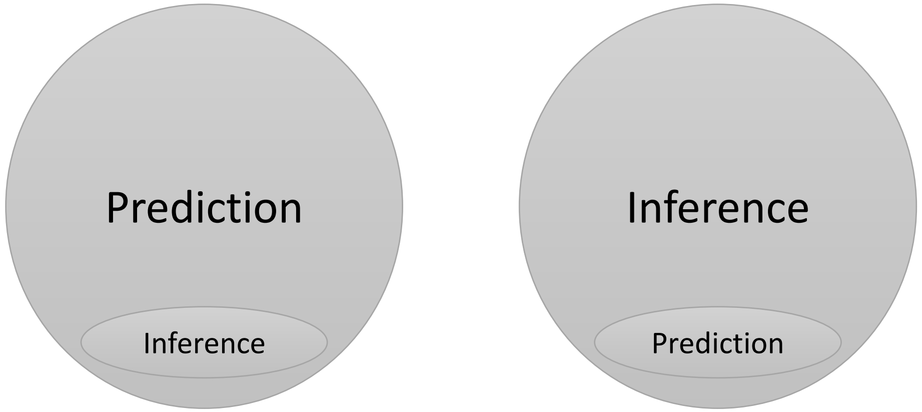
Class 5- Machine Learning concepts
Part II

Motivation

Machine learning fundamental concepts:

- Inference and prediction
- Part I: The Model
    - Parameters and hyperparameters
    - Parametric vs nonparametric ML models
- Part II: Evaluation metrics
- Part III: Bias-Variance tradeoff
- Part IV: Resampling methods
- Part V: How do machines learn?
- Part VI: Solvers/learners (GD, SGD, Adagrad, Adam, …)

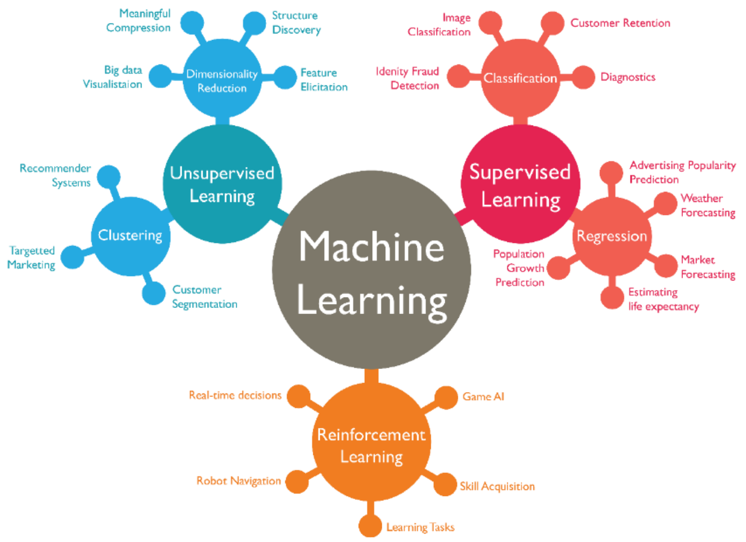


Part V
How do machines learn?

How do machines learn?

