## 前言

第一次看吴恩达老师机器学习视频时,在9.2节卡了两天才搞明白,特和大家分享一下.本人也是渣渣初学者,如果对文章有任何疑问或希望转载,请联系<u>ch\_yan@pku.edu.cn</u>如果读完后觉得有所收获,请在我的github里点个star吧~

## 潜在读者

这篇文章的潜在读者为:

- 1. 学习吴恩达机器学习课程, 看完9.1节及以前的内容而在9.2节一脸懵逼的同学
- 2. 知道偏导数是什么, 也知道偏导数的求导法则 这篇文章会帮助你完全搞懂9.2节是怎么回事, 除9.1节及以前的内容外, 不需要任何额外的机器学习 的知识.

## 前情提要

约定神经网络的层数为L, 其中第l层的的神经元数为 $s_l$ , 该层第i个神经元的输出值为 $a_i^{(l)}$ , 该层的每个神经元输出值计算如下:

$$a^{(l)} = egin{bmatrix} a_1^{(l)} \ a_2^{(l)} \ \dots \ a_{s_l}^{(l)} \end{bmatrix} = sigmoid(z^{(l)}) = rac{1}{1 + e^{-z^{(l)}}} \ \end{array}$$

其中 $sigmoid(z^{(l)})$ 是激活函数,  $z^{(l)}$ 是上一层神经元输出结果 $a^{(l-1)}$ 的线性组合( $\Theta^{(l-1)}$ 是参数矩阵):

$$z^{(l)} = \Theta^{(l-1)} a^{(l-1)} \tag{2}$$

$$\Theta_{(s_{l} \times s_{l-1})}^{(l-1)} = \begin{bmatrix}
\theta_{11}^{(l-1)} & \theta_{12}^{(l-1)} & \cdots & \theta_{1s_{l-1}}^{(l-1)} \\
\theta_{21}^{(l-1)} & \theta_{22}^{(l-1)} & \cdots & \theta_{2s_{l-1}}^{(l-1)} \\
\vdots & \vdots & \ddots & \vdots \\
\theta_{s_{l}1}^{(l-1)} & \theta_{s_{l}2}^{(l-1)} & \cdots & \theta_{s_{l}s_{l-1}}^{(l-1)}
\end{bmatrix}$$
(3)

参数(权重)矩阵 $\Theta^{(l-1)}$ 的任务就是将第l-1层的 $s_{l-1}$ 个参数线性组合为 $s_l$ 个参数,其中 $\theta^{l-1}_{ij}$ 表示 $a_j^{(l-1)}$ 在 $a_i^{(l)}$ 中的权重(没错,这里的i是终点对序号,j是起点的序号),用单一元素具体表示为:

$$a_i^{(l)} = \theta_{i1}^{(l-1)} * a_1^{(l-1)} + \theta_{i2}^{(l-1)} * a_2^{(l-1)} + \dots + \theta_{is_{l-1}}^{(l-1)} * a_{s_{l-1}}^{(l-1)} = \sum_{k=1}^{s_{l-1}} \theta_{ik}^{(l-1)} * a_k^{(l-1)}$$
(4)

另外, 在logistic回归中, 定义损失函数如下:

$$cost(a) = \begin{cases} \log(a) & y = 1\\ \log(1 - a) & y = 0 \end{cases} = y\log(a) + (1 - y)\log(1 - a), y \in \{0, 1\}$$
 (5)

## 正式开始

据此, 我们的思路是, 计算出神经网络中的损失函数 $J(\Theta)$ , 然后通过梯度下降来求 $J(\Theta)$ 的极小值. 以一个3\*4\*4\*3的神经网络为例. 在该神经网络中, 损失函数如下:

$$J(\Theta) = y_1 \log(a_1^{(4)}) + (1 - y_1) \log(1 - a_1^{(4)})$$

$$+ y_2 \log(a_2^{(4)}) (1 - y_2) \log(1 - a_2^{(4)})$$

$$+ y_3 \log(a_3^{(4)}) + (1 - y_3) \log(1 - a_3^{(4)})$$

$$+ y_4 \log(a_4^{(4)}) + (1 - y_4) \log(1 - a_4^{(4)})$$

$$(6)$$

反向算法的精髓就是提出了一种算法,让我们能快速地求出 $J(\Theta)$ 对 $\Theta$ 的各个分量的导数(这就是9.2和9.3节在做的工作). 相信大家在看到误差公式那里和我一样懵,我们接下来就从根本目标——求偏导数入手,先不管"误差"这个概念. 在求导的过程中,"误差"这一概念会更自然的浮现出来.

