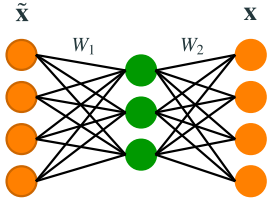
# Learning Dynamics of Linear Denoising Autoencoders

Arnu Pretorius, Steve Kroon and Herman Kamper

Stellenbosch University, South Africa

35th International Conference on Machine Learning, 2018

# Linear denoising autoencoders (DAE)




Expected reconstruction loss

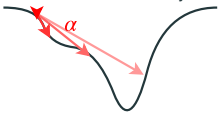
$$\frac{1}{2N}\sum_{i=1}^{N}\mathbb{E}\left[||\mathbf{x}_i - W_2W_1\tilde{\mathbf{x}}_i||^2\right]$$

$$W_2W_1 \approx I \qquad \Sigma_{xx} = \sum_{i=1}^{N}\mathbf{x}_i\mathbf{x}_i^T = V\Lambda V^T$$

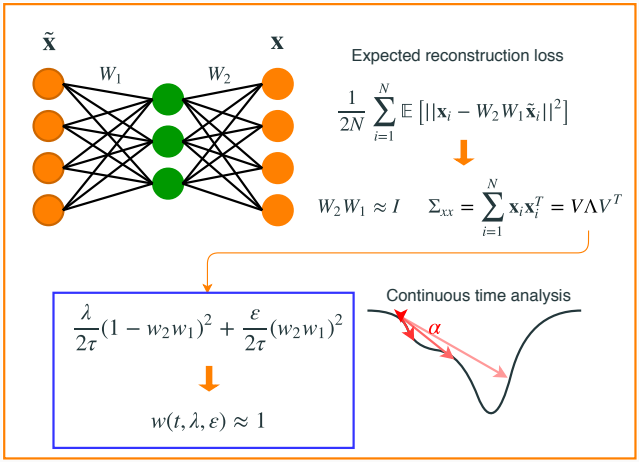
$$\frac{\lambda}{2\tau}(1 - w_2w_1)^2 + \frac{\varepsilon}{2\tau}(w_2w_1)^2$$

$$w(t, \lambda, \varepsilon) \approx 1$$

Continuous time analysis



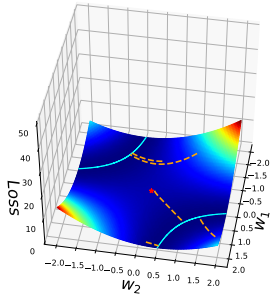
# Linear denoising autoencoders (DAE)

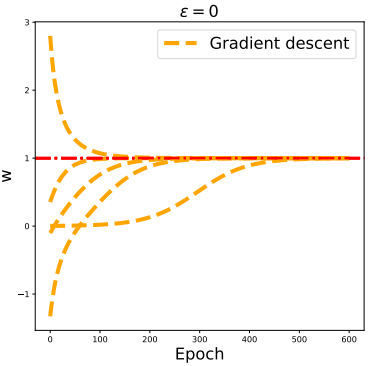



- *Exact solutions to the nonlinear dynamics of learning in deep linear neural networks*, Saxe, McClelland, Ganguli. ICLR, 2014.

# Learning dynamics

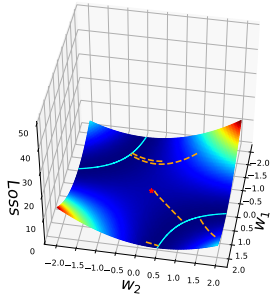
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow \text{GD learning dynamics}$$

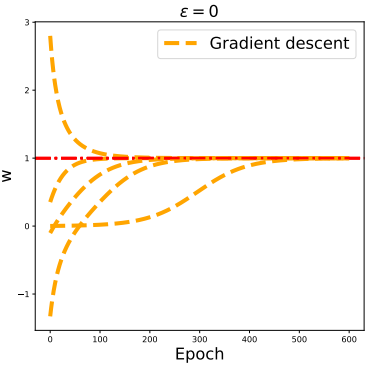


# Learning dynamics

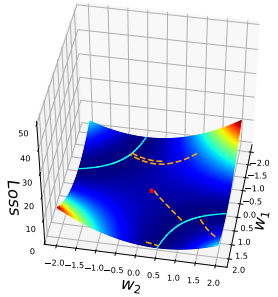
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow w(t, \lambda, \varepsilon) \longrightarrow \text{GD learning dynamics}$$

