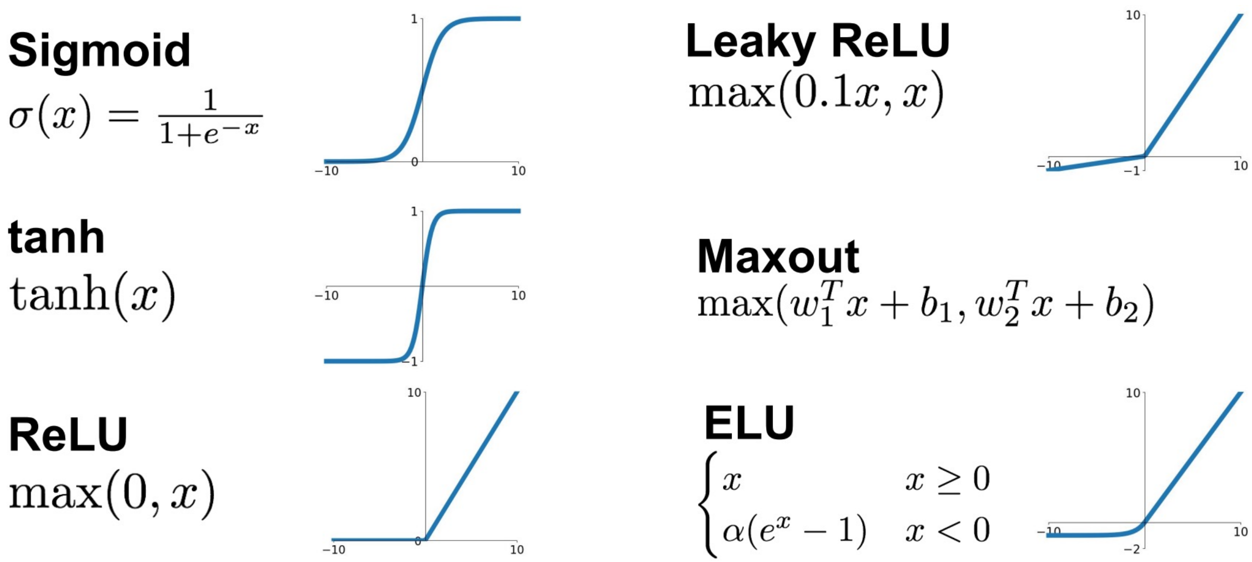


Figure from https://medium.com/@shrutijadon/survey-on-activation-functions-for-deep-learning-9689331ba092

Activation Functions

- Sigmoid Activation

```
print(linear_output.shape)
print(linear_output[0,0,0:20])
sigmoid = nn.Sigmoid()
sig_output = sigmoid(linear_output)
print(sig_output[0,0,0:20])
```

```
torch.Size([32, 3, 100])
tensor([ 0.1973, -0.1327,  1.2161,  0.5312, -1.1714,  0.1625, -0.1284, -0.1617,
         0.6658,  0.5343, -0.0825,  0.3412, -0.1179,  0.8846,  0.6028,  1.4662,
        -0.8332, -0.0781,  0.2253,  0.5549], grad_fn=<SliceBackward0>)
tensor([0.5492, 0.4669, 0.7714, 0.6298, 0.2366, 0.5405, 0.4679, 0.4597, 0.6606,
        0.6305, 0.4794, 0.5845, 0.4706, 0.7078, 0.6463, 0.8125, 0.3030, 0.4805,
        0.5561, 0.6353], grad_fn=<SliceBackward0>)
```

Notice that the **range** of sig_output and linear_output is different!

Build the Neural Network

- __init__()
  - Declare the layers to use

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

This example is from https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

Build the Neural Network

- __init__()
  - Declare the layers to use
- forward()
  - Construct the network

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
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        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

Define Loss function and Optimizer

- For classification tasks, it is common to use cross entropy loss
- Common optimizers are Stocastic Gradient Descent (SGD) and Adam

```
net = Net()
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

Load and Normalize the Dataset

- Define transformation

```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
```

- Load the dataset

```
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                          shuffle=True, num_workers=2)
```

Prepare the inputs and GTs **one sample** at a time

Collect the inputs and GTs into **minibatches**

Load and Normalize the Dataset

- Define transformation

```
transform = transforms.Compose(
    [transforms.ToTensor(),
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```

- Load the dataset

```
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                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                          shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=4,
                                         shuffle=False, num_workers=2)
```

Custom Dataset

- Pytorch has pre-defined classes for benchmark datasets

```
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
```

- To process your own data, you need to write a custom dataset class

```
from torch.utils.data.dataset import Dataset

class MyCustomDataset(Dataset):
    def __init__(self, ...):
        # stuff

    def __getitem__(self, index):
        # stuff
        return (img, label)

    def __len__(self):
        return count # of how many examples(images?) you have
```

