ディープな学習会

第5章 誤差逆伝播法

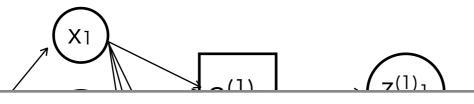
~後半~

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)} \mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)} \mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$

$$L(y, t) = -\sum_{i} t_{i} \log y_{i}$$

$$\mathbf{a}^{(1)} \mathbf{z}^{(1)} \mathbf{z$$

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$



$$L(y,t) = -\sum_{i} t_i \log y_i$$

y1

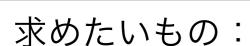
これからやること:パラメータの更新

(例)

$$W_{ij}^{(1)} \leftarrow W_{ij}^{(1)} + \eta \frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial W_{ij}^{(1)}}$$

 $7(1)_3$

 $a^{(2)}_{2}$

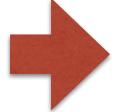


$$\frac{\partial L(y;t)}{\partial W_{ij}^{(1)}}, \quad \frac{\partial L(y;t)}{\partial b_i^{(1)}}, \quad \frac{\partial L(y;t)}{\partial W_{ij}^{(2)}}, \quad \frac{\partial L(y;t)}{\partial b_i^{(2)}}$$

 \cdots 784 × n + n + n × 10 + 10 = 795n+10

隠れ層数n = 50として、39760個のパラメータ

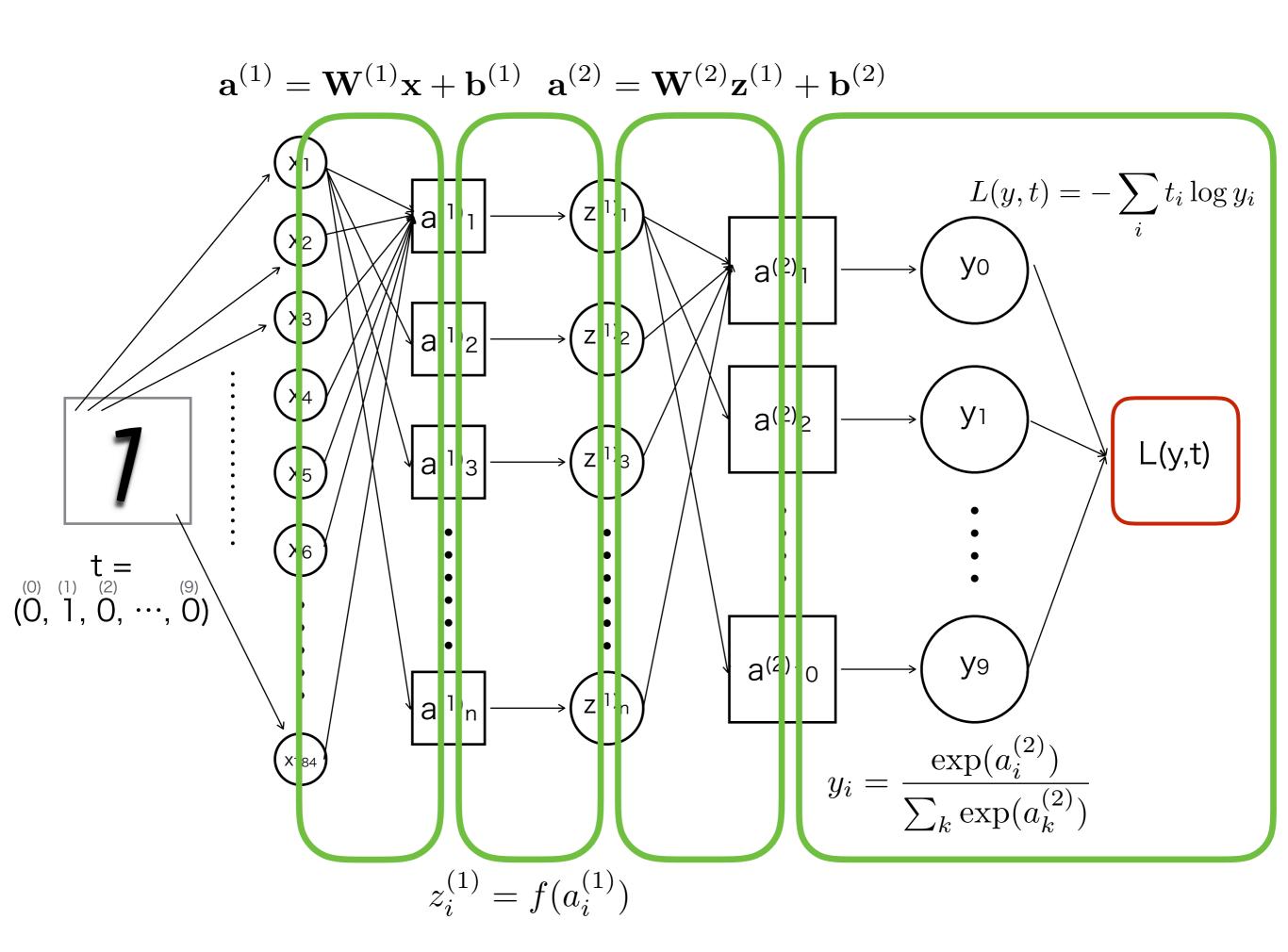
→ 数値微分すると, 79520回 predictを呼び出す!



