LAB 1: MNIST

MNIST digit recognition using deep neural network

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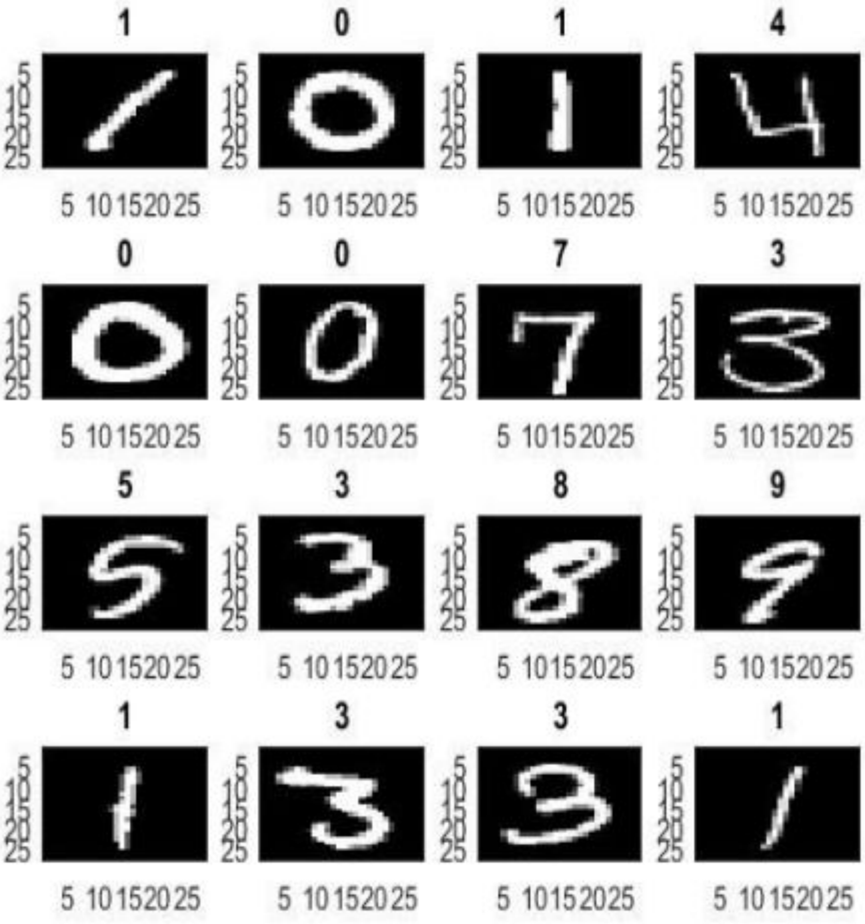
Introduction

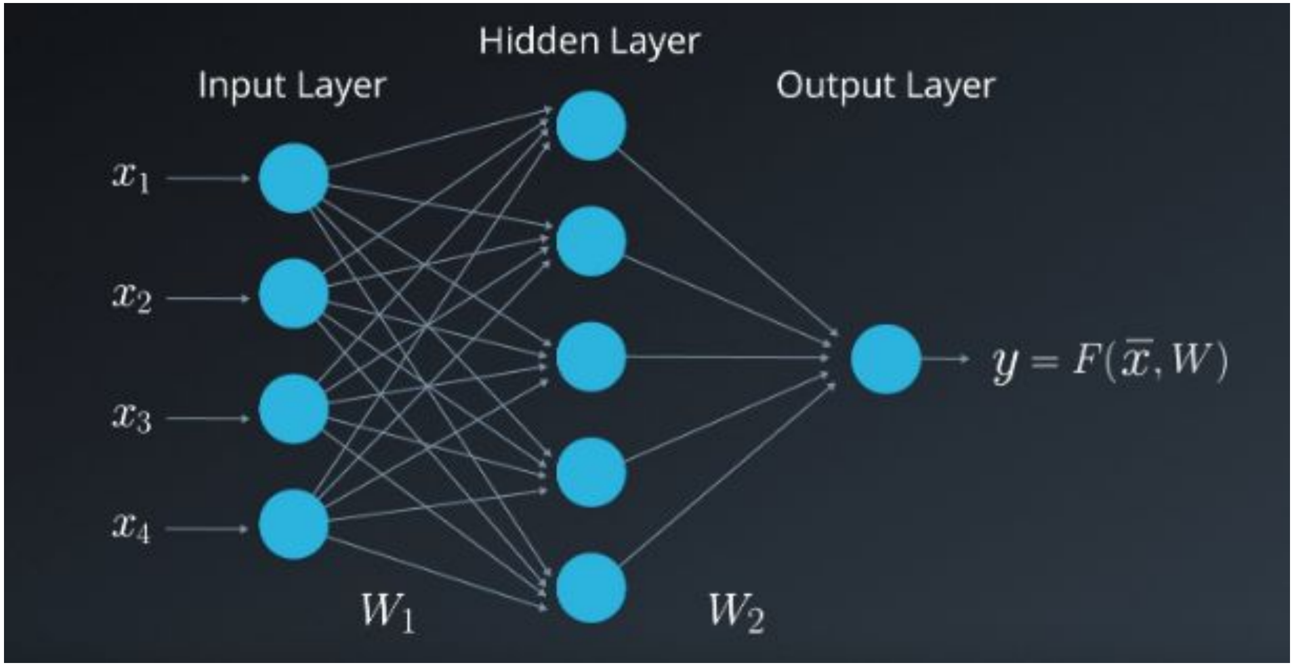
MNIST — Basic

- MNIST: Large hand written digit classification database
- Format
  - Input: 28 x 28 gray scale image
  - Output: 10 labels(0-9)
  - Centered on center of the mass



