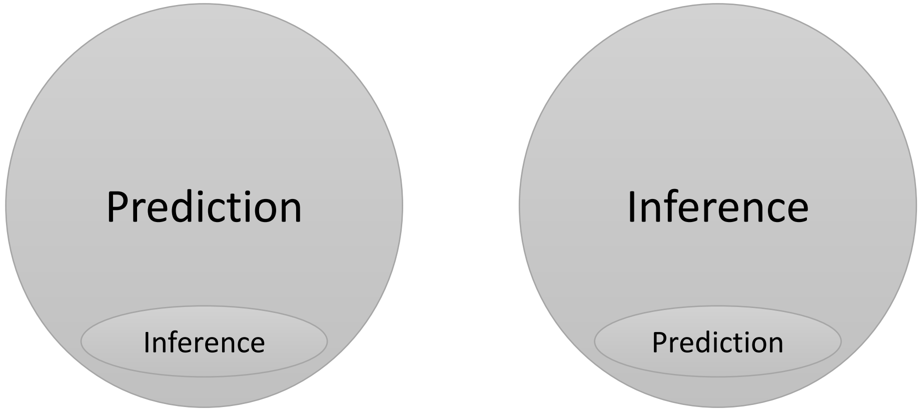
Class 5- Machine Learning concepts
Part II

Motivation

Machine learning fundamental concepts:

- Inference and prediction
- Part I: The Model
- Part II: Evaluation metrics
- Part III: Bias-Variance tradeoff
- Part IV: Resampling methods
- Part V: Solvers/learners (GD, SGD, Adagrad, Adam, …)
- Part VI: How do machines learn?
- Part VII: Scaling the features



Part V
Solvers (GD, SGD, Adagrad, Adam, …)

Solvers (learners)!

A Loss Function tells us "how good" our model is at making predictions for a given set of parameters. The cost function has its own curve and its own gradients. The slope of this curve tells us how to update our parameters to make the model more accurate.

The two most frequently used optimization algorithms when the loss function is differentiable are:

1) Gradient Descent (GD)
2) Stochastic Gradient Descent (SGD)

Gradient Descent: is an iterative optimization algorithm for finding the minimum of a function. To find a local minimum of a function using gradient descent, one starts at some random point and takes steps proportional to the negative of the gradient of the function at the current point.

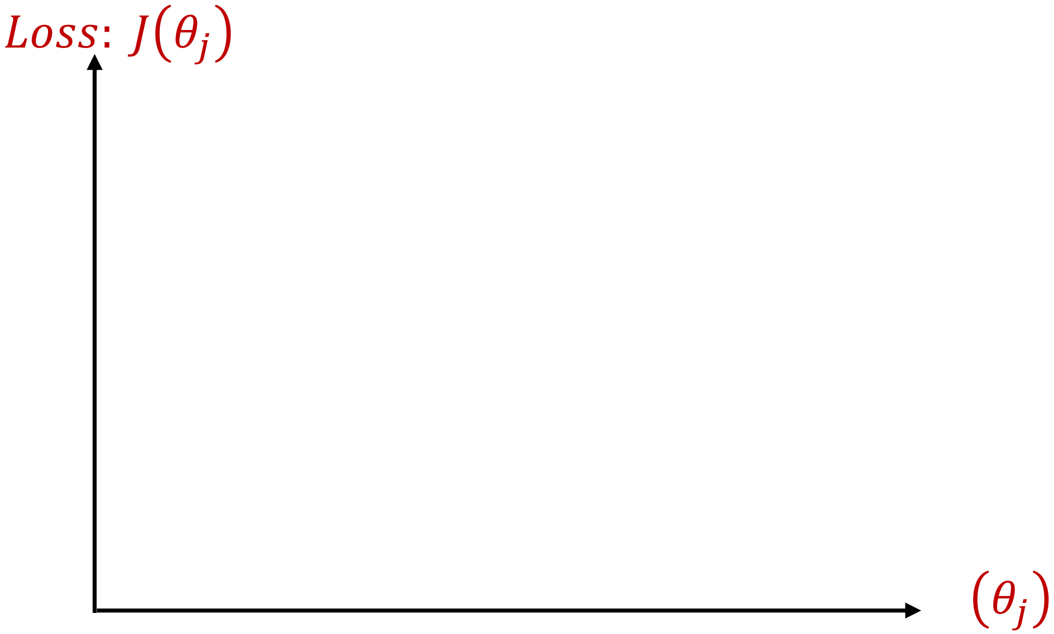
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