我们首先对于最后一层参数求导,即 $\Theta^{(3)}$ . 首先明确, $\Theta^{(3)}$ 是一个3\*4的矩阵( $\Theta^{(3)}a^{(3)}_{(4\times 1)}=z^{(4)}_{(3\times 1)}$ ), $\frac{\partial J}{\partial \Theta^{(3)}}$ 也是一个3\*4矩阵,我们需要对 $\Theta^{(3)}$ 的每一个分量求导. 让我们首先对 $\theta^{(3)}_{12}$ 求导:

$$\frac{\partial J}{\partial \theta_{12}^{(3)}} = \underbrace{\frac{\partial J}{\partial a_1^{(4)}}}_{(7.1)} * \underbrace{\frac{\partial a_1^{(4)}}{\partial z_1^{(4)}}}_{(7.2)} * \underbrace{\frac{\partial z_1^{(4)}}{\theta_{12}^{(3)}}}_{(7.3)}$$
(7)

分别由式(6),(1),(4)知:

$$(7.1) = \frac{\partial J}{\partial a_1^{(4)}} = \frac{y_1}{a_1^{(4)}} - \frac{1 - y_1}{1 - a_1^{(4)}} \tag{8}$$

$$(7.2) = \frac{\partial a_1^{(4)}}{\partial z_1^{(4)}} = \frac{-e^{-z_1^{(4)}}}{\left(1 + e^{-z_1^{(4)}}\right)^2} = \frac{1}{1 + e^{-z_1^{(4)}}} * \left(1 - \frac{1}{1 + e^{-z_1^{(4)}}}\right) = a_1^{(4)} \left(1 - a_1^{(4)}\right) \tag{9}$$

$$(7.3) = \frac{\partial z_1^{(4)}}{\theta_{12}^{(3)}} = a_2^{(3)} \tag{10}$$

代入(7)知:

$$\frac{\partial J}{\partial \theta_{12}^{(3)}} = (y_1(1 - a_1^{(4)}) - (1 - y_1)a_1^{(4)})a_2^{(3)} = (y_1 - a_1^{(4)})a_2^{(3)} \tag{11}$$

同理可知 $J(\Theta)$ 对 $\Theta^{(3)}$ 其他分量的导数. 将 $\frac{\partial J}{\partial \Theta^{(3)}}$ 写成矩阵形式:

$$\frac{\partial J}{\partial \Theta^{(3)}} = \begin{bmatrix} (y_1 - a_1^{(4)})a_1^{(3)} & (y_1 - a_1^{(4)})a_2^{(3)} & (y_1 - a_1^{(4)})a_3^{(3)} & (y_1 - a_1^{(4)})a_4^{(3)} \\ (y_2 - a_2^{(4)})a_1^{(3)} & (y_2 - a_2^{(4)})a_2^{(3)} & (y_2 - a_2^{(4)})a_3^{(3)} & (y_1 - a_1^{(4)})a_4^{(3)} \\ (y_3 - a_3^{(4)})a_1^{(3)} & (y_3 - a_3^{(4)})a_2^{(3)} & (y_3 - a_3^{(4)})a_3^{(3)} & (y_1 - a_1^{(4)})a_4^{(3)} \end{bmatrix}$$
(12)

如果我们定义一个"误差"向量为 $\delta^{(4)}=\left[ \left. (y_1-a_1^{(4)}) \right. \left. (y_2-a_2^{(4)}) \right. \left. (y_3-a_3^{(4)}) \right]^T$ ,衡量最后一层神经元的输出与真实值之间的差异,那么(12)可以写成两个矩阵相乘的形式:

$$\frac{\partial J}{\partial \Theta^{(3)}} = \delta^{(4)} \begin{bmatrix} a_1^{(3)} & a_2^{(3)} & a_3^{(3)} & a_4^{(3)} \end{bmatrix} = \delta_{(3\times1)}^{(4)} (a^{(3)})_{(1\times4)}^T$$
(13)

