Deep Learning for Computer Vision

Dr. Konda Reddy Mopuri
Mehta Family School of Data Science and Artificial Intelligence
IIT Guwahati
Aug-Dec 2022

Recap

- Gradient of a scalar valued function $f(\mathbf{x})$: $\mathbf{x} \rightarrow \left(\frac{\partial f}{\partial x_1}, \ldots, \frac{\partial f}{\partial x_D}\right)^T$

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- Gradient of a vector valued function $\mathbf{f}(\mathbf{x})$ is called Jacobian:

$$\mathbf{J} = \begin{bmatrix} \dfrac{\partial \mathbf{f}}{\partial x_1} & \cdots & \dfrac{\partial \mathbf{f}}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \nabla^{\mathrm{T}} f_1 \\ \vdots \\ \nabla^{\mathrm{T}} f_m \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f_1}{\partial x_1} & \cdots & \dfrac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial f_m}{\partial x_1} & \cdots & \dfrac{\partial f_m}{\partial x_n} \end{bmatrix}$$

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- For applying Gradient descent, we need gradient of individual sample loss with respect to all the model parameters

$$l_n = l(f(x_n; W, \mathbf{b}), y_n)$$

$\frac{\partial l_n}{\partial W_{i,j}^{(l)}}$ and $\frac{\partial l_n}{\partial \mathbf{b}_i^{(l)}}$

Forward pass operation

$$x^{(0)} = x \xrightarrow{W^{(1)},\mathbf{b}^{(1)}} s^{(1)} \xrightarrow{\sigma} x^{(1)} \xrightarrow{W^{(2)},\mathbf{b}^{(2)}} s^{(2)} \dots x^{(L-1)} \xrightarrow{W^{(L)},\mathbf{b}^{(L)}} s^{(L)} \xrightarrow{\sigma} x^{(L)} = f(x; W, \mathbf{b})$$

Formally, $x^{(0)} = x, f(x; W, \mathbf{b}) = x^{(L)}$

$$\forall l = 1, \dots, L \quad \begin{cases} s^{(l)} & = W^{(l)} x^{(l-1)} + \mathbf{b}^{(l)} \\ x^{(l)} & = \sigma(s^{(l)}) \end{cases}$$

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- $$J_{f_N \circ f_{N-1} \circ \ldots f_1(x)} = J_{f_N(f_{N-1}(\ldots f_1(x)))} \cdot J_{f_{N-1}(f_{N-2}(\ldots f_1(x)))} \cdot \cdots \cdot J_{f_2(f_1(x))} \cdot J_{f_1(x)}$$

  $J_{f(x)}$ is Jacobian of f computed at x.

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- $$\frac{\partial \ell}{\partial b_i^{(l)}} = \frac{\partial \ell}{\partial s_i^{(l)}} \frac{\partial s_i^{(l)}}{\partial b_i^{(l)}} = \frac{\partial \ell}{\partial s_i^{(l)}} \tag{2}$$

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- Then wrt the parameters
$$\frac{\partial \ell}{\partial w_{i,j}^{(l)}} = \frac{\partial \ell}{\partial s_i^{(l)}} x_j^{(l-1)} \text{ and } \frac{\partial \ell}{\partial b_i^{(l)}} = \frac{\partial \ell}{\partial s_i^{(l)}}$$

Jocobian in Tensorial form

- $\psi : \mathcal{R}^N \rightarrow \mathcal{R}^M$ then $\left[\frac{\partial \psi}{\partial x}\right] = \begin{bmatrix} \frac{\partial \psi_1}{\partial x_1} & \cdots & \frac{\partial \psi_1}{\partial x_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial \psi_M}{\partial x_1} & \cdots & \frac{\partial \psi_M}{\partial x_N} \end{bmatrix}$

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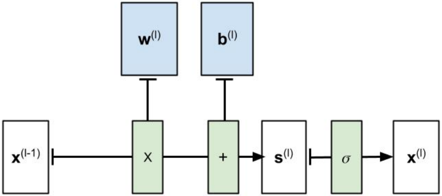
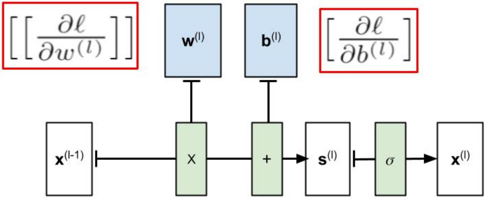
- $\psi : \mathcal{R}^{N \times M} \rightarrow \mathcal{R}$ then $\left[\left[\frac{\partial \psi}{\partial x}\right]\right] = \begin{bmatrix} \frac{\partial \psi}{\partial w_{1,1}} & \cdots & \frac{\partial \psi}{\partial w_{1,M}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \psi}{\partial w_{N,1}} & \cdots & \frac{\partial \psi}{\partial w_{N,M}} \end{bmatrix}$

