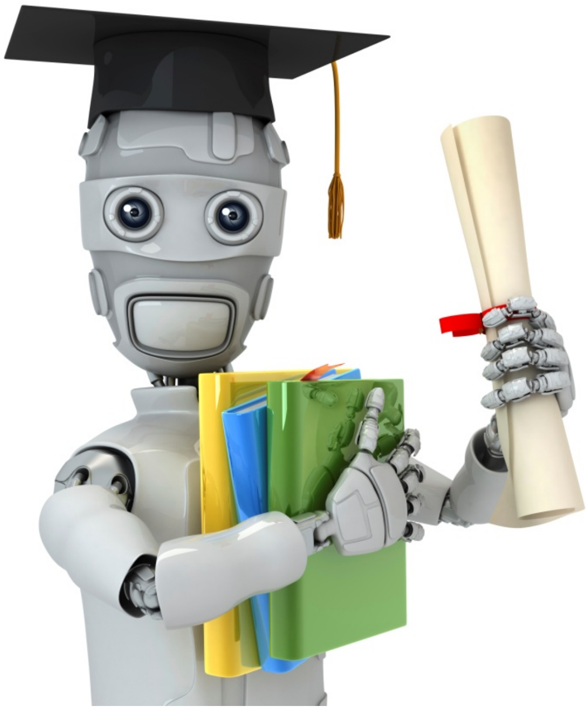


Machine Learning

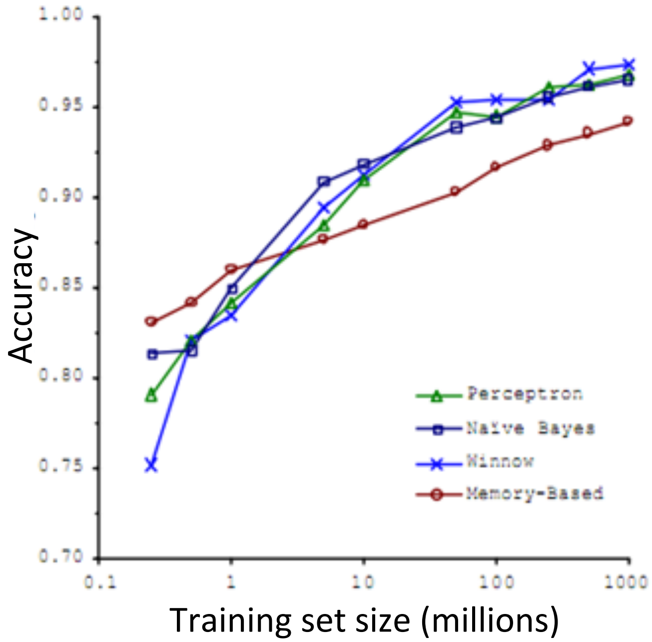
Large scale machine learning

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

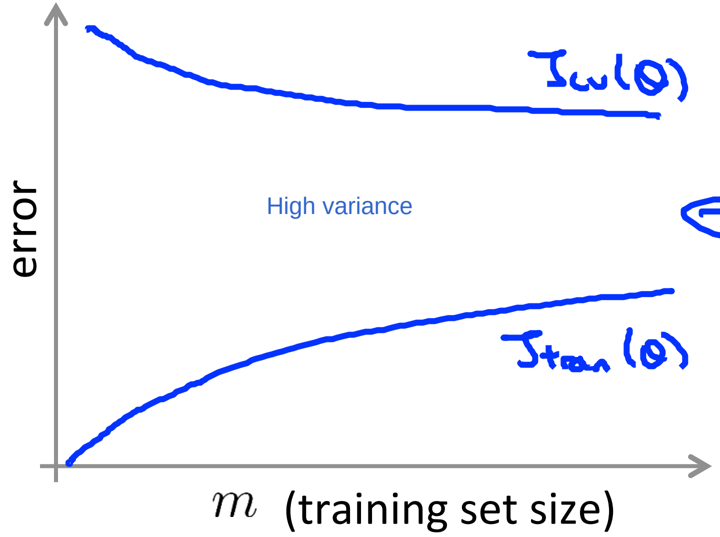
$m = 100,000,000$

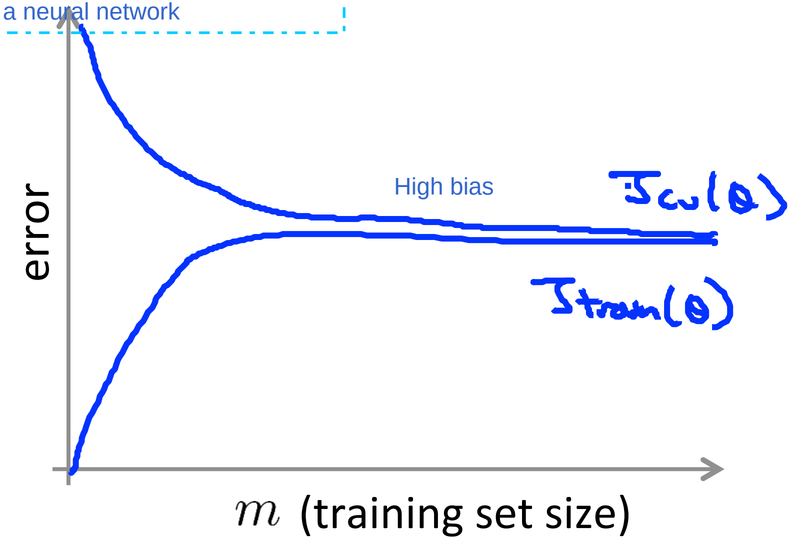
$m = 1,000$?

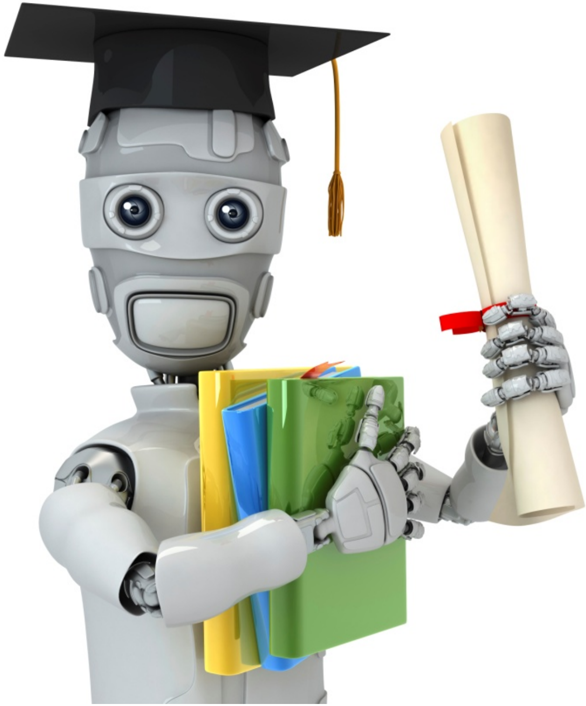
Plot a learning curve for a range of values of m and verify that the algorithm has high variance when m is small.