求められるなら予め解析的に求めない???

$$z_i = J(a_i)$$

L(y,t)



$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial W_{ij}^{(1)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(1)}} \frac{\partial a_{k}^{(1)}}{\partial W_{ij}^{(1)}}$$

$$= \sum_{k} \frac{\partial L}{\partial a_{k}^{(1)}} \delta_{ki} x_{j} = \frac{\partial L}{\partial a_{i}^{(1)}} x_{j}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial b_{i}^{(1)}} = \frac{\partial L}{\partial a_{i}^{(1)}}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial W_{ij}^{(2)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(2)}} \frac{\partial a_{k}^{(2)}}{\partial W_{ij}^{(2)}}$$

$$= \frac{\partial L}{\partial a_{i}^{(2)}} z_{j}^{(1)}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial b_{i}^{(2)}} = \frac{\partial L}{\partial a_{i}^{(2)}}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial w_{ij}^{(2)}} = \frac{\partial L}{\partial a_{i}^{(2)}}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial b_{i}^{(2)}} = \frac{\partial L}{\partial a_{i}^{(2)}}$$

$$\frac{\partial L(\boldsymbol{y}; \boldsymbol{t})}{\partial a_{i}^{(2)}} = \sum_{k} \frac{\partial L}{\partial w_{k}} \frac{\partial y_{k}}{\partial a_{i}^{(2)}}$$

$$t = (0, 1, 0, \cdots, 0)$$

$$\frac{\partial a_i^{(1)}}{\partial z_i^{(1)}} = \begin{cases} \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} \\ \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} \\ \frac{\partial z_i^{(1)}}{\partial z_i^{(1)}} & \frac$$

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$$L(y,t) = -\sum_{i} t_{i} \log y_{i}$$

$$\begin{vmatrix} \frac{\partial L(\boldsymbol{y};\boldsymbol{t})}{\partial a_i^{(2)}} = \sum_k \frac{\partial L}{\partial y_k} \frac{\partial y_k}{\partial a_i^{(2)}} \\ = \sum_k \frac{\partial L}{\partial y_k} \frac{\partial f'_{\text{SM}}(a_k^{(2)})}{\partial a_i^{(2)}} \\ = y_i - t_i \end{vmatrix}$$

y9

(2)



