ICTS 6156/8156: Machine Learning

Razvan Bunescu

Notes on gradient descent and feature scaling

1 Notes on lecture slides material

1.1 Gradient descent

Let $J(w) = \frac{1}{2}(w-4)^2 + 1$ and the initial guess $w_0 = 0$, for which $J(w_0) = 9$. Let the learning rate be $\eta = 0.5$. The gradient of J is $\nabla J(w) = w - 4$.

- 1. The gradient at w_0 is $\nabla J(w_0) = w_0 4 = -4$. The gradient update step is $w_1 = w_0 \eta \nabla J(w_0) = 0 0.5 * -4 = 2$. So, $w_1 = 2$ for which $J(w_1) = 3$.
- 2. The gradient at w_1 is $\nabla J(w_1) = w_1 4 = -2$. The gradient update step is $w_2 = w_1 \eta \nabla J(w_1) = 2 0.5 * -2 = 3$. So, $w_2 = 3$ for which $J(w_2) = 1.5$.
- 3. The gradient at w_2 is $\nabla J(w_2) = w_2 4 = -1$. The gradient update step is $w_3 = w_2 \eta \nabla J(w_2) = 3 0.5 * -1 = 3.5$ So, $w_4 = 3.5$ for which $J(w_3) = 1.125$.
- 4. and so on ... for ever?

Bonus points: For different values of η , plot on the same graph J(w) and the points (in blue) corresponding to the gradient steps. Try eta = 0.1, 0.5, 1, 2, ...

"Until J(w) does not improve": how do we quantify this? One method is to look at the *relative* change.

$$\Delta J = \left| \frac{J(w_t) - J(w_{t-1})}{J(w_{t-1})} \right|$$
(1)

If ΔJ is too small (0,0001) for a number of epochs (5 or 10), then you may consider stopping.

1.2 Feature scaling

Suppose feature x_j has values 1, 2, 3 in the training data (3 training examples). The sample mean is $m_j = \frac{1+2+3}{3} = 2$. The sample standard deviation is $\sigma_j = \sqrt{\frac{(1-m_j)^2 + (2-m_j)^2 + (3-m_j)^2}{3}} = \sqrt{\frac{2}{3}}$. Then the feature x_j which had values 1, 2, 3 will be scaled to the following values:

- 1. For training example 1, the new feature will be $\hat{x}_j = \frac{1-m_j}{\sigma_j} = \frac{1-2}{\sigma_j}$.
- 2. For training example 2, the new feature will be $\hat{x}_j = \frac{2-m_j}{\sigma_j} = \frac{2-2}{\sigma_j}$.
- 3. For training example 3, the new feature will be $\hat{x}_j = \frac{3-m_j}{\sigma_j} = \frac{3-2}{\sigma_j}$.