让我们先记下这个式子,做接下来的工作: 计算 $\frac{\partial J}{\partial \Theta^{(2)}}$ . 和计算 $\frac{\partial J}{\partial \Theta^{(3)}}$ 一样, 让我们先计算 $\frac{\partial J}{\theta_{12}^{(2)}}$ 

$$\frac{\partial J}{\partial \theta_{12}^{(2)}} = \underbrace{\frac{\partial J}{\partial a_1^{(3)}}}_{(14.1)} * \underbrace{\frac{\partial a_1^{(3)}}{\partial z_1^{(3)}}}_{(14.2)} * \underbrace{\frac{\partial z_1^{(3)}}{\theta_{12}^{(2)}}}_{(14.3)}$$
(14)

根据偏导数的求导法则,其中(14.1)式还可以做如下拆分:

$$(14.1) = \frac{\partial J}{\partial \theta_{12}^{(2)}} = \underbrace{\frac{\partial J}{\partial a_1^{(4)}} * \frac{\partial a_1^{(4)}}{\partial z_1^{(4)}} * \frac{\partial z_1^{(4)}}{\partial a_1^{(3)}}}_{(15.1)} + \underbrace{\frac{\partial J}{\partial a_2^{(4)}} * \frac{\partial a_2^{(4)}}{\partial z_2^{(4)}} * \frac{\partial z_2^{(4)}}{\partial a_2^{(3)}}}_{(15.2)} + \underbrace{\frac{\partial J}{\partial a_3^{(4)}} * \frac{\partial a_3^{(4)}}{\partial z_3^{(4)}} * \frac{\partial z_3^{(4)}}{\partial a_3^{(3)}}}_{(15.3)}$$
(15)

注意到(15.1), (15.2)与(15.3)式都和(7)式类似, 三式子可分别化为:

$$(15.1) = \frac{\partial J}{\partial a_1^{(4)}} * \frac{\partial a_1^{(4)}}{\partial z_1^{(4)}} * \frac{\partial z_1^{(4)}}{\partial a_1^{(3)}} = (y_1 - a_1^{(4)})\theta_{11}^{(3)}$$

$$(16)$$

$$(15.2) = \frac{\partial J}{\partial a_2^{(4)}} * \frac{\partial a_2^{(4)}}{\partial z_2^{(4)}} * \frac{\partial z_2^{(4)}}{\partial a_2^{(3)}} = (y_2 - a_2^{(4)})\theta_{21}^{(3)}$$

$$(17)$$

$$(15.3) = \frac{\partial J}{\partial a_3^{(4)}} * \frac{\partial a_3^{(4)}}{\partial z_3^{(4)}} * \frac{\partial z_3^{(4)}}{\partial a_3^{(3)}} = (y_3 - a_3^{(4)})\theta_{31}^{(3)}$$

$$(18)$$

将(16), (17), (18)代入(15):

$$(14.1) = \frac{\partial J}{\partial \theta_{12}^{(2)}} = (y_1 - a_1^{(4)})\theta_{11}^{(3)} + (y_2 - a_2^{(4)})\theta_{21}^{(3)} + (y_3 - a_3^{(4)})\theta_{31}^{(3)}$$
(19)

另外,与(9),(10)类似,可以得到(14.2)和(14.3):

$$(14.2) = \frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} = a_1^{(3)} (1 - a_1^{(3)}) \tag{20}$$

$$(14.3) = \frac{\partial z_1^{(3)}}{\theta_{12}^{(2)}} = a_2^{(2)} \tag{21}$$

将(19), (20), (21)共同代入(14), 得到 $\frac{\partial J}{\theta_{s}^{(2)}}$ :

$$\frac{\partial J}{\theta_{12}^{(2)}} = [(y_1 - a_1^{(4)})\theta_{11}^{(3)} + (y_2 - a_2^{(4)})\theta_{21}^{(3)} + (y_3 - a_3^{(4)})\theta_{31}^{(3)}]a_1^{(3)}(1 - a_1^{(3)})a_2^{(2)}$$
(22)

同理也可知 $J(\Theta)$ 对 $\Theta^{(2)}$ 其他分量的导数. 将 $\frac{\partial J}{\partial \Theta^{(2)}}$ 写成矩阵形式:

$$\frac{\partial J}{\partial \Theta^{(2)}} = \begin{cases} \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} & \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{21}^{(3)} & + (y_2 - a_2^{(4)})\theta_{21}^{(3)} & + (y_2 - a_2^{(4)})\theta_{21}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{31}^{(3)}] & + (y_3 - a_3^{(4)})\theta_{31}^{(3)}] & + (y_3 - a_3^{(4)})\theta_{31}^{(3)}] & + (y_3 - a_3^{(4)})\theta_{31}^{(3)}] \\ *a_1^{(3)}(1 - a_1^{(3)}) & *a_1^{(3)}(1 - a_1^{(3)}) & *a_1^{(3)}(1 - a_1^{(3)}) & *a_1^{(3)}(1 - a_1^{(3)}) \\ *a_1^{(2)}\} & *a_2^{(2)}\} & *a_3^{(2)}\} & *a_3^{(2)}\} & *a_4^{(2)}\} \end{cases}$$

$$= \begin{cases} \{[(y_1 - a_1^{(4)})\theta_{12}^{(3)} & \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} & \{[(y_1 - a_1^{(4)})\theta_{13}^{$$