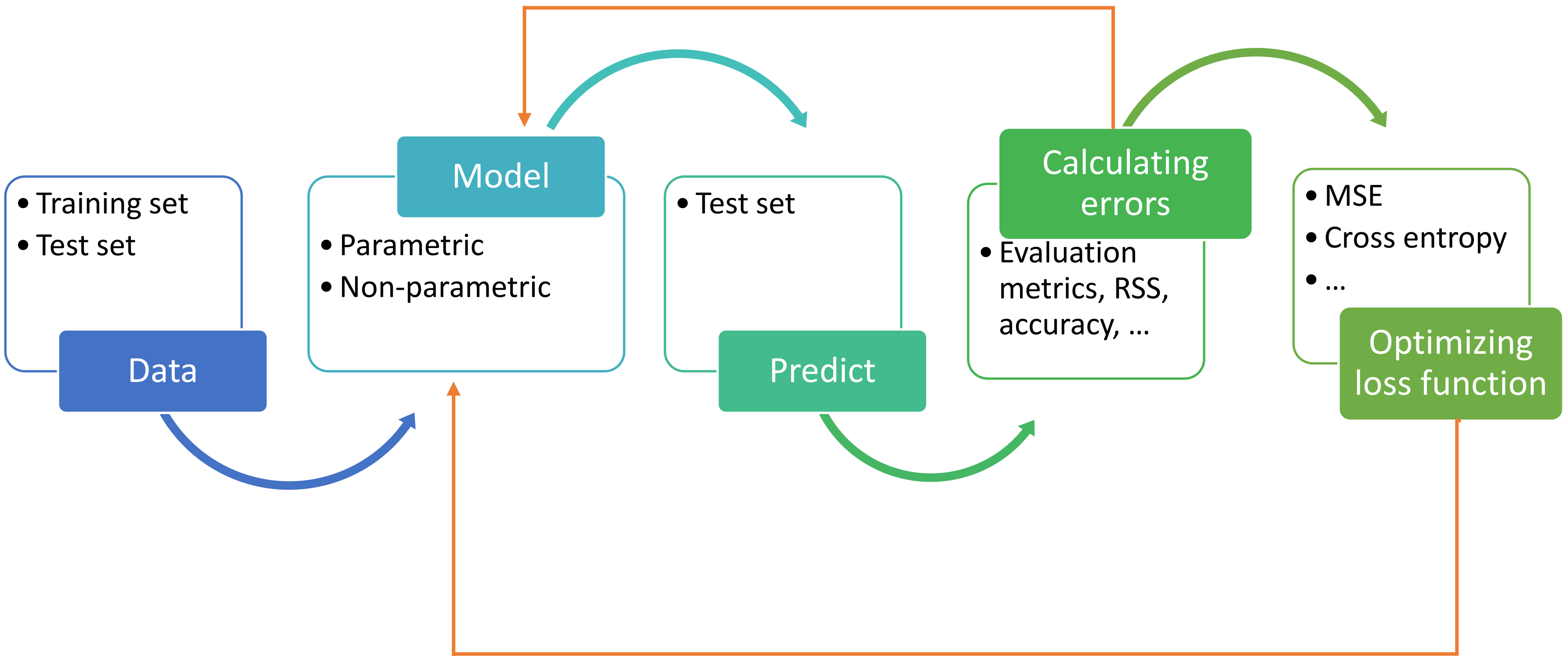
The short answer: Algorithms!

- Algorithm: a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer.
- Generally, the more data a machine learning algorithm is provided the more accurate it becomes.
- Different types of algorithms:
  - Supervised
  - Unsupervised
  - Reinforcement



How do machines learn?

Hyperparameter tuning using cross validation, elbow method, grid search, etc.



Updating the parameters of the model: this is the learning part

Part VI

Solvers (GD, SGD, Adagrad, Adam, …)

Solvers (learners)!

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.

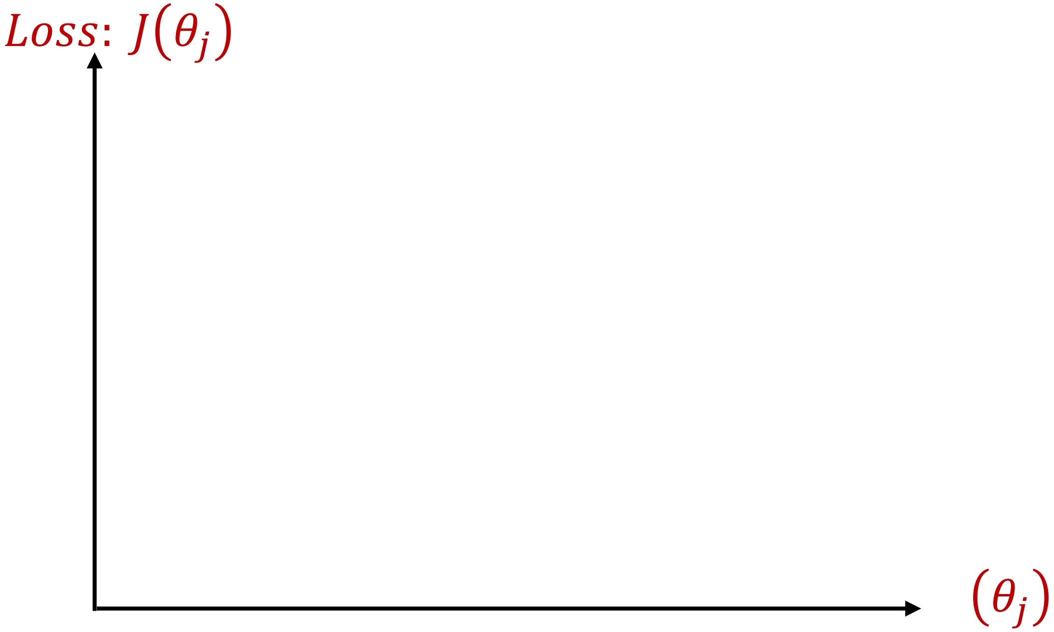
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

