

Introduction to Machine Learning

Module 1C: Optimization

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What do we optimize?

How do we optimize?





What do we optimize?

How do we optimize?

Why optimization is important (at the societal level)?





What do we optimize? -> Parameters of the model to make the loss minimum

How do we optimize?

Why optimization is important (at the societal level)?

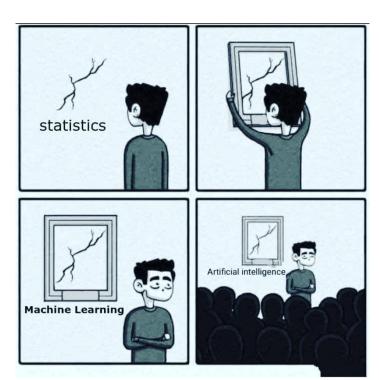




What do we optimize? -> Parameters of the model tomake the loss minimum

How do we optimize? -> Math!

Why optimization is important (at the societal level)?







What do we optimize? -> Parameters of the model tomake the loss minimum

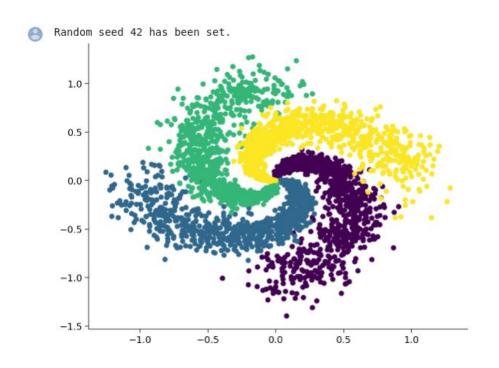
How do we optimize? -> Math!

Why optimization is important (at the societal level)? -> Creating fair algorithms





How to calculate the loss?



Multiclass classification: Cross-entropy vs. MSE?

Source: module1B-tutorial1



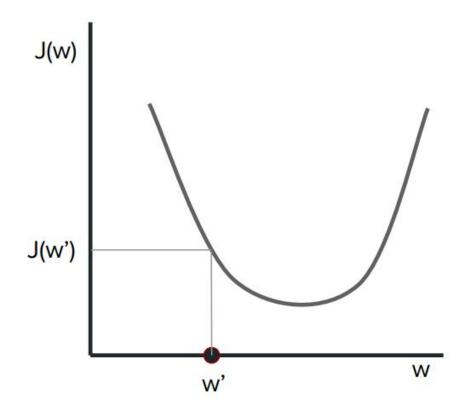


How to decide the loss function?

- Identify your problem (e.g., classification, regression?)
- Check the literature









Random search?

Algorithm:

sample random points around current w

if random point, w', yields lower objective (i.e. J(w') < J(w)): Accept w' as new position and store it in w





Random search?







Gradient Descent <3

Algorithm:

- Compute gradient (it points uphill)
- Do step in opposite direction of gradient
- Step size (learning rate), η







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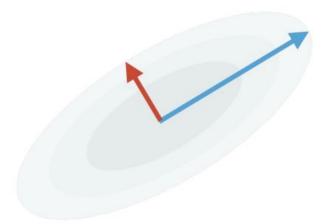
$$w_{t+1} = w_t - \eta \nabla J(w_t)$$





Gradient Descent

• How to choose learning rate?

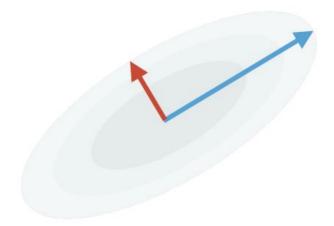


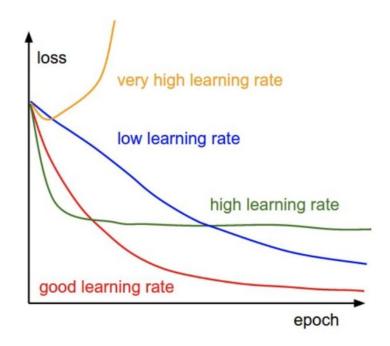




Gradient Descent

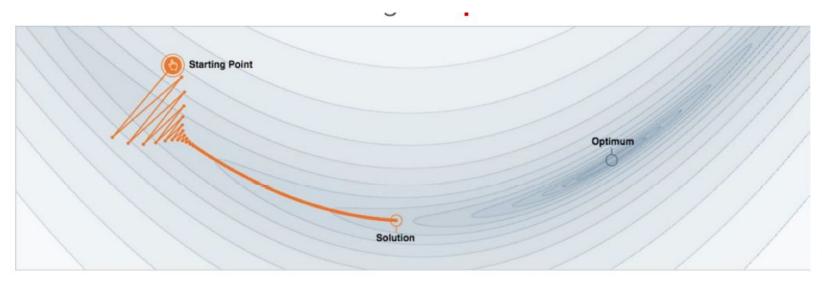
How to choose learning rate?











