Deep learning

5.7. Writing an autograd function

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We have seen how to write new `torch.nn.Modules`. We may have to implement new functions usable with autograd, so that `Modules` remain defined through their forward pass alone.
This is achieved by writing sub-classes of `torch.autograd.Function`, which have to implement two static methods:

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- `backward(...)`: takes as argument the context and as many `Tensors` as `forward` returns `Tensors`, and it should return as many values as `forward` takes argument, `Tensors` for the tensors, and `None` for the others.
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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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To compute the gradient, autograd evaluates the graph and calls `Dummy.backward(...)` when it reaches the corresponding node, with the same context as the one given to `Dummy.forward(...)`. 
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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.

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

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

killhead = KillHead.apply
```
It can be used for instance

\begin{verbatim}
y = torch.randn(3, 8)
x = torch.randn(y.size()).requires_grad_()

criterion = nn.MSELoss()
optimizer = torch.optim.SGD([x], lr = 1.0)

for k in range(5):
    r = killhead(x, 2)
    loss = criterion(r, y)
    print(k, loss.item())

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
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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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```python
x = torch.empty(10, 20, dtype = torch.float64).uniform_(-1, 1).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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class Something(Function):
    @staticmethod
    def forward(ctx, input1, input2):
        ctx.save_for_backward(input1, input2)
        return (input1 * input2).abs()

    @staticmethod
    def backward(ctx, grad_output):
        input1, input2 = ctx.saved_tensors
        return grad_output * input1.sign() * input2.abs(), \
            grad_output * input1.abs() * input2.sign()

something = Something.apply
The end