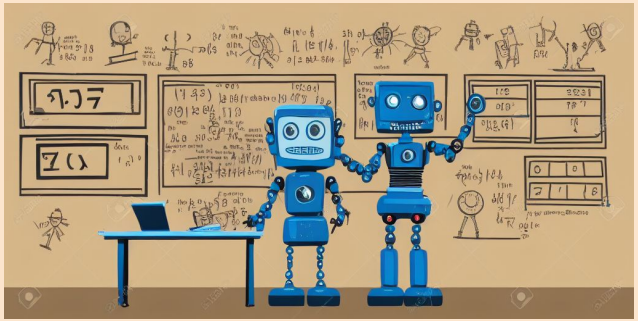

Advanced Workshop on Machine Learning

Lecture 1: Deep Neural Networks

(Image by a Stable Diffusion model)

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- 5th year at UCLA Anderson
- Stockholm School of Economics (Riga)

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Course Overview

Date	Topic	Assignment Due
10/2	(1) Review of Deep Learning (2) Autoencoders	EOD 10/8
10/9	Convolutional Neural Networks	EOD 10/15
10/16	Recurrent Neural Networks	EOD 10/22
10/23	Generative Adversarial Networks	EOD 10/29
11/6	Ensemble Methods	EOD 11/12

Course Resources

- Email: danylo.vashchilenko@anderson.ucla.edu
  - Contact me for Office Hours

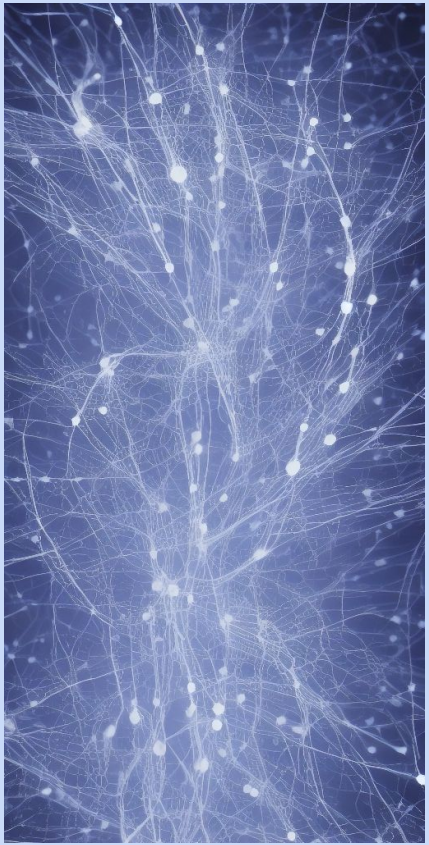
- BruinLearn: https://bruinlearn.ucla.edu/courses/172124
- Code: github.com/hellodanylo/ucla-deeplearning

Today’s Agenda

- Review of Deep Learning Theory and Practice
  - Model Architecture
  - Optimization Algorithms
  - Regularization Methods
  - Hyperparameter Optimization
- Autoencoders
  - Architectures: undercomplete, sparse
  - Training modes: reconstruction, denoising
- Case Study: Denoising Images

Part 1

Review of Deep Learning Theory and Practice



(Image by a Stable Diffusion model)

Deep Learning Domains (in scope)

- Image (photo, depth, radio, 3D, video, etc)
  - Classification
  - Object detection
  - Segmentation
  - Denoising
  - Generation

- Time-series
  - Forecasting
  - Classification
  - Anomaly detection

Deep Learning Domains (out of scope)

- Language
  - Classification
  - Text completion
  - Translation
  - Programming
  - Mathematics
  - DNA sequences
  - Protein sequences
- Sound
  - Voice ↔ Text conversion
  - Classification
  - Generation