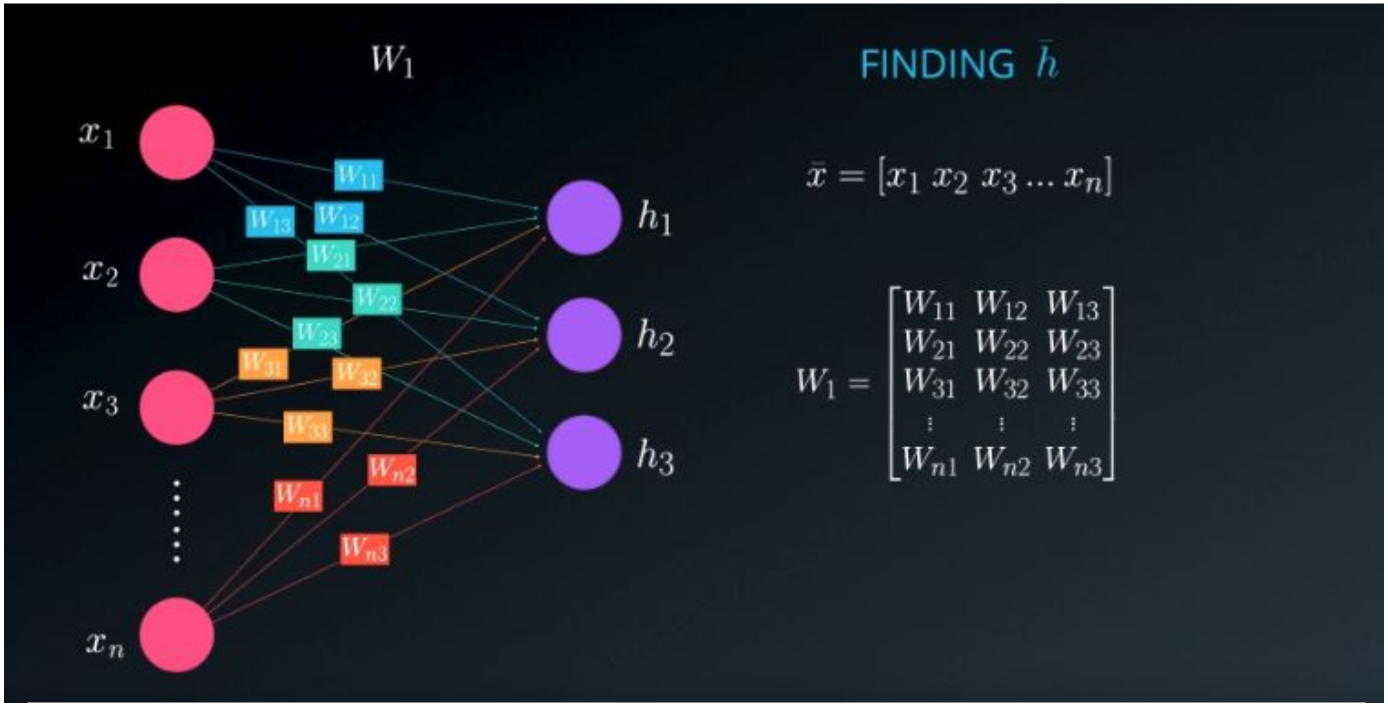
Multi-layer perceptron

- Layer 1: Input layer. – (28^2 x 1) dimension
- Layer 2: Hidden layer. – Multi-layer perceptron
- Layer 3: Output layer. – 10 labels(0-9)