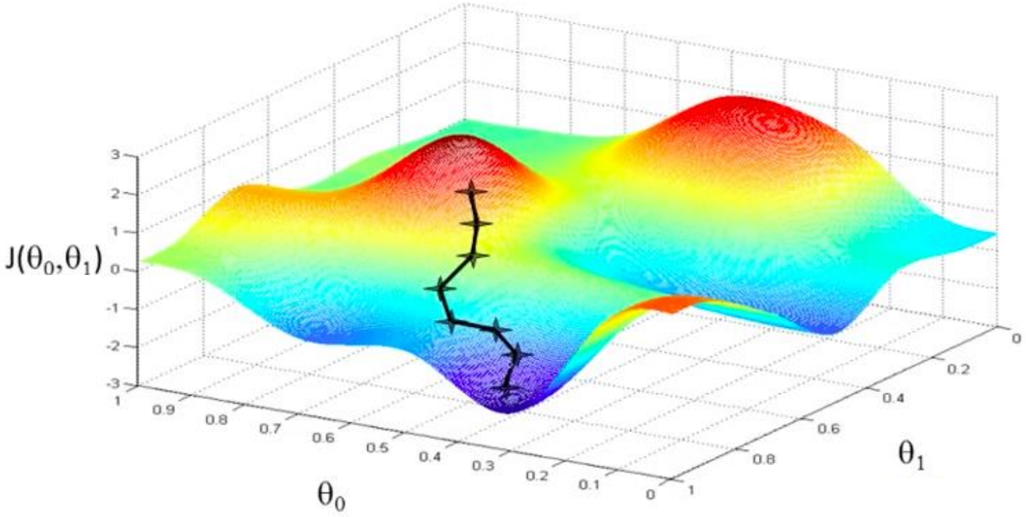
- θ_j is the model's j^{th} parameter
- α is the learning rate
- $J(\theta)$ is the loss function (which is differentiable)

