<u>0</u>

## Cost Function and Backpropagation

Video: Cost Function 6 min

Reading: Cost Function

▶ Video: Backpropagation

Reading: Backpropagation 10 min

▶ Video: Backpropagation Intuition 12 min

Reading: Backpropagation Intuition 4 min

## Backpropagation in Practice

Video: Implementation Note: Unrolling Parameters

Reading: Implementation Note: Unrolling Parameters 3 min

▶ Video: Gradient Checking

Reading: Gradient Checking

▶ Video: Random Initialization

Reading: Random

▶ Video: Putting It Together

Reading: Putting It Together

## **Application of Neural**

Review

## **Gradient Checking**

Gradient checking will assure that our backpropagation works as intended. We can approximate the derivative of our cost

$$\frac{\partial}{\partial \Theta} J(\Theta) \approx \frac{J(\Theta + \epsilon) - J(\Theta - \epsilon)}{2\epsilon}$$

With multiple theta matrices, we can approximate the derivative **with respect to**  $\Theta_j$  as follows:

$$\frac{\partial}{\partial \Theta_j} J(\Theta) \approx \frac{J(\Theta_1, \dots, \Theta_j + \epsilon, \dots, \Theta_n) - J(\Theta_1, \dots, \Theta_j - \epsilon, \dots, \Theta_n)}{2\epsilon}$$

A small value for  $\epsilon$  (epsilon) such as  $\epsilon=10^{-4}$ , guarantees that the math works out properly. If the value for  $\epsilon$  is too small, we can end up with numerical problems.

Hence, we are only adding or subtracting epsilon to the  $\Theta_j$  matrix. In octave we can do it as follows:

```
1 epsilon = 1e-4;
2 for i = 1:n,
3 thetaPlus = theta;
4 thetaPlus(i) += epsilon;
5 thetaMinus = theta;
6 thetaMinus(i) -= epsilon;
7 gradApprox(i) = (J(thetaPlus) - J(thetaMinus))/(2*epsilon)
8 end:
```

We previously saw how to calculate the deltaVector. So once we compute our gradApprox vector, we can check that gradApprox

 $Once you have verified {\bf once} \ that your backpropagation \ algorithm \ is \ correct, you \ don't \ need \ to \ compute \ grad Approx \ again. \ The \ again \ aga$ code to compute gradApprox can be very slow