COMP90051 Statistical Machine Learning

Workshop Week 6

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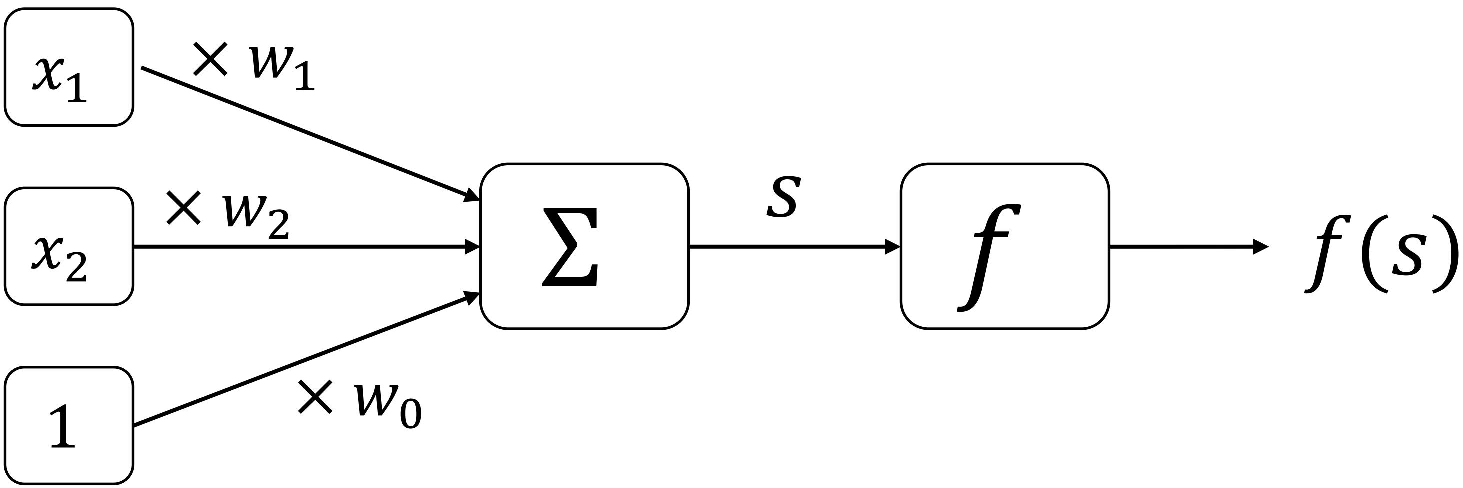
https://github.com/HanXudong/COMP90051_2020_S1

Review of the perceptron



- $f(s) = \begin{cases} 1 & \text{if s} \geq 0, \\ -1 & \text{otherwise} \end{cases}$

Perceptron training algorithm

PERCEPTRON($\mathbf{w}_0$)

$\mathbf{w}_1 \leftarrow \mathbf{w}_0$ $\quad \triangleright$ typically $\mathbf{w}_0 = \mathbf{0}$

for $t \leftarrow 1$ **to** T **do**

  RECEIVE($\mathbf{x}_t$)

  $\widehat{y}_t \leftarrow \text{sgn}(\mathbf{w}_t \cdot \mathbf{x}_t)$

  RECEIVE(y_t)

  if $(\widehat{y}_t \neq y_t)$ **then**

    $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_t \mathbf{x}_t$ $\quad \triangleright$ more generally $\eta y_t \mathbf{x}_t, \eta > 0$.

  else $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t$

return $\mathbf{w}_{T+1}$

Pytorch

- Pytorch is an open-source Python library designed for fast matrix computations on CPU/GPU. This includes both standard linear algebra and deep learning-specific operations. It is based on the neural network backend of the Torch library. A central feature of Pytorch is its use of Automatic on-the-fly differentiation (Autograd) to compute derivatives of (almost) all computations involving tensors, so we can make use of gradient-based updates to optimize some objective function. In this workshop we will introduce some fundamental operations in Pytorch and reimplement the Perceptron and logistic regression classifiers in Pytorch.