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

Add extra features or hidden units to a neural network







Machine Learning

Large scale machine learning

Stochastic gradient descent

Linear regression with gradient descent

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

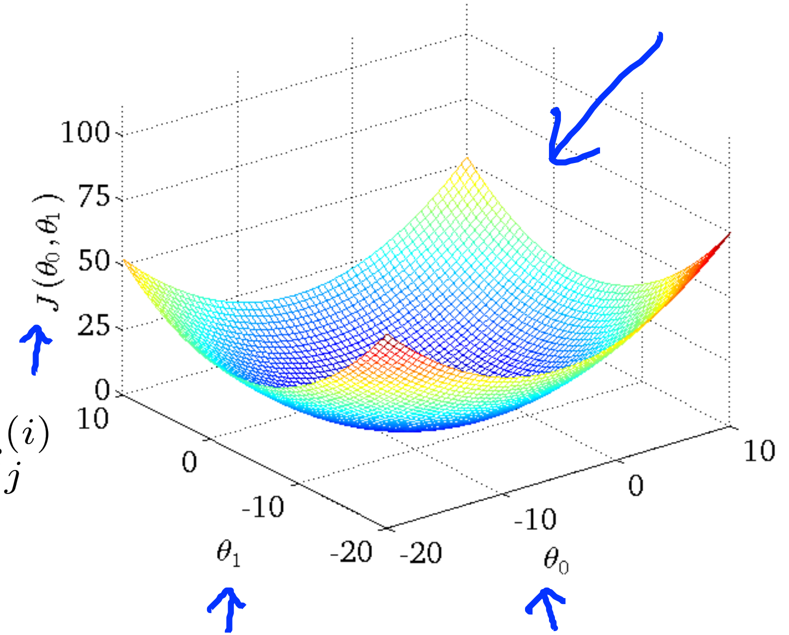
$$J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Repeat {