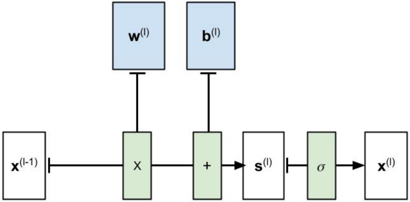
Forward Pass



Goal of Backward Pass



Begin from succeeding layer



$$\boxed{\frac{\partial \ell}{\partial x^{(l)}}}$$

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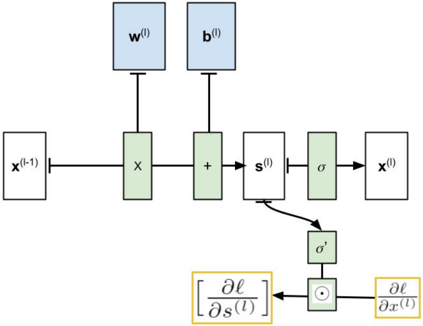

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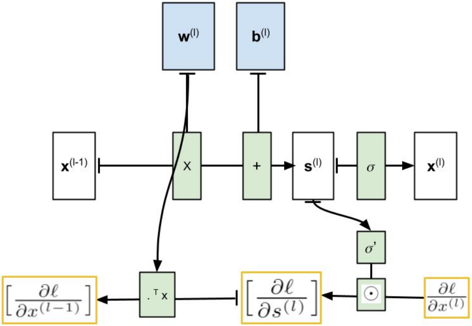

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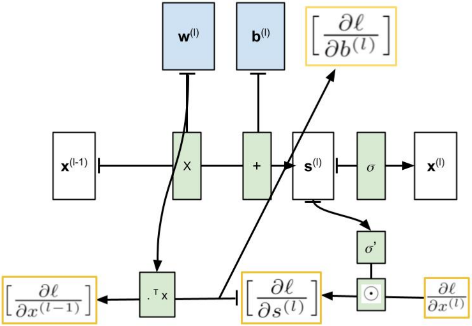

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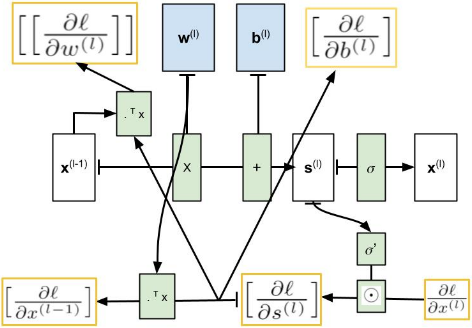

Update the parameters

- $W^{(l)} = W^{(l)} - \eta \left[\left[\frac{\partial \ell}{\partial w^{(l)}} \right] \right]$ and $\mathbf{b}^{(l)} = \mathbf{b}^{(l)} - \eta \left[\frac{\partial \ell}{\partial b^{(l)}} \right]$

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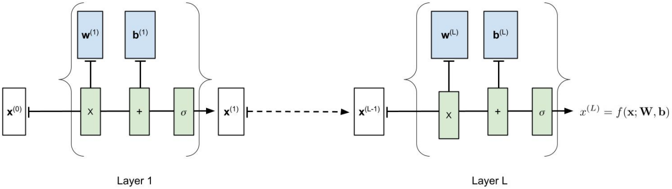
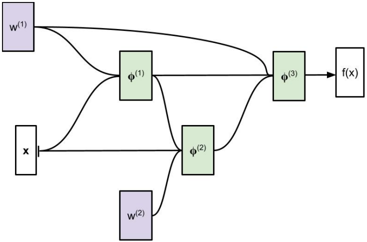
- In an untreated situation, BP Needs all the intermediate layer results to be in memory
- Takes twice the computations of forward pass