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 {

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

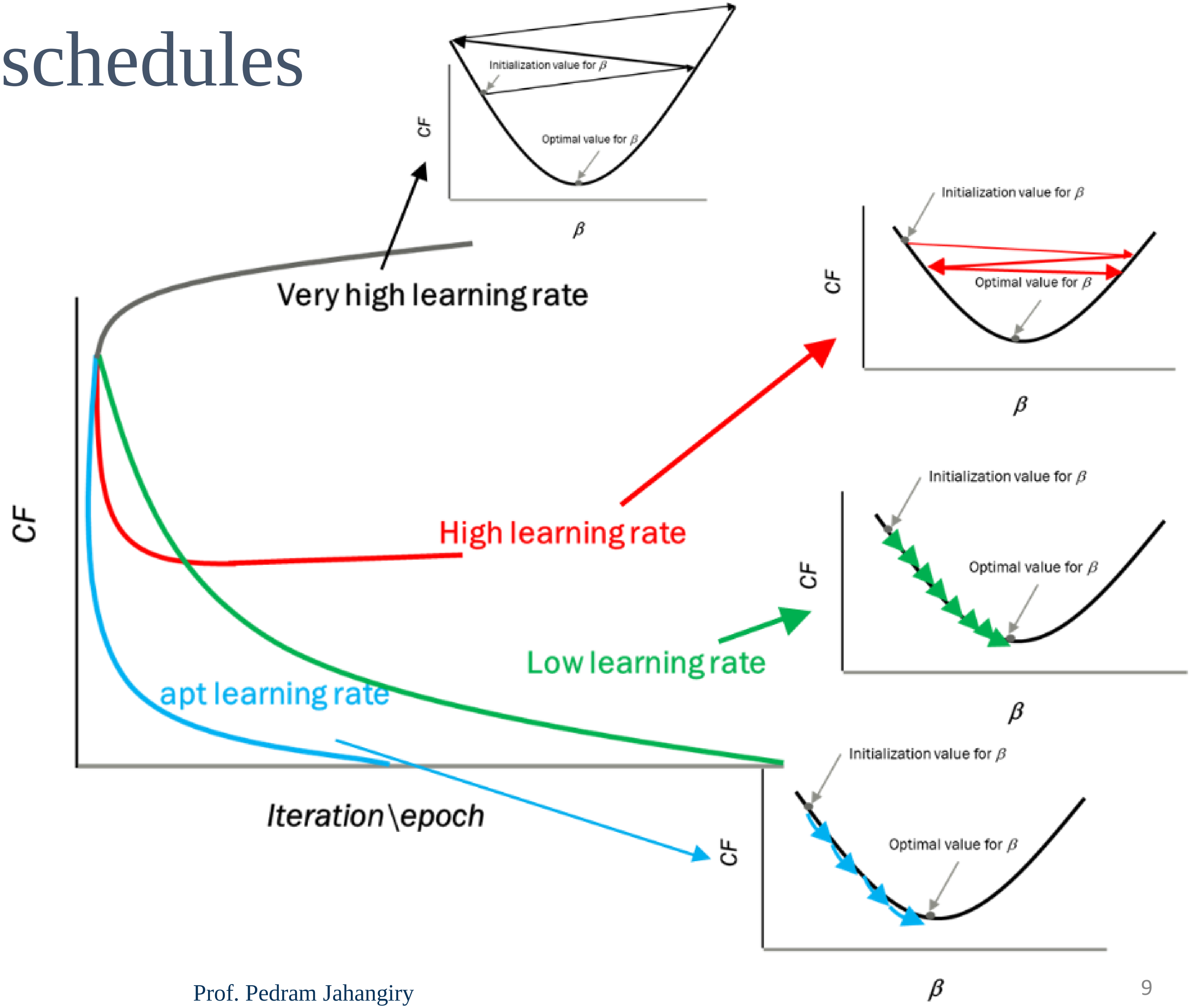
(for $j = 1$ and $j = 0$)

}

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?

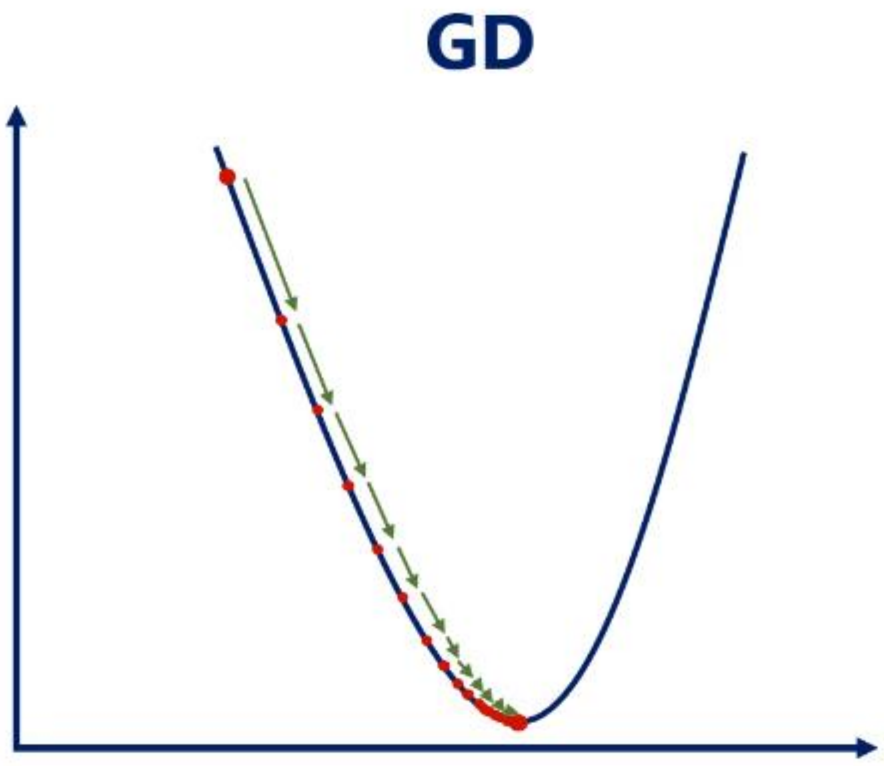
Disadvantages of gradient descent:

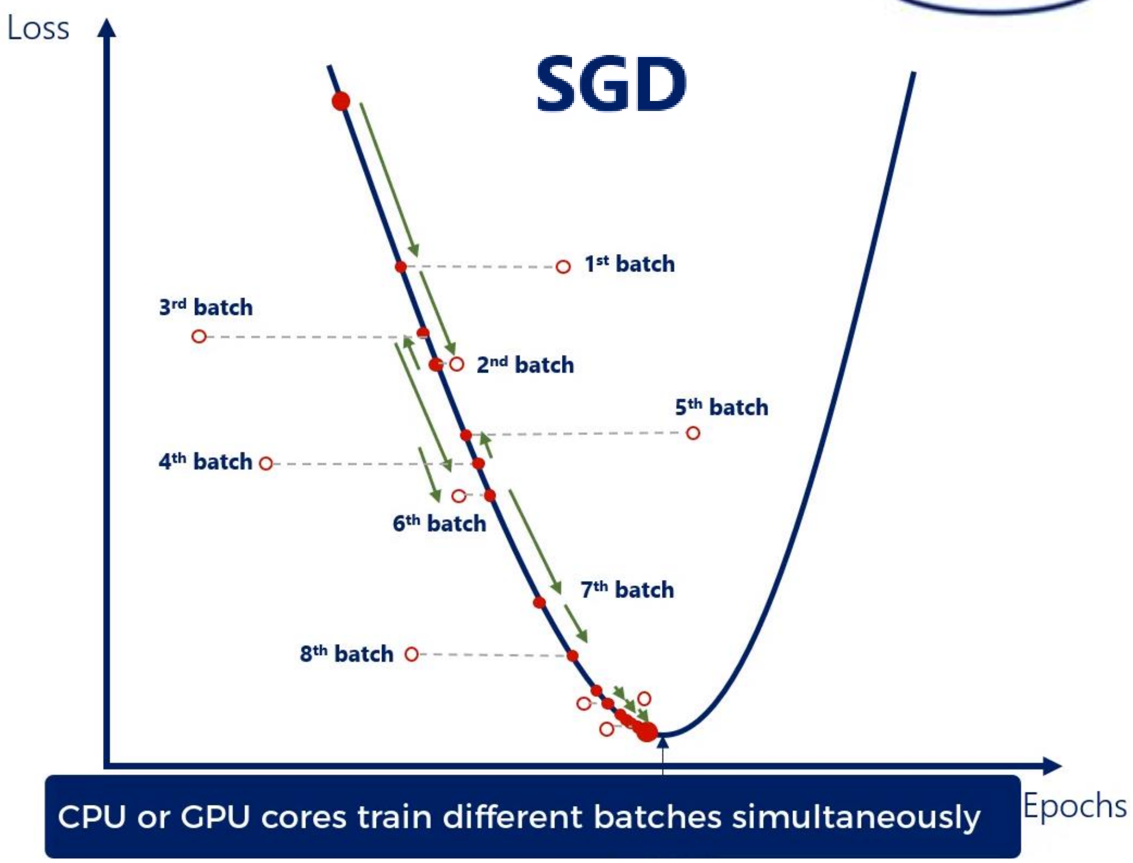
- Single batch: use the entire training set to <u>update</u> a parameter!
- Sensitive to the choice of the learning rate
- Slow for large datasets

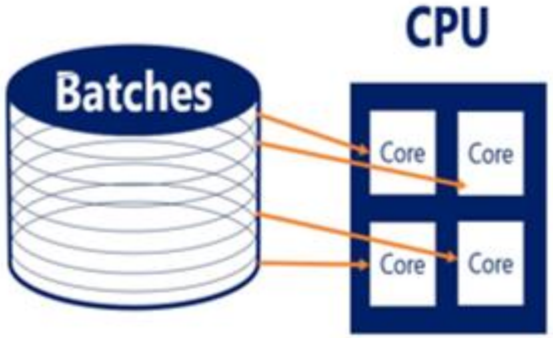
(Minibatch) Stochastic Gradient Descent: is a version of the algorithm that speeds up the computation by approximating the gradient using smaller batches (subsets) of the training data. SGD itself has various “upgrades”.