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

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

}



Linear regression with gradient descent

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

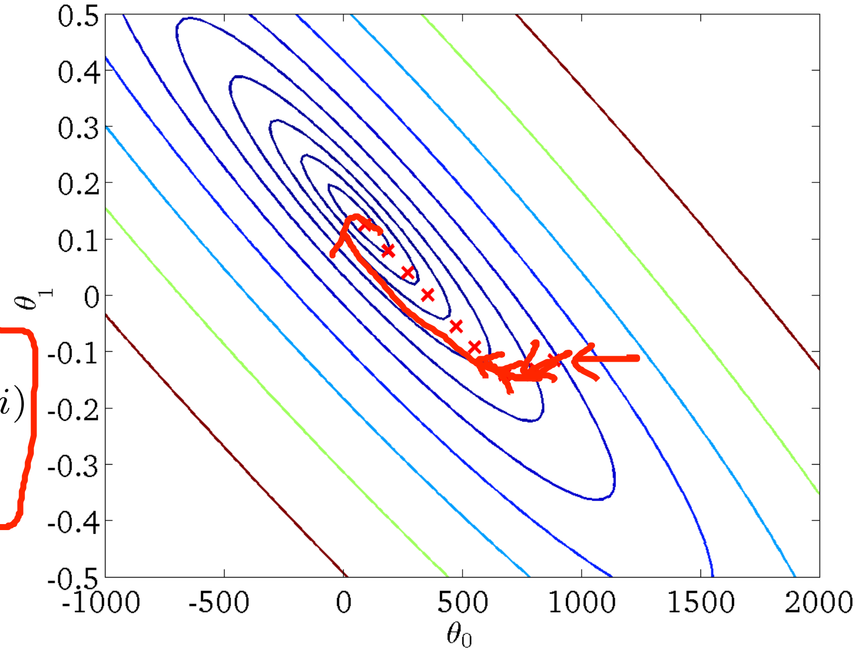
$$J_{train}(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$

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

Cost of theta with respect to training ex. x(i), y(i)

Batch gradient descent

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

Repeat {

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

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

}

Updates occurs to all features

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

Stochastic gradient descent

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

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

To avoid sorted data

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

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

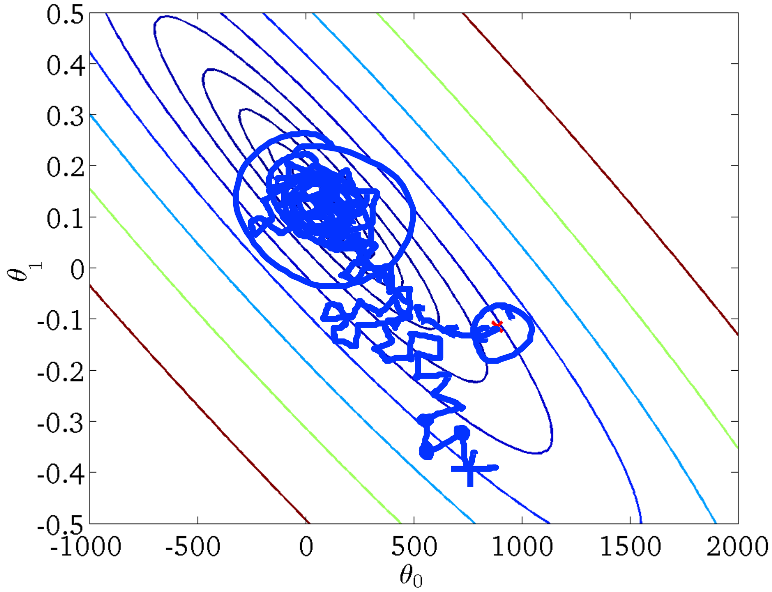
(for every $j = 0, \ldots, n$)

}

}

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

Moving the training ex. x(i) to its global minimum but not alaways that occurs as we usually get paramaters near to the global minimum