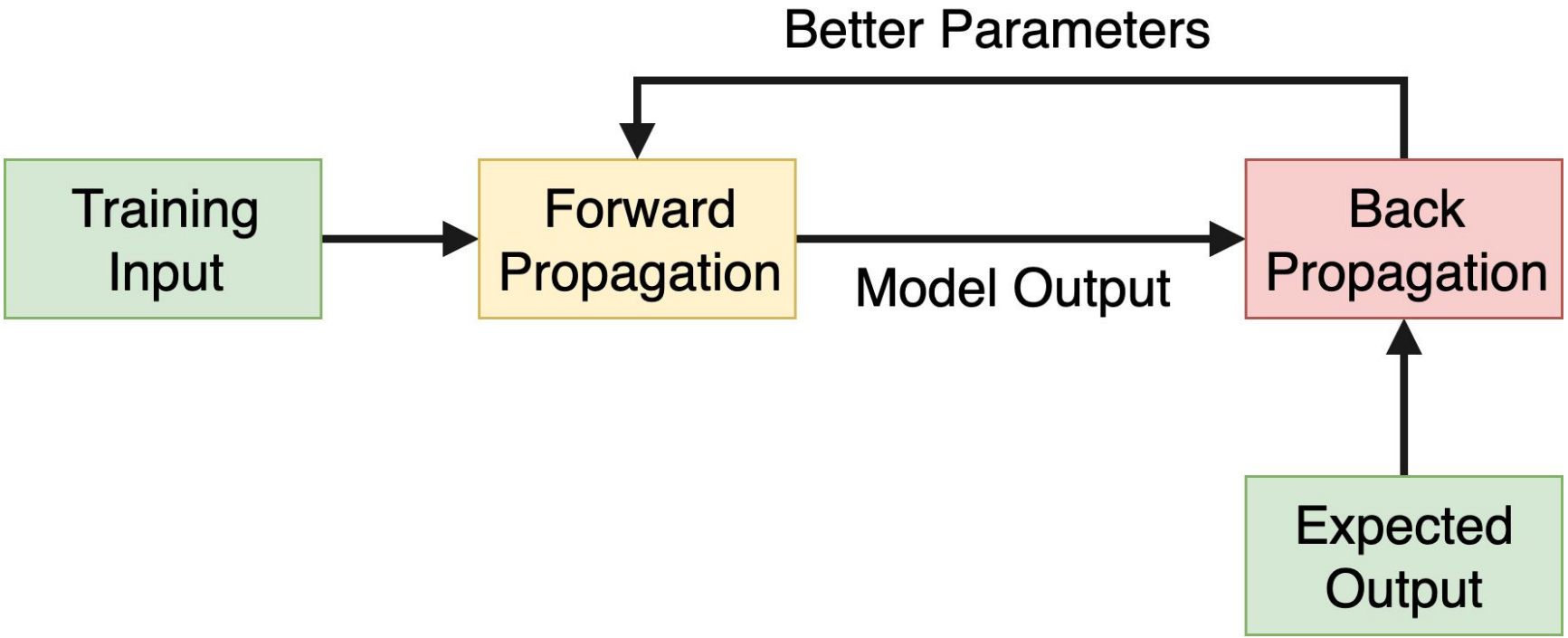
Deep Learning Domains (out of scope)

- Reinforcement Learning
  1. Chess
  2. Go
  3. Pacman
  4. Minecraft
  5. Self-driving
  6. Robotics

