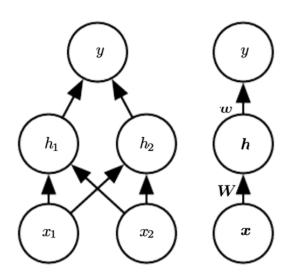


Deep Learning

Mohammad Reza Mohammadi 2021

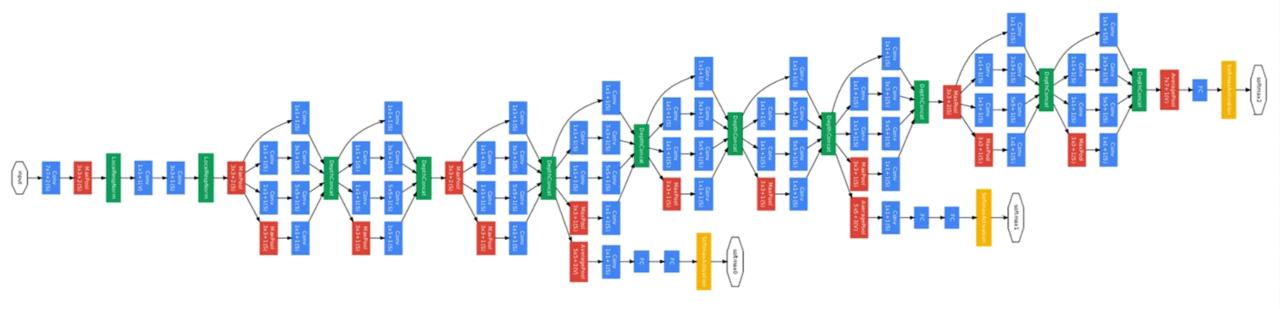
How to compute gradients?

- $h_i = g(\mathbf{x}^T \mathbf{W}_{:,i} + c_i) = f^{(1)}(\mathbf{x})$
- $y = f^{(2)}(f^{(1)}(x)) = f(x; W, c, w, b) = w^T \max\{0, W^T x + c\} + b$
- $J(\boldsymbol{\theta}) = \frac{1}{N} \sum (f^*(\boldsymbol{x}) f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b))^2$
- If we can compute $\frac{\partial J}{\partial W}$, $\frac{\partial J}{\partial c}$, $\frac{\partial J}{\partial w}$ and $\frac{\partial J}{\partial b}$ then we can learn the parameters
- What if we want to change loss?
 - Need to re-derive from scratch



How to compute gradients?

• Very tedious: Lots of matrix calculus, need lots of paper



Backpropagation: a simple example

$$f(x, y, z) = (x + y)z$$

e.g.,
$$x = -2$$
, $y = 5$, $z = -4$

$$q = x + y \qquad \Rightarrow f = qz$$

we want $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$ and $\frac{\partial f}{\partial z}$

$$\frac{\partial f}{\partial q} = z \qquad \frac{\partial f}{\partial z} = q$$

$$\frac{\partial q}{\partial x} = 1$$
 $\frac{\partial q}{\partial y} = 1$

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$$

$$\begin{array}{c}
x -2 \\
\frac{\partial f}{\partial x} = -4
\end{array}$$

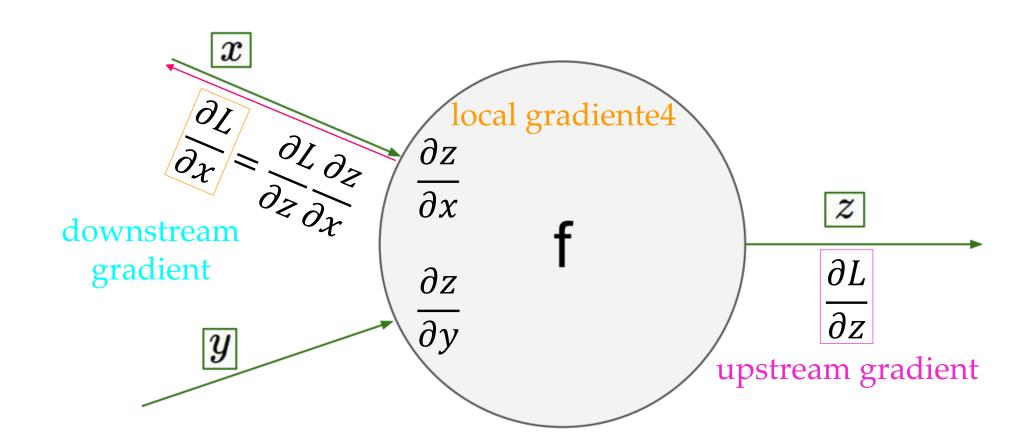
$$\begin{array}{c}
y \quad 5 \\
\frac{\partial f}{\partial q} = -4
\end{array}$$