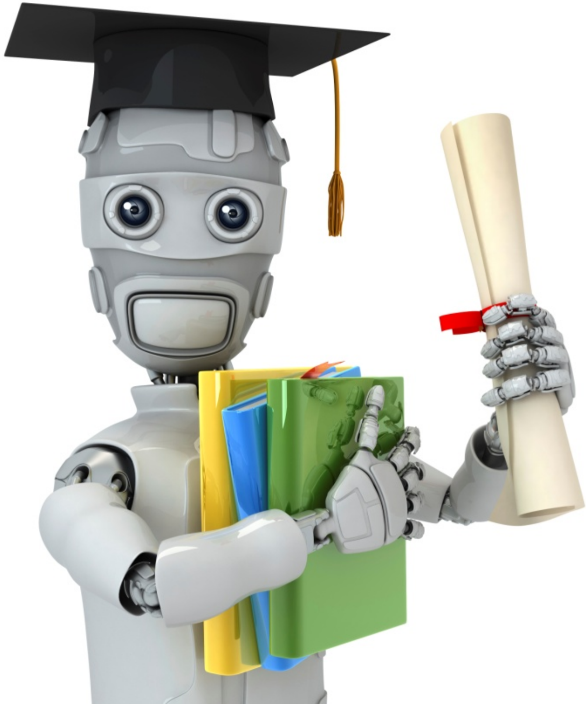


Repeating times depends on the size of the data set examples, if m is very large so iterating only once would be enough

When the training set size m is very large, stochastic gradient descent can be much faster than gradient descent.

The cost function J_train (θ)= 1/2*m (h θ (x (i)) - y (i)) 2 should go down with every iteration of batch gradient descent (assuming a well-tuned learning rate α) but not necessarily with stochastic gradient descent.

Andrew Ng



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 of b = m will lead to a batch gradient descent

Mini-batch gradient descent

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

Repeat {

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

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

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

}

}

→ b examples

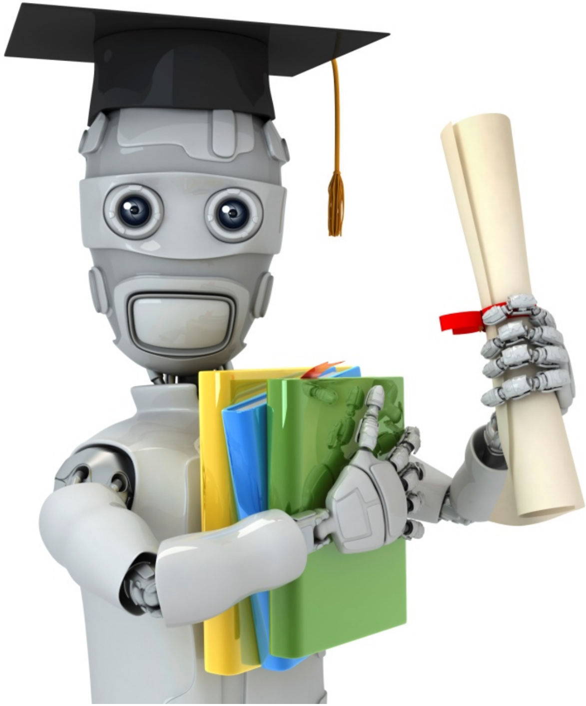
→ 1 example

Vectorization

$m = 300,000,000$

$b = 10$

Andrew Ng



Machine Learning

Large scale machine learning

Stochastic gradient descent convergence

Checking for convergence

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

$m = 300,000,000$

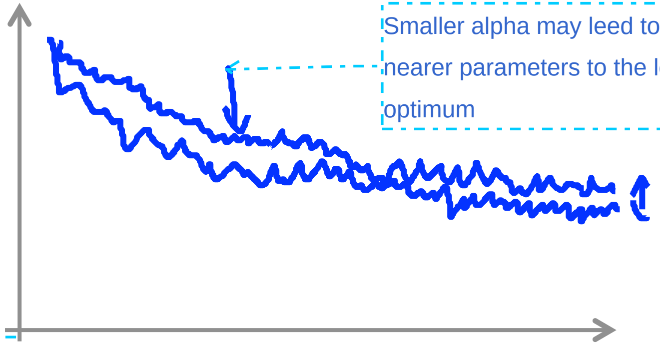
- Stochastic gradient descent:

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

  - $cost(\theta, (x^{(i)}, y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$
  - During learning, compute $cost(\theta, (x^{(i)}, y^{(i)}))$ before updating θ using $(x^{(i)}, y^{(i)})$.
  - Every 1000 iterations (say), plot $cost(\theta, (x^{(i)}, y^{(i)}))$ averaged over the last 1000 examples processed by algorithm.