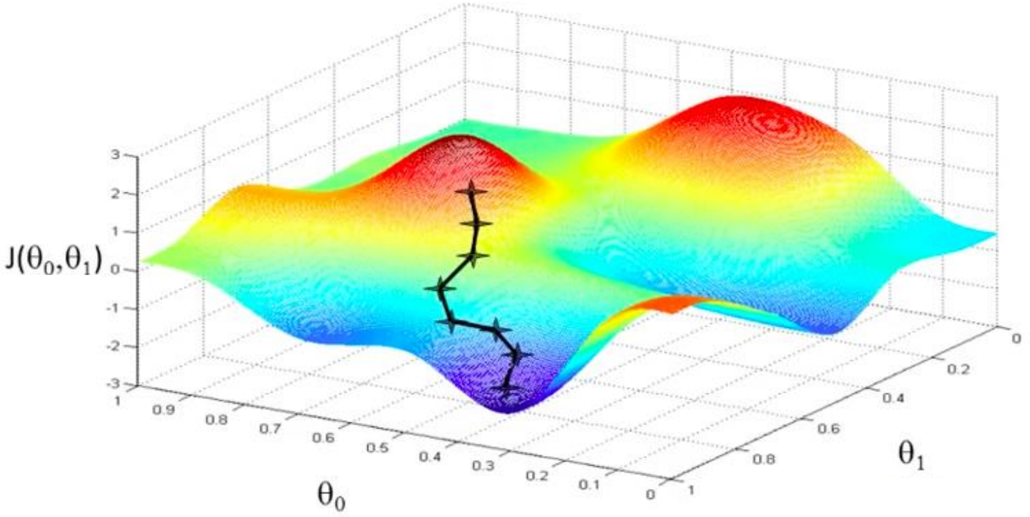
- θ_j is the model's j^{th} parameter
- α is the learning rate
- $J(\theta)$ is the loss function (which is differentiable)

Gradient Descent Visualization

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

Gradient descent proceeds in epochs. An epoch consists of using the training set entirely to update each parameter. The learning rate α controls the size of an update





repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

(for $j = 1$ and $j = 0$)

