

COMP90051

Statistical Machine Learning

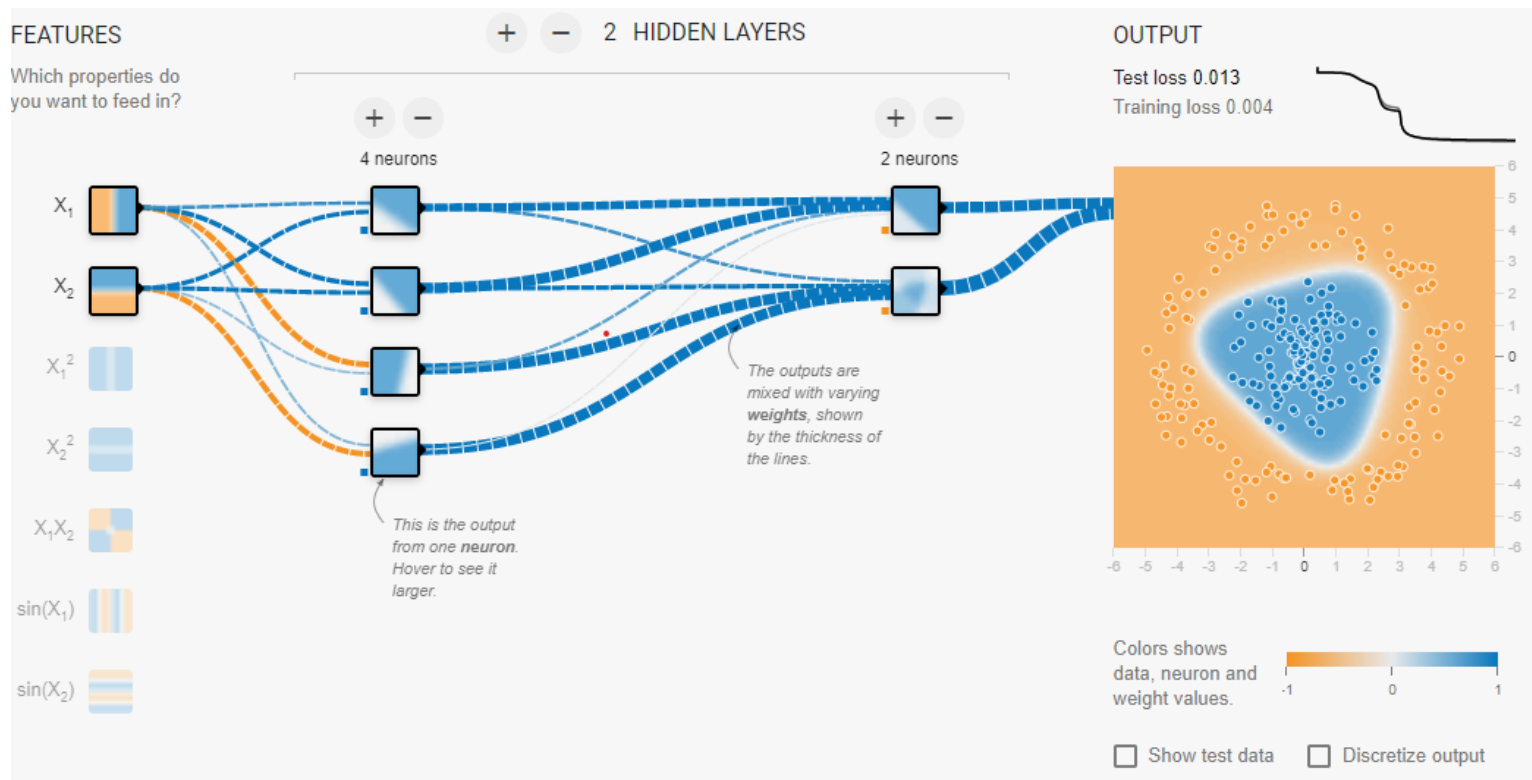
Workshop Week 7

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https://github.com/HanXudong/COMP90051_2020_S1