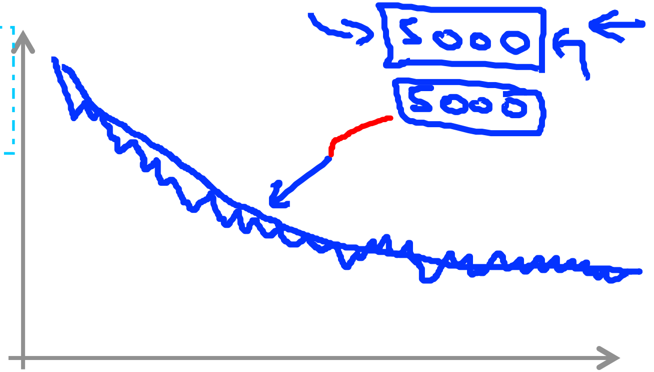
Checking for convergence

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



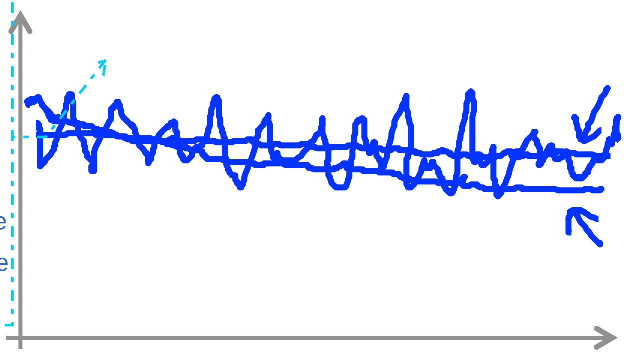
Smaller alpha may leed to much nearer parameters to the local optimum

No. of iterations



No. of iterations

It doesnt necessary to be that the algorithm isn't converging, may it be that averaged over no. of examples(1000) is to small so we're seeing to much, so if we inc. this no. we'll see the alogrithm converge