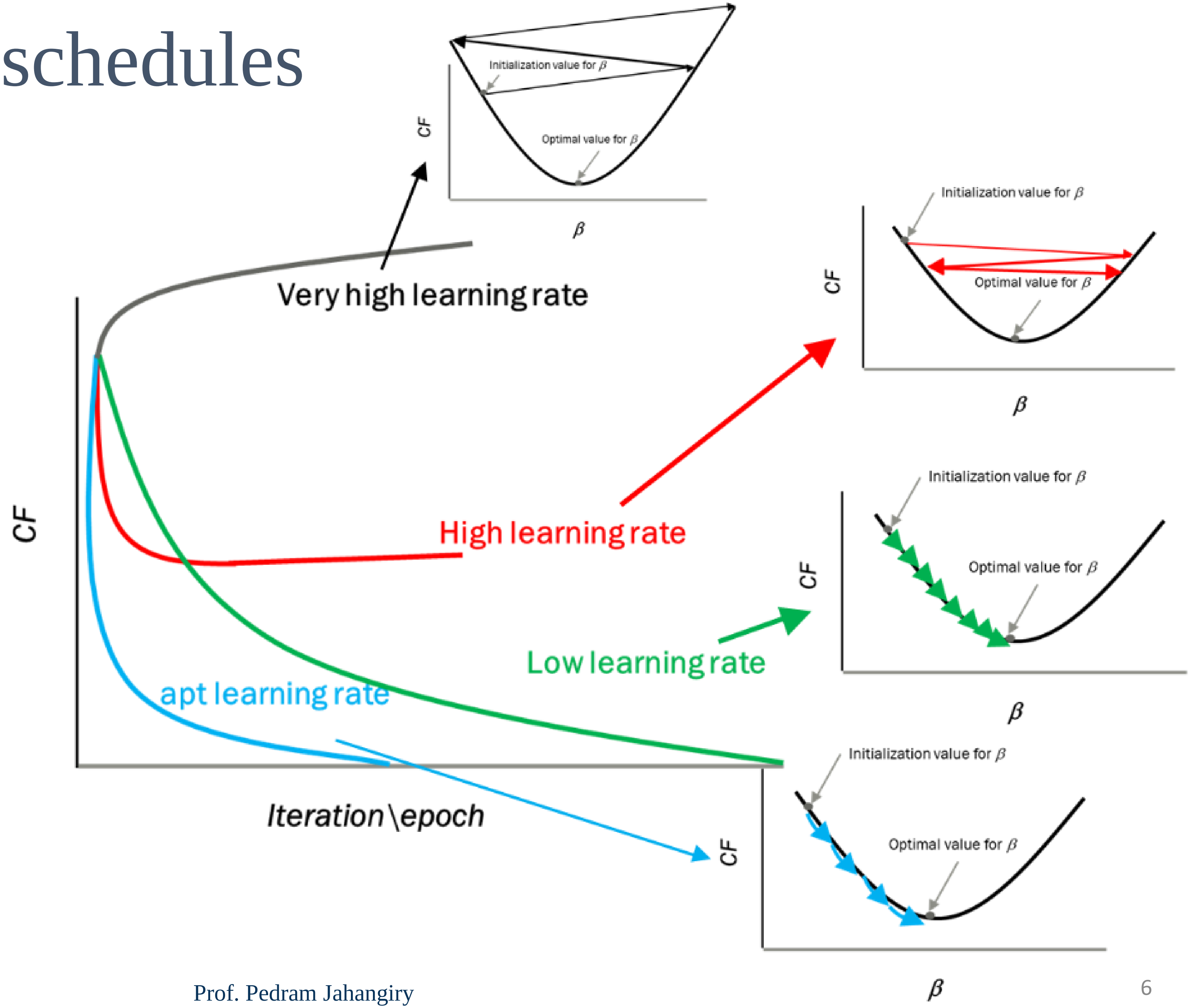
}

Learning rate schedules

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

- If α is too small, gradient descent can be slow

- If α is too large, gradient descent can overshoot the minimum. It may fail to converge, or even **diverge**.



Beyond Gradient Descent?

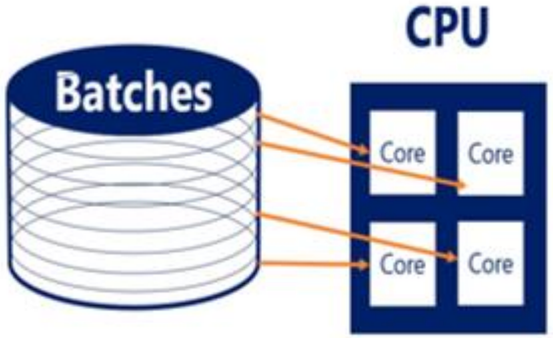
Disadvantages of gradient descent:

- Single batch: use the entire training set to update a parameter!
- Sensitive to the choice of the learning rate
- Slow for large datasets

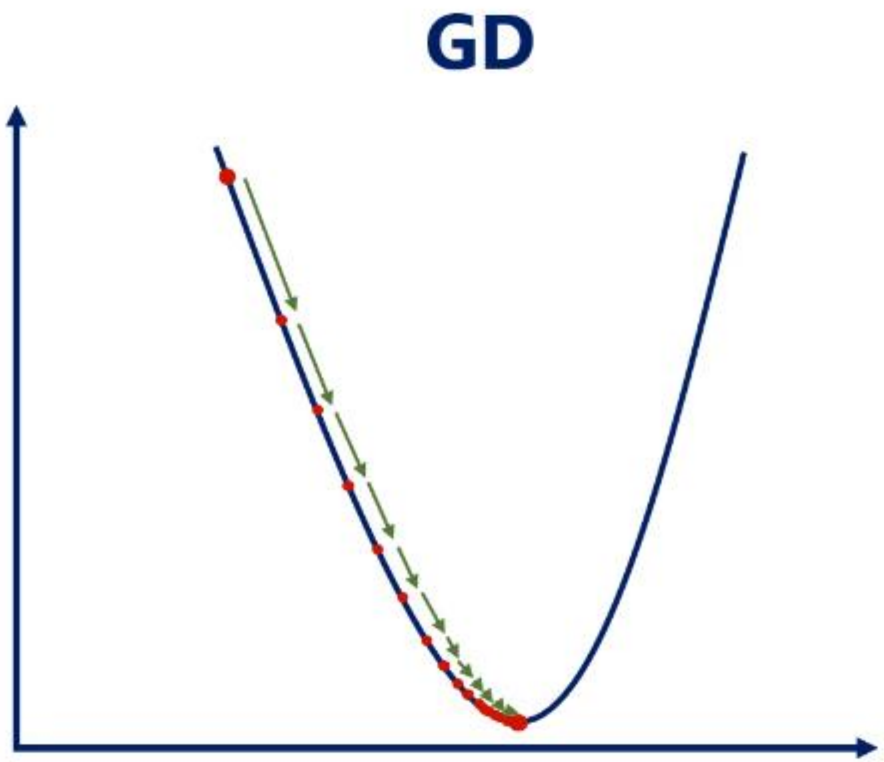
(Minibatch) Stochastic Gradient Descent: is a version of the algorithm that speeds up the computation by approximating the gradient using smaller batches (subsets) of the training data. SGD itself has various "upgrades".