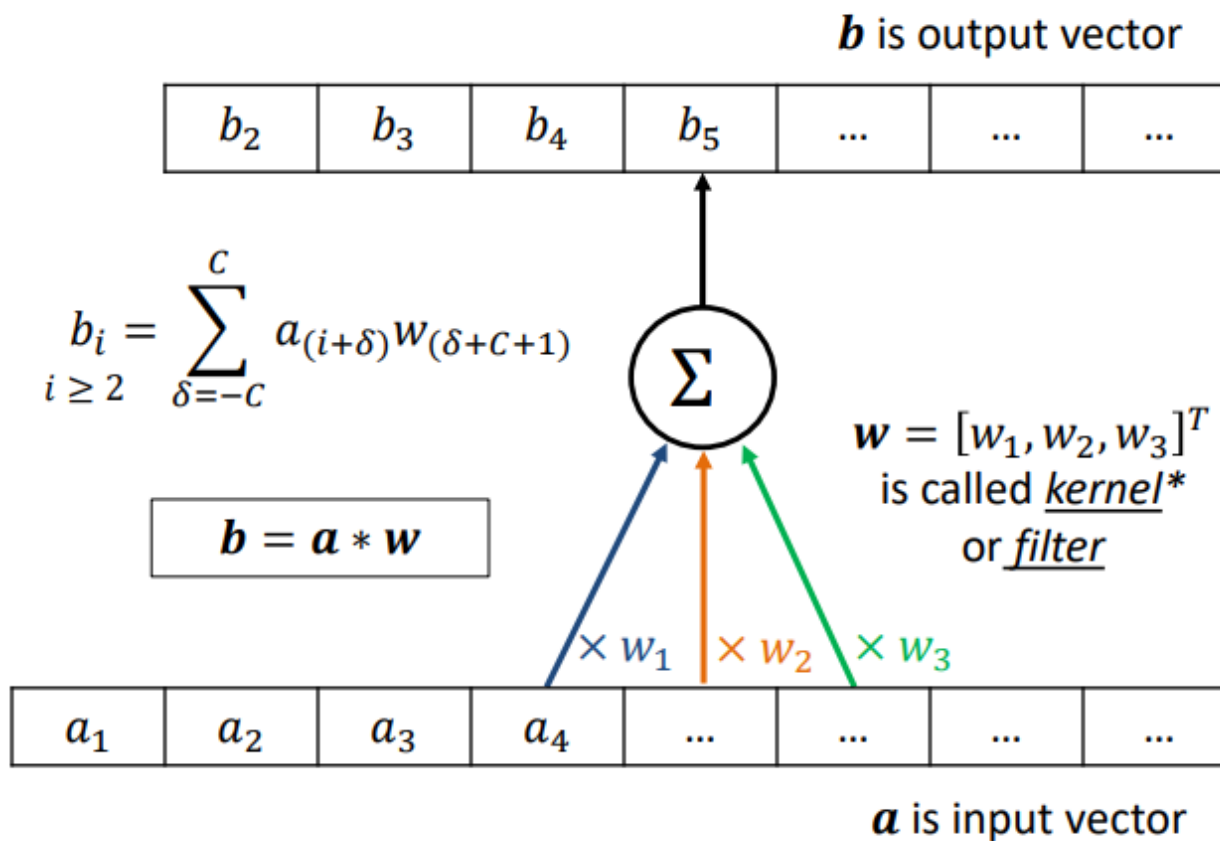
Computational Model

- <https://playground.tensorflow.org>



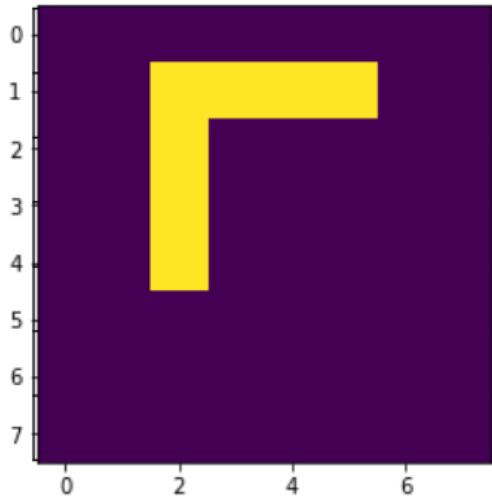
Model Design in PyTorch

Convolutional Neural Networks



Idea of filters

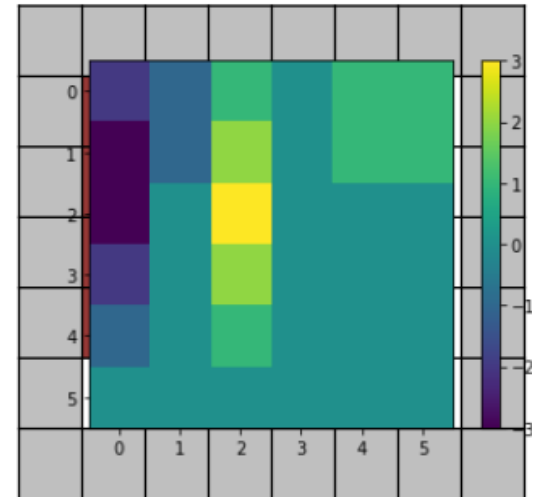
Filters are learned from training data!



Filters/Kernels

-1	0	1
-1	0	1
-1	0	1

Patterns/Features



1	1	1
0	0	0
-1	-1	-1

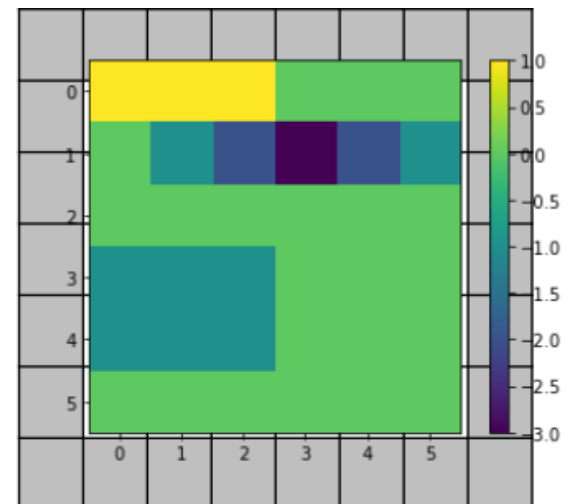


Image Classification on CIFAR-10

<https://www.cs.toronto.edu/~kriz/cifar.html>

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



Model design with torch.nn.Module

- Implement the constructor `__init__(self, ...)`. Here we define all network parameters.
- Override the forward method `forward(self, x)`. This accepts the input tensor `x` and returns our desired model output.
- Provided your operations are autograd-compliant, the backward pass is implemented **automatically** as PyTorch walks the computational graph backward.

```

import torch.nn as nn
import torch.nn.functional as F

class LogisticRegressionModel(nn.Module):

    def __init__(self, n_features, n_classes):
        super(LogisticRegressionModel, self).__init__()

        # Register weight matrix and bias term as model parameters - automatically tracks operations for gradient computation
        self.W = torch.nn.Parameter(torch.nn.init.xavier_uniform_(torch.empty([n_features, n_classes]))) # Weights