- ・まず順方向にL(y;t)を計算(途中の $z^{(1)},x$ も保存しておく)
- ・逆方向に、各レイヤーごと微分値・必要なパラメータを計算

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$

$$\frac{\partial L(\boldsymbol{y};\boldsymbol{t})}{\partial W_{ij}^{(1)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(1)}} \frac{\partial a_{k}^{(1)}}{\partial W_{ij}^{(1)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(1)}} \frac{\partial a_{k}^{(1)}}{\partial W_{ij}^{(2)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(2)}} \frac{\partial a_{k}^{(2)}}{\partial a_{i}^{(2)}} = \sum_{k} \frac{\partial L}{\partial a_{k}^{(2)}} \frac{\partial a_{k}^{(2)}}{\partial a_{k}^{(2)}} = \sum_{k} \frac{\partial L}{\partial a_{$$



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SoftMax & CrossEntropy Layer

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$

$$\frac{\partial L(\boldsymbol{y};\boldsymbol{t})}{\partial a_i^{(2)}} = \sum_{k} \frac{\partial L}{\partial y_k} \frac{\partial y_k}{\partial a_i^{(2)}}$$

$$= \sum_{k} \frac{\partial L}{\partial y_{k}} \frac{\partial f'_{\text{SM}}(a_{k}^{(2)})}{\partial a_{i}^{(2)}}$$

$$= y_{i} - t_{i}$$

class SoftmaxWithLoss:

def __init__(self):

self.loss = None

self.y = None

self.t = None

def forward(self, y, t):

self.t = t

self.y = y

self.loss =

cross_entropy_error(self.y, self.t)

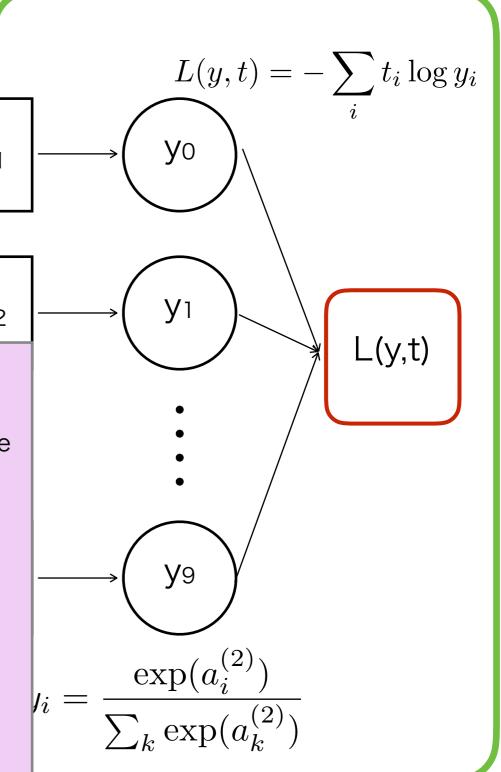
return self.loss

def backward(self, dout=1):

batch_size = self.t.shape[0]