1) Adagrad
2) Adam

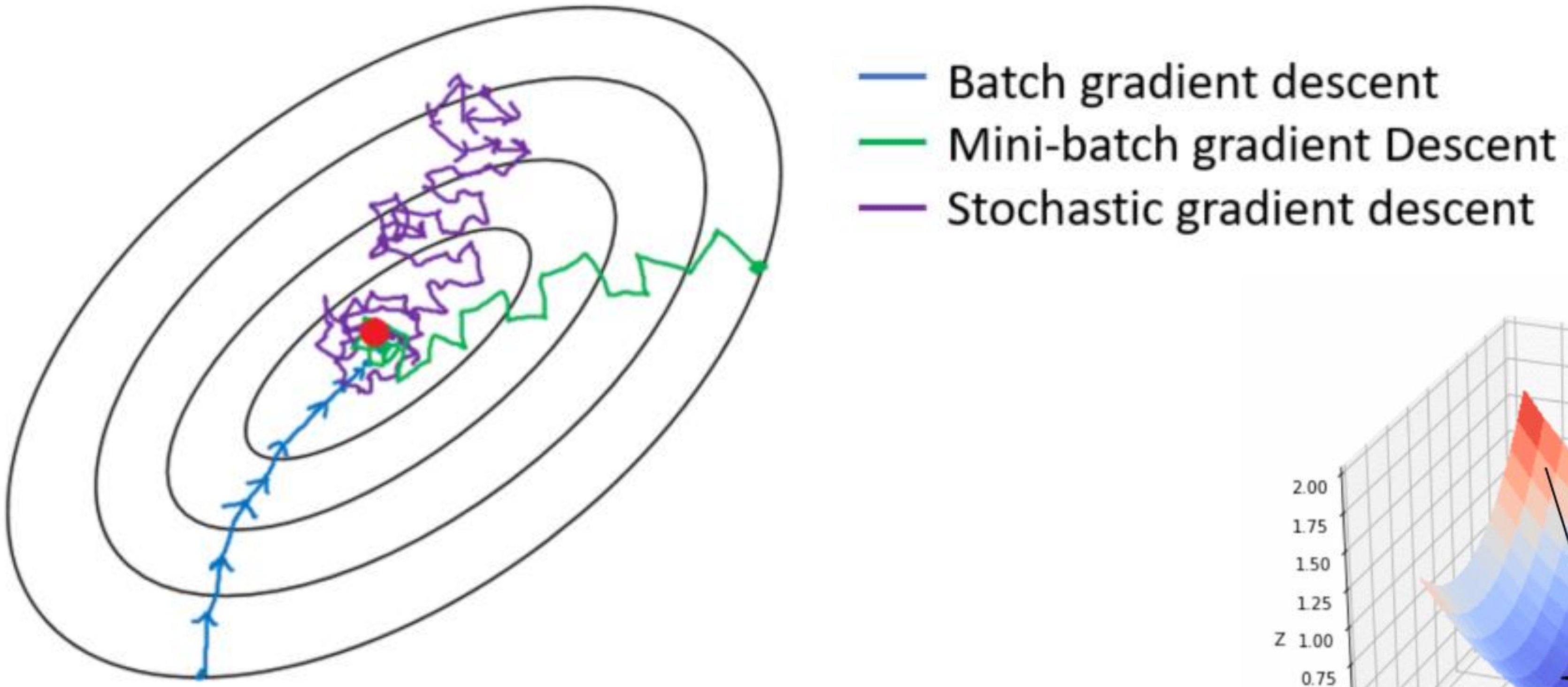
Why SGD?