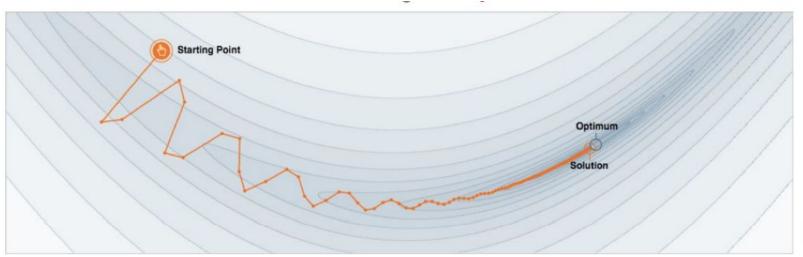
[Distill.pub]





Momentum <3

- Accelerates along flat directions
- Slows down along sharp directions



[Distill.pub]





How does the momentum work?

Momentum algorithm:

- Do a gradient descent step
- Apply the update from the last iteration, only smaller (momentum step)

$$w_{t+1} = w_t - \eta \nabla J(w_t) + \beta(w_t - w_{t-1})$$





Adaptive Methods <3

Learning rate schedules

$$w_{t+1} = w_t - \eta_t \nabla J(w_t)$$





Adaptive Methods <3

Learning rate schedules

$$w_{t+1} = w_t - \eta_t \nabla J(w_t)$$

Polynomial schedules, e.g.
$$\rightarrow \eta_t = \frac{\alpha}{c+t}, \ \eta_t = \frac{\alpha}{c+\sqrt{t}}$$

Exponential

Stepwise decay

Cosine/cyclical schedules



Adaptive Methods <3

- Adagrad (Duchi et al., 2011)
 - Adapts the learning rate for each parameter
 - Using running sum squares of past gradients
 - Typically used in stochastic form:
 - Instead of full gradient, use gradient from mini-batch

$$[w_{t+1}]_i = [w_t]_i - \frac{\eta}{\sqrt{[v_{t+1}]_i + \epsilon}} [\nabla J(w_t)]_i$$

$$[v_{t+1}]_i = \sum_{s=1}^t [\nabla J(w_s)]_i^2$$

Adaptive Methods <3

- RMSprop
 - Uses a moving average instead of sum used by Adagrad
 - Moving average can be useful on non-convex objectives

$$[w_{t+1}]_i = [w_t]_i - \frac{\eta}{\sqrt{[v_{t+1}]_i + \epsilon}} [\nabla J(w_t)]_i$$

$$[v_{t+1}]_i = \alpha [v_t]_i + (1 - \alpha) [\nabla J(w_t)]_i^2$$



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Adam: RMSprop + momentum





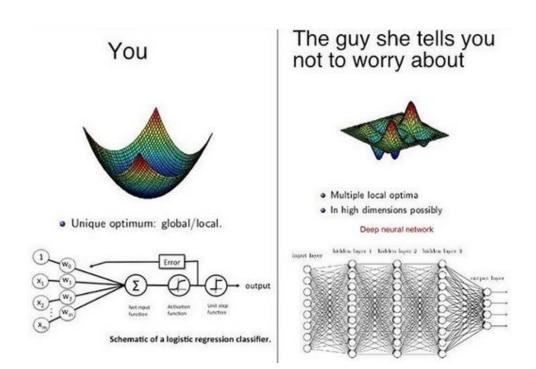
Non-convexity Problem





Non-convexity Problem

- Convex <3 -> have the same global and local minimum
- Non-convex -> have different global and local minimum







Non-convexity Problem

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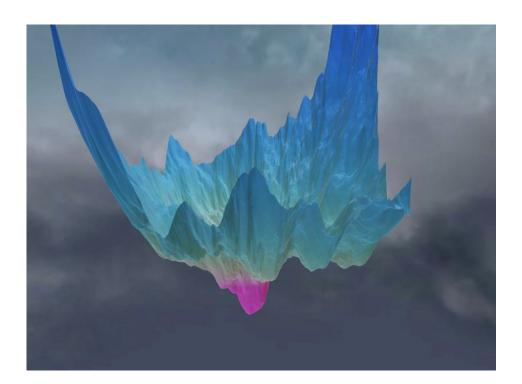
Great non-convexity, comes with great responsibility!