Custom Dataset Example

```python
class LandmarkDataset(Dataset):
    def __init__(self, image_paths, transform=False):
        self.image_paths = image_paths
        self.transform = transform

    def __len__(self):
        return len(self.image_paths)

    def __getitem__(self, idx):
        image_filepath = self.image_paths[idx]
        image = cv2.imread(image_filepath)
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

        label = image_filepath.split('/')[-2]
        label = class_to_idx[label]
        if self.transform is not None:
            image = self.transform(image=image)["image"]

        return image, label
```

```python
#######################################################
#                  Create Dataset
#######################################################

train_dataset = LandmarkDataset(train_image_paths,train_transforms)
valid_dataset = LandmarkDataset(valid_image_paths,test_transforms)
test_dataset = LandmarkDataset(test_image_paths,test_transforms)
```

This example is from https://towardsdatascience.com/custom-dataset-in-pytorch-part-1-images-2df3152895

Train the Network

```
for epoch in range(2):  # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999:    # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

Train the Network

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                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

Save and Load Model

- Save model weights
  - Model weights are stored in an internal state dictionary

```
torch.save(model.state_dict(), 'model_weights.pth')
```

- Load model weights

```
model.load_state_dict(torch.load('model_weights.pth'))
model.eval()
```

Summary: Essential Components

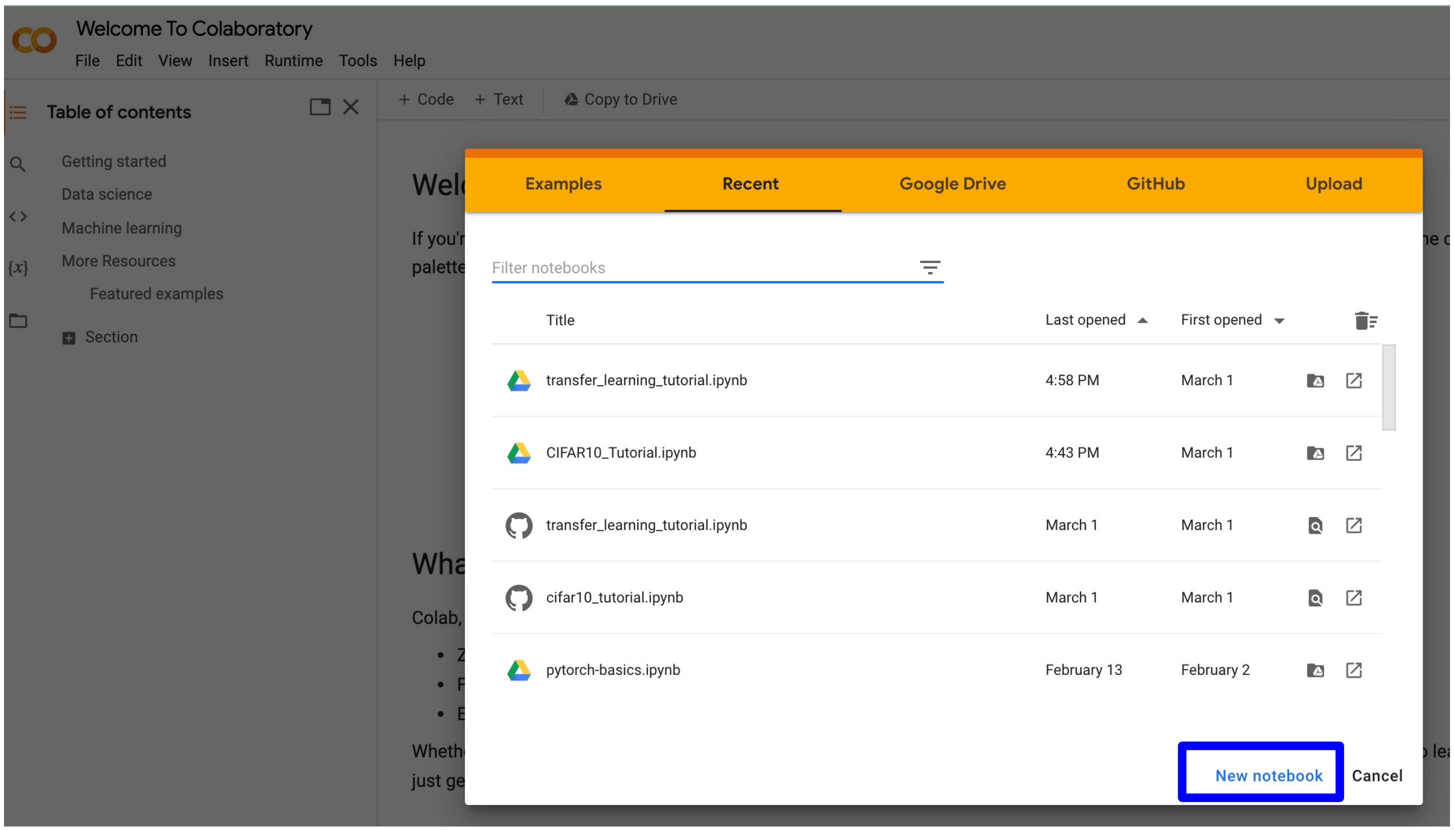
- Dataset
- Model
- Loss function
- Optimizer

Jupyter notebook Tutorials

- CIFAR-10 Tutorial:
  - https://yaoyichi.github.io/spatial-ai/lab/CIFAR10_Tutorial.ipynb
- Transfer Learning Tutorial
  - https://yaoyichi.github.io/spatial-ai/lab/transfer_learning_tutorial.ipynb

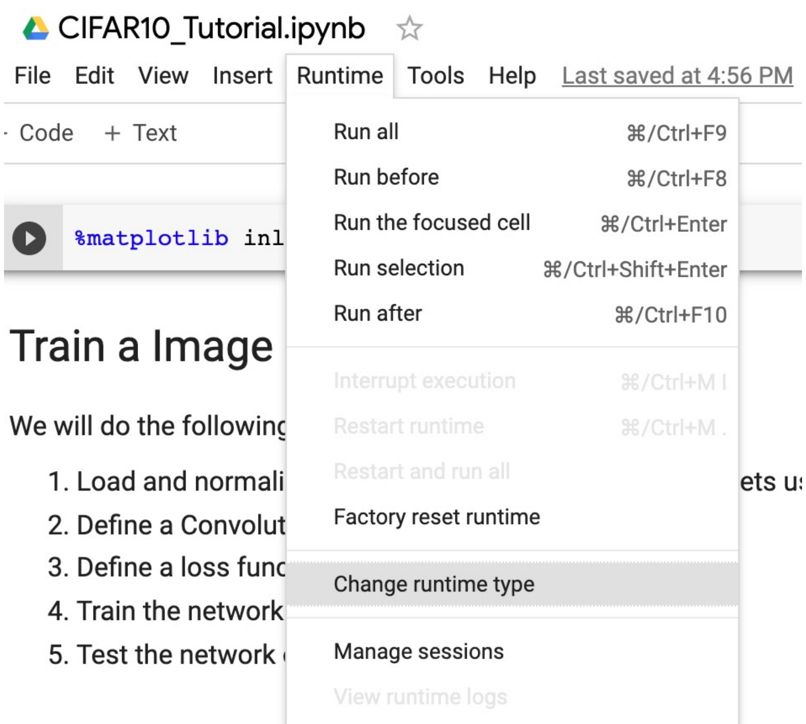
How to use Google Colab?

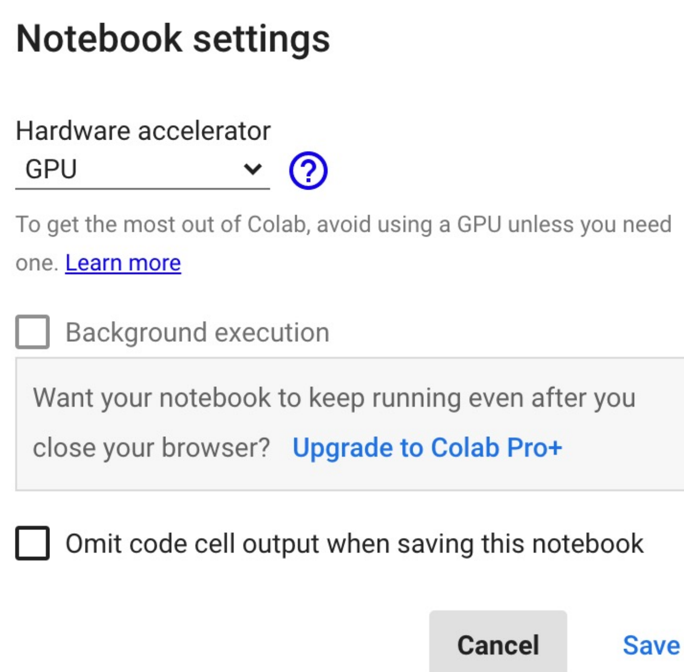
Go to https://colab.research.google.com/, click New notebook to create a live jupyter notebook instance



How to use Google Colab?

To enable GPU, go to *Runtime-> Change runtime type*, set the *Hardware accelerator* to be GPU.





Acknowledgement

- Some materials are adapted from
  - Pytorch official tutorial
  - Stanford CS231N course
  - Stanford CS224N course