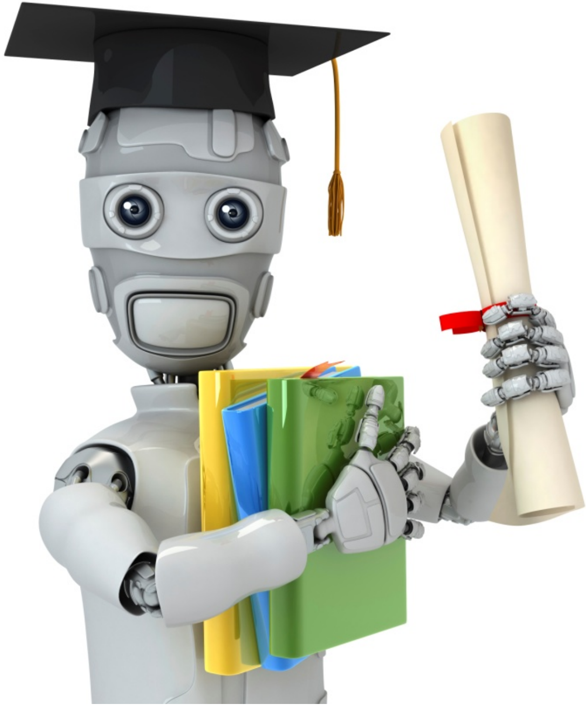


Machine Learning

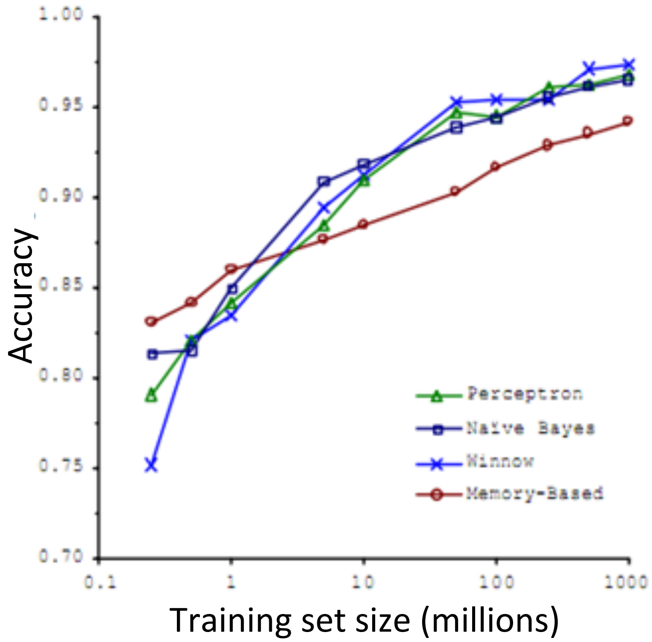
Large scale machine learning

Learning with large datasets

Machine learning and data

Classify between confusable words.
E.g., {to, two, too}, {then, than}.

For breakfast I ate two eggs.



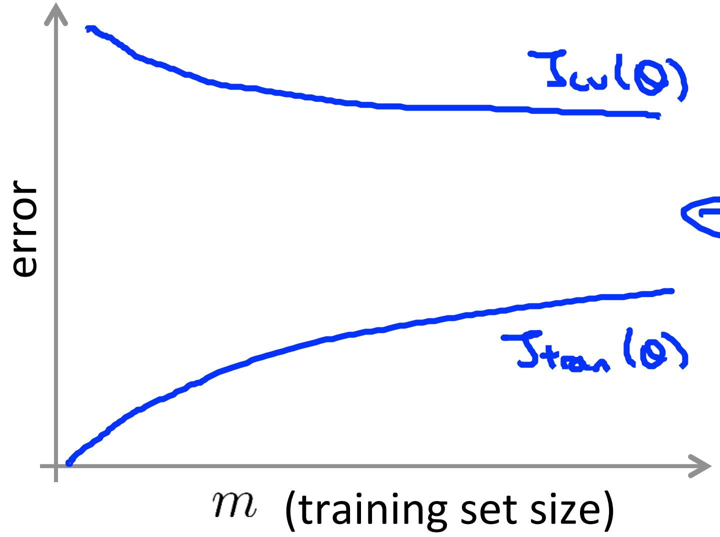
"It's not who has the best algorithm that wins.
It's who has the most data."

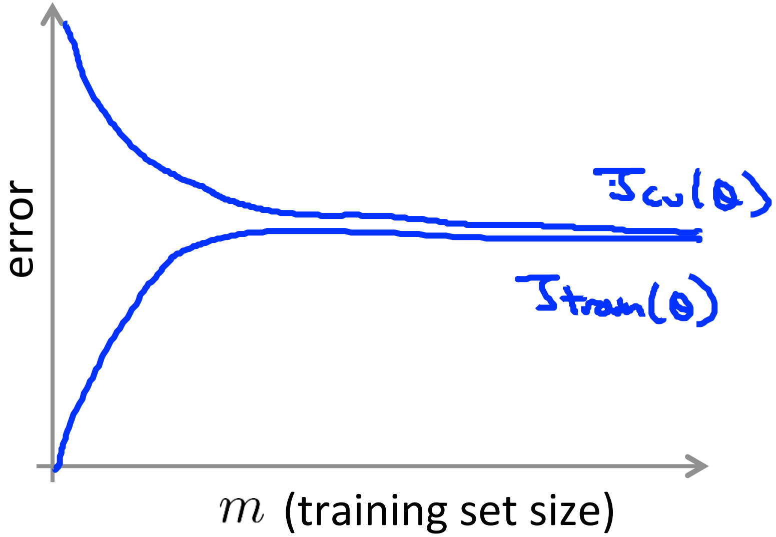
[Figure from Banko and Brill, 2001]

