TTIC 31230, Fundamentals of Deep Learning

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Backpropagation for Scalar Source Code

Backpropagation (backprop)

Backpropagation is the method frameworks use to compute $\nabla_{\Phi} \mathcal{L}_{\Phi}(z)$ for source code $\mathcal{L}_{\Phi}(z)$.

Some Simple Source Code

The expression

$$\mathcal{L} = \sqrt{x^2 + y^2}$$

can be transformed to the assignment sequence

$$u = x^{2}$$

$$v = y^{2}$$

$$r = u + v$$

$$\mathcal{L} = \sqrt{r}$$

Source Code

1.
$$u = x^2$$

$$2. w = y^2$$

$$3. r = u + w$$

$$4. \mathcal{L} = \sqrt{r}$$

For each variable z, the derivative $\partial \mathcal{L}/\partial z$ will get computed in reverse order.

$$(4) \partial \mathcal{L}/\partial r = \frac{1}{2\sqrt{r}}$$

$$(3) \partial \mathcal{L}/\partial u = \partial \mathcal{L}/\partial r$$

$$(3) \partial \mathcal{L}/\partial w = \partial \mathcal{L}/\partial r$$

$$(2) \partial \mathcal{L}/\partial y = (2y) * (\partial \mathcal{L}/\partial w)$$

$$(1) \partial \mathcal{L}/\partial x = (2x) * (\partial \mathcal{L}/\partial u)$$

A More Abstract Example (Still Scalar Values)

$$y = f(x)$$

$$z = g(y, x)$$

$$u = h(z)$$

$$\mathcal{L} = u$$

For now assume all values are scalars (single numbers rather than arrays).

We will "backpopagate" the assignments the reverse order.

$$y = f(x)$$

$$z = g(y, x)$$

$$u = h(z)$$

$$\mathcal{L} = \mathbf{u}$$

$$\partial \mathcal{L}/\partial u = 1$$

$$y = f(x)$$

$$z = g(y, x)$$

$$u = h(z)$$

$$\mathcal{L} = u$$

$$\partial \mathcal{L}/\partial u = 1$$

 $\partial \mathcal{L}/\partial z = (\partial \mathcal{L}/\partial u)(\partial u/\partial z)$ (this uses the value of z)

$$y = f(x)$$

$$z = g(y, x)$$

$$u = h(z)$$

$$\mathcal{L} = u$$

$$\partial \mathcal{L}/\partial u = 1$$

 $\partial \mathcal{L}/\partial z = (\partial \mathcal{L}/\partial u)(\partial u/\partial z)$ (this uses the value of z)
 $\partial \mathcal{L}/\partial y = (\partial \mathcal{L}/\partial z)(\partial z/\partial y)$ (this uses the value of y and x)

$$y = f(\mathbf{x})$$

$$z = g(y, \mathbf{x})$$

$$u = h(z)$$

$$\mathcal{L} = u$$

 $\partial \mathcal{L}/\partial u = 1$ $\partial \mathcal{L}/\partial z = (\partial \mathcal{L}/\partial u)(\partial u/\partial z)$ (this uses the value of z) $\partial \mathcal{L}/\partial y = (\partial \mathcal{L}/\partial z)(\partial z/\partial y)$ (this uses the value of y and x) $\partial \mathcal{L}/\partial x = ???$ Oops, we need to add up multiple occurrences.

$$y = f(\mathbf{x})$$

$$z = g(y, \mathbf{x})$$

$$u = h(z)$$

$$\mathcal{L} = u$$

Each framework program variable denotes an object (in the sense of C++ or Python).

x.value and x.grad are attributes of the object x.

Values are computed "forward" while gradients are computed "backward".

$$y = f(x)$$

 $z = g(y, x)$
 $u = h(z)$
 $\mathcal{L} = u$
 $z.\text{grad} = y.\text{grad} = x.\text{grad} = 0$
 $u.\text{grad} = 1$

Invariant: The gradients are correct for the red program.

$$y = f(x)$$
 $z = g(y, x)$
 $u = h(z)$
 $\mathcal{L} = u$
 $z.\operatorname{grad} = y.\operatorname{grad} = x.\operatorname{grad} = 0$
 $u.\operatorname{grad} = 1$
 $z.\operatorname{grad} += u.\operatorname{grad} * (\partial u/\partial z)$

Invariant: The gradients are correct for the red program.

$$y = f(x)$$
 $z = g(y, x)$
 $u = h(z)$
 $\mathcal{L} = u$
 $z.\operatorname{grad} = y.\operatorname{grad} = x.\operatorname{grad} = 0$
 $u.\operatorname{grad} = 1$
 $z.\operatorname{grad} += u.\operatorname{grad} * (\partial u/\partial z)$
 $y.\operatorname{grad} += z.\operatorname{grad} * (\partial z/\partial y)$
 $x.\operatorname{grad} += z.\operatorname{grad} * (\partial z/\partial x)$

$$y = f(x)$$
 $z = g(y, x)$
 $u = h(z)$
 $\mathcal{L} = u$
 $z.\operatorname{grad} = y.\operatorname{grad} = x.\operatorname{grad} = 0$
 $u.\operatorname{grad} = 1$
 $z.\operatorname{grad} += u.\operatorname{grad} * (\partial u/\partial z)$
 $y.\operatorname{grad} += z.\operatorname{grad} * (\partial z/\partial y)$
 $x.\operatorname{grad} += z.\operatorname{grad} * (\partial z/\partial x)$
 $x.\operatorname{grad} += y.\operatorname{grad} * (\partial y/\partial x)$
 $w.\operatorname{grad} +\operatorname{holds} \frac{\partial \mathcal{L}}{\partial w}$

\mathbf{END}