Computational Model

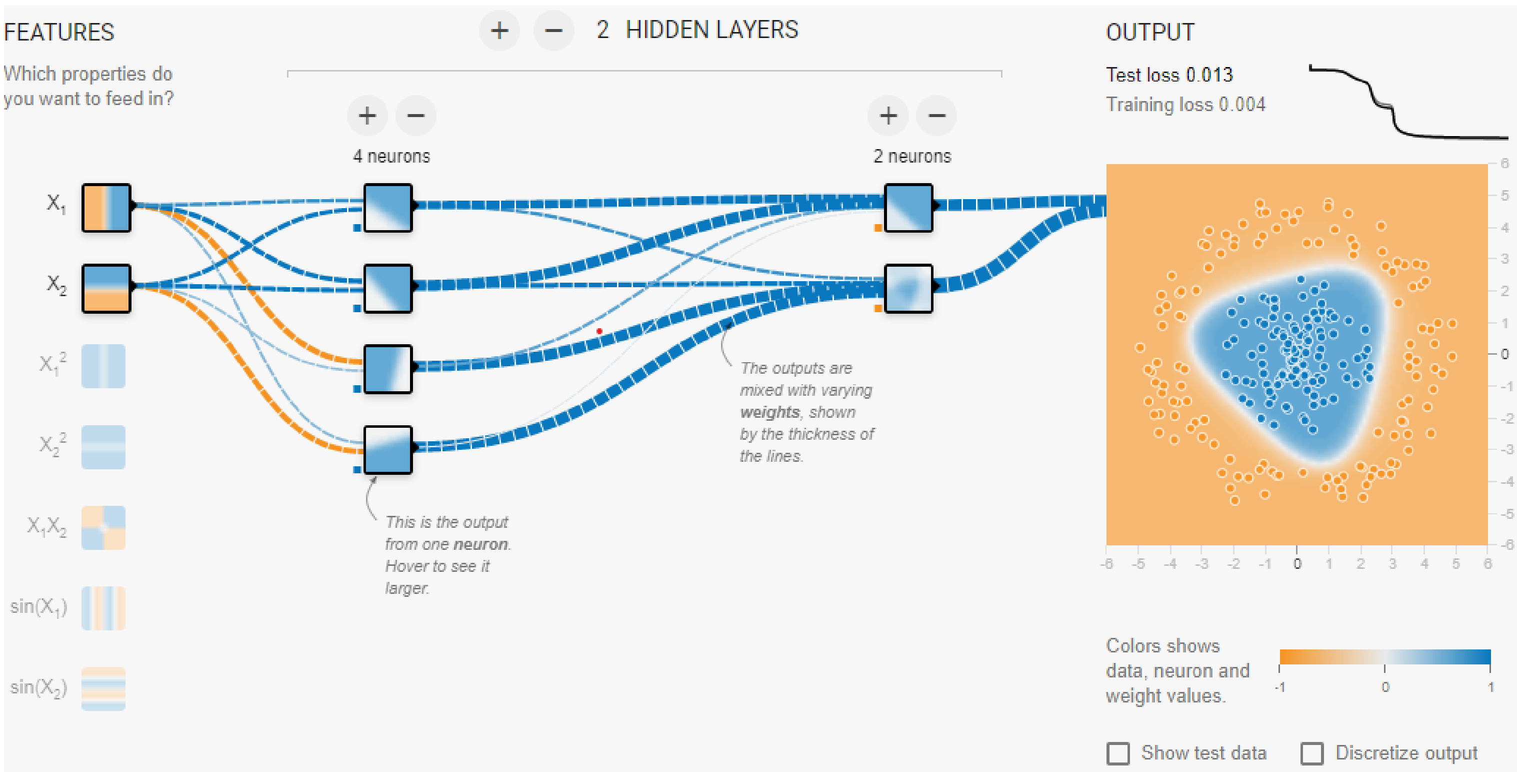
- TensorFlow: Static Graphs
  Nodes represent operations (e.g. Matrix multiplication).
  Edges represent tensors and flow between nodes.

- User defines computational graph beforehand, to be executed at later stage.

Scalar	Vector	Matrix	Tensor
0	1	2	3+

Computational Model

- https://playground.tensorflow.org



Computational Model

- Pytorch: Dynamic
  Necessary computation graph metadata is generated automatically each time an operation is executed.
- Multiple advantages:

I. Allows different computational architecture for each training example/batch - more flexible algorithms, especially for dynamically sized data.

