

Optimization & Deep Learning

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The Convergence of Gradient Descent

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$$\omega \leftarrow \omega - \eta \frac{\partial E}{\partial \omega}$$

gradient of
objective function

weight vector

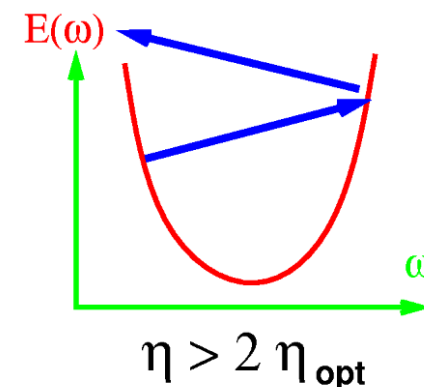
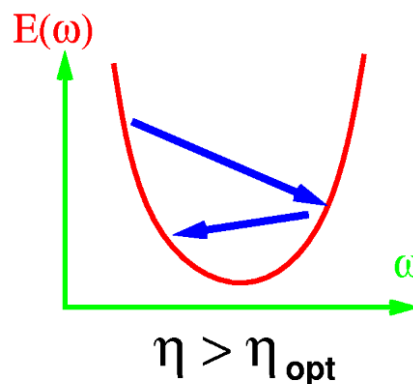
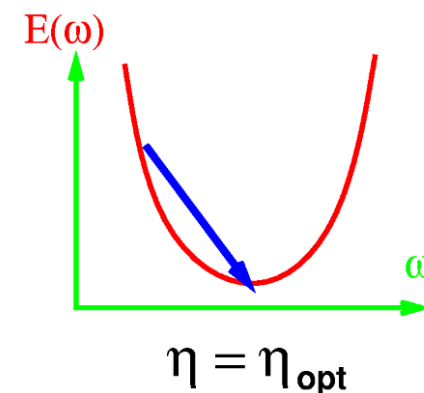
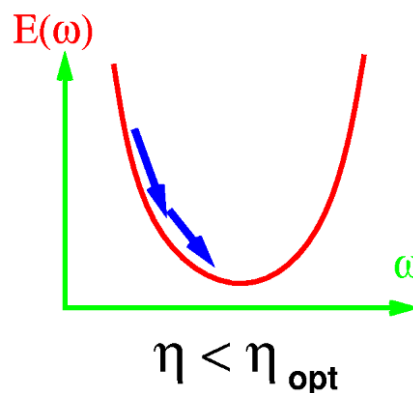
learning rate

■ Batch Gradient

■ There is an optimal learning rate

■ Equal to inverse 2nd derivative

$$\eta_{\text{opt}} = \left(\frac{\partial^2 E}{\partial \omega^2} \right)^{-1}$$