        self.b = torch.nn.Parameter(torch.zeros([n_classes])) # Biases

    def forward(self, x):
        """
        Forward pass for logistic regression.
        Input: Tensor x of shape [N,C,H,W]
        Output: Logits W @ x + b
        """
        batch_size = x.shape[0]

        x = x.view(batch_size, -1) # Flatten image into vector, retaining batch dimension
        out = torch.matmul(x, self.W) + self.b # Compute scores
        return out

```

```
def train(model, train_loader, test_loader, optimizer, n_epochs=10):  
    """  
    Generic training loop for supervised multiclass learning  
    """  
  
    LOG_INTERVAL = 250  
    running_loss, running_accuracy = list(), list()  
    start_time = time.time()  
    criterion = torch.nn.CrossEntropyLoss()  
  
    for epoch in range(n_epochs): # Loop over training dataset `n_epochs` times  
  
        epoch_loss = 0.  
  
        for i, data in enumerate(train_loader): # Loop over elements in training set  
  
            x, labels = data  
  
            logits = model(x)  
  
            predictions = torch.argmax(logits, dim=1)  
            train_acc = torch.mean(torch.eq(predictions, labels).float()).item()  
  
            loss = criterion(input=logits, target=labels)  
  
            loss.backward() # Backward pass (compute parameter gradients)  
            optimizer.step() # Update weight parameter using SGD  
            optimizer.zero_grad() # Reset gradients to zero for next iteration
```