Learning with large datasets

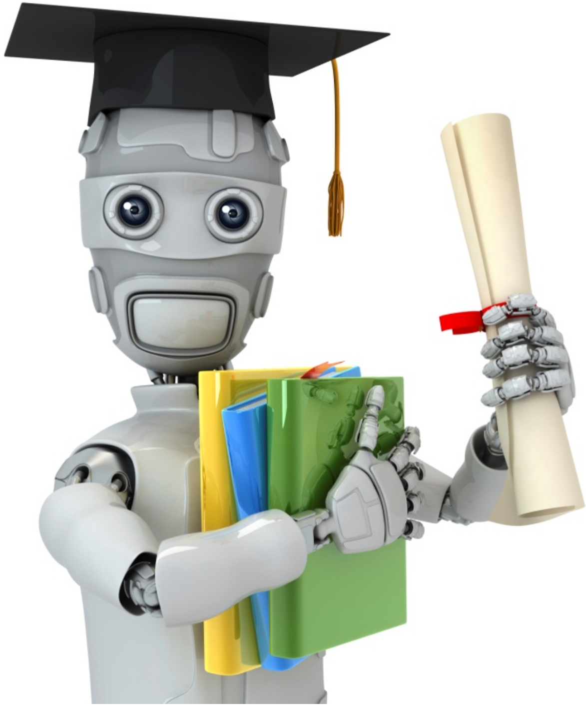
$m = 100,000,000$ | $m = 1,000?$

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





Andrew Ng



Machine Learning

Large scale machine learning

Stochastic gradient descent

Linear regression with gradient descent

$$h_\theta(x) = \sum_{j=0}^{n} \theta_j x_j$$

Linear Regression Hypothesis

Linear Regression Cost Function

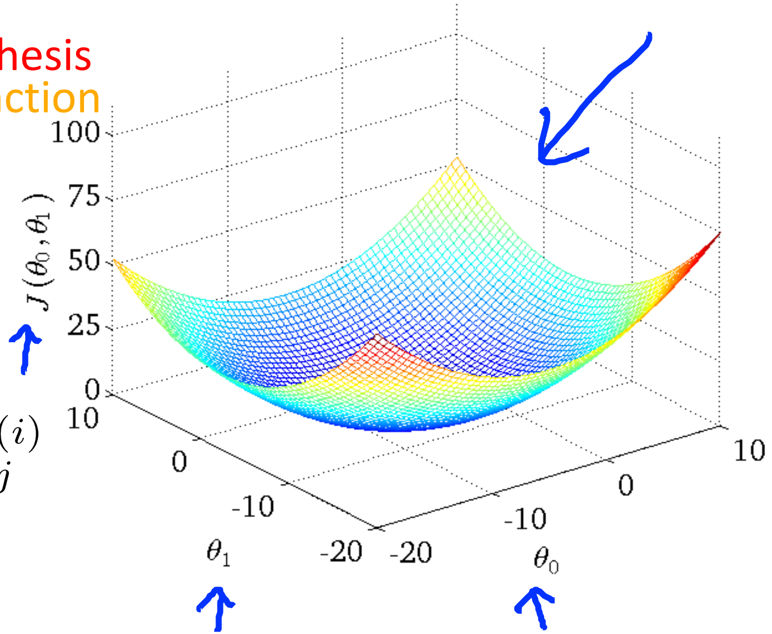
$$J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Repeat {

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

(for every $j = 0, \dots, n$)

