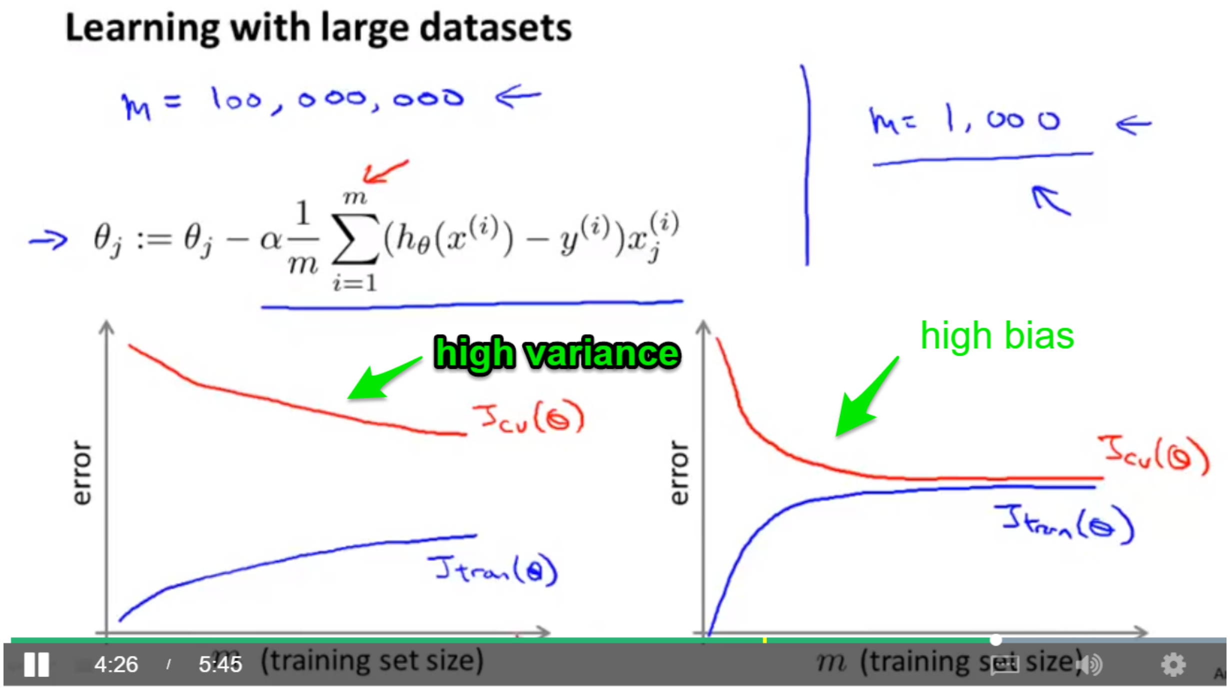
Gradient Descent with Large Data set

- before implementing large data set, try small data set first!
    - verify small data set whether it work or not.
        - by plotting learning curve. when **variance** is **high**, we should try large data set.



- facing problem: **computational expensive for gradient**
- ## Stochastic Gradient Descent
    - what the GD we used in the past could be called **batch gradient descent.**
    - main idea: **using subset to lower computational cost.**
    - **algorithm**
        1. randomly shuffle data set
        2. loop for a subset of examples and iterate to descend gradient by:

2. For $i = 1 \ldots m$

$$\Theta_j := \Theta_j - \alpha(h_\Theta(x^{(i)}) - y^{(i)}) \cdot x_j^{(i)}$$

    - attribute:
        - may not converge into global minimum but would be close.
        - though we still have to look through whole data set, but sometimes before going through, we **already get convergent result**. This let us can stop training earlier.
- ## 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

    - just using subset to compute too~
    - and here comes a **hyper-parameter** , b would be hard to choose. Pro.Wang suggested that b could be 10.

Typical values for b range from 2-100 or so.

For example, with b=10 and m=1000:

Repeat:

For $i = 1, 11, 21, 31, \ldots, 991$

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

- advantages: use vectorized implementations to parallel computing.