Let's Look at a single linear unit

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- Single unit, 2 inputs

- Quadratic loss

- $$E(W) = 1/p \sum_p (Y - W \cdot X_p)^2$$

- Dataset: classification: $Y=-1$ for blue, $+1$ for red

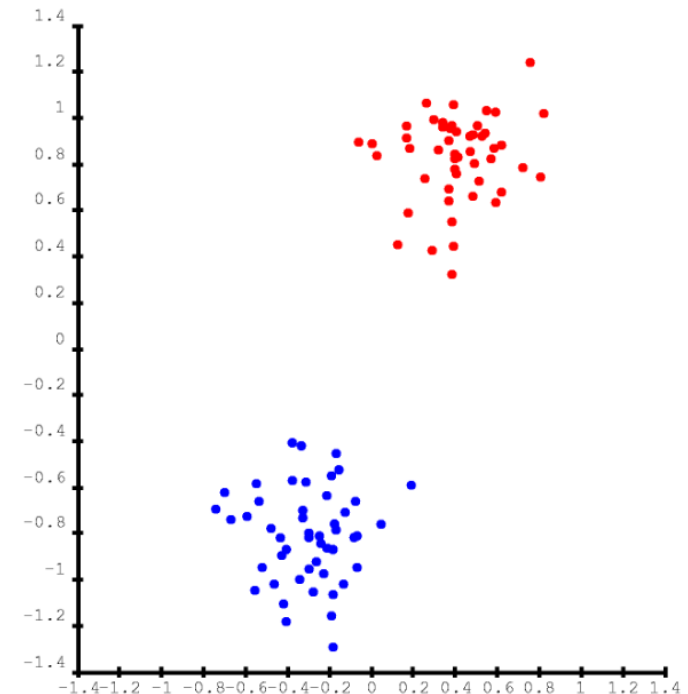
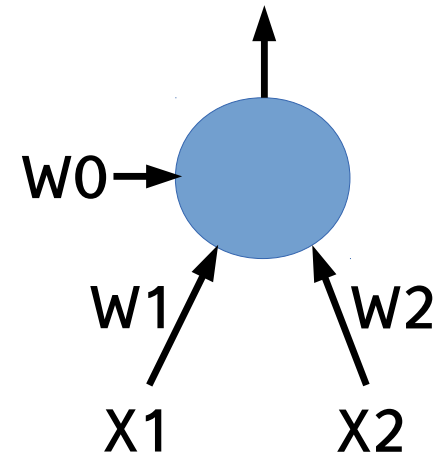
- Hessian is covariance matrix of input vectors

- $$H = 1/p \sum X_p X_p^T$$

- To avoid ill conditioning: **normalize the inputs**

- Zero mean

- Unit variance for all variable



Convergence is Slow When Hessian has Different Eigenvalues

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Batch Gradient, small learning rate

Batch Gradient, large learning rate

Learning rate:

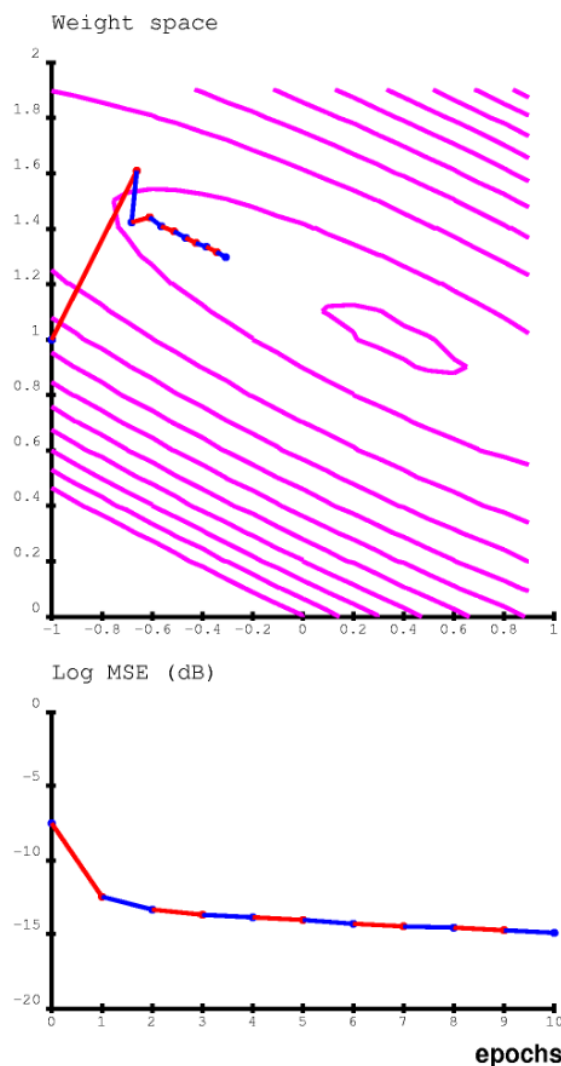
$$\eta = 1.5$$

Hessian largest eigenvalue:

$$\lambda_{\max} = 0.84$$

Maximum admissible Learning rate:

$$\eta_{\max} = 2.38$$



Learning rate:

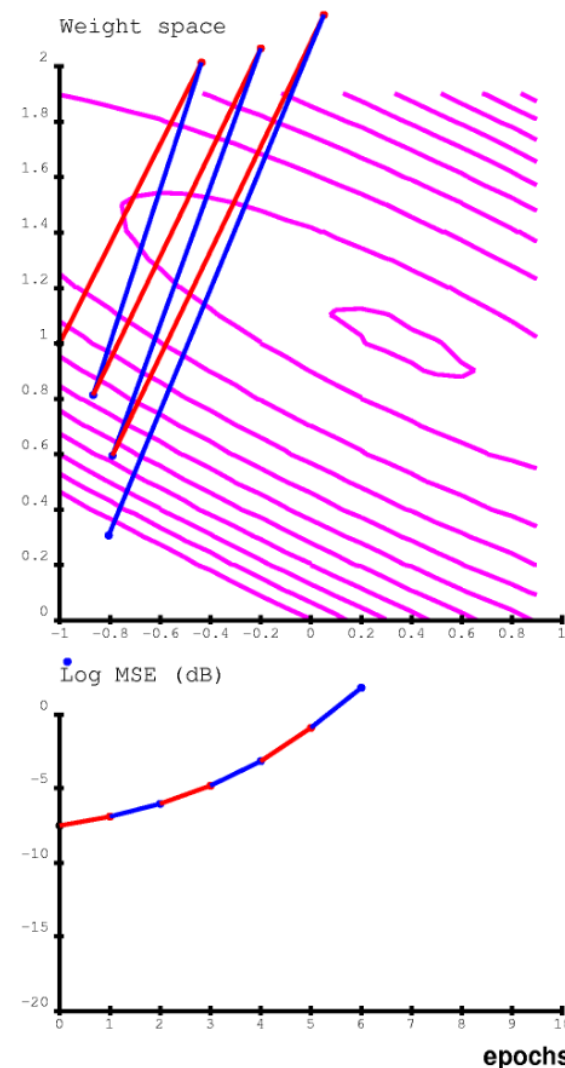
$$\eta = 2.5$$

Hessian largest eigenvalue:

$$\lambda_{\max} = 0.84$$

Maximum admissible Learning rate:

$$\eta_{\max} = 2.38$$



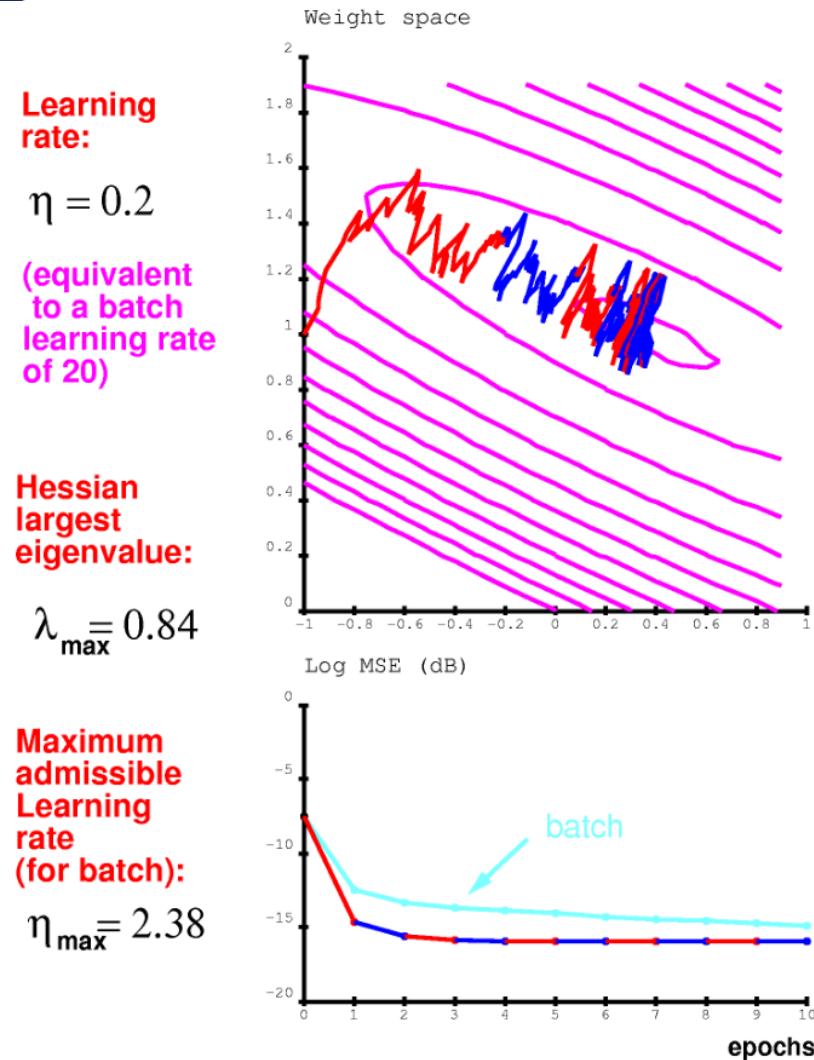
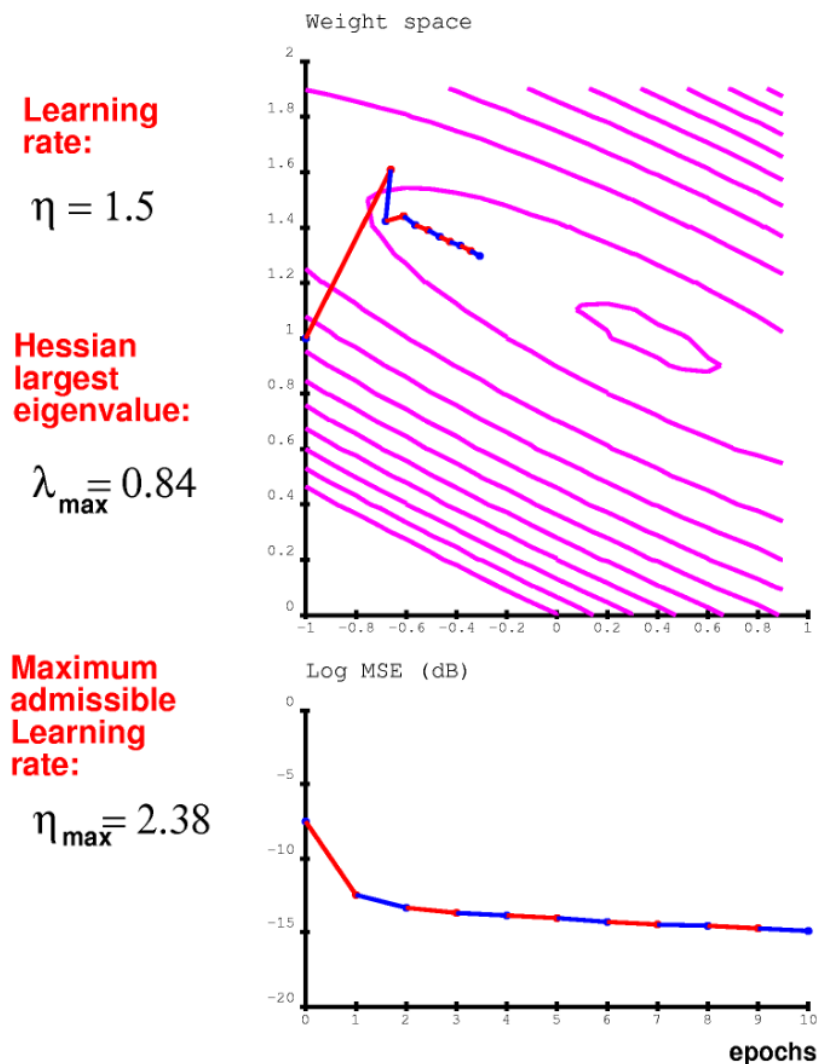
Convergence is Slow When Hessian has Different Eigenvalues

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Batch Gradient, small learning rate

Stochastic Gradient: **Much Faster**

But fluctuates near the minimum



Multilayer Nets Have Non-Convex Objective Functions

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1-1-1 network

► $Y = W1 * W2 * X$

trained to compute the identity function with quadratic loss

► Single sample $X=1, Y=1$ $L(W) = (1 - W1 * W2)^2$

Solution: $W2 = 1/W1$ hyperbola.