Non-convexity Problem

Initialization matters!!
https://losslandscape.com/explorer







Non-convexity Problem

Overparameterization





Computation Cost Problem





Computation Cost Problem

Minibatch training <3





Computation Cost Problem

Minibatch training <3 -> stochastic gradient descent



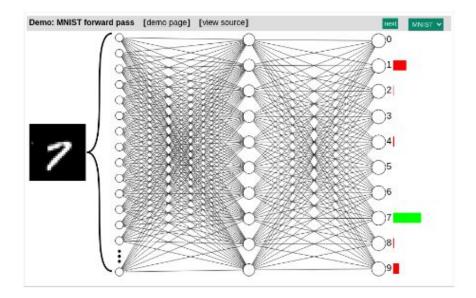


Computation Cost Problem

- Minibatch training <3 -> stochastic gradient descent
 - Minibatch size:
 - Too small batch size: optimization bounces around alot, and can lead to slower convergence to a minimum.
 - Too big batch size: won't fit on GPU
 - Rule of thumb -> pick the largest batch size that fits in the GPU

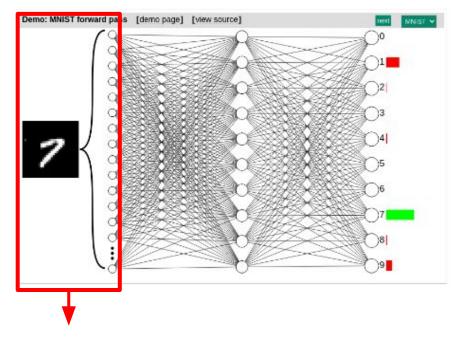








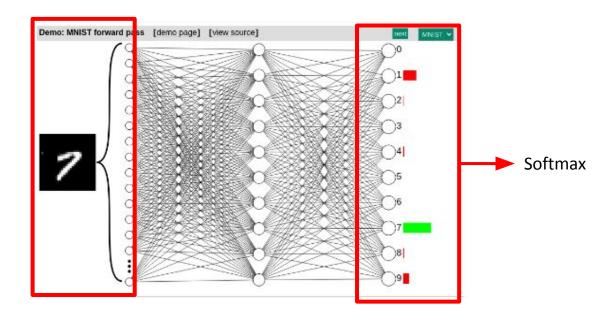




28 x 28 image -> 784 vector

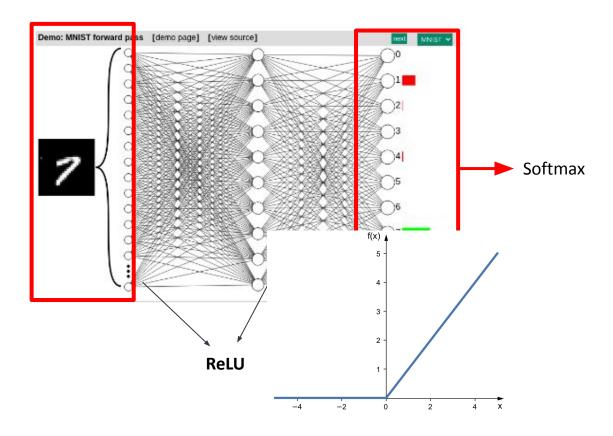












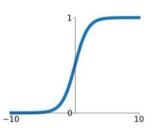




Activation Functions

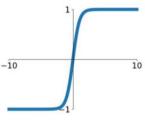
Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$



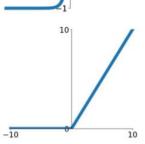
tanh

tanh(x)



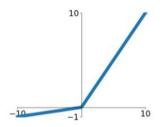
ReLU

 $\max(0,x)$



Leaky ReLU

 $\max(0.1x, x)$



Maxout

 $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