1) Adagrad
2) Adam

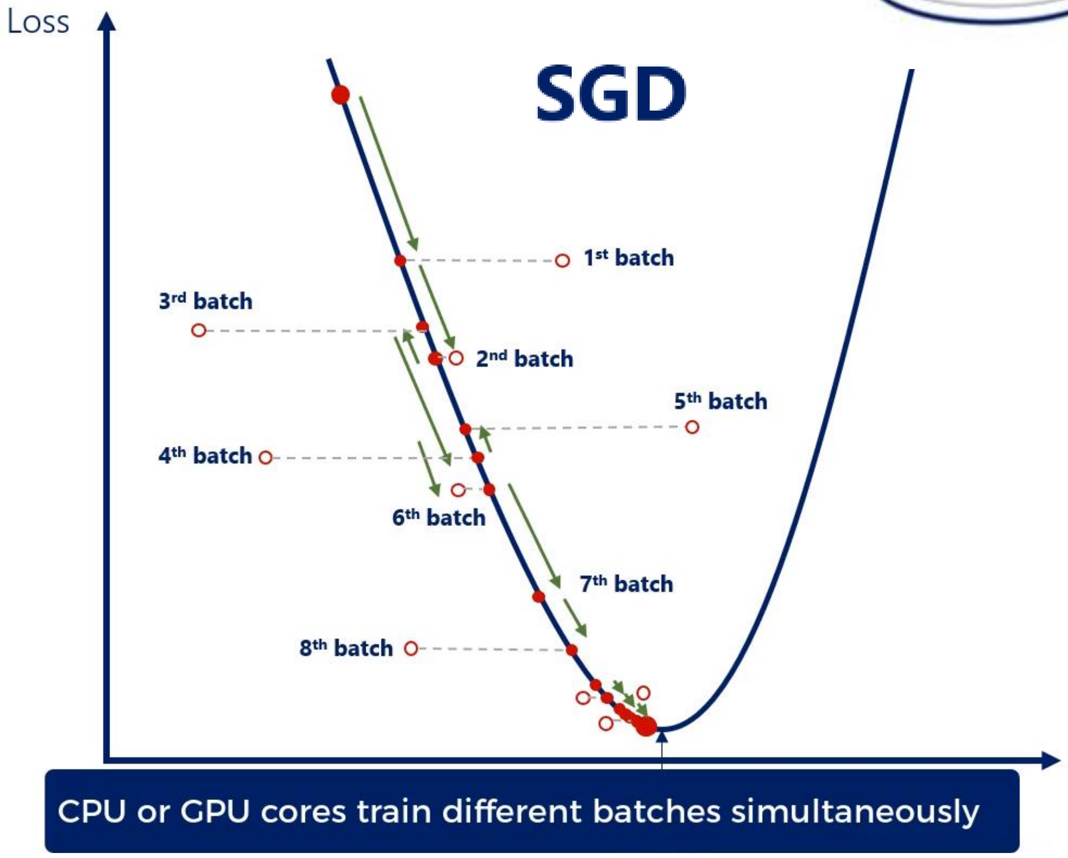
Why SGD?