$$\begin{array}{c}
t -12 \\
\frac{\partial f}{\partial f} = 1
\end{array}$$

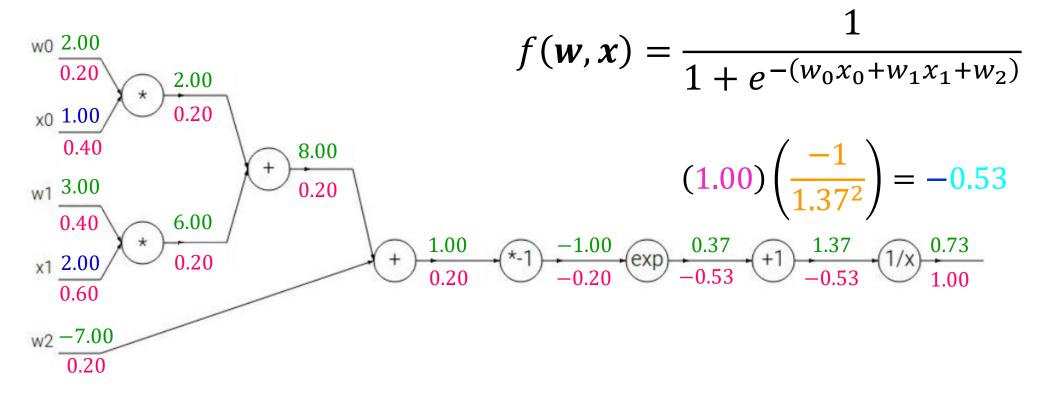
$$\begin{array}{c}
\frac{\partial f}{\partial f} = 1
\end{array}$$

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

Backpropagation

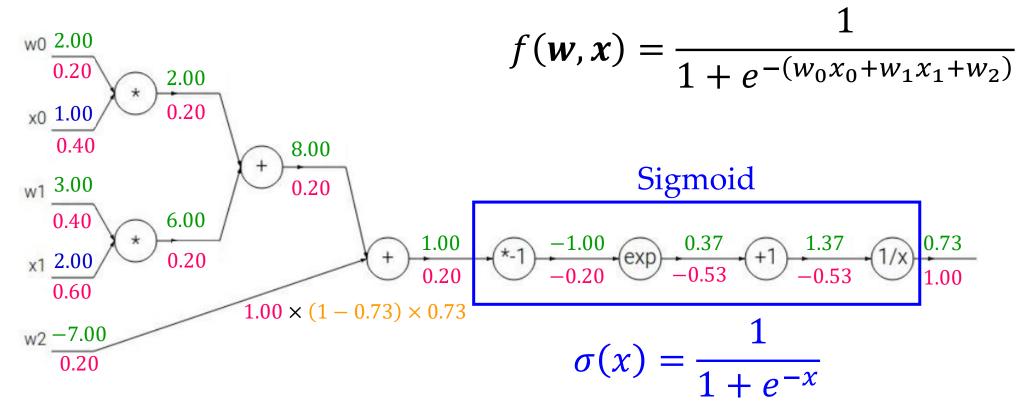


Backpropagation: Linear + Sigmoid



$$\frac{\partial(ax)}{\partial x} = a \qquad \frac{\partial(c+x)}{\partial x} = 1 \qquad \frac{\partial(e^x)}{\partial x} = e^x \qquad \frac{\partial(1/x)}{\partial x} = \frac{-1}{x^2}$$