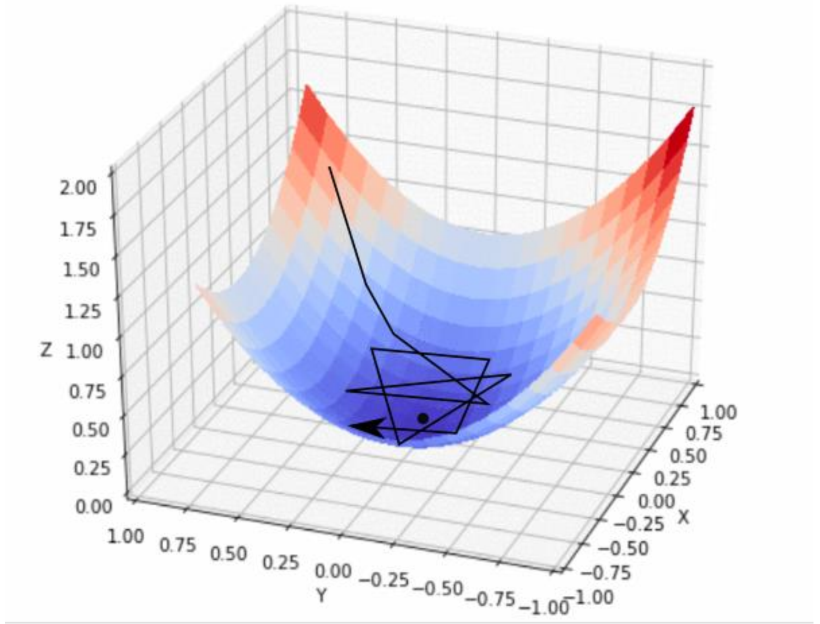

GD


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


CPU
Batches
Core
Core
Core
Core

SGD vs GD


Batch gradient descent
Mini-batch gradient Descent
Stochastic gradient descent


2.00
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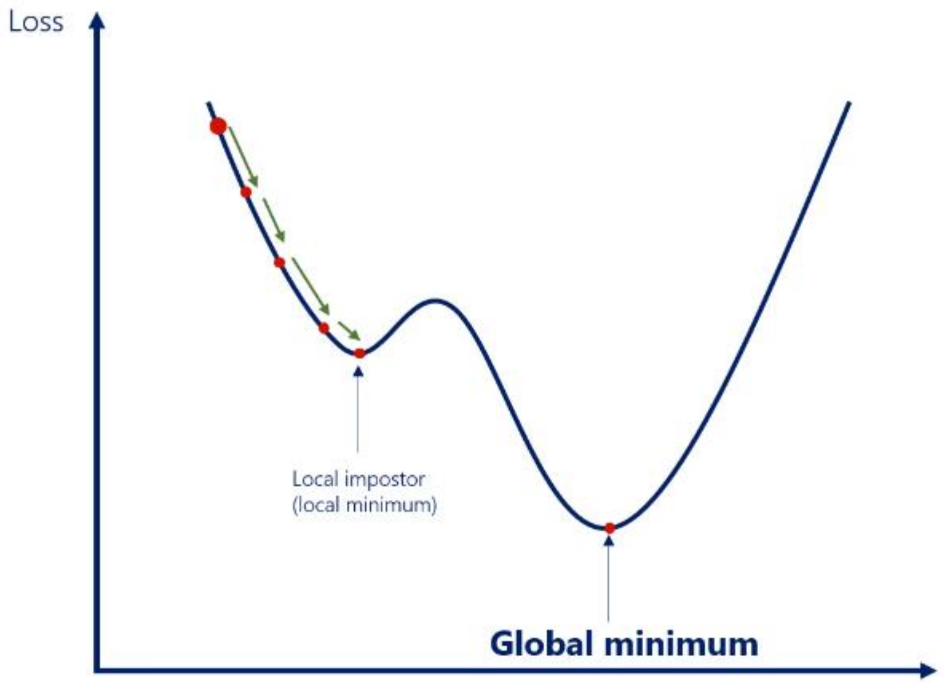
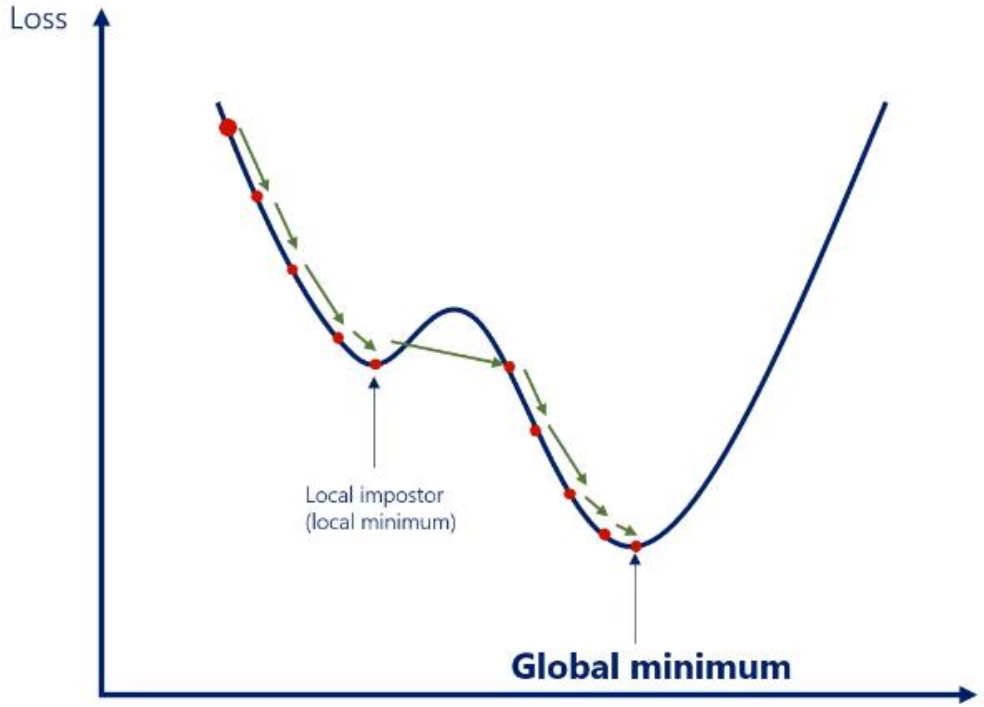
0.00
−0.25 X
−0.50
−0.75
−1.00