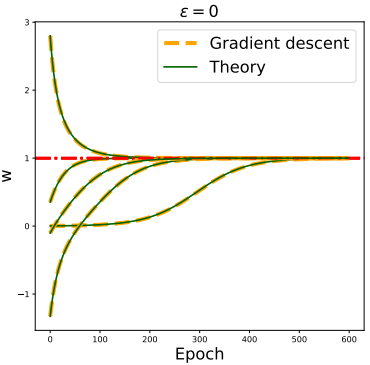


# Learning dynamics

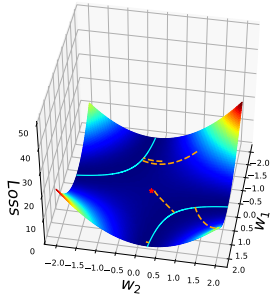
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow w(t, \lambda, \varepsilon) \longrightarrow \text{GD learning dynamics}$$

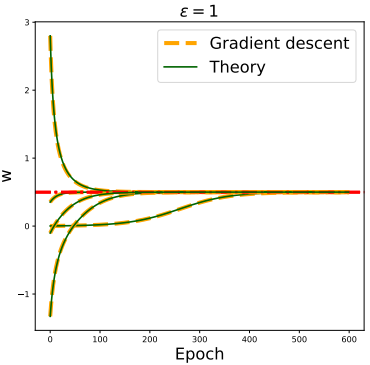


# Learning dynamics

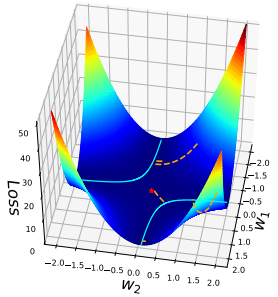
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow w(t, \lambda, \varepsilon) \longrightarrow \text{GD learning dynamics}$$

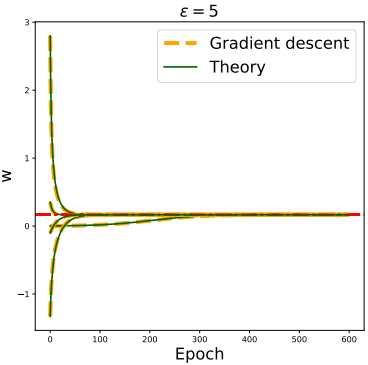


# Learning dynamics

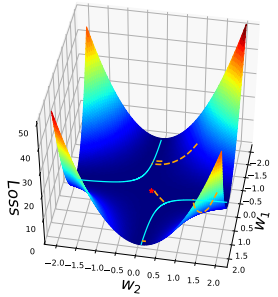
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow w(t, \lambda, \varepsilon) \longrightarrow \text{GD learning dynamics}$$

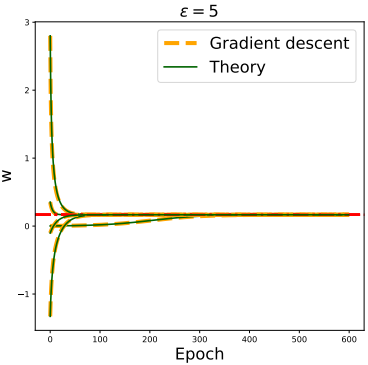


# Learning dynamics

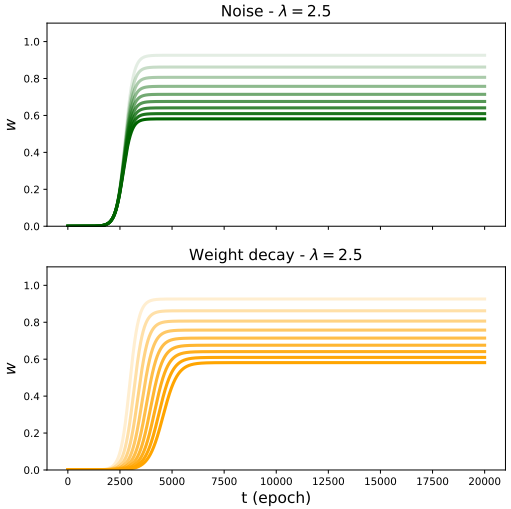
$$\ell_\varepsilon = \frac{\lambda}{2\tau}(1 - w_2 w_1)^2 + \frac{\varepsilon}{2\tau}(w_2 w_1)^2 \longrightarrow w(t, \lambda, \varepsilon) \longrightarrow \text{GD learning dynamics}$$



