Map-reduce

Batch gradient descent:
$$\theta_j := \theta_j - \alpha \frac{1}{400} \sum_{i=1}^{400} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

Machine 1: Use $(x^{(1)}, y^{(1)}), \dots, (x^{(100)}, y^{(100)}).$

Machine 2: Use $(x^{(101)}, y^{(101)}), \dots, (x^{(200)}, y^{(200)})$.

$$\longrightarrow temp_j^{(2)} = \sum_{i=101}^{200} (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$

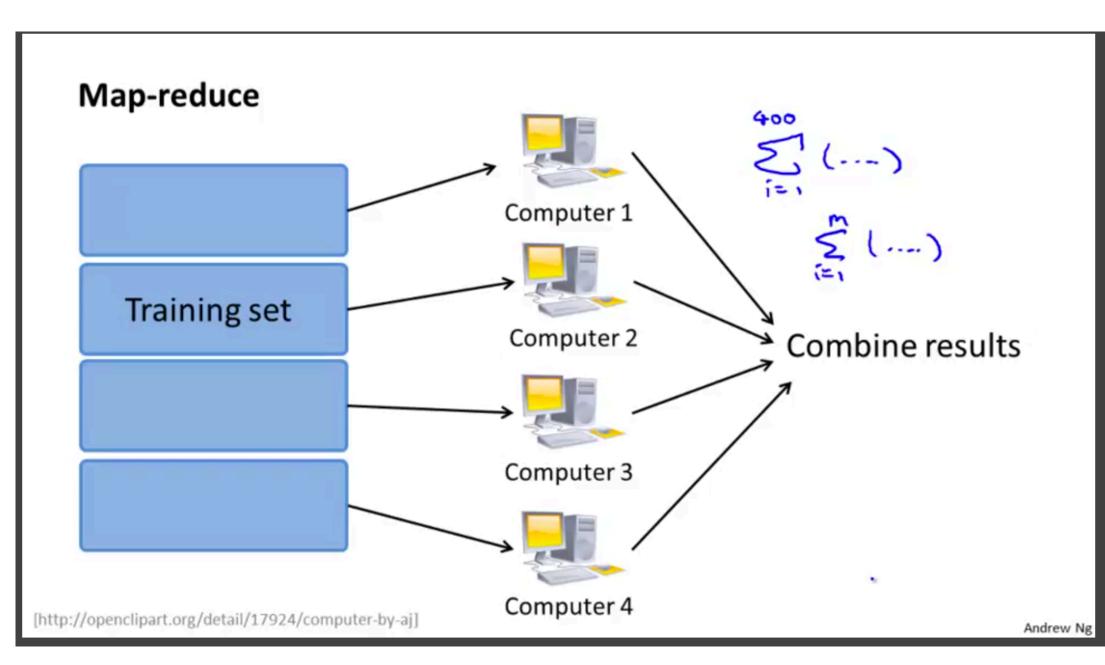
Machine 3: Use $(x^{(201)}, y^{(201)}), \dots, (x^{(300)}, y^{(300)}).$

$$temp_j^{(3)} = \sum_{i=201}^{300} (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$

Machine 4: Use $(x^{(301)}, y^{(301)}), \dots, (x^{(400)}, y^{(400)}).$

$$temp_j^{(4)} = \sum_{i=301}^{400} (h_{\theta}(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$

(xm, (m)



Map-reduce and summation over the training set

Many learning algorithms can be expressed as computing sums of functions over the training set.

E.g. for advanced optimization, with logistic regression, need:

$$J_{train}(\theta) = -\frac{1}{m} \sum_{i=1}^{m} \underline{y^{(i)} \log h_{\theta}(x^{(i)}) - (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)}))}$$

$$\Rightarrow \frac{\partial}{\partial \theta_{j}} J_{train}(\theta) = \frac{1}{m} \sum_{i=1}^{m} (\underline{h_{\theta}(x^{(i)}) - y^{(i)}) \cdot x_{j}^{(i)}}$$

temp
$$i=1$$

temp $i=1$
 $temp (i) \leftarrow temp (i) \leftarrow temp (ii)$