- **tuned learning rate α / check whether GD is converging**
  - facing problem:
    - in small data set we compute J(Θ) each iteration and after training, we plot the J(Θ) to check
    - however computing J(Θ) need to **scan through whole data set**, when our data set is large. the cost is unacceptable.
  - method:
    - instead of computing J(Θ), we compute **cost(Θ,(x^i,y^i))**

      → Stochastic gradient descent:

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

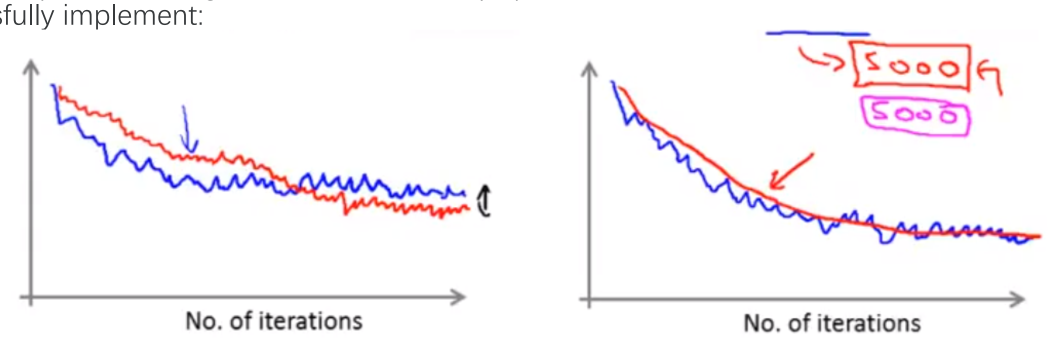
      → $cost(\theta, (x^{(i)}, y^{(i)})) = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$

      → During learning, compute $cost(\theta, (x^{(i)}, y^{(i)}))$ before updating θ using $(x^{(i)}, y^{(i)})$.

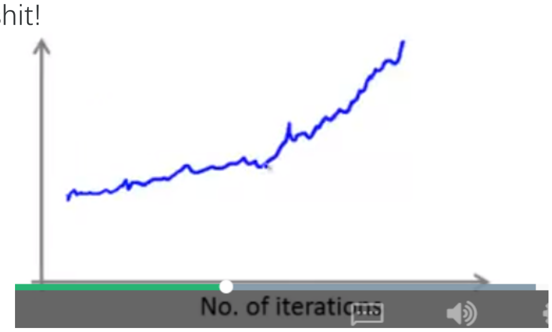
      changeable

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

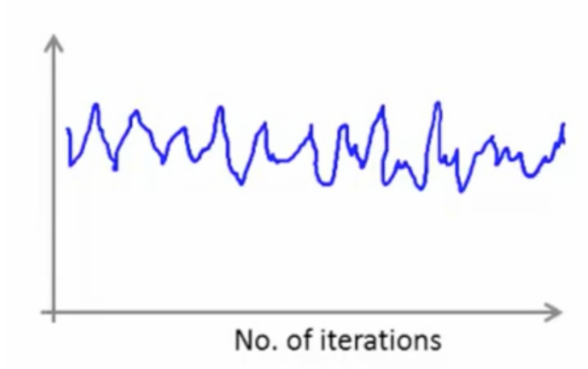
    - then plot the **average_cost-iteration** to examine.
    - pic may like this:(due to average, there are **noise** in pic)
      - successfully implement:



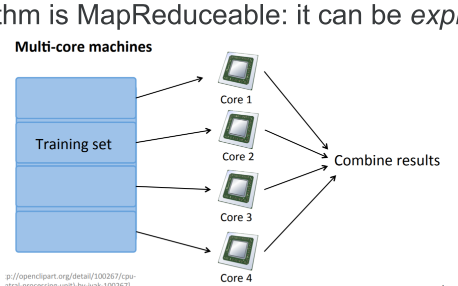
      - bull shit!



      - sometimes:



- we need to try a large iterations like 1000→5000, to see whether the problem caused by noise or divergence.

- # Online Learning
  - facing **continuous data stream.** (e.g. shopping online) It's not smart to train the model periodically. Instead, we need to update our model **instantly.**
  - **main idea:**
    - **don't save data. Use and discard.**
    - **update θ by feeding example.**
  - **algorithm**
    - like SGD, just compute GD with one example.
    - for instance,linear regression :
      - $\Theta := \Theta - \alpha(h(X)-Y))X$
      - here y can be user behavior like whether click or not.
  - advantages:
    - save place (data used as one-time)
    - dynamic (sensitive to user preference changing)
  - more examples:
    1. improve CTR (Click-Through-Rate)
    2. contents recommendation (combining with collaborative filter)
    3. Commodity pricing
- # Map and Reduce
  - split the task and distribute it
  - algorithm is MapReduceable: it can be *expressed as computing sums of functions over the training set*.
    - 

    - on multiple cores or machines