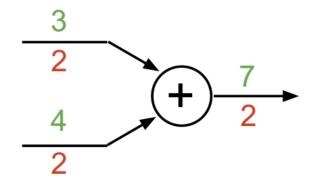
Backpropagation: Linear + Sigmoid



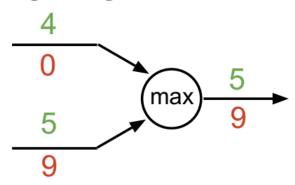
$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1+e^{-x})^2} = \frac{1-1+e^{-x}}{1+e^{-x}} \frac{1}{1+e^{-x}} = (1-\sigma(x))\sigma(x)$$

Patterns in gradient flow

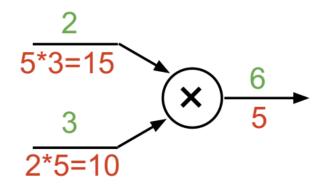
add gate: gradient distributor



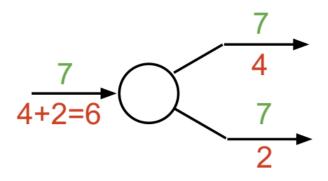
max gate: gradient router



mul gate: "swap multiplier"

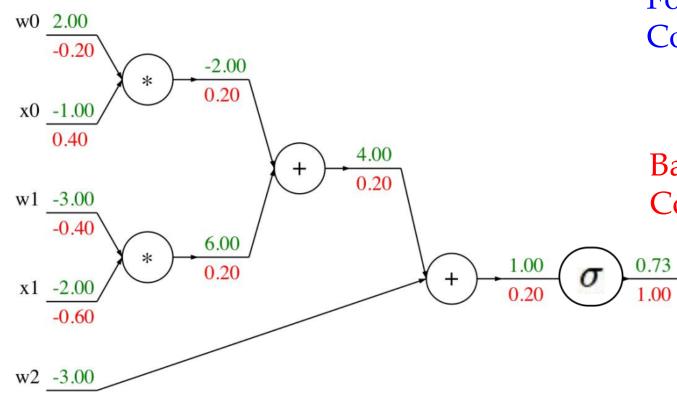


copy gate: gradient adder



Backpropagation

0.20



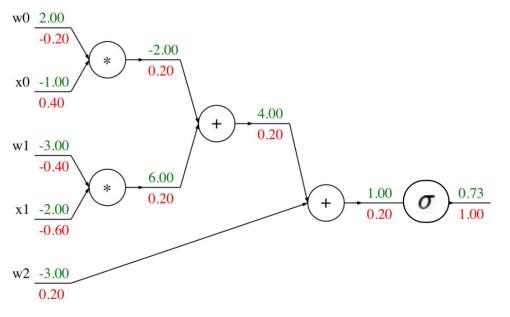
Forward pass: Compute output

Backward pass: Compute grads

```
def f(w0, x0, w1, x1, w2):
    s0 = w0 * x0
    s1 = w1 * x1
    s2 = s0 + s1
    s3 = s2 + w2
    L = sigmoid(s3)
```

```
grad_L = 1.0
grad_s3 = grad_L * (1 - L) * L
grad_w2 = grad_s3
grad_s2 = grad_s3
grad_s0 = grad_s2
grad_s1 = grad_s2
grad_w1 = grad_s1 * x1
grad_x1 = grad_s1 * w1
grad_w0 = grad_s0 * x0
grad_x0 = grad_s0 * w0
```