dx = (self.y - self.t) / batch_size

return dx

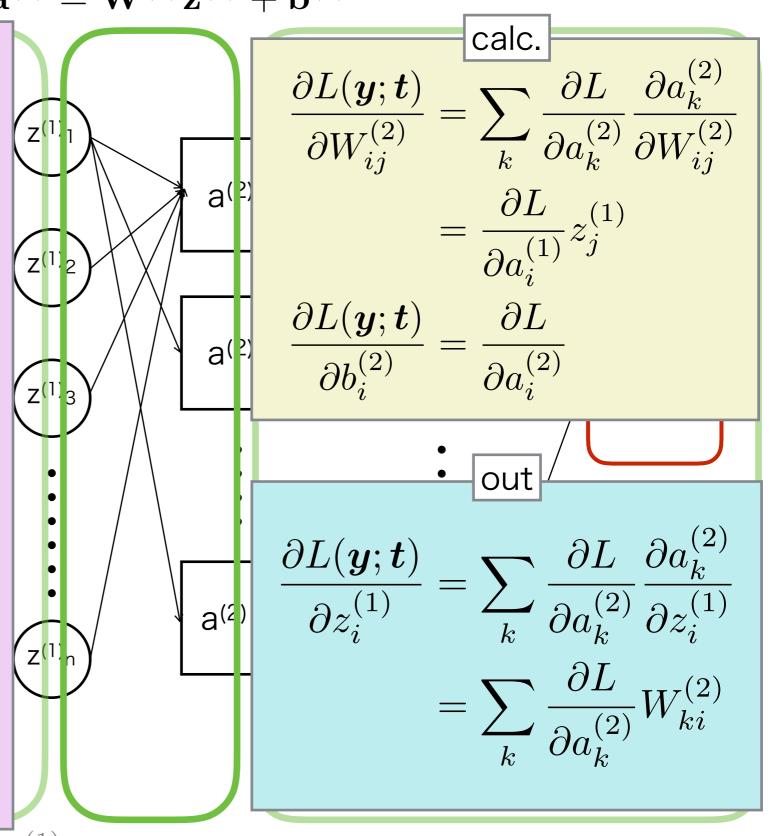


Affine Layer (2)

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$

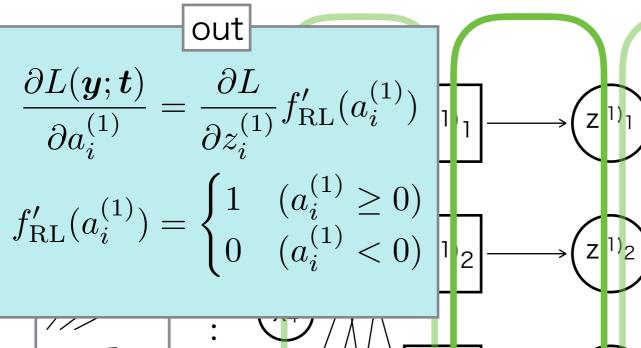
class Affine: def __init__(self, W, b): self.W = Wself.b = bself.x = Noneself.dW = None self.db = None def forward(self, x): self.x = xout = np.dot(x, self.W) + self.breturn out def backward(self, dout): dx = np.dot(dout, self.W.T)self.dW = np.dot(self.x.T, dout) self.db = np.sum(dout, axis=0) return dx $z_i^{(1)} = f(a_i^{(1)})$

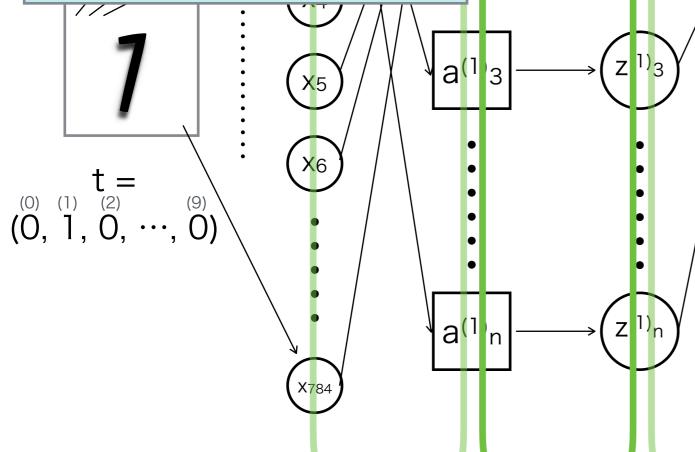
(O),



ReLu Layer

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$





class Relu:

def __init__(self):
 self.mask = None

def forward(self, x):

self.mask = (x < 0)

out = x.copy()

out[self.mask] = 0

return out

def backward(self, dout):