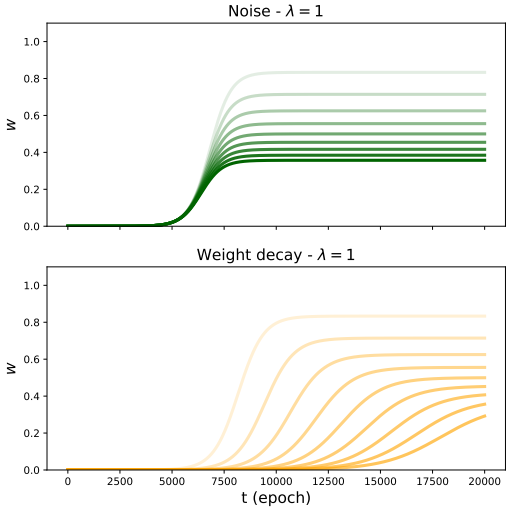




- Fixed point: $w^* = \frac{\lambda}{\lambda+\varepsilon}$

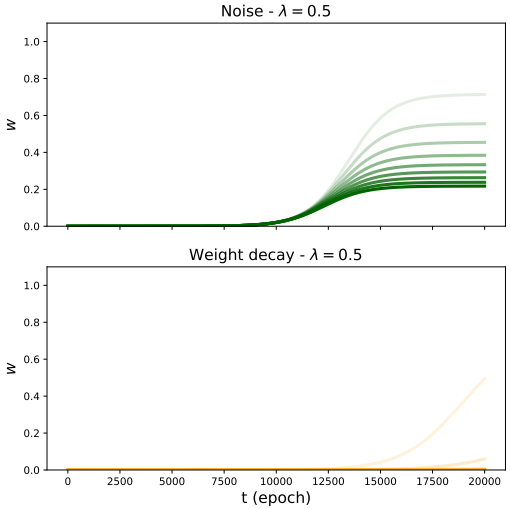
# The relationship between noise and weight decay



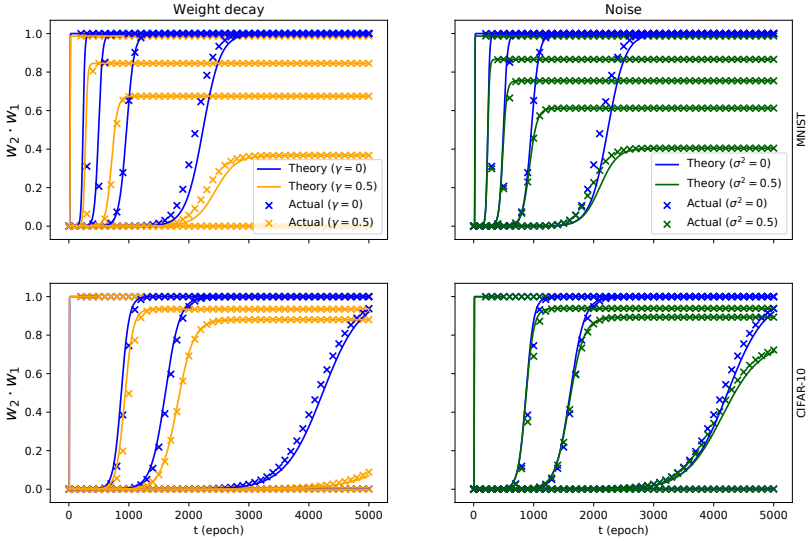
# The relationship between noise and weight decay



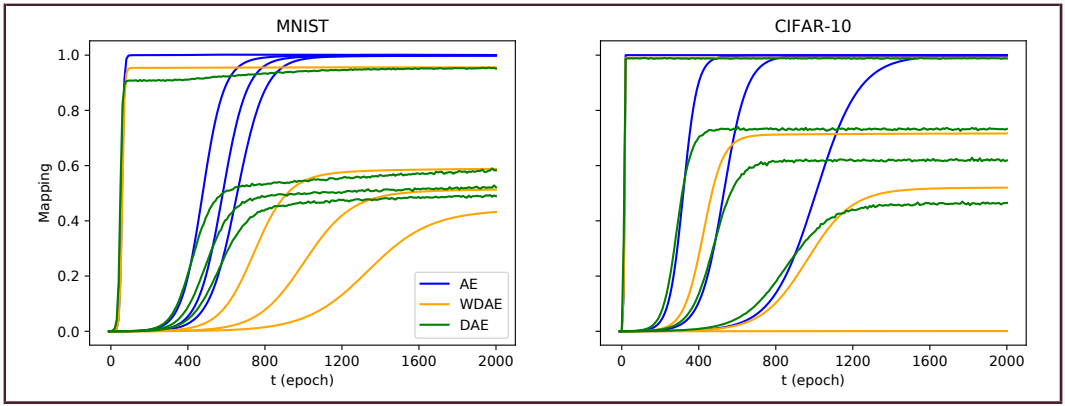
# The relationship between noise and weight decay