}



Linear Regression with Batch Gradient Descent

Andrew Ng

Linear regression with gradient descent

$$h_\theta(x) = \sum_{j=0}^{n} \theta_j x_j$$

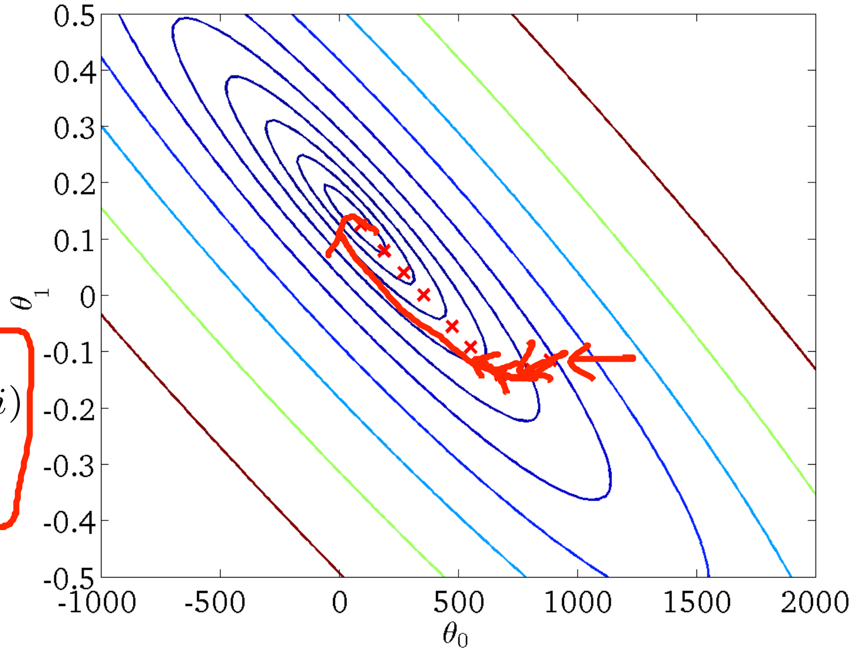
$$J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Repeat {

$$\theta_j := \theta_j - \alpha \boxed{\frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}}$$

(for every $j = 0, \ldots, n$)

}



$M = 300,000,000$

Batch gradient descent

Andrew Ng

Batch gradient descent

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

Repeat {

$$\theta_j := \theta_j - \alpha \boxed{\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}}$$

$\frac{\partial}{\partial \theta_j} J_{train}(\theta)$

(for every $j = 0, \ldots, n$)

}

$m = 300{,}000{,}000$

Stochastic gradient descent

$$cost(\theta, (x^{(i)}, y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$$

$$J_{train}(\theta) = \frac{1}{m}\sum_{i=1}^{m} cost(\theta, (x^{(i)}, y^{(i)}))$$

1. Randomly shuffle dataset.
2. Repeat {

   for $i = 1, \ldots, m$ {

   $\theta_j := \theta_j - \alpha \boxed{(h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}}$

   (for $j = 0, \ldots, n$)

   }

   }

$\frac{\partial}{\partial \theta_j} cost(\theta, (x^{(i)}, y^{(i)}))$

$(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), (x^{(3)}, y^{(3)}), \ldots$

Andrew Ng

Stochastic gradient descent

1. Randomly shuffle (reorder) training examples

2. Repeat { 1-10x

    for $i := 1, \ldots, m$ {

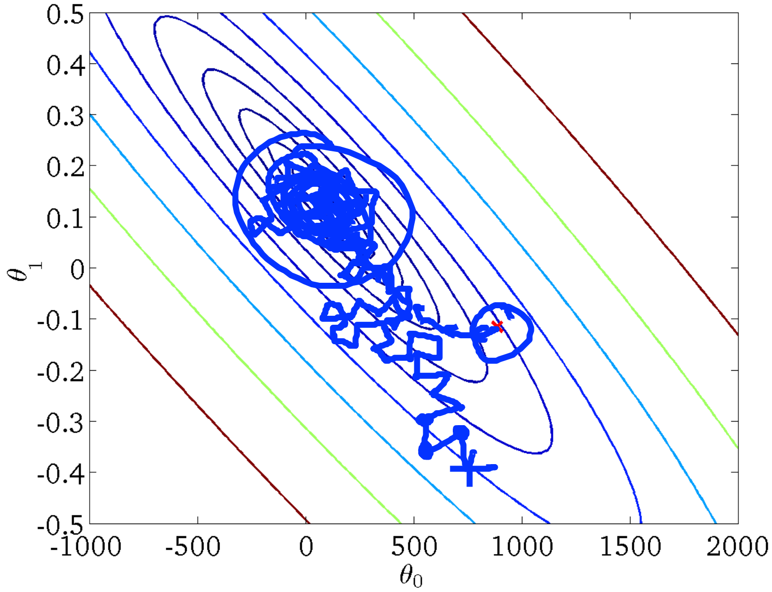
    $$\theta_j := \theta_j - \alpha(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$$

    (for every $j = 0, \ldots, n$)