dout[self.mask] = 0

 $\sum_{k} \exp(a_k)$

dx = dout

return dx

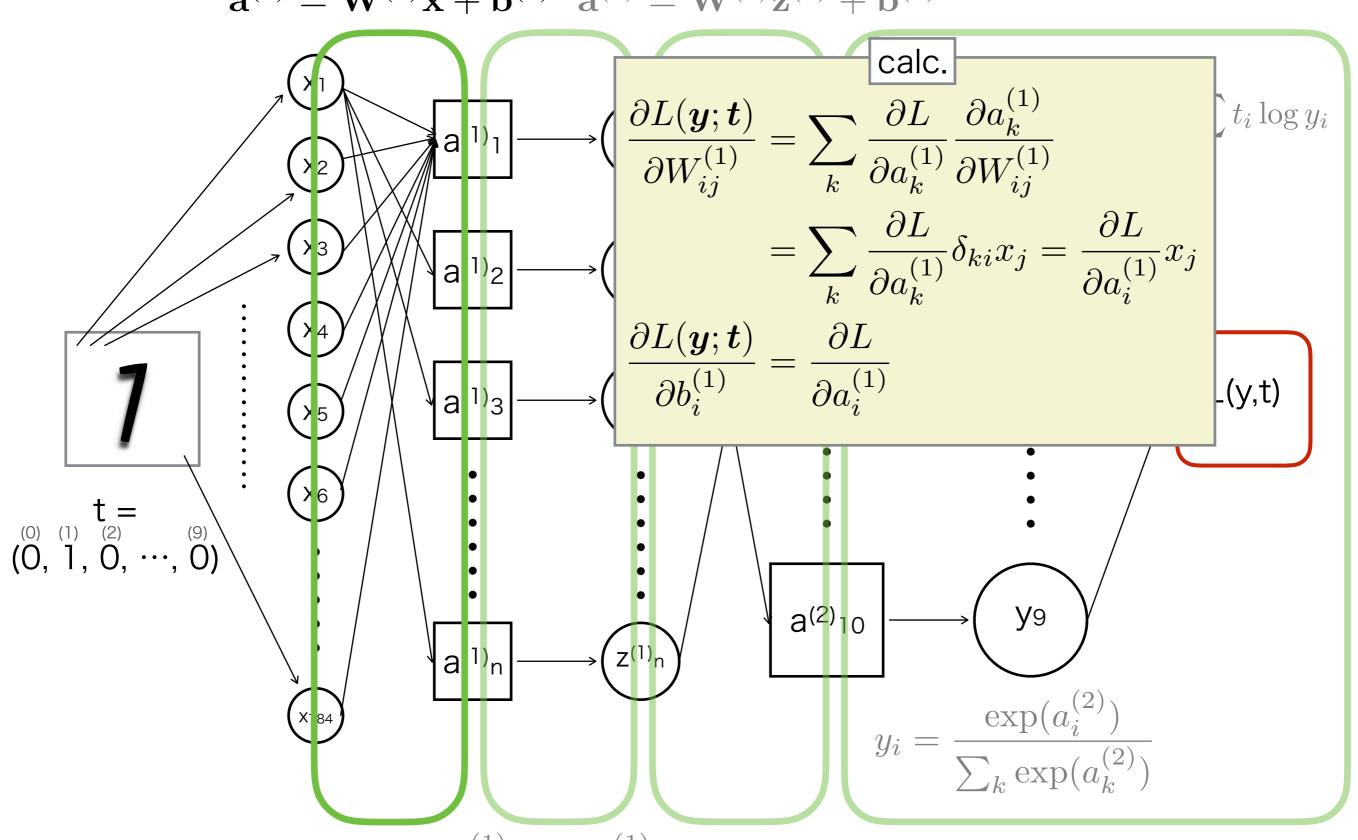
$$z_i^{(1)} = f(a_i^{(1)})$$

 $\log y_i$

,t)

Affine Layer (1)

$$\mathbf{a}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \quad \mathbf{a}^{(2)} = \mathbf{W}^{(2)}\mathbf{z}^{(1)} + \mathbf{b}^{(2)}$$



$$z_i^{(1)} = f(a_i^{(1)})$$