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Basics of Neural Network Programming

Logistic Regression

This is a learning algorithm that you use when the output label y in a supervised learning problem are all either zero or one, so for binary classification problem.

Logistic Regression

Given x, want $\hat{y} = P(y=1 \mid x)$

$0 \le \hat{y} \le 1$

$x \in \mathbb{R}^{n_x}$

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

Output $\hat{y} = \sigma(\underbrace{w^T x + b}_{z})$

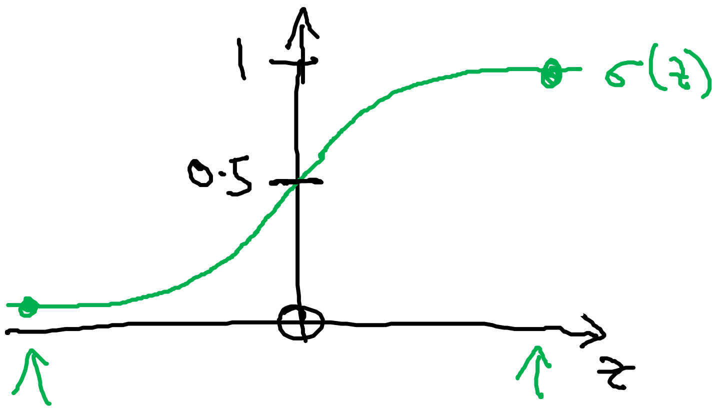
$x_0 = 1$, $x \in \mathbb{R}^{n_x+1}$

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

$$\underbrace{\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_{n_x} \end{bmatrix} \begin{array}{l} \} b \leftarrow \\ \left.\begin{array}{l} \\ \\ \\ \\ \end{array}\right\} w \leftarrow \end{array}}$$

When implement neural network, it will be easier to just keep B and W as separate parameters

So in this class, we will not use any of this notational convention



$$\sigma(z) = \frac{1}{1+e^{-z}}$$

If z large $\sigma(z) \approx \frac{1}{1+0} = 1$

if z is very small or If z large negative number

$$\sigma(z) = \frac{1}{1+e^{-z}} \approx \frac{1}{1+\text{Bignum}} \approx 0$$

So when you implement logistic regression, your job is to try to learn parameters W and B so that y hat becomes a good estimate of the chance of Y equal to one.

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Basics of Neural Network Programming

Logistic Regression cost function

Logistic Regression cost function

$\rightarrow \hat{y}^{(i)} = \sigma(w^T x^{(i)} + b)$, where $\sigma(z^{(i)}) = \frac{1}{1+e^{-z^{(i)}}}$

$z^{(i)} = w^T x^{(i)} + b$

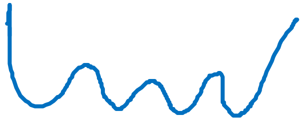
Given $\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$, want $\hat{y}^{(i)} \approx y^{(i)}$.

$x^{(i)}$
$y^{(i)}$
$z^{(i)}$

i-th example.

$\boxed{\text{Loss}}$ (error) function: $\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2$

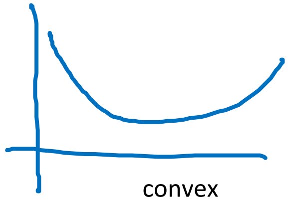
the function I will need to define the measure how good our output y-hat is when true labels is y. And square error seems like it might be a reasonable except it makes gradient descent not work well.



non-convex

$\boxed{\mathcal{L}(\hat{y}, y)} = -\left(\boxed{y \log \hat{y}} + (1-y)\log(1-\hat{y})\right) \leftarrow$

optimization problem becomes non-convex
so you end up with optimization with multiple local optima
so gradient descent may not find the global optimum



convex

If $y = 1$: $\mathcal{L}(\hat{y}, y) = -\log \hat{y} \leftarrow$ Want $\log \hat{y}$ large, want $\hat{y}$ large.

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

$\boxed{\text{Cost}}$ function: $J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log \hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right]$

Lost function was defined with respect to a single training example. It measures how well you're doing on a single training example.
Cost function, which measure how well you're doing on the entire training set, is the cost of your parameters.

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So in training your logistic regression model, we're going to find parameters W and B that minimize the overall cost function J written at the bottom

It turns out that logistic regression can be viewed as a very very small neural network.