Introduction

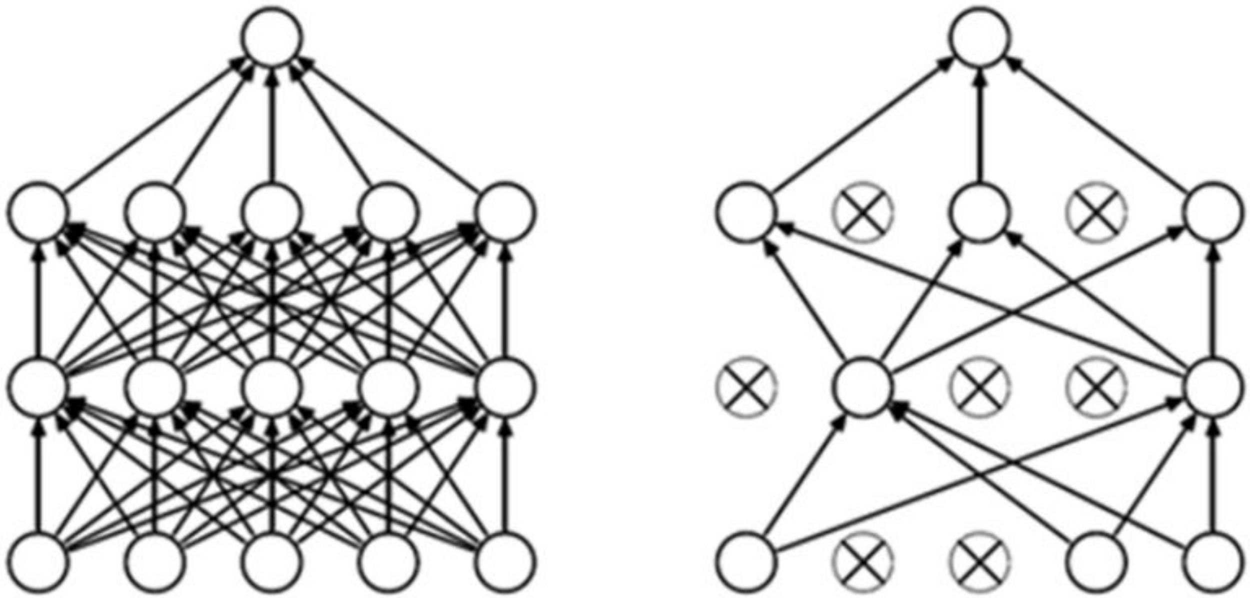
Multi-layer perceptron



$$[h'_1 \quad h'_2 \quad h'_3] = [x_1 \quad x_2 \quad x_3 \quad \ldots\ldots \quad x_n] \cdot \begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \\ \vdots & & \\ W_{n1} & W_{n2} & W_{n3} \end{bmatrix}$$

Multi-layer perceptron – dropout

- One of the biggest problems of deep learning is overfitting to training data.
- The dropout is a learning method using only a part of deep ne
- We can partially solve the overfitting problem through dropout method.



(a) Standard Neural Net (b) After applying dropout.

Assignment - 1

Pytorch MLP Basic – nn.Linear

CLASS `torch.nn.Linear(in_features: int, out_features: int, bias: bool = True)` [SOURCE]

Applies a linear transformation to the incoming data: $y = xA^T + b$

Parameters

- **in_features** – size of each input sample
- **out_features** – size of each output sample
- **bias** – If set to `False`, the layer will not learn an additive bias. Default: `True`

Shape:

- Input: $(N, *, H_{in})$ where $*$ means any number of additional dimensions and $H_{in} = \text{in\_features}$
- Output: $(N, *, H_{out})$ where all but the last dimension are the same shape as the input and $H_{out} = \text{out\_features}$.

Variables

- **~Linear.weight** – the learnable weights of the module of shape $(\text{out\_features}, \text{in\_features})$. The values are initialized from $\mathcal{U}(-\sqrt{k}, \sqrt{k})$, where $k = \frac{1}{\text{in\_features}}$
- **~Linear.bias** – the learnable bias of the module of shape (out_features). If `bias` is `True`, the values are initialized from $\mathcal{U}(-\sqrt{k}, \sqrt{k})$ where $k = \frac{1}{\text{in\_features}}$

Assignment - 1

Pytorch MLP Basic – nn.Dropout

CLASS `torch.nn.Dropout(p: float = 0.5, inplace: bool = False)` [SOURCE]

During training, randomly zeroes some of the elements of the input tensor with probability `p` using samples from a Bernoulli distribution. Each channel will be zeroed out independently on every forward call.

This has proven to be an effective technique for regularization and preventing the co-adaptation of neurons as described in the paper Improving neural networks by preventing co-adaptation of feature detectors .

Furthermore, the outputs are scaled by a factor of $\frac{1}{1-p}$ during training. This means that during evaluation the module simply computes an identity function.

Parameters

- **p** – probability of an element to be zeroed. Default: 0.5
- **inplace** – If set to `True`, will do this operation in-place. Default: `False`

Shape:

- Input: $(*)$. Input can be of any shape
- Output: $(*)$. Output is of the same shape as input

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Dataset preparation

```
batch_size = 32

kwargs = {'num_workers': 1, 'pin_memory': True} if cuda else {}

train_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=True, download=True,
                   transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
    batch_size=batch_size, shuffle=True, **kwargs)

validation_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=False, transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
    batch_size=batch_size, shuffle=False, **kwargs)
```

- Load MINIST dataset using data loader
- Input size: 28 x 28 gray scale image
- Output: classes of (“0”, .. “9”) for each training digit