# Experimental results: Linear autoencoder networks



# Experimental results: Nonlinear autoencoders using ReLU



**Thank you for listening!**

**Source code to reproduce all the results**

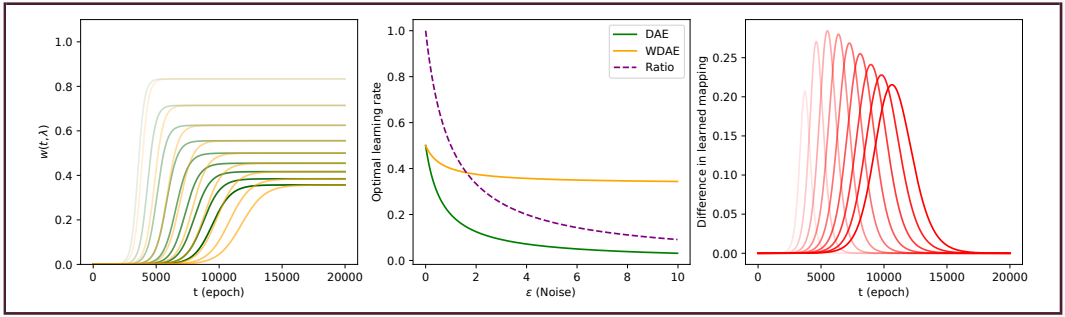
https://github.com/arnupretorius/lindaedynamics_icml2018

# The relationship between noise and weight decay

## Optimal discrete time learning rates

- Ratio for DAE to WDAE:

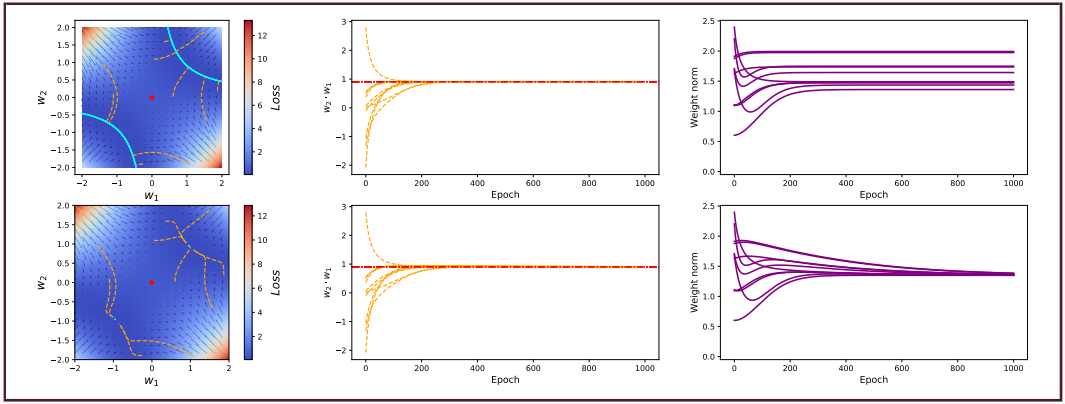
$$R = \frac{2\lambda + \gamma}{2\lambda + 3\varepsilon}.$$



# The relationship between noise and weight decay

## Motivation for weight decay

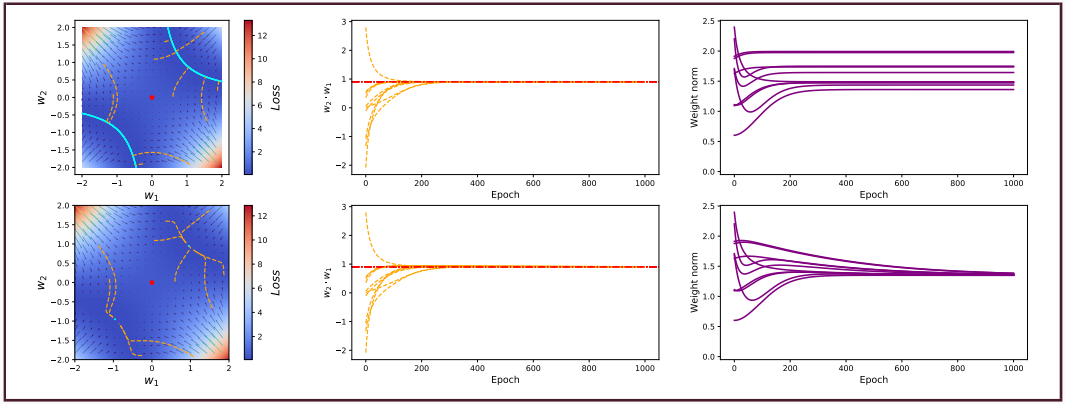
- Smaller weights $\implies$ smoother models $\implies$ better generalisation



# The relationship between noise and weight decay

## Motivation for weight decay

- Smaller weights $\implies$ smoother models $\implies$ better generalisation
- Small weight initialisation?



# The relationship between noise and weight decay

## Motivation for weight decay

- Smaller weights $\implies$ smoother models $\implies$ better generalisation
- Small weight initialisation?