Stanford CS230 Notes

1 Introduction to Deep Learning

1.1 What is a Neural Network?

neuron, links.

1.2 Supervised Learning with Neural Networks

Supervised Learning

Examples: Standard NN, Convolutional NN, Recurrent NN

Structured Data: tabular data; Unstructured Data: audio/image/text

1.3 Why is Deep Learning taking off?

Amount of labeled data.

2 Basics of Neural Network Programming

2.1 Binary Classification

2.1.1 Binary Classification

image \rightarrow 1 (cat) vs 0 (non cat)

2.1.2 Notation

m: number of examples

 n_x : input size

 n_y : output size

x: input, column vector

y: output, 0/1

X: input matrix, shape = (n_x, m)

Y: output matrix, shape = (1, m)

 $x^{(i)}$: superscript (i) will denote the i^{th} example.

2.2 Logistic Regression

Given: $x \in \mathbb{R}^{n_x}$, $0 \le \hat{y} \le 1$

Parameters: $w \in \mathbb{R}^{n_x}, b \in \mathbb{R}$

Output:

$$z = w^T x + b \tag{1}$$

$$\hat{y} = \sigma(z) \tag{2}$$

$$\sigma(z) \approx \frac{1}{1 + e^{-z}} \tag{3}$$

$$z \approx \infty, \sigma(z) \approx \frac{1}{1+0} = 1$$
 (4)

$$z \approx -\infty, \sigma(z) \approx \frac{1}{1+\infty} = 0$$
 (5)

Simplified Parameters: $x_0 = 1, x \in \mathbb{R}^{n_x+1}$

$$\theta_0 = b, \theta_1 \dots \theta_{n_x} = w \tag{6}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \dots \\ \theta_{n_x} \end{bmatrix} \tag{7}$$

$$\hat{y} = \sigma(\theta^T x) \tag{8}$$

2.3 Logistic Regression cost function

Given $\{(x^{(1)}, y^{(1)}, ..., (x^{(m)}, y^{(m)})\}$, want $\hat{y}^{(i)} \approx y^{(i)}$.

Loss (error) function (mean square error/cross entropy):

$$\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$$
 (9)

$$\mathcal{L}(\hat{y}, y) = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y})) \tag{10}$$

If y = 1: $\mathcal{L}(\hat{y}, y) = -\log \hat{y}$, want \mathcal{L} small, want \hat{y} large, want \hat{y} equal to 1. If y = 0: $\mathcal{L}(\hat{y}, y) = -\log (1 - \hat{y})$, want \mathcal{L} small, want \hat{y} small, want \hat{y} equal to 0.

Cost function:

$$J(w,b) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}, y)$$
 (11)

$$J(w,b) = -\frac{1}{m} \sum_{i=1}^{m} [y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log 1 - \hat{y}^{(i)}]$$
 (12)

Given a random variable X with probability mass function $p_X(x)$, the self information of measuring X as outcome x is defined as:

$$I_X(x) = \log[p_X(x)] = \log(\frac{1}{p_X(x)})$$
 (13)

Shannon Entroy of X:

$$H(X) = \sum_{x} -p_X(x) \log p_X(x)$$
(14)

$$=\sum_{x} p_X(x)I_X(x) \tag{15}$$

$$=E[I_X(x)] (16)$$

Cross Entropy of the true distributions p and estimated distribution q:

$$H(p,q) = E_p[-\log q] = -\sum_{x \in \mathcal{X}} p(x) \log q(x)$$
(17)

2.4 Gradient Descent

Want to find w, b that minimize J(w, b).

Repeat:

$$w := w - \alpha \frac{\mathrm{d}J(w, b)}{\mathrm{d}w} \tag{18}$$

$$b := b - \alpha \frac{\mathrm{d}J(w, b)}{\mathrm{d}b} \tag{19}$$

 α : learning rate

2.5 Derivatives

$$f(a) = 3a, \frac{\mathrm{d}f(a)}{\mathrm{d}a} = 3 = \frac{\mathrm{d}}{\mathrm{d}a}f(a) \tag{20}$$

$$f(a) = a^2, \frac{\mathrm{d}}{\mathrm{d}a}f(a) = 2a \tag{21}$$

$$f(a) = a^3, \frac{\mathrm{d}}{\mathrm{d}a} f(a) = 3a^2$$
 (22)

$$f(a) = \log_e a = \ln a, \frac{\mathrm{d}}{\mathrm{d}a} f(a) = \frac{1}{a}$$
 (23)

$$f(x) = \log_a x, \frac{\mathrm{d}}{\mathrm{d}x} f(x) = \frac{1}{x \ln a}$$
 (24)

$$f(x) = a^x, \frac{\mathrm{d}}{\mathrm{d}x} f(x) = a^x \ln a \tag{25}$$

$$\log_a b = \frac{\log_c b}{\log_c a} = \frac{\ln a}{\ln b} \tag{26}$$

2.6 Computation Graph

$$J(a,b,c) = 3(a+bc) \tag{27}$$

$$=3(a+u) \tag{28}$$

$$=3v\tag{29}$$

$$u = bc (30)$$

$$v = a + u \tag{31}$$

$$J = 3v \tag{32}$$

2.7 Derivatives with a Computation Graph

$$a = 5, b = 3, c = 2$$

$$\frac{\mathrm{d}J}{\mathrm{d}v} = 3\tag{33}$$

$$\frac{\mathrm{d}J}{\mathrm{d}a} = \frac{\mathrm{d}J}{\mathrm{d}v}\frac{\mathrm{d}v}{\mathrm{d}a} \tag{34}$$

$$= 3 * 1 \tag{35}$$

$$=3\tag{36}$$

$$\frac{\mathrm{d}J}{\mathrm{d}u} = \frac{\mathrm{d}J}{\mathrm{d}v}\frac{\mathrm{d}v}{\mathrm{d}u} \tag{37}$$

$$=3\tag{38}$$

$$\frac{\mathrm{d}J}{\mathrm{d}b} = \frac{\mathrm{d}J}{\mathrm{d}u}\frac{\mathrm{d}u}{\mathrm{d}b} \tag{39}$$

$$= 3 * c \tag{40}$$

$$= 3 * 2 \tag{41}$$

$$= 6 \tag{42}$$

$$\frac{\mathrm{d}J}{\mathrm{d}c} = \frac{\mathrm{d}J}{\mathrm{d}u}\frac{\mathrm{d}u}{\mathrm{d}c} \tag{43}$$

$$= 3 * b \tag{44}$$

$$= 3 * 3 \tag{45}$$

$$=9\tag{46}$$