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Network definition class

```python
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(28*28, 50)
        self.fc1_drop = nn.Dropout(0.2)
        self.fc2 = nn.Linear(50, 50)
        self.fc2_drop = nn.Dropout(0.2)
        self.fc3 = nn.Linear(50, 10)

    def forward(self, x):
        x = x.view(-1, 28*28)
        x = F.relu(self.fc1(x))
        x = self.fc1_drop(x)
        x = F.relu(self.fc2(x))
        x = self.fc2_drop(x)
        return F.log_softmax(self.fc3(x))
```

Network definition

Feed forward of input data

Activation function

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Training

```python
def train(epoch, log_interval=100):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        if cuda:
            data, target = data.cuda(), target.cuda()
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]₩tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))
```

Get output

Calculate loss

Backpropagation using optimizer

Print training log

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Validation

```python
def validate(loss_vector, accuracy_vector):
    model.eval()
    val_loss, correct = 0, 0
    for data, target in validation_loader:
        if cuda:
            data, target = data.cuda(), target.cuda()
        data, target = Variable(data, volatile=True), Variable(target)
        output = model(data)
        val_loss += F.nll_loss(output, target).data[0]
        pred = output.data.max(1)[1] # get the index of the max log-probability
        correct += pred.eq(target.data).cpu().sum()

    val_loss /= len(validation_loader)
    loss_vector.append(val_loss)

    accuracy = 100. * correct / len(validation_loader.dataset)
    accuracy_vector.append(accuracy)

    print('₩nValidation set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)₩n'.format(
        val_loss, correct, len(validation_loader.dataset), accuracy))
```

Calculate validation loss

Calculate accuracy of validation set

Print log of accuracy of validation set

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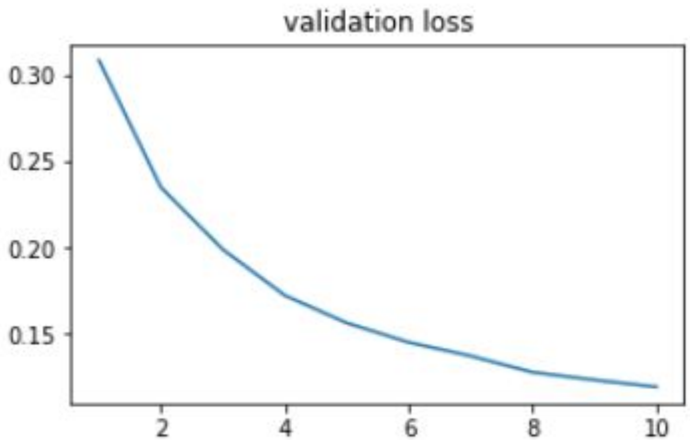
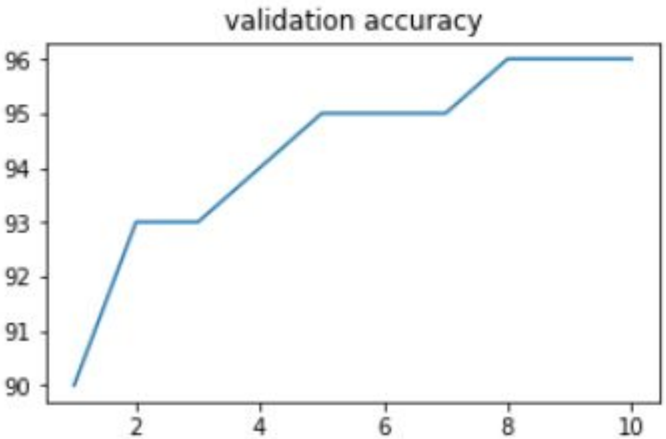
```
plt.figure(figsize=(5,3))
plt.plot(np.arange(1,epochs+1), lossv)
plt.title('validation loss')

plt.figure(figsize=(5,3))
plt.plot(np.arange(1,epochs+1), accv)
plt.title('validation accuracy');
```

Plot the loss and accuracy graph
We can visualize the performance and the loss of our network in validation sets.





MNIST with Simple CNN

CONV2D

CLASS `torch.nn.Conv2d(in_channels: int, out_channels: int, kernel_size: Union[T, Tuple[T, T]], stride: Union[T, Tuple[T, T]] = 1, padding: Union[T, Tuple[T, T]] = 0, dilation: Union[T, Tuple[T, T]] = 1, groups: int = 1, bias: bool = True, padding_mode: str = 'zeros')` [SOURCE]

Parameters

- **in_channels** (*int*) – Number of channels in the input image
- **out_channels** (*int*) – Number of channels produced by the convolution
- **kernel_size** (*int or tuple*) – Size of the convolving kernel
- **stride** (*int or tuple, optional*) – Stride of the convolution. Default: 1
- **padding** (*int or tuple, optional*) – Zero-padding added to both sides of the input. Default: 0
- **padding_mode** (*string, optional*) – `'zeros'`, `'reflect'`, `'replicate'` or `'circular'`. Default: `'zeros'`
- **dilation** (*int or tuple, optional*) – Spacing between kernel elements. Default: 1
- **groups** (*int, optional*) – Number of blocked connections from input channels to output channels. Default: 1
- **bias** (*bool, optional*) – If `True`, adds a learnable bias to the output. Default: `True`