Batches
CPU
Core
Core
Core
Core

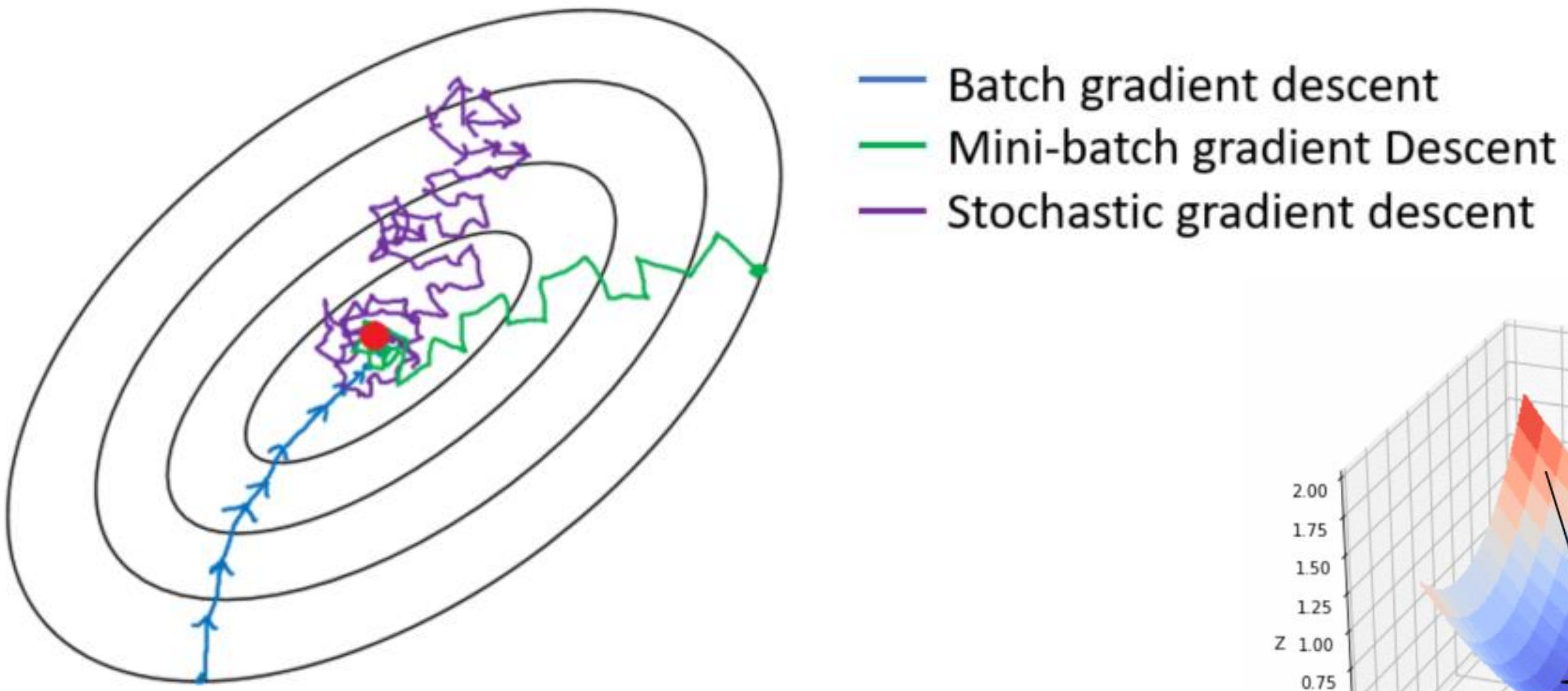


GD

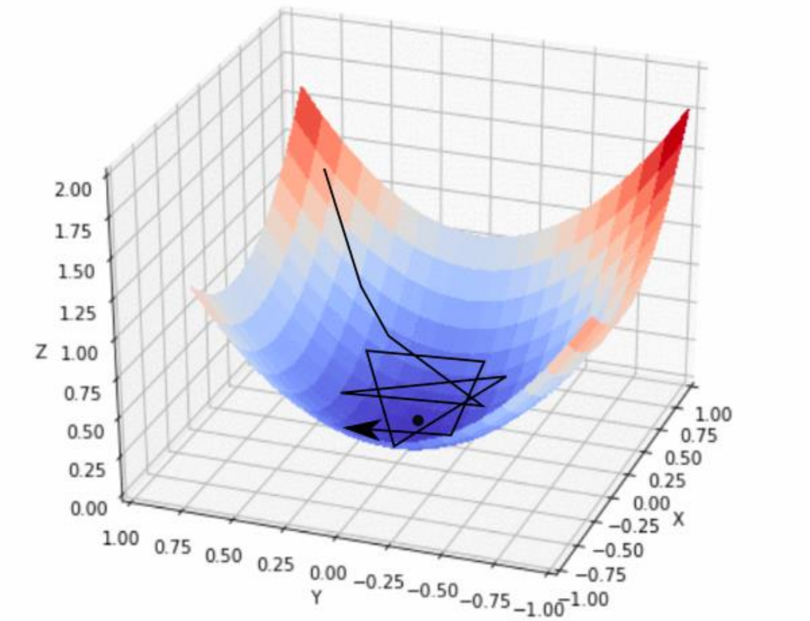


Loss
SGD
1st batch
2nd batch
3rd batch
4th batch
5th batch
6th batch
7th batch
8th batch
CPU or GPU cores train different batches simultaneously

