17.4.24(机器学习的一些建议, BP算法MATLAB实现)

机器学习的一些建议 (Advice for Applying Machine Learning)

- Get more training examples fixes high variance
- Try smaller sets of features fixe high voice
- Try getting additional features fixed high bias
- Try adding polynomial features $(x_1^2, x_2^2, x_1x_2, \text{etc}) \rightarrow \text{fixe high bias}$
- Try decreasing & fixes high him
- Try increasing \(\rightarrow \text{ fixes high variance} \)

当我们的拟合曲线是过拟合时:我们一般的解决办法是,获得更多的训练集,尝试减少特征的数量,尝试增加ambda。当我们的拟合曲线是欠拟合时,解决办法:尝试更多的特征,尝试增加多项式特征,尝试减少ambda。

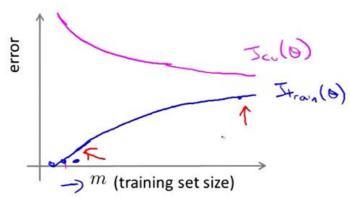
学习曲线是学习算法的一个很好的 合理检验 (sanity check)。学习曲线是将

训练集误差和交叉验证集误差作为训练集实例数量(m)的函数绘制的图表。

Learning curves

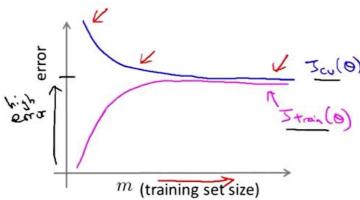
$$J_{train}(\theta) = \frac{1}{2m} \sum_{\substack{i=1\\m_{cv}}}^{m} (h_{\theta}(x^{(i)}) - y^{(i)})^{2} \leftarrow$$

$$J_{cv}(\theta) = \frac{1}{2m_{cv}} \sum_{\substack{i=1\\i=1}}}^{m} (h_{\theta}(x^{(i)}_{cv}) - y^{(i)}_{cv})^{2}$$



当训练集较少时,得出来的假设函数,在cv集或更多的训练集时,就不能很好地拟合。

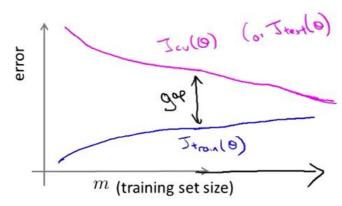
High bias



If a learning algorithm is suffering from high bias, getting training data will not (by itself) help much.

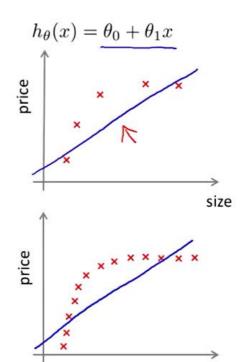
上图所示的学习函数, 欠拟合时, 增加训练集的数据不会有什么帮助。

High variance



If a learning algorithm is suffering from high variance, getting more training data is likely to help.

如果学习曲线如上图所示, 过拟合时, 增加更多的训练集可能会有帮助。 cost function 正则化的时候, 去掉theta0, 就是要去掉和X0对应的。



size

$$h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_{100} x^{100}$$

$$\text{(and small } \lambda)$$

$$\text{size}$$

Neural network:

$$h_{\Theta}(x) \in \mathbb{R}^{K} \quad (h_{\Theta}(x))_{i} = i^{th} \text{ output}$$

$$J(\Theta) = -\frac{1}{m} \left[\sum_{i=1}^{m} \sum_{k=1}^{K} y_{k}^{(i)} \log(h_{\Theta}(x^{(i)}))_{k} + (1 - y_{k}^{(i)}) \log(1 - (h_{\Theta}(x^{(i)}))_{k}) \right]$$

$$+ \frac{\lambda}{2m} \sum_{l=1}^{L-1} \sum_{i=1}^{s_{l}} \sum_{j=1}^{s_{l+1}} (\Theta_{ji}^{(l)})^{2}$$

正则化加上的就是所有theta的和*(lambda/2m)。

神经网络的代价函数,多分类问题,所以要把实际分类值做处理(用for循环),处理成下图类型,才能和假设函数求出来的预测值进行计算。

$$y = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \dots \quad \text{or} \quad \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}.$$

反向传播求解每层的delte (实际误差)想法:

2. For each output unit k in layer 3 (the output layer), set

$$\delta_k^{(3)} = (a_k^{(3)} - y_k),$$

where $y_k \in \{0, 1\}$ indicates whether the current training example belongs to class k ($y_k = 1$), or if it belongs to a different class ($y_k = 0$). You may find logical arrays helpful for this task (explained in the previous programming exercise).

3. For the hidden layer l = 2, set

$$\delta^{(2)} = (\Theta^{(2)})^T \delta^{(3)} \cdot * g'(z^{(2)})$$

4. Accumulate the gradient from this example using the following formula. Note that you should skip or remove $\delta_0^{(2)}$. In Octave/MATLAB, removing $\delta_0^{(2)}$ corresponds to delta_2 = delta_2(2:end).

$$\Delta^{(l)} = \Delta^{(l)} + \delta^{(l+1)}(a^{(l)})^T$$

 Obtain the (unregularized) gradient for the neural network cost function by dividing the accumulated gradients by ¹/_m:

$$\frac{\partial}{\partial \Theta_{ij}^{(l)}} J(\Theta) = D_{ij}^{(l)} = \frac{1}{m} \Delta_{ij}^{(l)}$$

实际代码:

```
delte2 = s1 - y_temp;
Theta2_grad = delte2'*s/m+lambda*[zeros(size(Theta2,1),1) Theta2(:,2:size(Theta2,2))]/m;
temp = X*Theta1';
delte1 = delte2*Theta2(:,2:size(Theta2,2)).*sigmoidGradient(temp);
Theta1_grad = delte1'*x/m+lambda*[zeros(size(Theta1,1),1) Theta1(:,2:size(Theta1,2))]/m;
```

所有的数据在一起用矩阵计算,就是先用输出层的预测值减去处理过的实际值,求出delte(L),然后用delte(l)与delte(l+1)之间的关系公式求出delte(l),以此类推,求出所有隐藏层的delte。求出所有的delte以后,用梯度求解公式求对应的梯度。求解梯度的时候要正则化。

$$\begin{split} \frac{\partial}{\partial \Theta_{ij}^{(l)}} J(\Theta) &= D_{ij}^{(l)} = \frac{1}{m} \Delta_{ij}^{(l)} & \text{for } j = 0 \\ \frac{\partial}{\partial \Theta_{ij}^{(l)}} J(\Theta) &= D_{ij}^{(l)} = \frac{1}{m} \Delta_{ij}^{(l)} + \frac{\lambda}{m} \Theta_{ij}^{(l)} & \text{for } j \geq 1 \end{split}$$

正则化的时候还是不算theta(0).