No. of iterations

No. of iterations

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 {

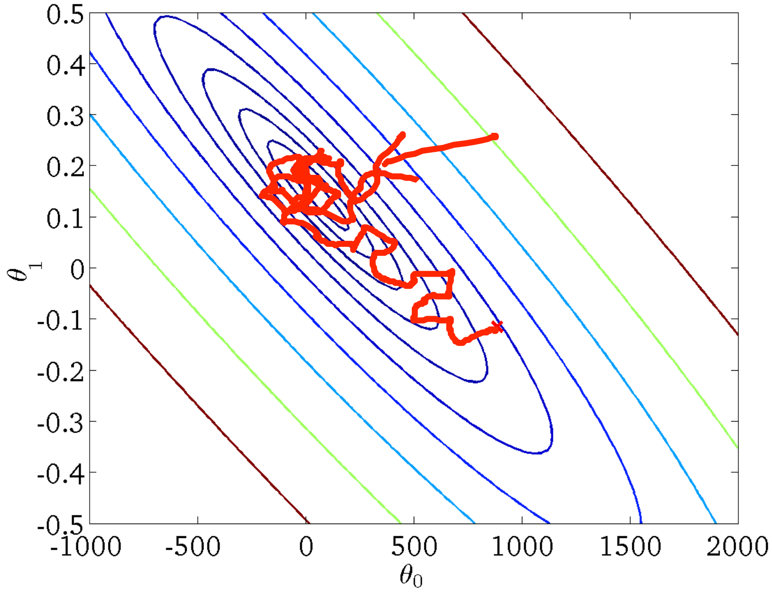
   for $i := 1, \ldots, m$ {

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

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

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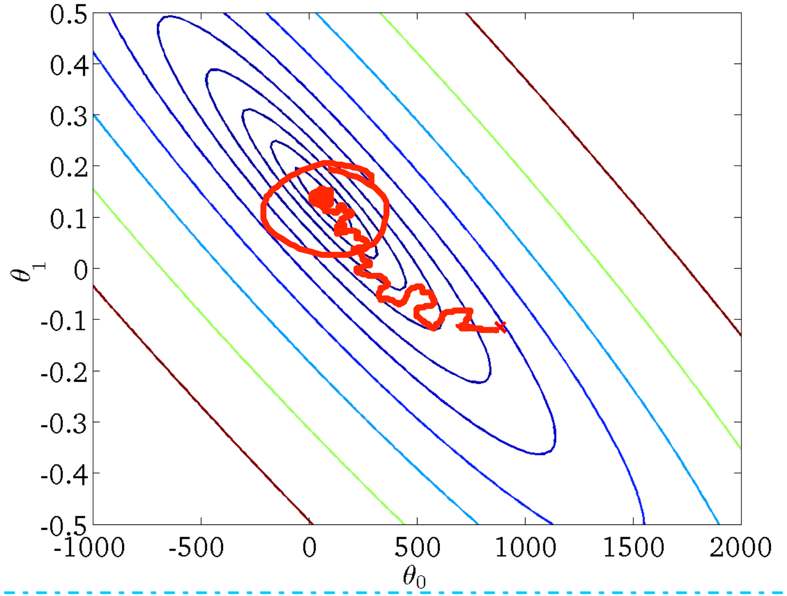
    (for $j = 0, \ldots, n$)

    }

}

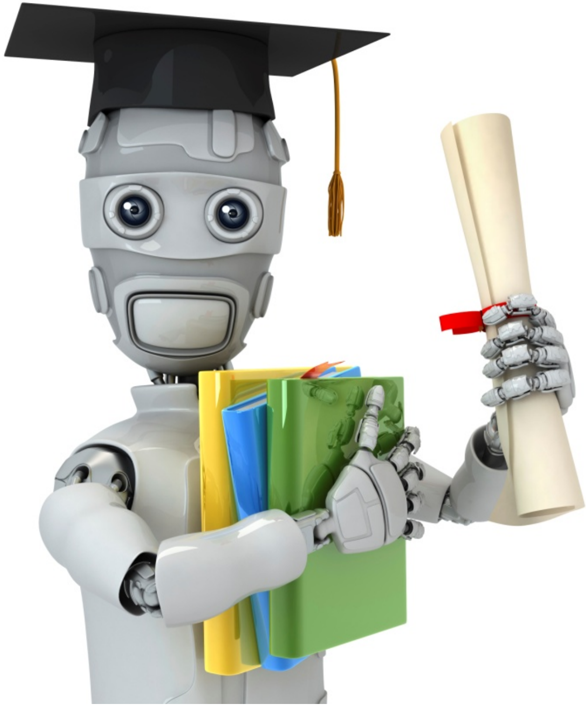


Current iteration we're (from 1:m)

If const.1,2 are managed to set well, we'll end up with a much more nearer to the global minimum as alpha is decreasing each iteration

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

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 ($y = 0$).

We may say that our features (x) are source, destination & price

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

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

}

Learn 1 examples and then discard it

$\rightarrow$ Can adapt to changing user preference.

Andrew Ng

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.

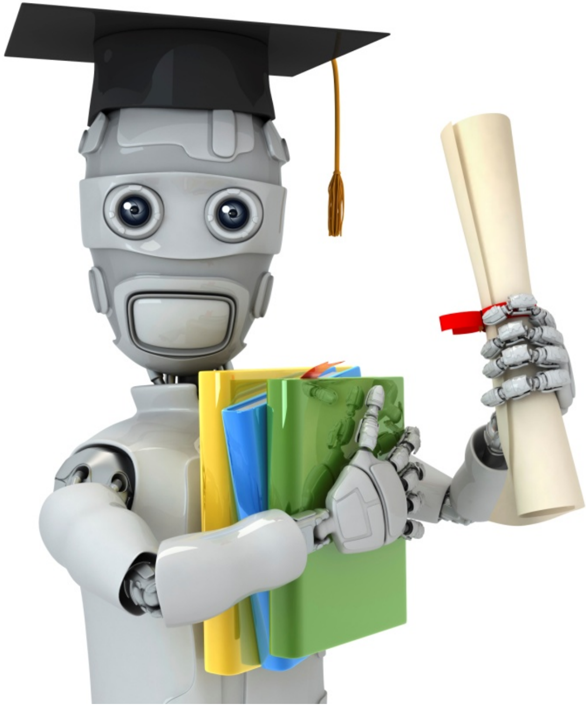
(x, y)

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

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

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

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

Map-reduce

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

$(x^{(1)}, y^{(1)})$ … $(x^{(m)}, y^{(m)})$

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 $(x^{(301)}, y^{(301)}), \ldots, (x^{(400)}, y^{(400)})$.