(23)只是看起来很复杂,实际上只是一个普通的(4\*4)矩阵. 让我们先参考(13)将 $a^{(2)}$  拆出来:

$$\frac{\partial J}{\partial \Theta^{(2)}}_{4\times4} = \begin{bmatrix} \{[(y_1 - a_1^{(4)})\theta_{11}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{21}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{31}^{(3)} ] \\ * a_1^{(3)} (1 - a_1^{(3)}) \} \\ \{[(y_1 - a_1^{(4)})\theta_{12}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{22}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{32}^{(3)} ] \\ * a_2^{(3)} (1 - a_2^{(3)}) \} \\ \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{23}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{33}^{(3)} ] \\ * a_3^{(3)} (1 - a_3^{(3)}) \} \\ \{[(y_1 - a_1^{(4)})\theta_{14}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{24}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{34}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{34}^{(4)} \\ + (y_3 - a$$

其中(24.2)是我们熟悉的 $a^{(2)}$ ", 而我们先暂时定义(24.1)为 $\delta^{(3)}$ (先不管它的实际意义), 引入Hadamard 积的概念(就是9.2节视频中的·\*符号), 对 $\delta^{(3)}$ 进一步拆分:

$$\delta^{(3)} = \begin{bmatrix} \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{21}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{31}^{(3)}]\} \\ \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{32}^{(3)}]\} \\ \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{23}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{23}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{23}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{33}^{(3)}]\} \\ \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{23}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{33}^{(3)}]\} \end{bmatrix} \\ \{[(y_1 - a_1^{(4)})\theta_{13}^{(3)} \\ + (y_2 - a_2^{(4)})\theta_{24}^{(3)} \\ + (y_3 - a_3^{(4)})\theta_{34}^{(3)}]\} \end{bmatrix} \\ \begin{bmatrix} \theta_{11}^{(3)} & \theta_{21}^{(3)} & \theta_{31}^{(3)} \\ \theta_{12}^{(3)} & \theta_{23}^{(3)} & \theta_{33}^{(3)} \\ \theta_{13}^{(3)} & \theta_{23}^{(3)} & \theta_$$

综合(24), (25)式可以得到:

$$\frac{\partial J}{\partial \Theta^{(2)}} = \delta^{(3)} a^{(2)}^T \tag{26}$$

其中

$$\delta^{(3)} = \Theta^{(3)} \delta^{(4)} \circ \frac{\partial a^{(3)}}{\partial z^{(3)}}$$
 (27)

至此, 基本大功告成. 让我们将(26), (27)与(13)对照观察:

$$\frac{\partial J}{\partial \Theta^{(3)}} = \delta^{(4)} a^{(3)^{T}} 
\frac{\partial J}{\partial \Theta^{(2)}} = \delta^{(3)} a^{(2)^{T}} 
\delta^{(3)} = \Theta^{(3)^{T}} \delta^{(4)} \circ \frac{\partial a^{(3)}}{\partial z^{(3)}}$$
(28)

归纳总结即可推广到L层的神经网络:

$$\frac{\partial J}{\partial \Theta^{(l)}} = \delta^{(l+1)} a^{(l)^T} \tag{29}$$

$$\delta^{(l)} = \begin{cases}
0 & l = 0 \\
\Theta^{(l)^T} \delta^{(l+1)} \circ \frac{\partial a^{(l)}}{\partial z^{(l)}} & 1 \leqslant l \leqslant L - 1 \\
y - a^{(l)} & l = L
\end{cases}$$

其中 $\frac{\partial a^{(l)}}{\partial z^{(l)}}$ 就是sigmoid(x).

根据(29), 我们就可以顺利、轻松、较快速地迭代求出 $J(\Theta)$ 对 $\Theta$ 的各个分量的导数. 完结, 撒花 ~