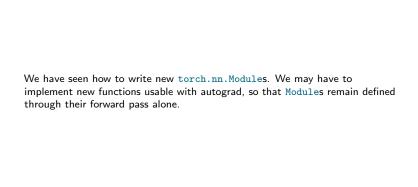
# EE-559 - Deep learning

# 5.7. Writing an autograd function

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This is achieved by writing sub-classes of torch.autograd.Function, which have to implement two static methods:

 forward(...) takes as argument a context to store information needed for the backward pass, and the quantities it should process, which are Tensors for the differentiable ones, but can also be any other types. It should return one or several Tensors. This is achieved by writing sub-classes of torch.autograd.Function, which have to implement two static methods:

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Evaluating such a Function is done through its apply(...) method, which takes as many arguments as forward(...), context excluded.

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This machinery is hidden to you and this level of details should not be required for normal operations.

Consider a function to set to zero the first n components of a tensor.

```
class KillHead(Function):
    @staticmethod
    def forward(ctx, input, n):
        ctx.n = n
        result = input.clone()
        result[:, 0:ctx.n] = 0
        return result

    @staticmethod
    def backward(ctx, grad_output):
        result = grad_output.clone()
        result[:, 0:ctx.n] = 0
        return result, None
```

#### It can be used for instance

```
y = torch.empty(3, 8).normal_()
x = torch.empty(y.size()).normal_().requires_grad_()
criterion, eta = nn.MSELoss(), 1e-0
for k in range(5):
    r = killhead(x, 2)
    loss = criterion(r, y)
    if k > 0: x.grad.zero_()
    loss.backward()
    print(k, loss.item())
    with torch.no_grad():
        x.sub_(eta * x.grad)
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### prints

```
0 1.5175858736038208
1 1.310139536857605
2 1.1358269453048706
3 0.9893561005592346
4 0.8662799000740051
```

The torch.autograd.gradcheck(...) function checks numerically that the backward function is correct, *i.e.* 

$$\forall i,j, \ \left| \frac{f_i(x_1,\ldots,x_j+\epsilon,\ldots,x_D)-f_i(x_1,\ldots,x_j-\epsilon,\ldots,x_D)}{2\epsilon} - (J_f(x))_{i,j} \right| \leq \alpha$$

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$$x = \text{torch.empty}(10,\ 20,\ \text{dtype} = \text{torch.float64}).\text{uniform}_(-1,\ 1).\text{requires\_grad}_()$$
 input =  $(x,\ 4)$  if gradcheck(killhead, input, eps = 1e-6, atol = 1e-4): print('All good captain.') else: print('Ouch')

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 input =  $(x,\ 4)$  
$$\text{if gradcheck}(\text{killhead, input, eps} = 1\text{e-}6,\ \text{atol} = 1\text{e-}4):$$
 print('All good captain.') 
$$\text{else:}$$
 print('Ouch')



It is advisable to use torch.float64s for such a check.

Consider a function that takes two similar sized  ${\tt Tensors}$  and apply component-wise

$$(u,v)\mapsto |uv|.$$

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