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MNIST with Simple CNN

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where

$$H_{out} = \left\lfloor \frac{H_{in} + 2 \times \text{padding}[0] - \text{dilation}[0] \times (\text{kernel\_size}[0] - 1) - 1}{\text{stride}[0]} + 1 \right\rfloor$$

$$W_{out} = \left\lfloor \frac{W_{in} + 2 \times \text{padding}[1] - \text{dilation}[1] \times (\text{kernel\_size}[1] - 1) - 1}{\text{stride}[1]} + 1 \right\rfloor$$

Examples

```
>>> # With square kernels and equal stride
>>> m = nn.Conv2d(16, 33, 3, stride=2)
>>> # non-square kernels and unequal stride and with padding
>>> m = nn.Conv2d(16, 33, (3, 5), stride=(2, 1), padding=(4, 2))
>>> # non-square kernels and unequal stride and with padding and dilation
>>> m = nn.Conv2d(16, 33, (3, 5), stride=(2, 1), padding=(4, 2), dilation=(3, 1))
>>> input = torch.randn(20, 16, 50, 100)
>>> output = m(input)
```

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MNIST with Simple CNN

MAXPOOL2D

CLASS `torch.nn.MaxPool2d(kernel_size: Union[T, Tuple[T, ...]], stride: Optional[Union[T, Tuple[T, ...]]] = None, padding: Union[T, Tuple[T, ...]] = 0, dilation: Union[T, Tuple[T, ...]] = 1, return_indices: bool = False, ceil_mode: bool = False)` [SOURCE]

Applies a 2D max pooling over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C, H, W), output (N, C, H_{out}, W_{out}) and `kernel_size` (kH, kW) can be precisely described as:

$$out(N_i, C_j, h, w) = \max_{m=0,\ldots,kH-1} \max_{n=0,\ldots,kW-1} \text{input}(N_i, C_j, \text{stride}[0] \times h + m, \text{stride}[1] \times w + n)$$

If `padding` is non-zero, then the input is implicitly zero-padded on both sides for `padding` number of points. `dilation` controls the spacing between the kernel points. It is harder to describe, but this link has a nice visualization of what `dilation` does.

The parameters `kernel_size`, `stride`, `padding`, `dilation` can either be:

- a single `int` – in which case the same value is used for the height and width dimension
- a `tuple` of two ints – in which case, the first *int* is used for the height dimension, and the second *int* for the width dimension

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MNIST with Simple CNN

Shape:

- Input: (N, C, H_{in}, W_{in})
- Output: (N, C, H_{out}, W_{out}), where

$$H_{out} = \left\lfloor \frac{H_{in} + 2 * \text{padding}[0] - \text{dilation}[0] \times (\text{kernel\_size}[0] - 1) - 1}{\text{stride}[0]} + 1 \right\rfloor$$

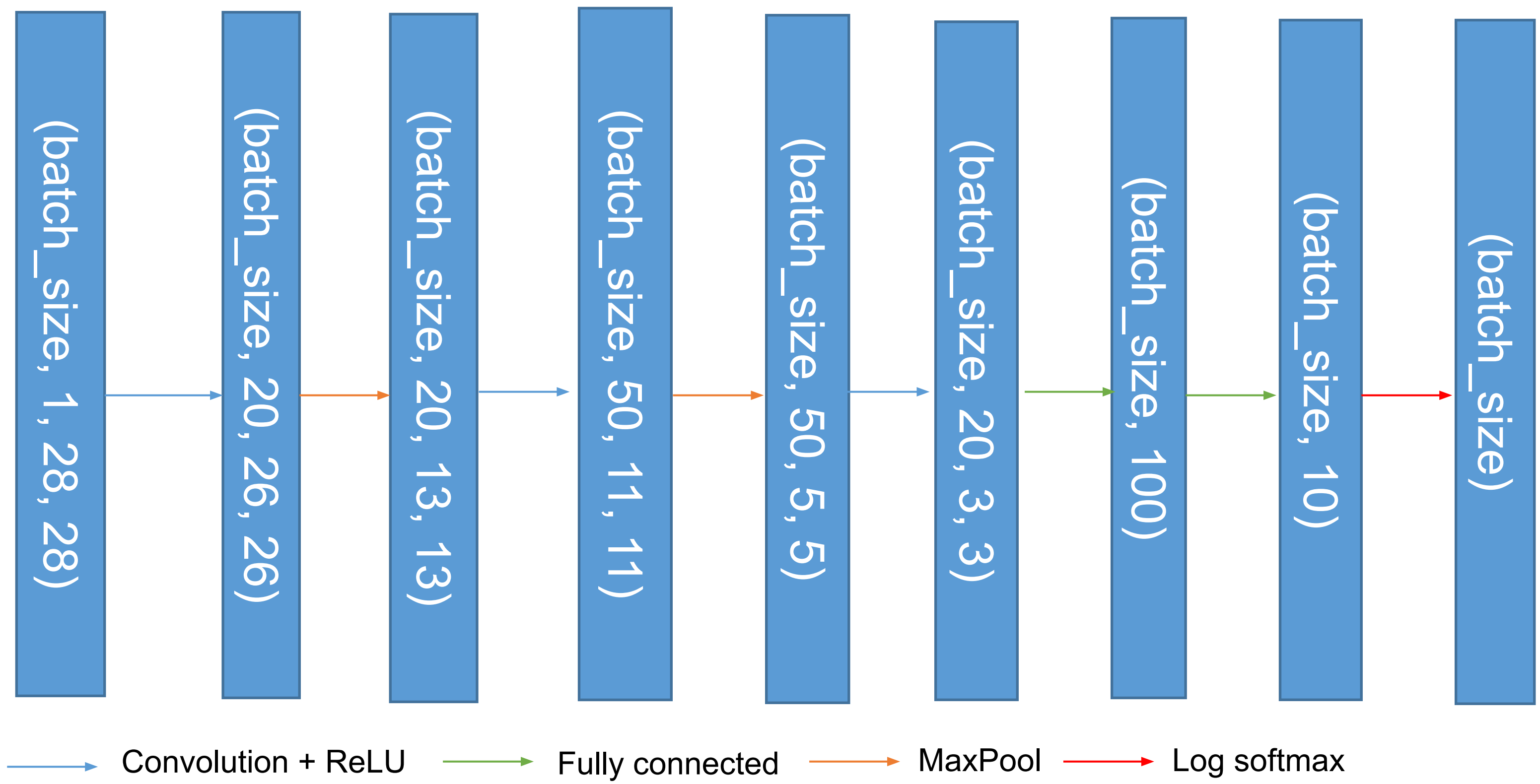
$$W_{out} = \left\lfloor \frac{W_{in} + 2 * \text{padding}[1] - \text{dilation}[1] \times (\text{kernel\_size}[1] - 1) - 1}{\text{stride}[1]} + 1 \right\rfloor$$