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

Sent to a master server

Combine:

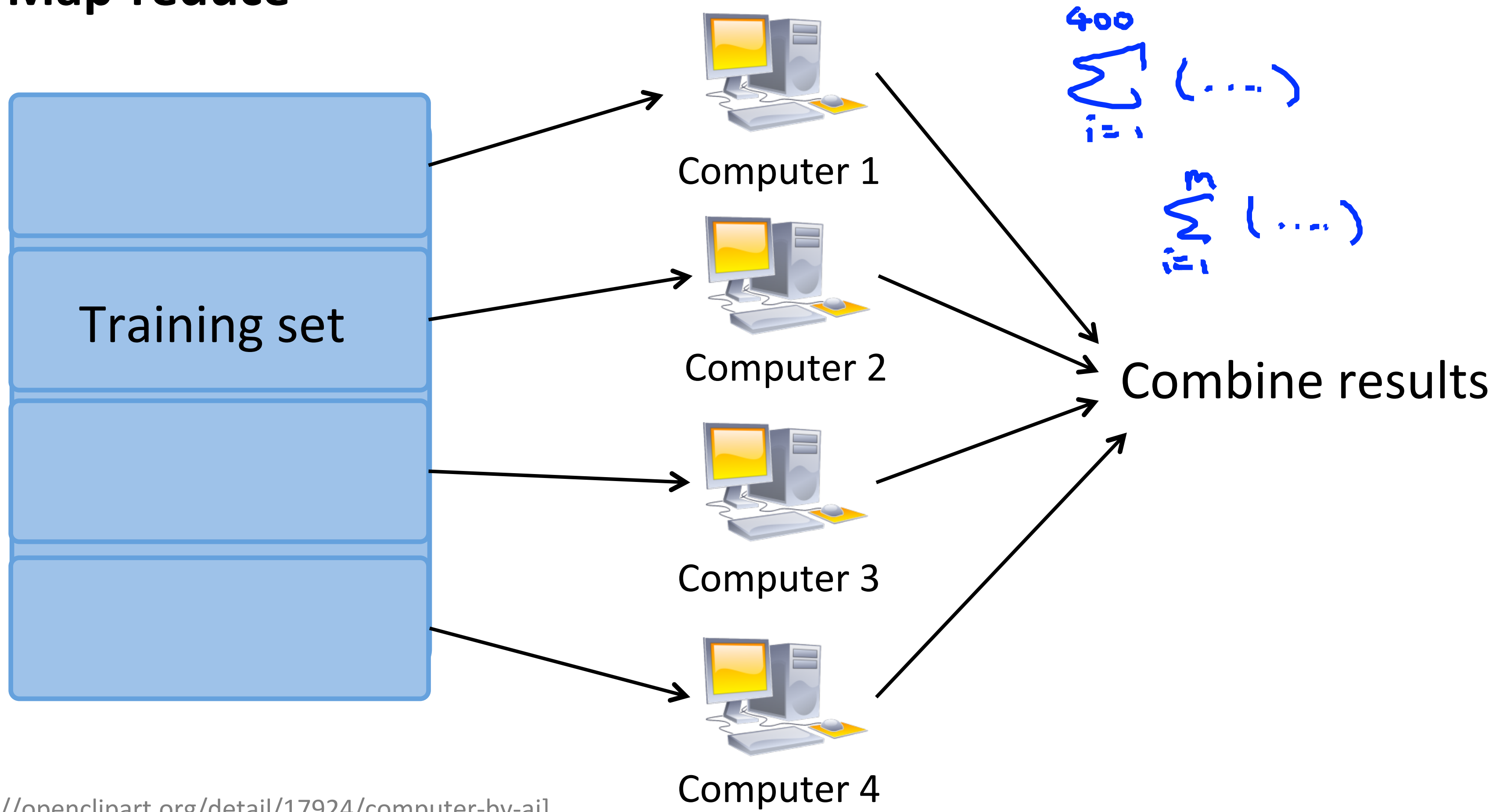
$\theta_j := \theta_j - \alpha \frac{1}{400} \left(temp_j^{(1)} + temp_j^{(2)} + temp_j^{(3)} + temp_j^{(4)} \right)$

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

[Jeffrey Dean and Sanjay Ghemawat]

We approach near to 4x speed up if we used 4 machines for computations.
we end up not to 4x bec. of network latencies & combination processings, etc

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.

