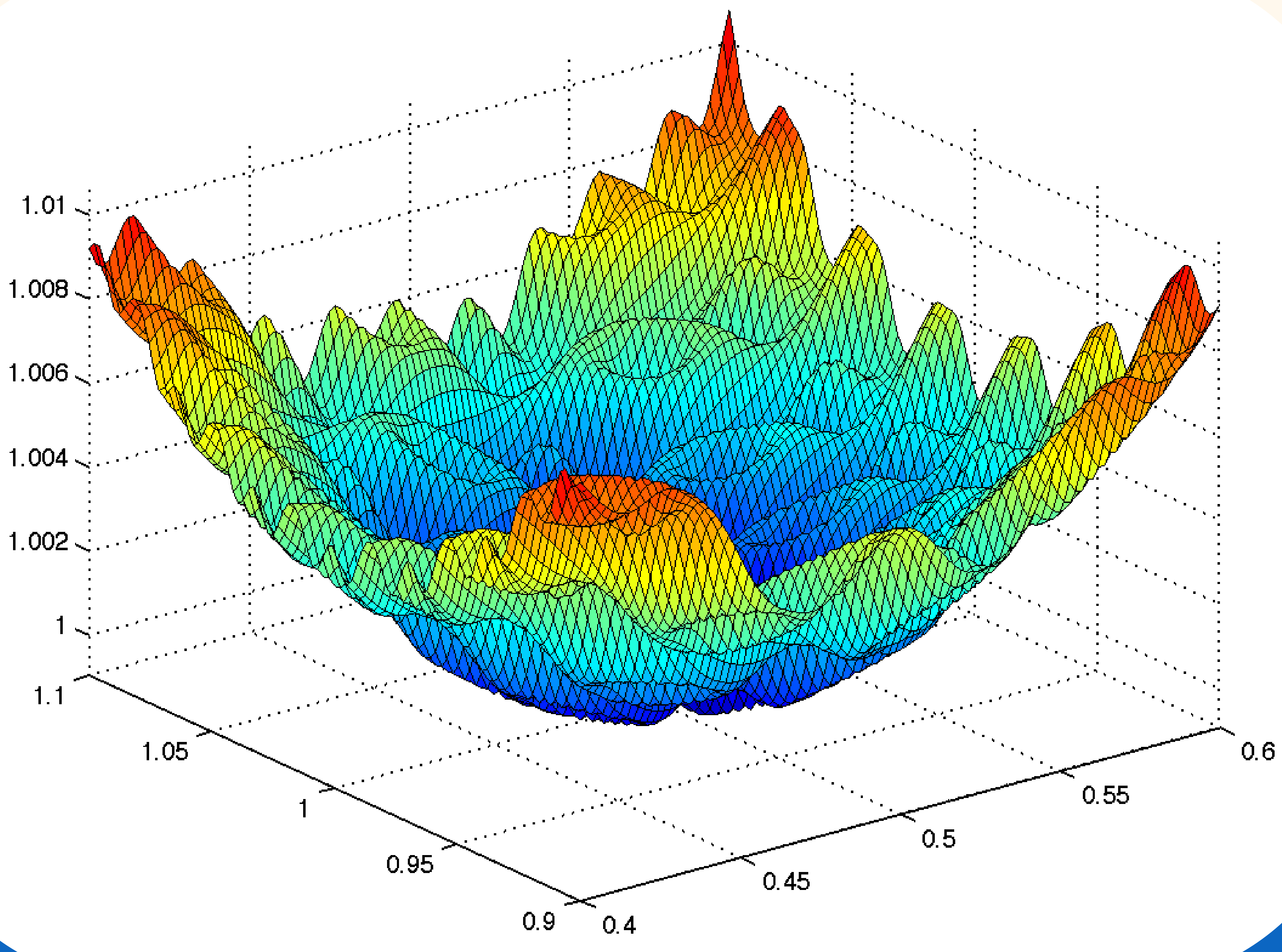
9 Most Popular Optimization Algorithms in Deep Learning

✓Pros, ✗Cons, 💡Use Cases



1

Stochastic Gradient Descent (SGD):

- **Pros:** It is simple to implement and computationally efficient. It can be used for a wide range of problems, including linear regression and neural networks.
- **Cons:** It can be sensitive to the choice of learning rate and may require manual tuning. It can also get stuck in local minima.
- **Use case:** It is commonly used in large-scale machine learning problems, where the dataset is too large to be processed in one pass.

2

Mini-batch Gradient Descent:

- **Pros:** It is more computationally efficient than SGD because it processes multiple examples at once. It can also be less sensitive to the choice of learning rate.
- **Cons:** It can still get stuck in local minima and may require manual tuning.
- **Use case:** Mini-batch gradient descent is a common optimization algorithm for training deep neural networks.

3

Nesterov Accelerated Gradient (NAG):

- **Pros:** It can help the optimization to converge faster and escape from local minima by providing a better approximation of the gradient.

- **Cons:** It can overshoot the global minimum if the momentum term is set too high.

- **Use case:** It is commonly used in deep learning, especially in training large neural networks.

4

Adagrad:

- **Pros:** It adapts the learning rate for each parameter, allowing for efficient optimization of non-uniformly scaled data.

- **Cons:** It can have a monotonically decreasing learning rate, which can cause the optimization to converge too slowly.

- **Use case:** It is particularly well-suited for problems with sparse data, such as natural language processing.

5

Adadelta:

- **Pros:** It adapts the learning rate based on the historical gradient information, which can be more robust to the choice of initial learning rate.
- **Cons:** It can be sensitive to the choice of the hyper-parameter.
- **Use case:** Itis a good choice for problems where the data is noisy or the optimization is prone to getting stuck in local minima.

6

RMSprop:

- **Pros:** It adapts the learning rate based on the historical gradient information, which can help the optimization converge more quickly.
- **Cons:** Like Adagrad and Adadelta, it can be sensitive to the choice of the hyper-parameter.
- **Use case:** It is a good choice for problems where the data is noisy or the optimization is prone to getting stuck in local minima.

7

Adam (Adaptive Moment Estimation):

- **Pros:** It combines the advantages of both momentum and RMSprop by adapting the learning rate for each parameter and building up a momentum in the direction of the steepest descent.
- **Cons:** It can be sensitive to the choice of the hyper-parameters.
- **Use case:** It is a popular optimization algorithm for training deep neural networks.

8

Adamax:

- **Pros:** It is similar to Adam but uses the infinity-norm of the gradient instead of the second-order moment, which can be more robust to the choice of the hyper-parameters.

- **Cons:** It can be sensitive to the choice of the hyper-parameters.

- **Use case:** It is particularly well-suited for problems where the data is sparse or the optimization is prone to getting stuck in local minima, similar to Adagrad.

9

Nadam (Nesterov-accelerated Adaptive Moment Estimation):

- **Pros:** It combines the advantages of NAG and Adam by providing a better approximation of the gradient and adapting the learning rate for each parameter.
- **Cons:** It can be sensitive to the choice of the hyper-parameters.
- **Use case:** It is a good choice for training deep neural networks, especially in cases where the optimization is prone to getting stuck in local minima.

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