SGD vs GD

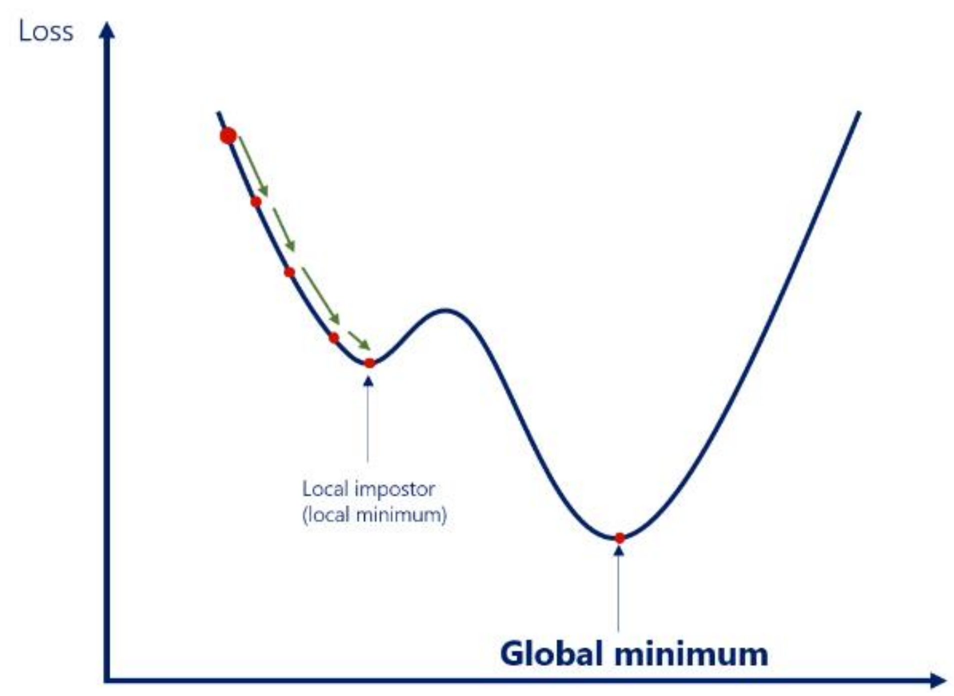


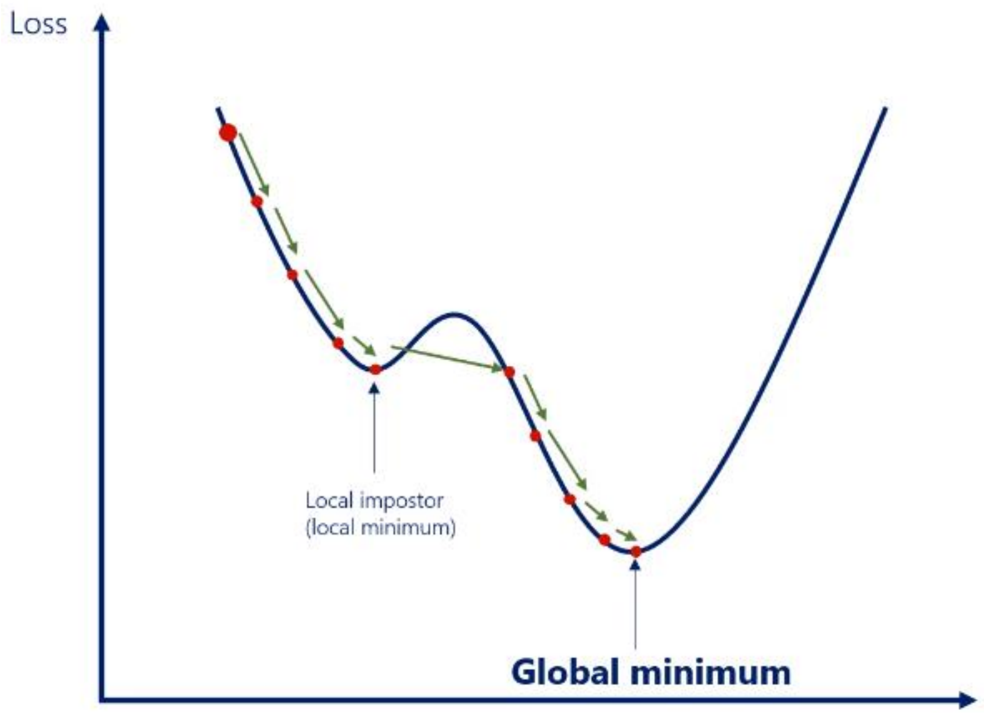
Batch gradient descent
Mini-batch gradient Descent
Stochastic gradient descent



Z
X
Y

Why upgrade SGD?