Beyond MLP

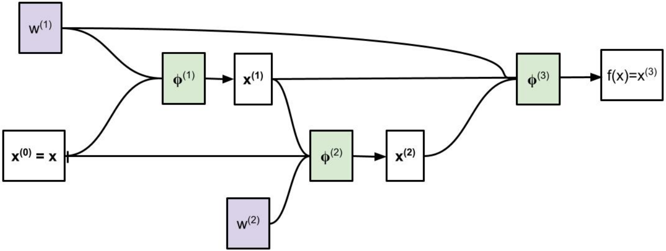
- We can generalize MLP





To an arbitrary Directed Acyclic Graph (DAG)

Forward pass in the computational graph



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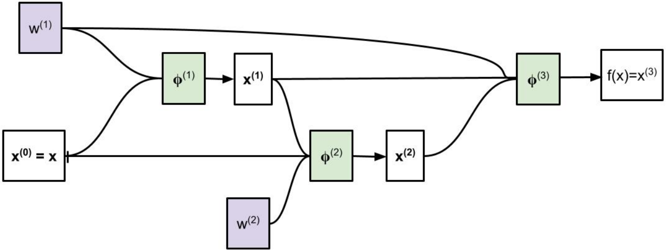

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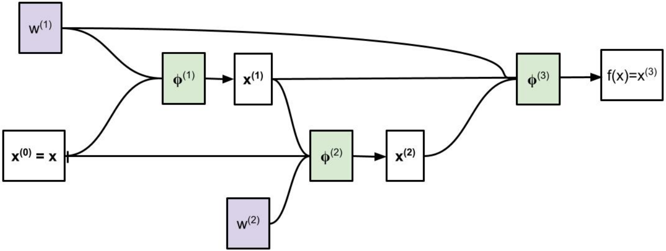

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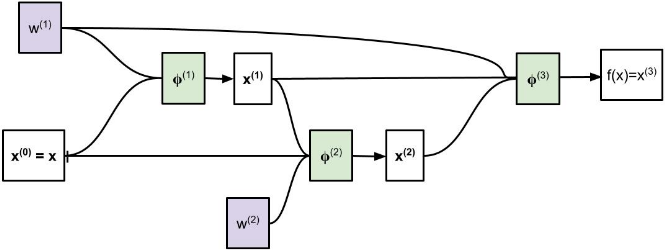

- $x^{(0)} = x$
- $x^{(1)} = \phi^{(1)}(x^{(0)}; w^{(1)})$
- $x^{(2)} = \phi^{(2)}(x^{(0)}, x^{(1)}; w^{(2)})$
- $f(x) = x^{(3)} = \phi^{(3)}(x^{(1)}, x^{(2)}; w^{(1)})$

Notation: Jacobian of a general transformation

- $$\text{if } (a_1 \dots a_Q) = \phi(b_1 \dots b_R) \text{ then we use the notation} \tag{3}$$

$$\left[\frac{\partial a}{\partial b}\right] = J_\phi^T = \begin{bmatrix} \frac{\partial a_1}{\partial b_1} & \cdots & \frac{\partial a_Q}{\partial b_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial a_1}{\partial b_R} & \cdots & \frac{\partial a_Q}{\partial b_R} \end{bmatrix} \tag{4}$$

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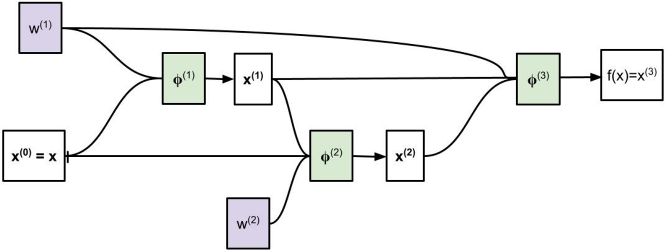
- $$\text{if } (a_1 \ldots a_Q) = \phi(b_1 \ldots b_R; c_1 \ldots c_S) \text{ then we use the notation} \tag{5}$$
  $$\left[\frac{\partial a}{\partial c}\right] = J_{\phi|c}^T = \begin{bmatrix} \frac{\partial a_1}{\partial c_1} & \cdots & \frac{\partial a_Q}{\partial c_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial a_1}{\partial C_S} & \cdots & \frac{\partial a_Q}{\partial c_S} \end{bmatrix} \tag{6}$$

