

Optimizing Neural Networks



- Neural Networks Quiz
- Advanced Optimizers beyond SGD

Agenda

- Dropout for Regularization
- Batch Normalization for Regularization
- Weight Initialization Techniques



Let's begin the discussion by answering a few questions on neural networks



What does momentum in SGD with Momentum help achieve?

- A Accelerates convergence using past gradients
- B Adjusts learning rates adaptively
- c Reduces the variance of gradient updates
- Prevents overshooting during optimization



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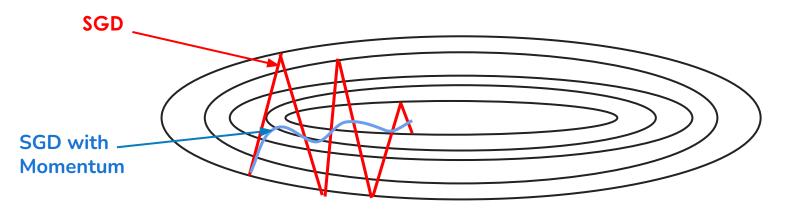
- Reduces the variance of gradient updates
- Prevents overshooting during optimization

Stochastic Gradient Descent with Momentum



SGD with momentum **accelerates convergence** by incorporating past gradients to maintain a consistent direction towards the minima

Momentum enhances this process by **reducing oscillations** and **facilitating smoother optimization trajectories**



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Which statement correctly describes how Adam and SGD with Momentum handle the learning rate?

- The learning rate is constant throughout training for both Adam and SGD with Momentum.
- Adam adjusts the learning rates separately for each parameter, while SGD with Momentum maintains a fixed learning rate.
- SGD with Momentum changes the learning rate depending on gradient magnitude, whereas Adam sticks to a consistent learning rate.
- Both Adam and SGD with Momentum utilize a dynamic learning rate approach throughout the training process.



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Learning Rates in ADAM & SGD with momentum



SGD with Momentum

Adam

Stochastic Gradient Descent with Momentum

Adaptive Moment Estimation

Adds a momentum component

Adds a momentum component

Fixed Learning Rate

Adaptive Learning Rate

The learning rate is different for each model parameter and depends on the value of the gradient

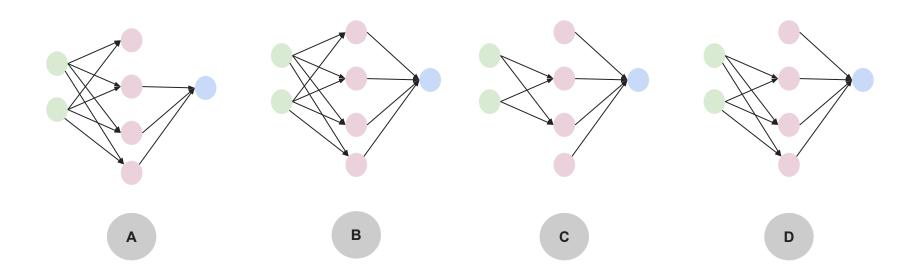
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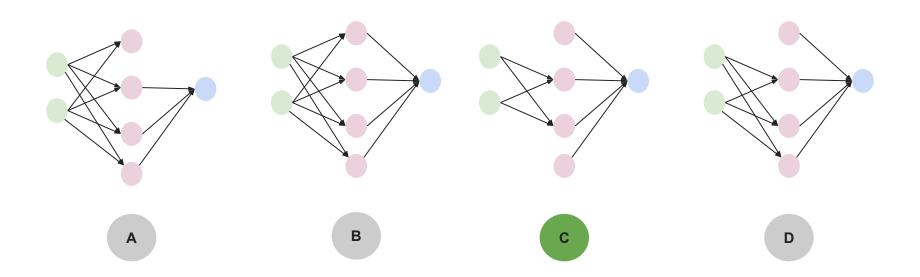