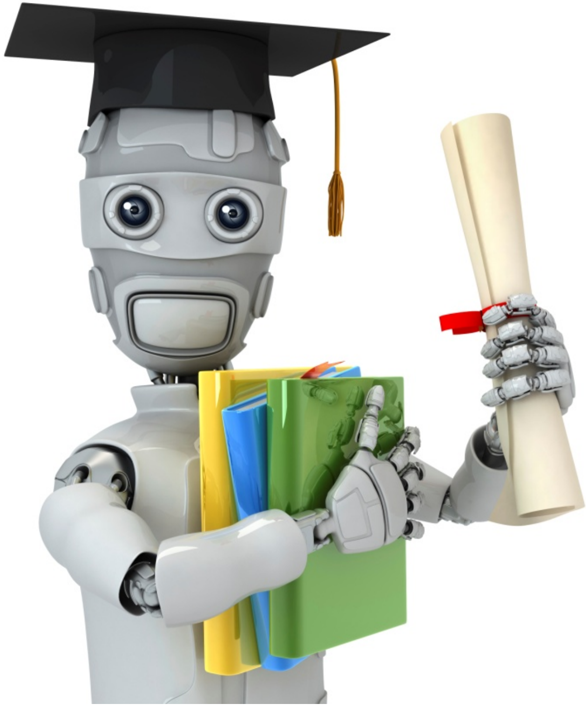
    }

}

$m = 300,000,000$



Gradually goes toward the minimum



Machine Learning

Large scale machine learning

Mini-batch gradient descent

Mini-batch gradient descent

→ **Batch gradient descent:** Use all m examples in each iteration

→ **Stochastic gradient descent:** Use 1 example in each iteration

Mini-batch gradient descent: Use b examples in each iteration

b = mini-batch size. $b = 10$.   2 - 100

Get $\boxed{b = 10}$ examples $(x^{(i)}, y^{(i)}), \ldots, (x^{(i+9)}, y^{(i+9)})$

$$\theta_j := \theta_j - \alpha \frac{1}{\boxed{10}} \sum_{k=i}^{\boxed{i+9}} \left(h_\theta(x^{(k)}) - y^{(k)}\right) x_j^{(k)}$$

$i := i + 10;$

Mini-batch gradient descent

Say $\boxed{b = 10}$, $m = \boxed{1000}$.

Repeat {

for $i = 1, 11, 21, 31, \ldots, \boxed{991}$ {

$$\theta_j := \theta_j - \alpha \boxed{\frac{1}{\boxed{10}} \sum_{k=i}^{\boxed{i+9}} (h_\theta(x^{(k)}) - y^{(k)}) x_j^{(k)}}$$

(for every $j = 0, \ldots, n$)

}

}

→ b examples

→ 1 example

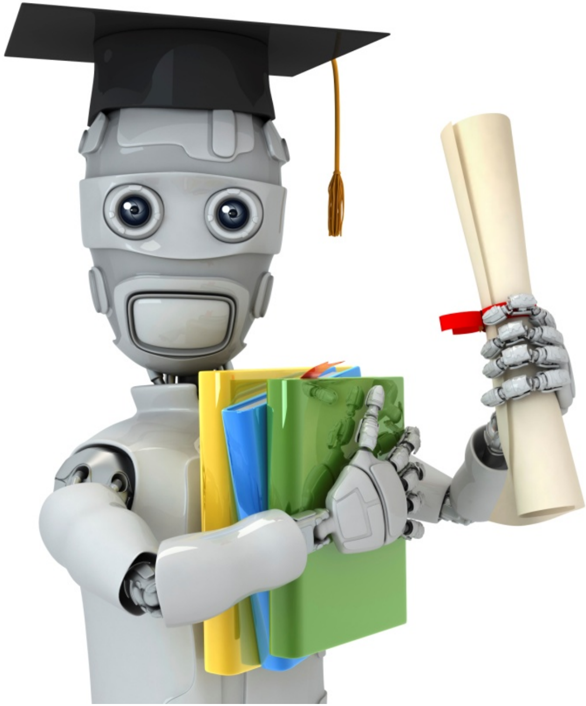
Vectorization

m = 300,000,000

b = 10

Use b examples for each iteration

where b is the mini-batch size



Machine Learning

Large scale machine learning

Stochastic gradient descent convergence

Checking for convergence

By plotting the cost function

- Batch gradient descent:
  - Plot $J_{train}(\theta)$ as a function of the number of iterations of gradient descent.
  - $$\boxed{J_{train}(\theta)} = \frac{1}{2m}\boxed{\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2}$$

