# Advanced Optimization

Logistic Regression Model Logistic Regression

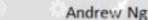
Cost function  $J(\theta)$ . Want  $\min_{\theta} J(\theta)$ .

Given  $\theta$ , we have code that can compute

- 
$$J(\theta)$$

- 
$$\frac{\partial}{\partial \theta_j} J(\theta)$$
 (for  $j=0,1,\ldots,n$  )

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Cost function  $J(\theta)$ . Want  $\min_{\theta} J(\theta)$ .

Given  $\underline{\theta}$ , we have code that can compute

$$\frac{J(\theta)}{J(\theta)} = 0, 1, \dots, n$$
 (for  $j = 0, 1, \dots, n$ )

Gradient descent:

$$\rightarrow \theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

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Given  $\theta$ , we have code that can compute

$$-J( heta) - rac{\partial}{\partial heta_j} J( heta)$$
 (for  $j=0,1,\ldots,n$  )

## Optimization algorithms:

Gradient descent

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#### Optimization algorithms:

- Gradient descent
  - Conjugate gradient
  - BFGS
  - L-BFGS

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## Optimization algorithms:

- Gradient descent
  - Conjugate gradient
  - BFGS
  - L-BFGS

#### Advantages:

- No need to manually pick  $\alpha$
- Often faster than gradient descent.

# Disadvantages:

More complex
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#### Example:

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}$$

$$J(\theta) = (\theta_1 - 5)^2 + (\theta_2 - 5)^2$$

$$\frac{\partial}{\partial \theta_1} J(\theta) = 2(\theta_1 - 5)$$

$$\frac{\partial}{\partial \theta_2} J(\theta) = 2(\theta_2 - 5)$$

Example: 
$$\theta_1$$
  $\theta_2$   $\theta_2$   $\theta_3$   $\theta_4$   $\theta_5$   $\theta_7$   $\theta$ 

$$J(\theta) = (\theta_1 - 5)^2 + (\theta_2 - 5)^2$$

$$\frac{\partial}{\partial \theta_1} J(\theta) = 2(\theta_1 - 5)$$

$$\frac{\partial}{\partial \theta_2} J(\theta) = 2(\theta_2 - 5)$$

Example: 
$$\theta_1$$
  $\theta_2$   $\theta_2$   $\theta_3$   $\theta_4$   $\theta_5$   $\theta_7$   $\theta_7$   $\theta_7$   $\theta_8$   $\theta$ 

$$J(\theta) = (\theta_1 - 5)^2 + (\theta_2 - 5)^2$$

$$\frac{\partial}{\partial \theta_1} J(\theta) = 2(\theta_1 - 5)$$

$$\frac{\partial}{\partial \theta_2} J(\theta) = 2(\theta_2 - 5)$$

```
function [jVal, gradient]
          = costFunction(theta)
  jVal = (theta(1)-5)^2 + ...
          (theta(2)-5)^2;
  gradient = zeros(2,1);
  gradient(1) = 2*(theta(1)-5);
  gradient(2) = 2*(theta(2)-5);
```

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Example: 
$$\theta_1$$
  $\theta_2$   $\theta_3$   $\theta_4$   $\theta_4$   $\theta_5$   $\theta_5$   $\theta_5$   $\theta_5$   $\theta_6$   $\theta$ 

 $\rightarrow \frac{\partial}{\partial \theta_2} J(\theta) = 2(\theta_2 - 5)$ 

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```
theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \end{bmatrix}
function [jVal, gradient] = costFunction(theta)
          jVal = [code to compute J(\theta)];
         gradient(1) = [code to compute \frac{\partial}{\partial \theta_0} J(\theta)];
         gradient(2) = [code to compute \frac{\partial}{\partial \theta_1} J(\theta)];
         gradient (n+1) = [code to compute \frac{\partial}{\partial \theta_n} J(\theta)^{\text{Windows'u Etkinleştir}} kinleştirmek için Ayarlar'a gidin.
```

theta = 
$$\begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} + \text{theta(1)}$$
function [jVal, gradient] = costFunction(theta)
$$\text{jVal} = [\text{code to compute } J(\theta)];$$

$$\text{gradient(1)} = [\text{code to compute } \frac{\partial}{\partial \theta_0} J(\theta)];$$

$$\text{gradient(2)} = [\text{code to compute } \frac{\partial}{\partial \theta_1} J(\theta)];$$

$$\vdots$$

$$\text{gradient(n+1)} = [\text{code to compute } \frac{\partial}{\partial \theta_n} J(\theta)]^{\text{Vindows'u Etkinleştir}}$$

theta = 
$$\begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} = \frac{1}{1} \frac{$$

# Exercise

• Suppose you want to use an advanced optimization algorithm to minimize the cost function for logistic regression with parameters  $\theta_0$  and  $\theta_1$ . You write the following code :

- function [jVal, gradient] = costFunction(theta) jVal = % code to compute J
- $gradient(1) = CODE#1\% derivative for theta_0$
- $gradient(1) = CODE#1\% derivative for theta_0$

# Exercise

What should CODE#1 and CODE#2 above compute?

What should CODE#1 and CODE#2 above compute?

- O CODE#1 and CODE#2 should compute  $J(\theta)$ .
- O CODE#1 should be  $\theta_1$  and CODE#2 should be  $\theta_2$ .
- $\bigcirc \text{ CODE#1 should compute } \ \frac{1}{m} \sum_{i=1}^m \left[ (h_\theta(x^{(i)}) y^{(i)}). \, x_0^{(i)} \right] (= \frac{\partial}{\partial \theta_0} J(\theta)) \, ,$

and CODE#2 should compute 
$$\frac{1}{m}\sum_{i=1}^m \left[ (h_{\theta}(x^{(i)}) - y^{(i)}).x_1^{(i)} \right] (= \frac{\partial}{\partial \theta_1} J(\theta))$$

O None of them.