Modular implementation



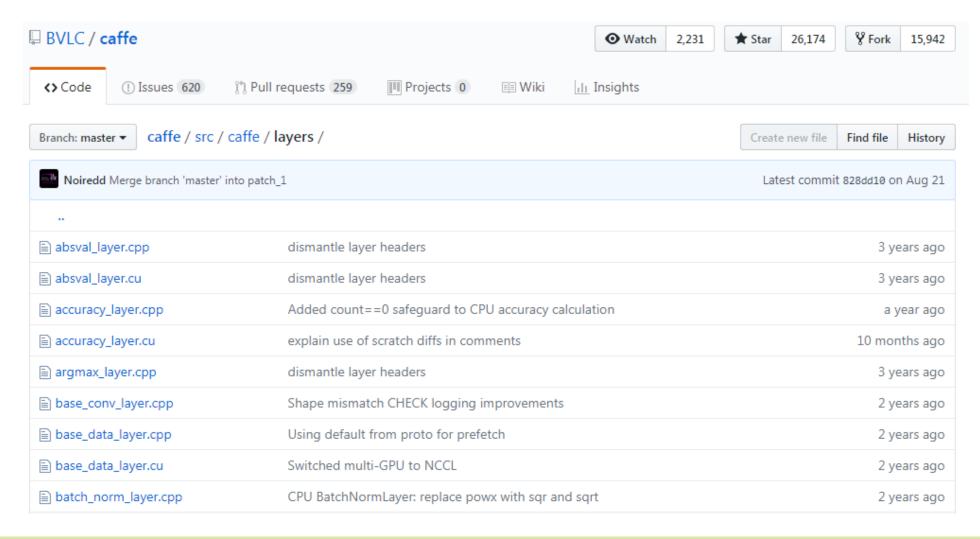
```
class ComputationalGraph(object):
   # . . .
   def forward(inputs):
        # 1. [pass inputs to input gates...]
        # 2. forward the computational graph:
        for gate in self.graph.nodes topologically sorted():
            gate.forward()
        return loss # the final gate in the graph outputs the loss
   def backward():
        for gate in reversed(self.graph.nodes topologically sorted()):
            gate.backward() # little piece of backprop (chain rule applied)
        return inputs gradients
```

Multiply Gate

```
class MultuplyGate(object):
 x,y are scalars
  def forward(x,y):
    z = x*y
    self.x = x # Cache
    self.y = y # Cache
   # We cache x and y because we know that the derivatives contains them.
   return 2
  def backward(dz):
   dx = self.y * dz
                             #self.y is dx
   dy = self.x * dz
   return [dx, dy]
```

z = x y

Caffe layers



Sigmoid layer

```
template <typename Dtype>
void SigmoidLayer<Dtype>::Forward cpu(const vector<Blob<Dtype>*>& bottom,
        const vector<Blob<Dtype>*>& top) {
    const Dtype* bottom data = bottom[0]->cpu data();
    Dtype* top data = top[0]->mutable cpu data();
    const int count = bottom[0]->count();
    for (int i = 0; i < count; ++i) {
        top_data[i] = sigmoid(bottom_data[i]); \sigma(x) = \frac{1}{1 + e^{-x}}
template <typename Dtype>
void SigmoidLayer<Dtype>::Backward cpu(const vector<Blob<Dtype>*>& top,
        const vector<bool>& propagate_down,
        const vector<Blob<Dtype>*>& bottom) {
    if (propagate down[0]) {
        const Dtype* top data = top[0]->cpu data();
        const Dtype* top diff = top[0]->cpu diff();
        Dtype* bottom diff = bottom[0]->mutable cpu diff();
        const int count = bottom[0]->count();
        for (int i = 0; i < count; ++i) {</pre>
            const Dtype sigmoid_x = top_data[i]; bottom_diff[i] = top_diff[i] * sigmoid_x * (1. - sigmoid_x); \frac{d\sigma(x)}{dx} = \sigma(x)(1 - \sigma(x))
```

Custom layer in Keras



Search Keras documentation...

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Why choose Keras?

Community & governance

Contributing to Keras

Making new layers and models via subclassing

Author: fchollet

Date created: 2019/03/01 Last modified: 2020/04/13

Description: Complete guide to writing Layer and Model objects from scratch.

View in Colab



GitHub source

» Developer guides / Making new layers and models via subclassing