$M = 300,000,000$

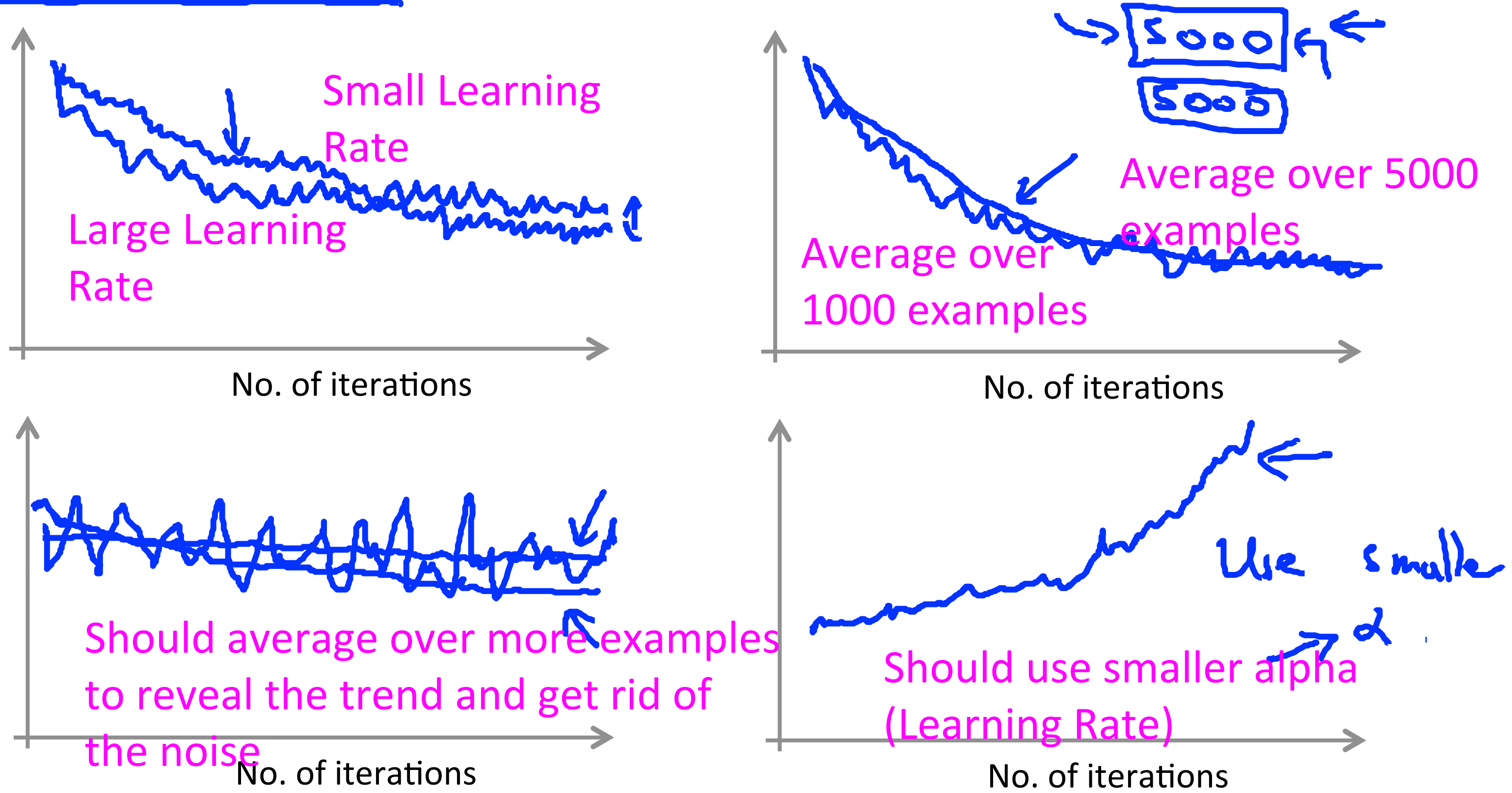
- Stochastic gradient descent:
  - $cost(\theta, (x^{(i)}, y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$
  - During learning, compute $cost(\theta, (x^{(i)}, y^{(i)}))$ before updating θ using $(x^{(i)}, y^{(i)})$.

$(x^{(i)}, y^{(i)}), (x^{(i+1)}, y^{(i+1)}), \ldots$

- Every 1000 iterations (say), plot $cost(\theta, (x^{(i)}, y^{(i)}))$ averaged over the last 1000 examples processed by algorithm.

Checking for convergence

Plot $cost(\theta, (x^{(i)}, y^{(i)}))$, averaged over the last 1000 (say) examples



Andrew Ng

Stochastic gradient descent

$$cost(\theta, (x^{(i)}, y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$$

$$J_{train}(\theta) = \frac{1}{2m}\sum_{i=1}^{m} cost(\theta, (x^{(i)}, y^{(i)}))$$

1. Randomly shuffle dataset.
2. Repeat {

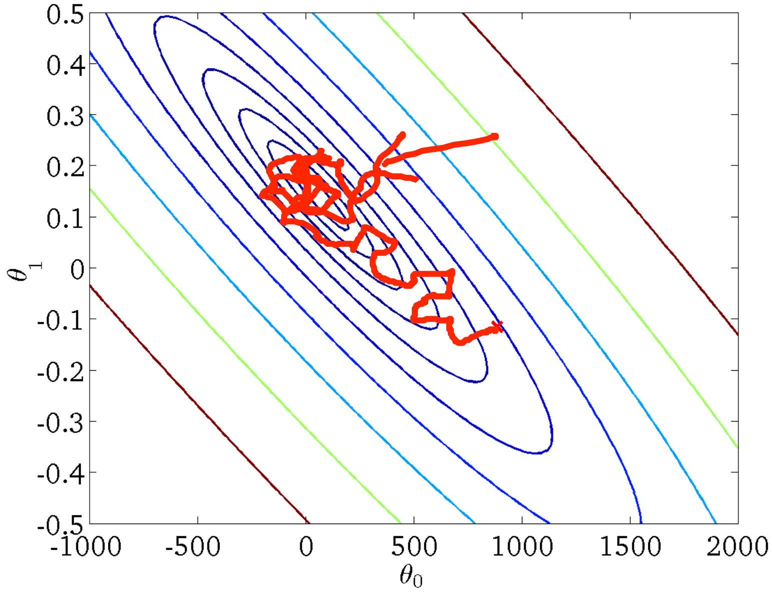
    for $i := 1, \ldots, m$ {

    $$\theta_j := \theta_j - \alpha(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$$

    (for $j = 0, \ldots, n$)