Examples:

```
>>> # pool of square window of size=3, stride=2
>>> m = nn.MaxPool2d(3, stride=2)
>>> # pool of non-square window
>>> m = nn.MaxPool2d((3, 2), stride=(2, 1))
>>> input = torch.randn(20, 16, 50, 32)
>>> output = m(input)
```

Assignment - 2

MNIST with Simple CNN

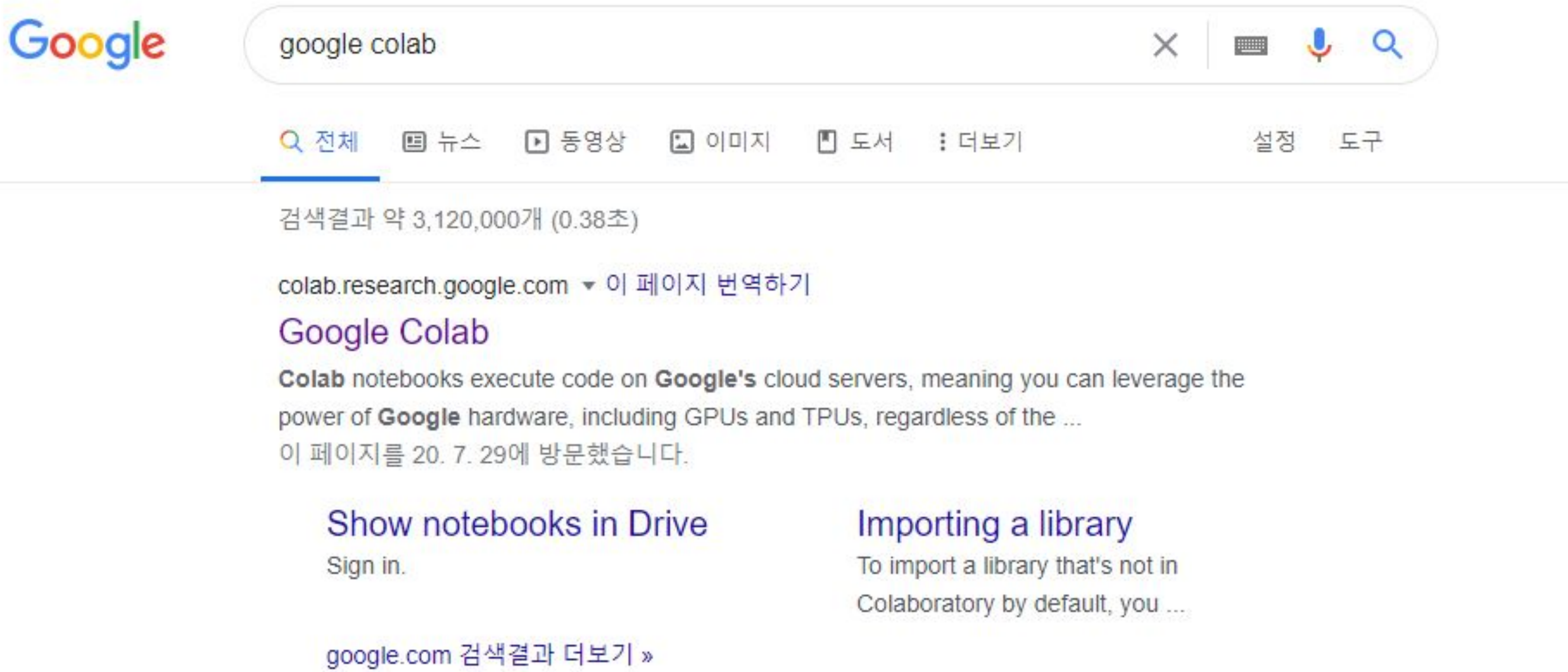


Caution: when you use construct CNN, do not use stride or padding size, Just use proper kernel size to match dimension

MNIST with VGG like-CNN

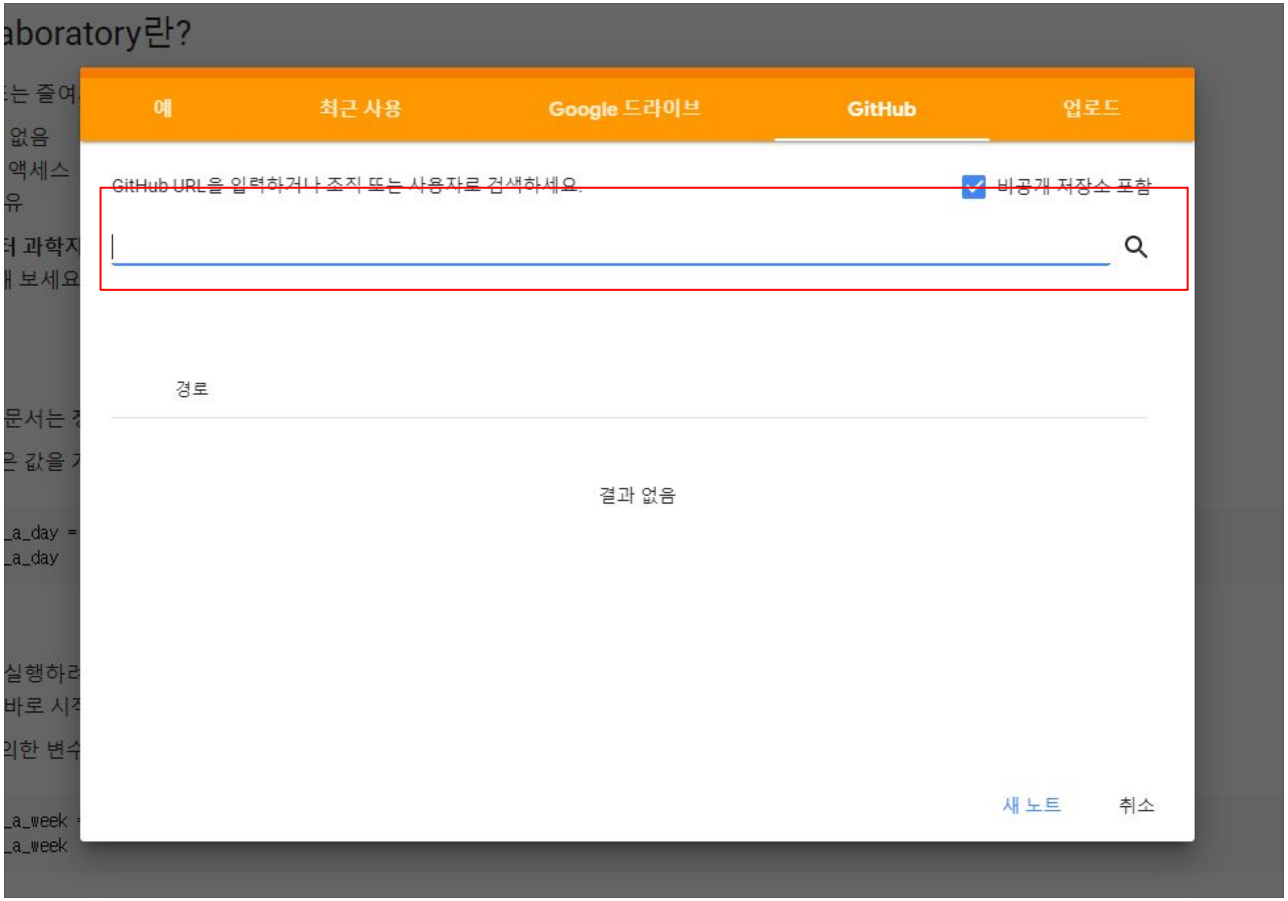
layer	output dimension	layer	output dimension
0	(batch_size, 1, 28, 28)	13 - Linear1	(batch_size,100)
1 - Conv + ReLU	(batch_size, 64, 30, 30)	14 - Dropout	(batch_size,100)
2 - max pooling 2D(2x2)	(batch_size, 64, 15, 15)	15 - Linear2	(batch_size,100)
3 - Conv + ReLU	(batch_size, 128, 17, 17)	16 - Dropout	(batch_size,10)
4 - max pooling 2D(2x2)	(batch_size, 128, 8, 8)	17 - Linear3	(batch_size)
5 - Conv + Conv + ReLU	(batch_size, 256, 10, 10)		
7 - max pooling 2D(2x2)	(batch_size, 256, 5, 5)		
8 - Conv + Conv + ReLU	(batch_size, 512, 5, 5)		
9 - max pooling 2D(2x2)	(batch_size, 512, 2, 2)		
10 - Conv + Conv + ReLU	(batch_size, 512, 2, 2)		
11 - max pool 2D(2x2)	(batch_size, 512, 1, 1)		
12 - stretch tensor	(batch_size, 512)		