Why upgrade SGD?

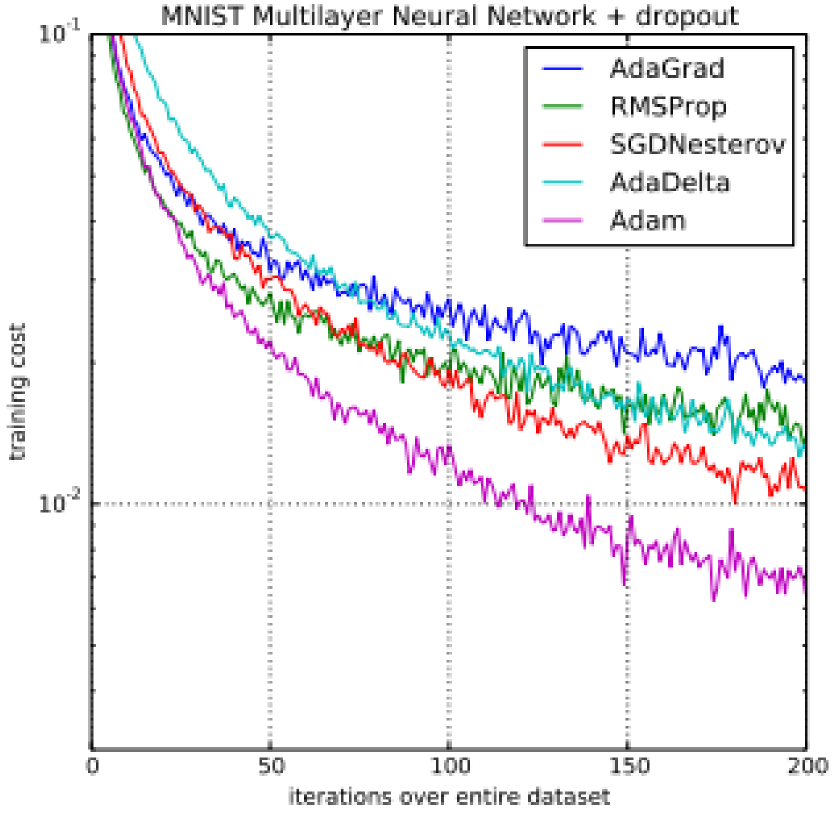




SGD upgrades

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

- Adam (Adaptive Moment Estimation): is a method that helps accelerate SGD by orienting the gradient descent in the relevant direction and reducing oscillations.



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).