    }

}



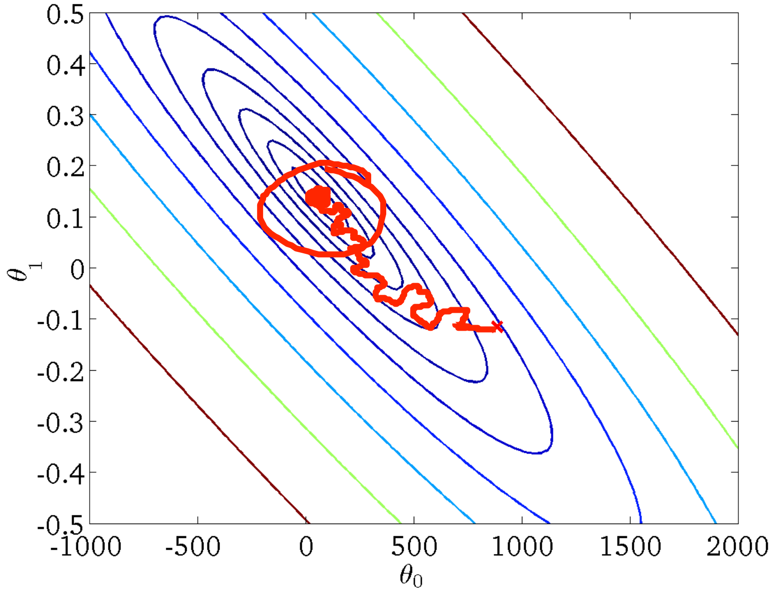
Learning rate α is typically held constant. Can slowly decrease α over time if we want θ to converge. (E.g. $\alpha = \frac{\texttt{const1}}{\texttt{iterationNumber + const2}}$)

Andrew Ng

Stochastic gradient descent

$$cost(\theta,(x^{(i)},y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$$

$$J_{train}(\theta) = \frac{1}{2m}\sum_{i=1}^{m} cost(\theta,(x^{(i)},y^{(i)}))$$



1. Randomly shuffle dataset.
2. Repeat {

    for $i := 1, \ldots, m$ {

    $$\theta_j := \theta_j - \alpha(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$$

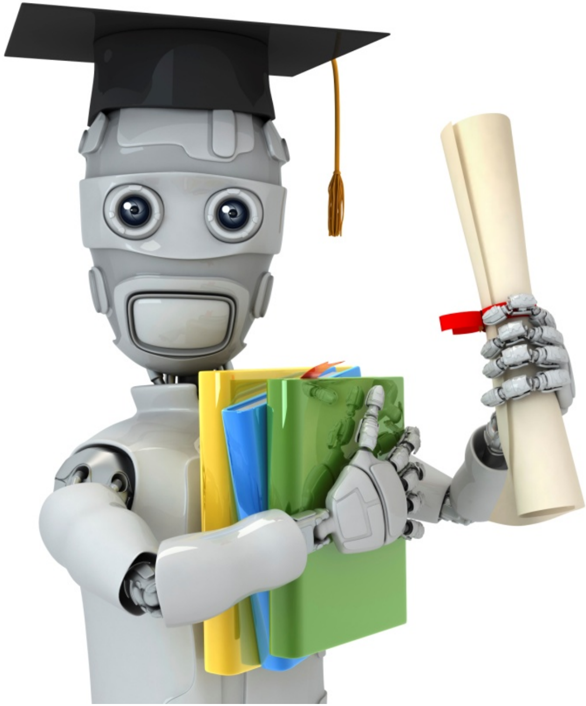
    (for $j = 0, \ldots, n$)

    }

}

Learning rate α is typically held constant. Can slowly decrease α over time if we want θ to converge. (E.g. $\alpha = \frac{\texttt{const1}}{\boxed{\texttt{iterationNumber}} + \texttt{const2}}$) $\alpha \to 0$

Andrew Ng



Machine Learning

Large scale machine learning

Online learning

Online learning

Shipping service website where user comes, specifies origin and destination, you offer to ship their package for some asking price, and users sometimes choose to use your shipping service ($y = 1$), sometimes not ($y = 0$).

Features x capture properties of user, of origin/destination and asking price. We want to learn $p(y = 1|x; \theta)$ to optimize price.

price

logistic regression

Repeat forever {

Get $\boxed{(x, y)}$ corresponding to user.

Update θ using $\boxed{(x, y)}$: ~~$(x^{(i)}, y^{(i)})$~~

$\rightarrow \theta_j := \theta_j - \alpha (h_\theta(x) - y) \cdot x_j \quad (j = 0, \ldots, n)$

}

$\rightarrow$ Can adapt to changing user preference.

Other online learning example:

Product search (learning to search)

User searches for "Android phone 1080p camera"

Have 100 phones in store. Will return 10 results.

$x =$ features of phone, how many words in user query match name of phone, how many words in query match description of phone, etc.