Enter the colab



Colab 사용법

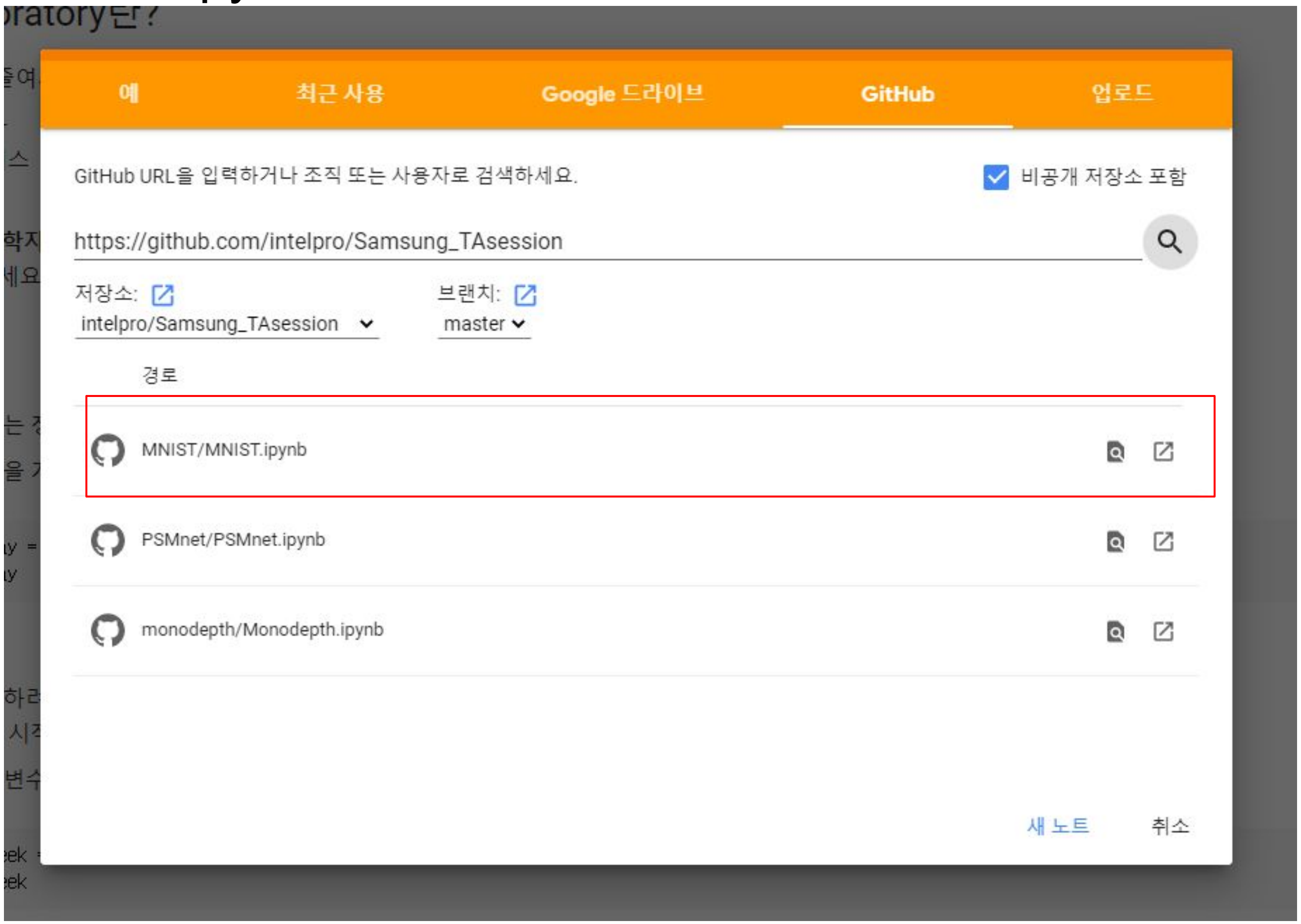
Enter the colab + 아래의 주소를 입력한다.



https://github.com/intelpro/Samsung_TAsession

Colab 사용법

MNIST.ipynb 클릭



Colab 사용법

런타임 -> 런타임 유형 변경 -> 하드웨어 가속기(GPU)