Backward pass



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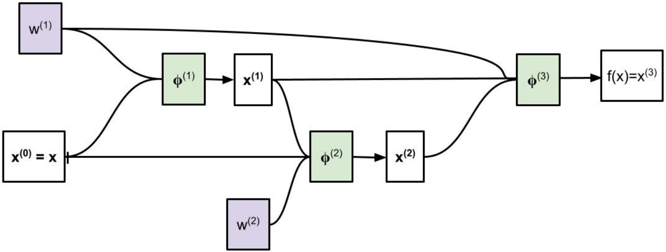

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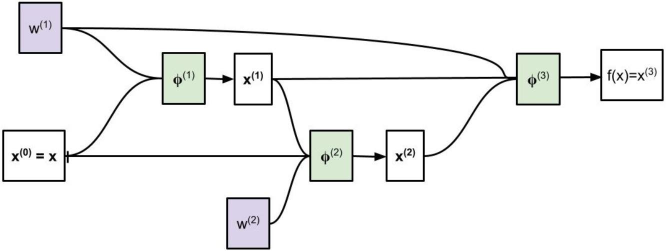

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- $$\begin{aligned}\left[\frac{\partial \ell}{\partial x^{(1)}}\right] &= \left[\frac{\partial x^{(3)}}{\partial x^{(1)}}\right]\left[\frac{\partial \ell}{\partial x^{(3)}}\right] + \left[\frac{\partial x^{(2)}}{\partial x^{(1)}}\right]\left[\frac{\partial \ell}{\partial x^{(2)}}\right] \\ &= J^T_{\phi^{(3)}|x^{(1)}}\left[\frac{\partial \ell}{\partial x^{(3)}}\right] + J^T_{\phi^{(2)}|x^{(1)}}\left[\frac{\partial \ell}{\partial x^{(2)}}\right]\end{aligned}$$

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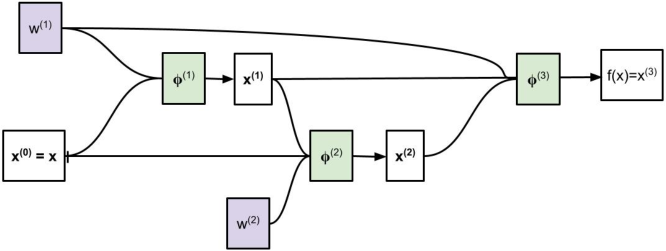

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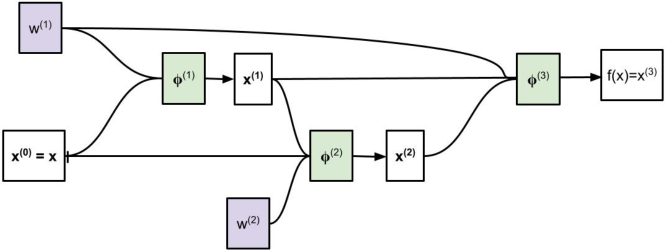

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$$= J^T_{\phi^{(3)}|w^{(1)}}\left[\frac{\partial \ell}{\partial x^{(3)}}\right] + J^T_{\phi^{(1)}|w^{(1)}}\left[\frac{\partial \ell}{\partial x^{(1)}}\right]$$

- $$\left[\frac{\partial \ell}{\partial w^{(2)}}\right] = \left[\frac{\partial x^{(2)}}{\partial w^{(2)}}\right]\left[\frac{\partial \ell}{\partial x^{(2)}}\right] = J^T_{\phi^{(2)}|w^{(2)}}\left[\frac{\partial \ell}{\partial x^{(2)}}\right]$$

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- Flexible: Computational graph can be dynamic, so is the forward pass

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- Default is False
- `requires_grad_()` function can be used to set to any value

Autograd

- `torch.autograd.grad(o/p,i/p)` returns gradients of outputs wrt the inputs

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- Standard function used to train the models.
- Since it ACCUMULATES the gradients, one may need to set `Tensor.grad` to zero before calling it
- Accumulation is helpful (e.g. sum of losses, or sum over different mini-batches, etc.)

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- Useful for operations such as parameter updation

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- Used when gradient should not be propagated beyond a variable, or to update the leaf nodes in the graph

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Some Notes

- By default, autograd deletes the computational graph after it is evaluated
- `retain_graph` indicates to keep it
- Autograd can compute higher-order derivatives
- Specified with `create_graph = True`

Demo

▸ Colab Notebook: Backword()