逻辑回归

逻辑回归的概念：

逻辑回归也被称为广义线性回归模型，它与线性回归模型的形式基本上相同，都具有 ax+b，其中 a 和 b 是待求参数，其区别在于他们的因变量不同，多重线性回归直接将 ax+b 作为因变量，即 y = ax+b，而 logistic 回归则通过函数 S 将 ax+b 对应到一个隐状态 p，p = S(ax+b)，然后根据 p 与 1-p 的大小决定因变量的值。这里的函数 S 就是 Sigmoid 函数。

$$S(t)=1/(1+e^{-t})$$

通过函数 S 的作用，我们可以将输出的值限制在区间[0， 1]上，p(x)则可以用来表示概率 p(y=1|x)，即当一个 x 发生时，y 被分到 1 那一组的概率。

逻辑回归模型的代价函数：

逻辑回归一般使用交叉熵作为代价函数。关于代价函数的具体细节，请参考代价函数，这里只给出交叉熵公式：

$$J(\theta)=-\frac{1}{m}\left[\sum_{i=1}^{m}\left(y^{(i)}\log h_\theta(x^{(i)})+(1-y^{(i)})\log(1-h_\theta(x^{(i)}))\right)\right]$$

m：训练样本的个数；

$h_\theta(x)$：用参数 θ 和 x 预测出来的 y 值；

y：原训练样本中的 y 值，也就是标准答案

上角标(i)：第 i 个样本

代码实现：

1.py

实验截图：

训练数据：

```
[[1.0, -0.017612, 14.053064], [1.0, -1.395634, 4.662541], [1.0, -0.752157, 6.53862], [1.0,
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6.151823], [1.0, -0.036453, 2.690988], [1.0, -0.196949, 0.444165], [1.0, 1.014459, 5.754399],
[1.0, 1.985298, 3.230619], [1.0, -1.693453, -0.55754], [1.0, -0.576525, 11.778922], [1.0,
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[[ 5.262118  ]
 [ 0.60847797]
 [-0.75168429]]
[[0.00490753]
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 [0.28512035]
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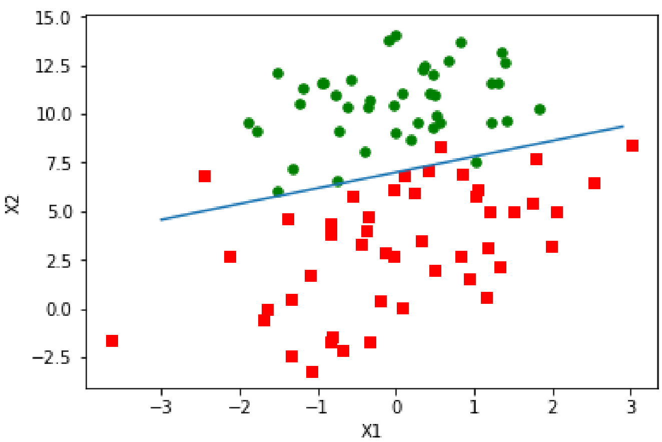

测试数据：

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