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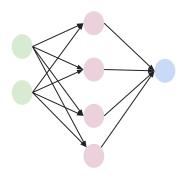
Dropout

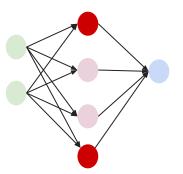


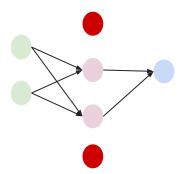
Step 1 - Choose a dropout rate p (p = 0.5 here)

Step 2 - Randomly select 100*p% of the neurons (50% here)

Step 3 - Deactivate the selected neurons by setting them to zero.







2

3

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How does Dropout contribute to dealing with overfitting in neural networks?

- A Decreasing the complexity of the neural network
- B Increasing the complexity of the neural network

Changing the activation function of a neuron

By adding Gaussian noise to the input



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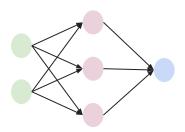
Dropout for Regularization



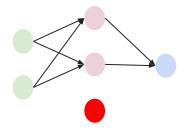
Dropout prevents overfitting by randomly deactivating neurons during training

Independence: Fosters independent learning among neurons

Ensemble: Creates a diverse ensemble of networks as neurons are deactivated randomly during training and the final result is an average prediction



Before Dropout



After Dropout

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How many learnable parameters are there in a batch normalization layer?

A 4

B 3

D



How many learnable parameters are there in a batch normalization layer?

A 4

B 3

D 2

Batch Normalization - Working



Step 1 - Normalization: Normalize X (input) by subtracting its mean and dividing by its standard deviation.

No learnable parameters in Step 1

Step 2 - Scaling: Scale the output of Step 1 by multiplying it with a learnable parameter gamma

Step 3 - Shifting: Shift the output of Step 2 by adding an offset (learnable parameter beta)



Which of the following accurately describes the purpose of batch normalization in neural networks?

- A Minimizing overfitting by adding noise to the input data.
- B Preventing vanishing gradients by initializing weights appropriately.

c Reducing internal covariate shift by normalizing layer activations.

Decreasing model complexity by adding more parameters.



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Batch Normalization - Purpose



Stabilizing Training: Reduces internal covariate shift.

Regularization: Acts as a form of regularization.

Improved Gradient Flow: Enhances gradient flow for faster convergence.



How does weight initialization contribute to improved learning in a neural network?

- A By introducing uniform gradients.
- By ensuring symmetric neuron behavior.
- **c** By adjusting initial weights.
- By hindering adaptation.



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Weight Initialization



Sets up the starting point for learning in a neural network

Helps break symmetry among neurons

Prevents gradient problems

Makes learning faster and more efficient overall



What is the common problem that can arise when weights are initialized randomly in a neural network?

- A Vanishing Gradients
- **B** Exploding Gradients
- C Vanishing or Exploding Gradients
- D Learning rate becoming too high



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Weight Initialization



Randomly initializing weights in a neural network can lead to two critical problems during training

Vanishing gradients: Occurs when the gradients (derivatives) become extremely small, slowing down or halting the learning process

Exploding gradients: Occurs when the gradients become excessively large, causing instability and hindering effective learning

Specific weight initialization strategies help overcome these problems

Xavier (or Glorot) Initialization - sigmoid and tanh activations

He Initialization - ReLU and variants of ReLU



Happy Learning!





APPENDIX

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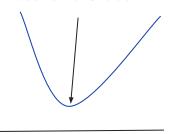
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Need for Advanced Optimizers



Convex Optimization

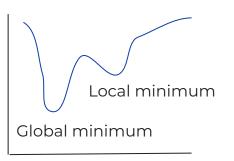
Local and Global minima



Efficient optimization, Global convergence

Guaranteed global convergence under conditions

Non-Convex Optimization



Complex, Local optima, Challenging optimization

No guarantee, Prone to local optima