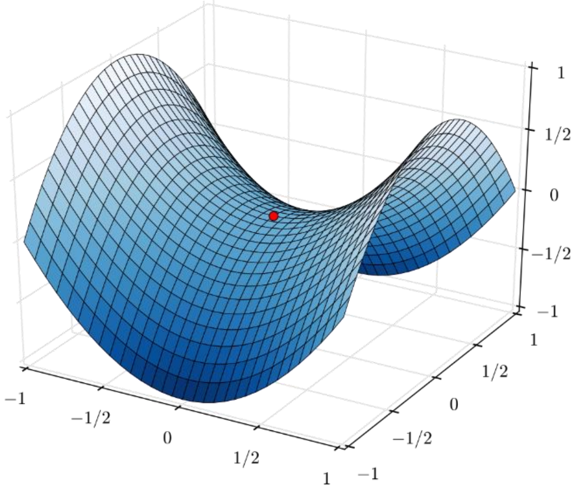
Beyond Stochastic Gradient Descent?

Disadvantages of Stochastic gradient descent:

- Get trapped in suboptimal local minima (for non-convex loss functions)
- The same learning rate applies to all parameter updates

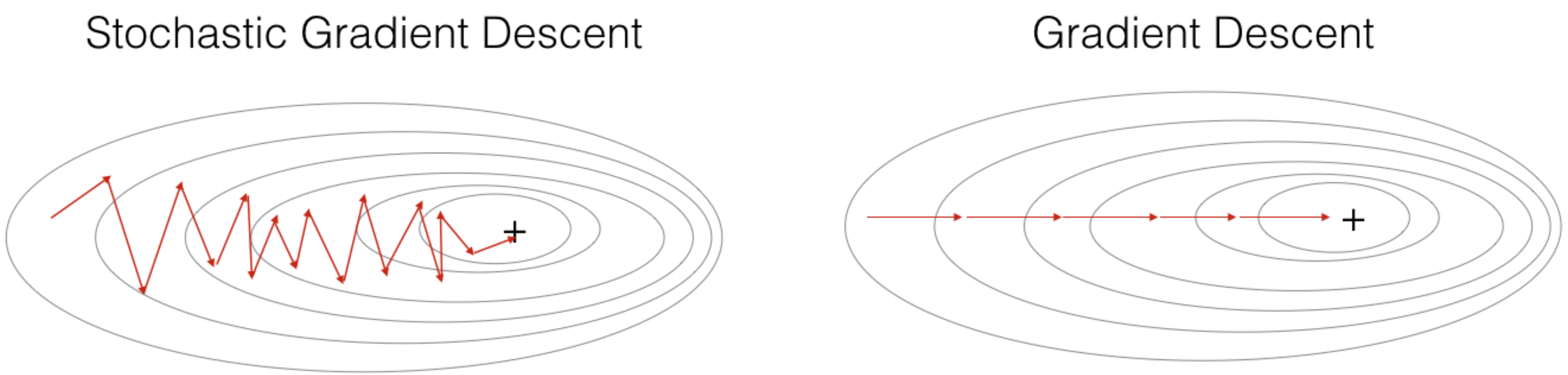
SGD upgrades:

1) Momentum
2) Adagrad
3) Adam



Momentum

- Momentum is a method that helps accelerate SGD in the relevant direction and dampens oscillations.
- Essentially, when using momentum, we push a ball down a hill. The ball accumulates momentum as it rolls downhill, becoming faster and faster on the way.



Adagrad

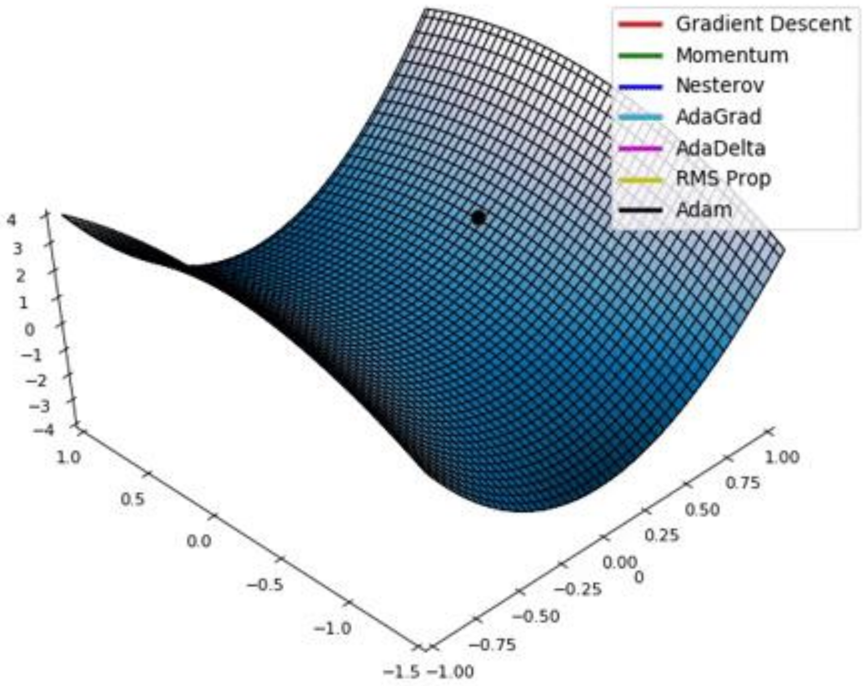
- Adaptive Gradient Algorithm is a version of SGD that scales the learning rate for each parameter according to the history of gradients. As a result, the learning rate is reduced for very large gradients and vice-versa.