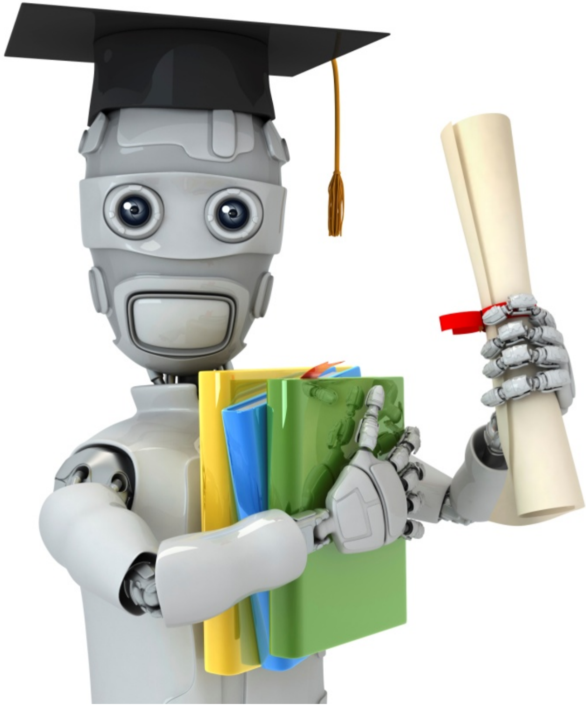
(x, y)

$y = 1$ if user clicks on link. $y = 0$ otherwise.

Learn $\boxed{p(y = 1|x; \theta)}$. predicted CTR

Use to show user the 10 phones they're most likely to click on.

Other examples: Choosing special offers to show user; customized selection of news articles; product recommendation; ...



Machine Learning

Large scale machine learning

Map-reduce and data parallelism

$m = 400$ $\quad$ $m = 400{,}000{,}000$

Map-reduce

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

$(x^{(1)}, y^{(1)})$
$\vdots$
$(x^{(m)}, y^{(m)})$

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

$temp_j^{(1)} = \sum_{i=1}^{100} (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$

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

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

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

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

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

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

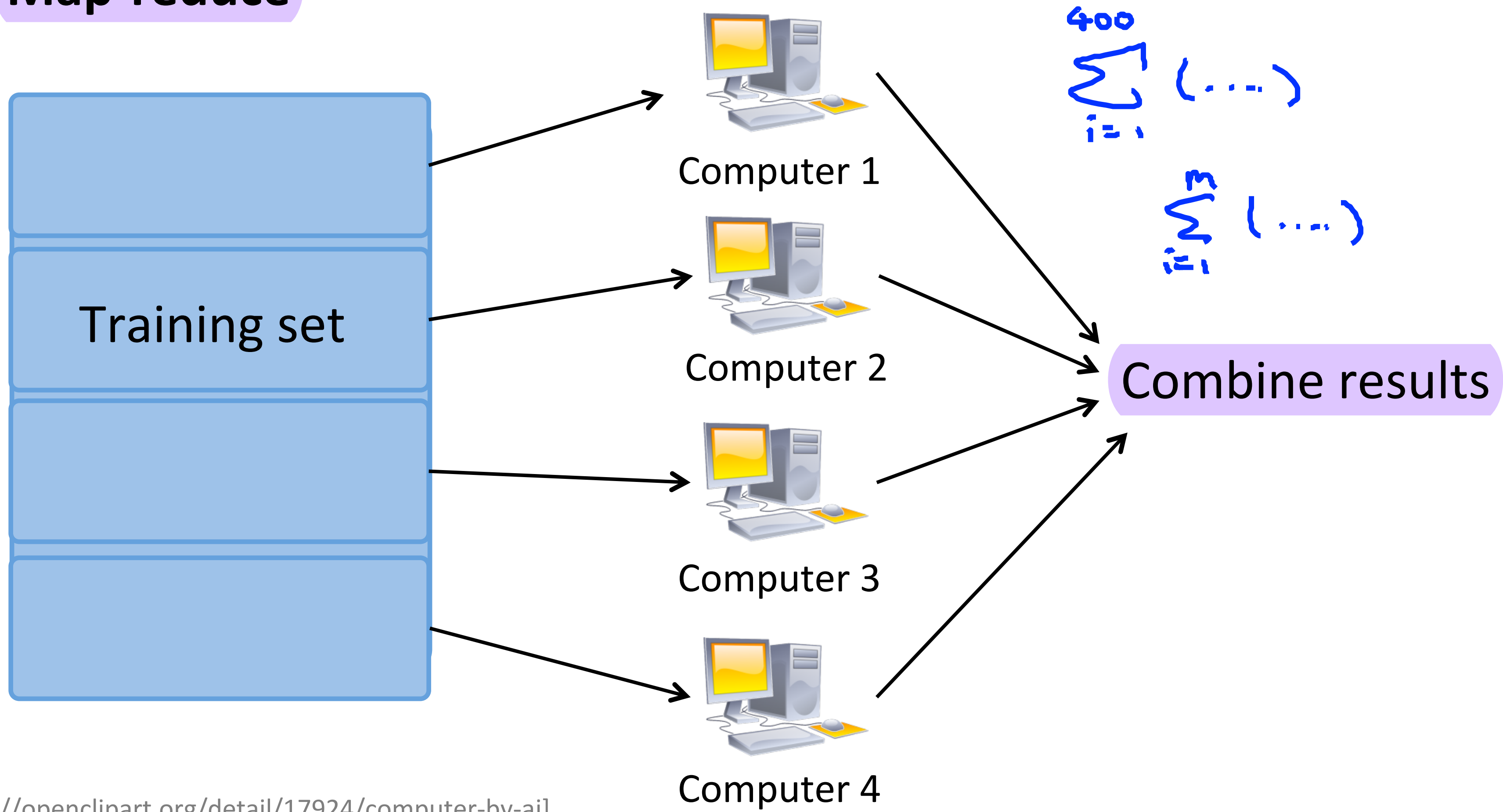
Combine:

$\theta_j := \theta_j - \alpha \frac{1}{400} \left(temp_j^{(1)} + temp_j^{(2)} + temp_j^{(3)} + temp_j^{(4)} \right)$

$(j = 0, \ldots, n)$

[Jeffrey Dean and Sanjay Ghemawat]

Map-reduce



[http://openclipart.org/detail/17924/computer-by-aj]

Map-reduce and summation over the training set

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

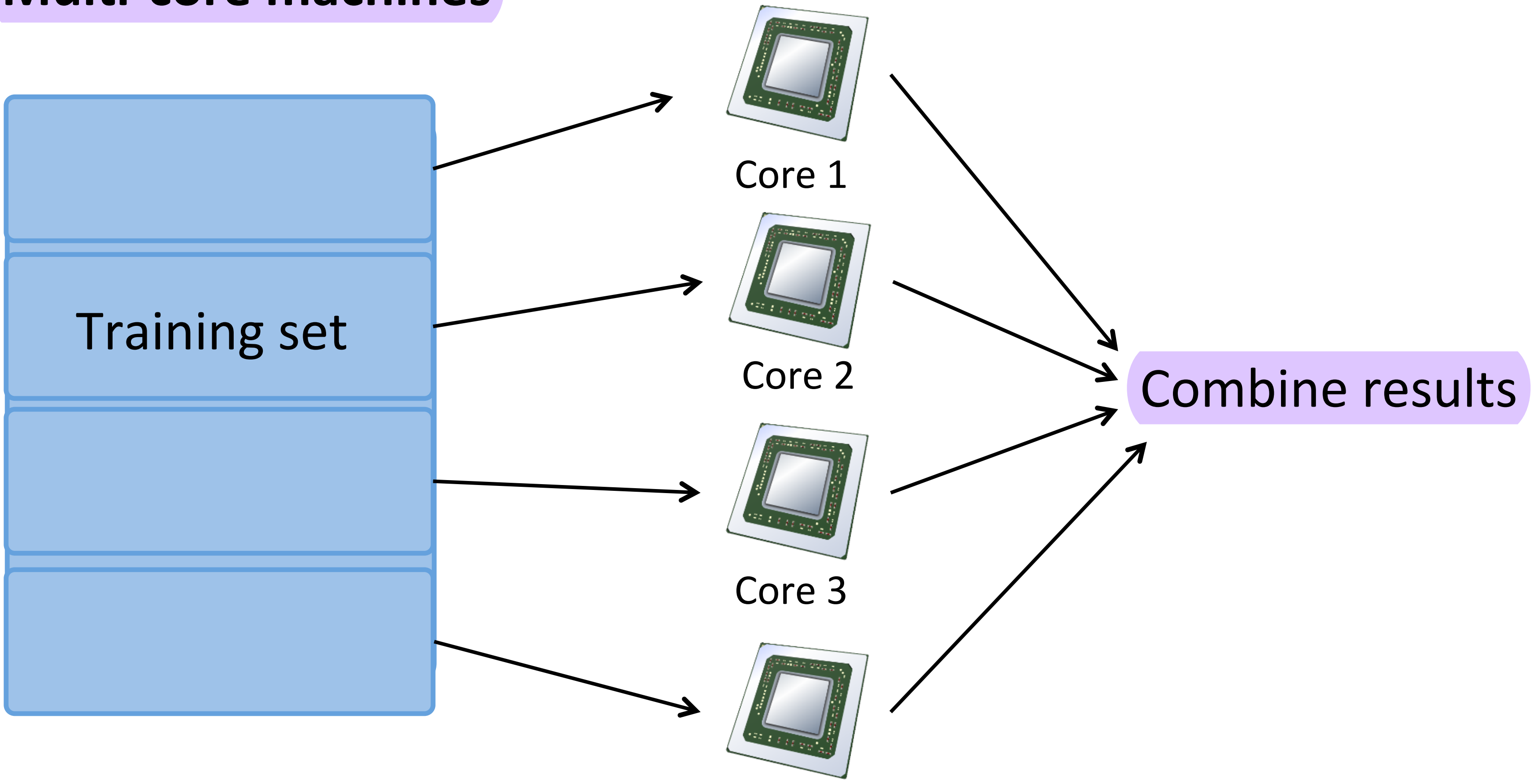
E.g. for advanced optimization, with logistic regression, need:

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

$$\frac{\partial}{\partial\theta_j} J_{train}(\theta) = \frac{1}{m}\sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$

$temp^{(i)}$ $temp_j^{(i)}$

Multi-core machines



[http://openclipart.org/detail/100267/cpu-(central-processing-unit)-by-ivak-100267]