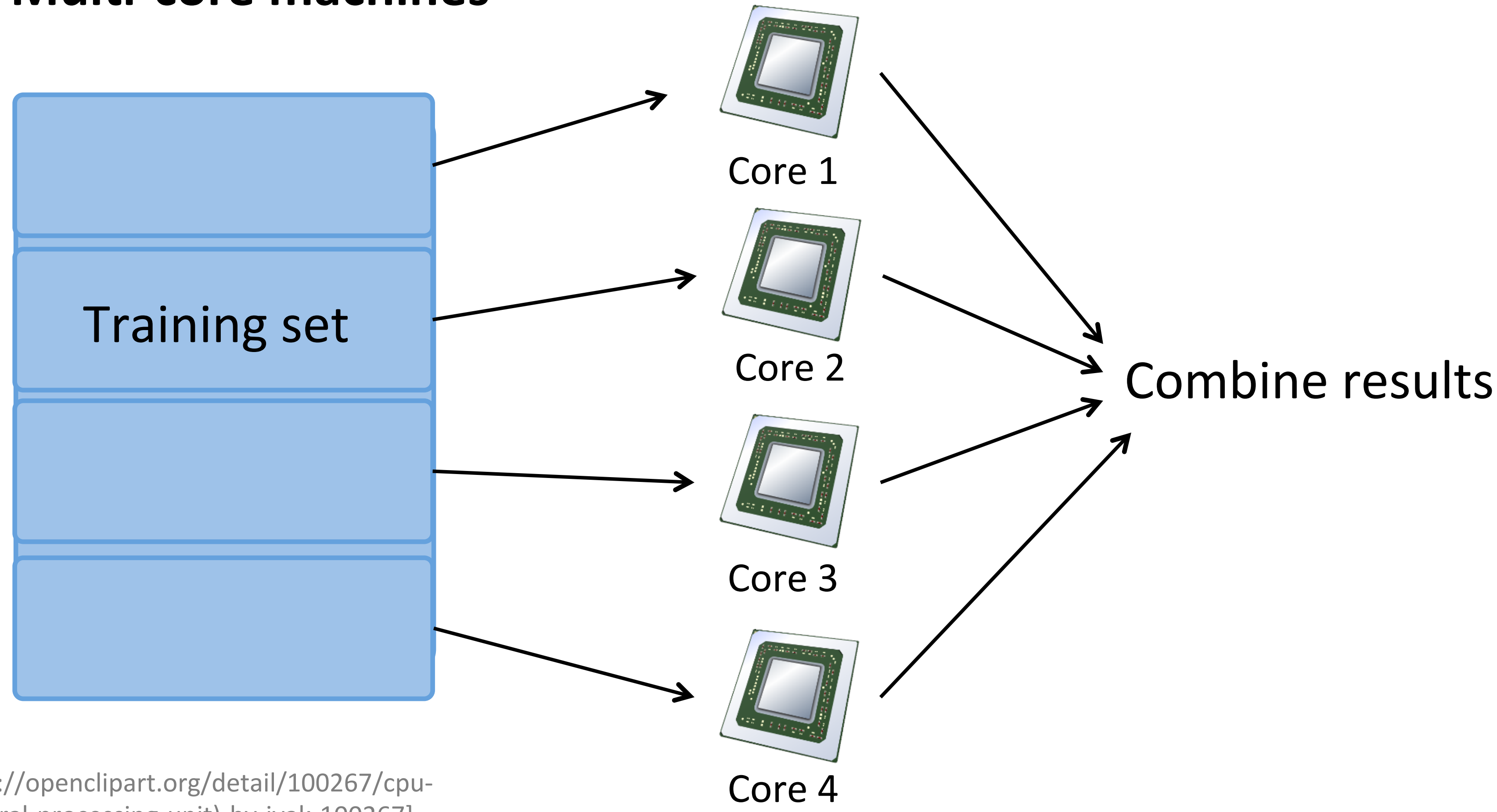
E.g. for advanced optimization, with logistic regression, need:

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

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

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

Multi-core machines



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