- It adapts the learning rate to the parameters, performing smaller updates (low learning rates) for parameters associated with frequently occurring features, and larger updates (high learning rates) for parameters associated with infrequent features. For this reason, it is well-suited for dealing with sparse data.

Adam

- Adaptive Moment Estimation takes both momentum and adaptive learning rate (RMSprop) and putting them together.

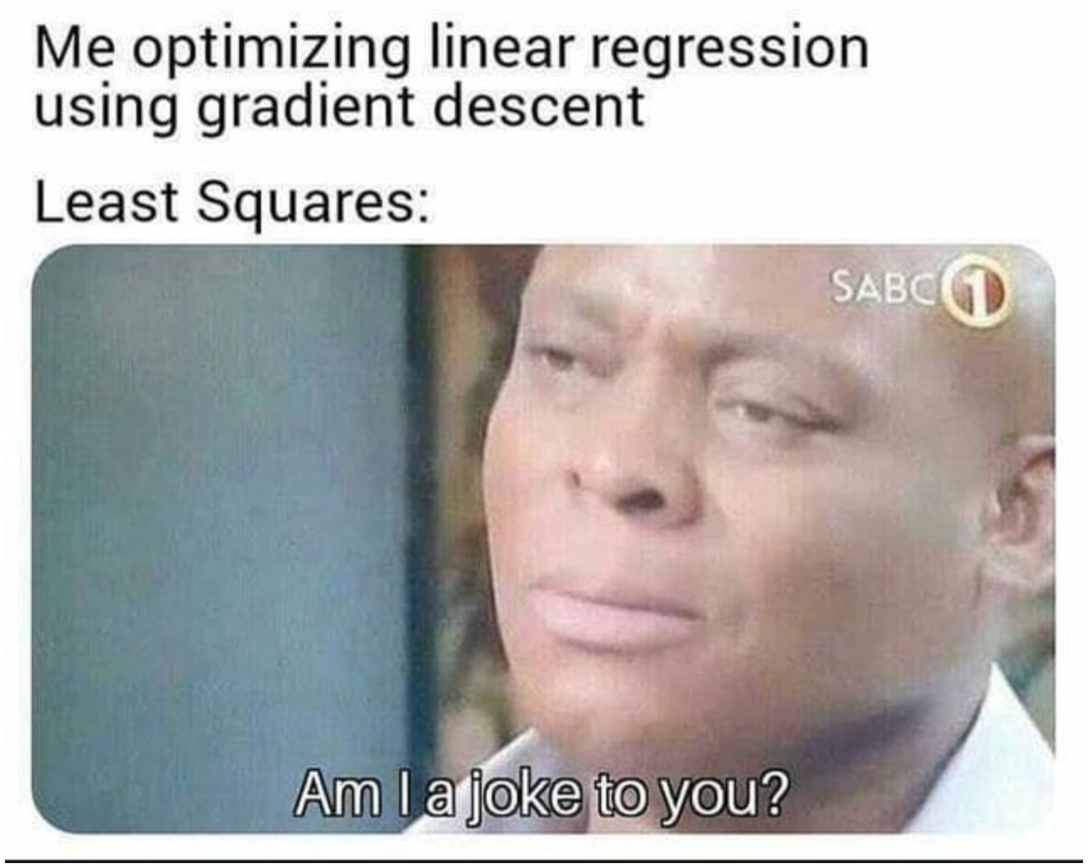
- Whereas momentum can be seen as a ball running down a slope, Adam behaves like a heavy ball with friction, which thus prefers flat minima in the error surface



Final message!

Notice that gradient descent and its variants are not machine learning algorithms. They are solvers of minimization problems in which the function to minimize has a gradient (in most points of its domain).

Question of the day!




thank you all
CLASS DISMISSED