II. Control flow (if, while) can be implemented in host language.

Basic Operations

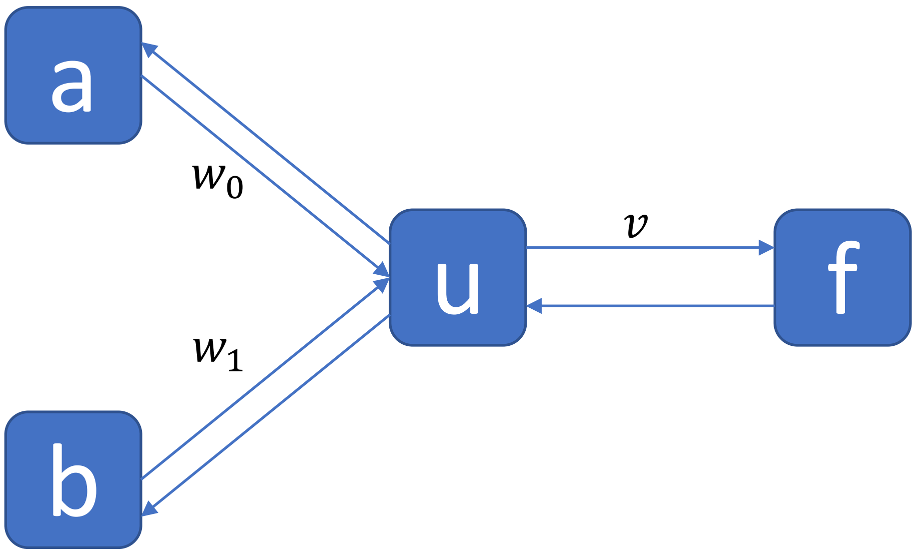
- The basic API is extremely similar to NumPy
- Try!
- https://pytorch.org/docs/stable/torch.html#math-operations

AUTOGRAD MECHANICS

- https://pytorch.org/docs/stable/notes/autograd.html

```
>>> x = torch.randn(5, 5)  # requires_grad=False by default
>>> y = torch.randn(5, 5)  # requires_grad=False by default
>>> z = torch.randn((5, 5), requires_grad=True)
>>> a = x + y
>>> a.requires_grad
False
>>> b = a + z
>>> b.requires_grad
True
```

Autograd



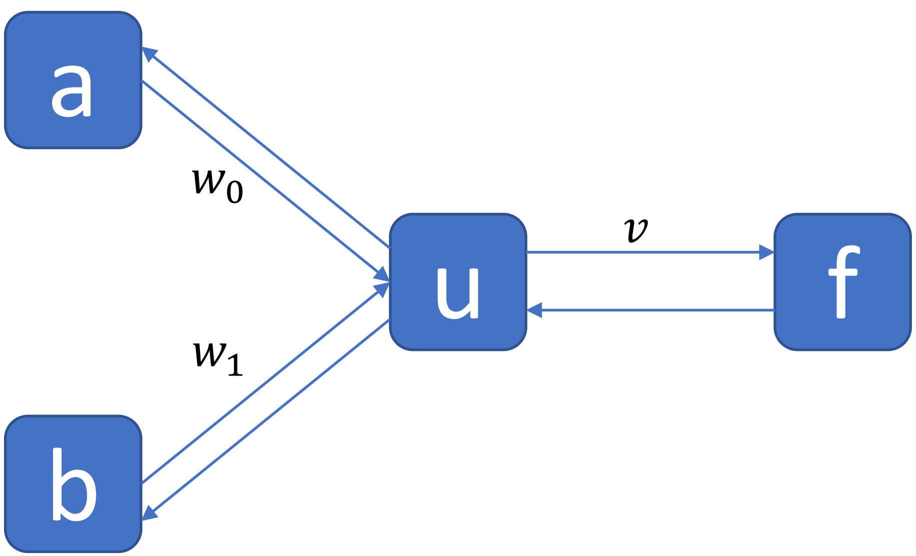
Choice of loss function
MSE

Data:
$a = 2, \mathrm{b} = 3, y = 10$

Init:
$$w_0 = w_1 = v = 1$$

$$u = a \times w_0 + b \times w_1$$
$$f = u \times v$$

- MSE $\quad \mathrm{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- $\frac{\partial L}{\partial v} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial v} = 2(\hat{y}_i - y_i) \times u = -50$
- $\frac{\partial L}{\partial w_0} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial u}\frac{\partial u}{\partial w_0} = 2(\hat{y}_i - y_i) \times v \times a = -20$
- $\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial u}\frac{\partial u}{\partial w_1} = 2(\hat{y}_i - y_i) \times v \times b = -30$



$u = a \times w_0 + b \times w_1$
$f = u \times v$

```
import torch

a = torch.tensor(2.0)
b = torch.tensor(3.0)
w0 = torch.tensor(1.0, requires_grad = True)
w1 = torch.tensor(1.0, requires_grad = True)
v = torch.tensor(1.0, requires_grad = True)

u = a*w0 + b*w1
f = v*u

print(u, f)

criterion = torch.nn.MSELoss()
loss = criterion(f, torch.tensor(10.0))

print(loss)

loss.backward()

print(w0.grad, w1.grad, v.grad)
```