Convolutional Networks

- Convolutional Layer #1 | 8 5×5 filters with a stride of 1, ReLU activation function.
- Max Pooling #1 | Kernel size 2 with a stride of 1.
- Convolutional Layer #2 | 16 5×5 filters with a stride of 1, ReLU activation function.
- Max Pooling #2 | Kernel size 2 with a stride of 1.
- Fully Connected Layer #1 | 400 input units (flattened convolutional output), 256 output units.
- Fully Connected Layer #2 | 256 input units, 10 output units - yields logits for classification.

```
OUT_C1 = 8
OUT_C2 = 16
DENSE_UNITS = 256
```

```
class BasicConvNet(nn.Module):
    def __init__(self, out_c1, out_c2, dense_units, n_classes=10):
        super(BasicConvNet, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=out_c1, kernel_size=5)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(in_channels=out_c1, out_channels=out_c2, kernel_size=5)
        self.fc1 = nn.Linear(16 * 5 * 5, dense_units)
        self.logits = nn.Linear(dense_units, n_classes)

    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))
        out = self.logits(x)
        return out
```

```
conv2D_model = BasicConvNet(OUT_C1, OUT_C2, DENSE_UNITS)
```

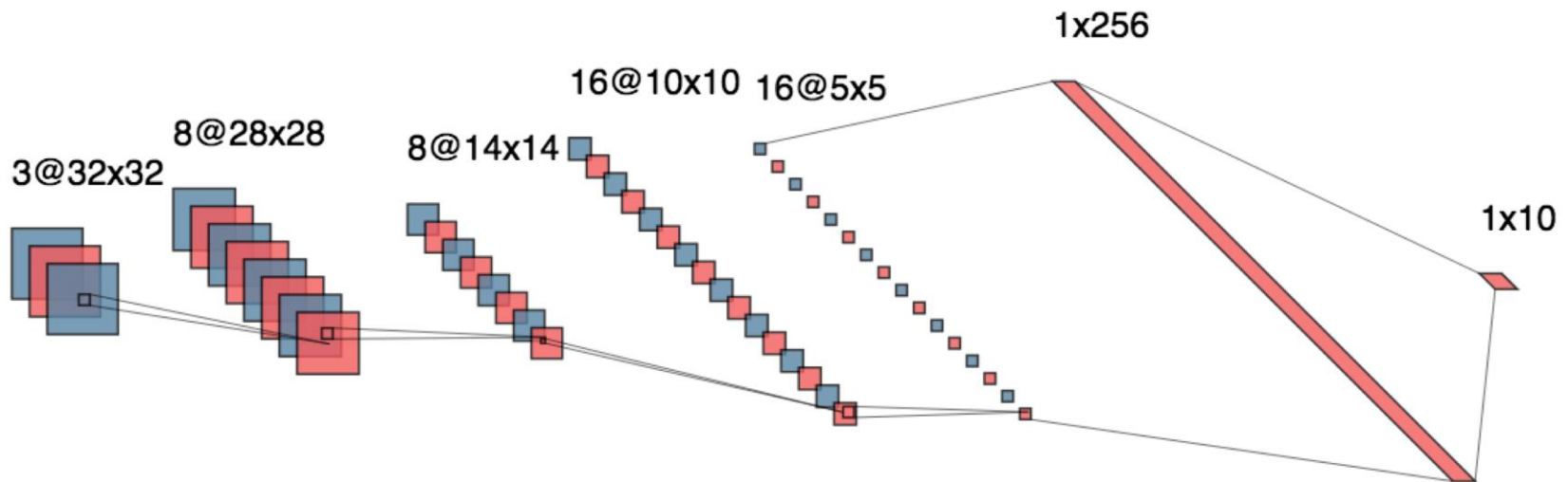
Downsampling Max-Pool

1	2	3	4
1	3	2	5
3	2	1	5
2	4	5	3

kernel_size=2, stride=2

3	5
4	5

Calculate the number of parameters



Convolution I Max-Pool Convolution II Max-Pool Dense

Convolution I: $3 \times 8 \times 5 \times 5 + 8$

<https://pytorch.org/docs/stable/nn.html#torch.nn.Conv2d>

Dense I: $16 \times 5 \times 5 \times 256 + 256$

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) \star \text{input}(N_i, k)$$

where \star is the valid 2D **cross-correlation** operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

For a certain output channel

- 1 bias term
- 1 kernel for each input channel
- Kernels (aka filters) are learned from data (have parameters).

Our example

- Input channel 3, kernel size 5x5, for each output channel, there are $3 \times 5 \times 5 + 1$ parameters.

Autoencoders