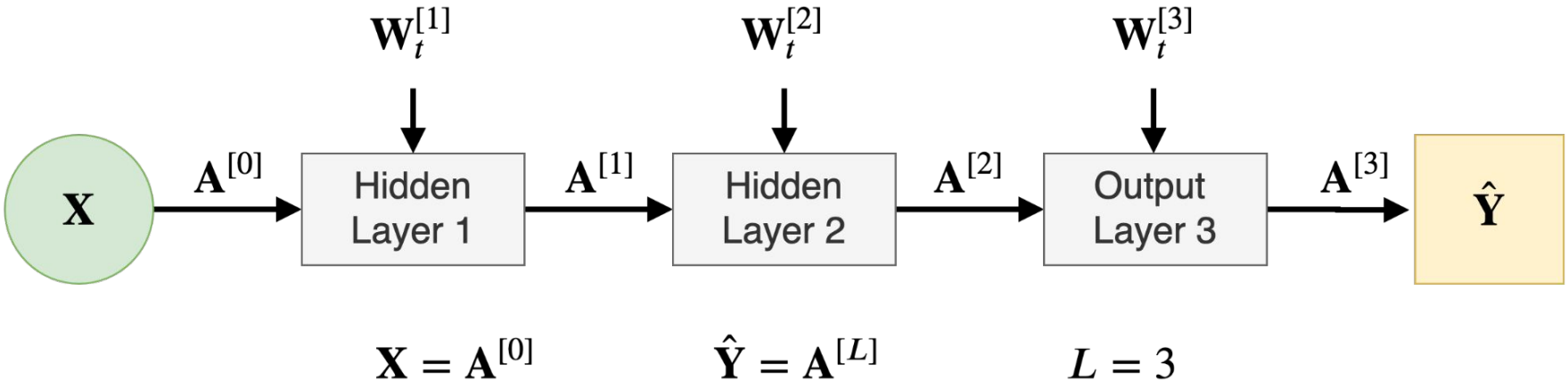
Managerial Economics of Deep Learning

Project Methodology	Project Duration	Compute Resource	Required Training
Design new architecture and train from scratch	Months	Expensive	Machine Learning Researcher
Use existing architecture and/or transfer learning	**Weeks**	**Cheaper**	**Machine Learning Engineer**
Find a pre-trained model and/or buy Inference as a Service API	Days	Almost Free	Software Engineer

Supervised Training Iteration



Feedforward Architecture

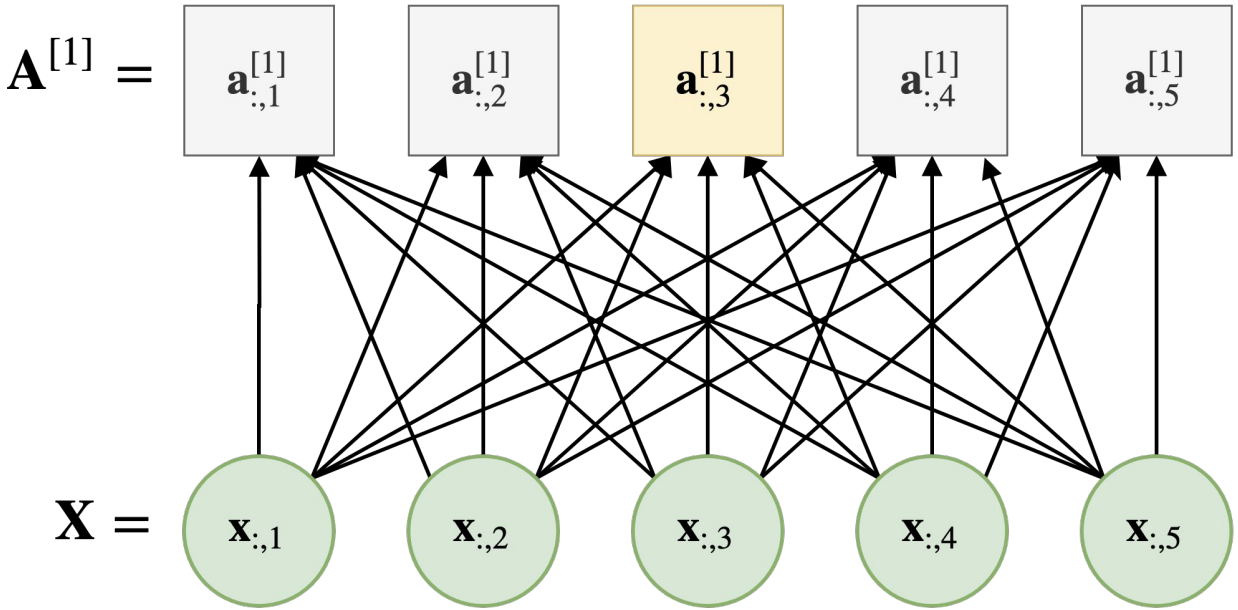


Forward Propagation in a 3-Layer Feed-forward Network

Dense Layer: Neuron Activation

$$\mathbf{z}^{[1]}_{:,3} = \mathbf{X} \cdot \mathbf{w}^{[1]T}_{3,:} + b^{[1]}_3$$

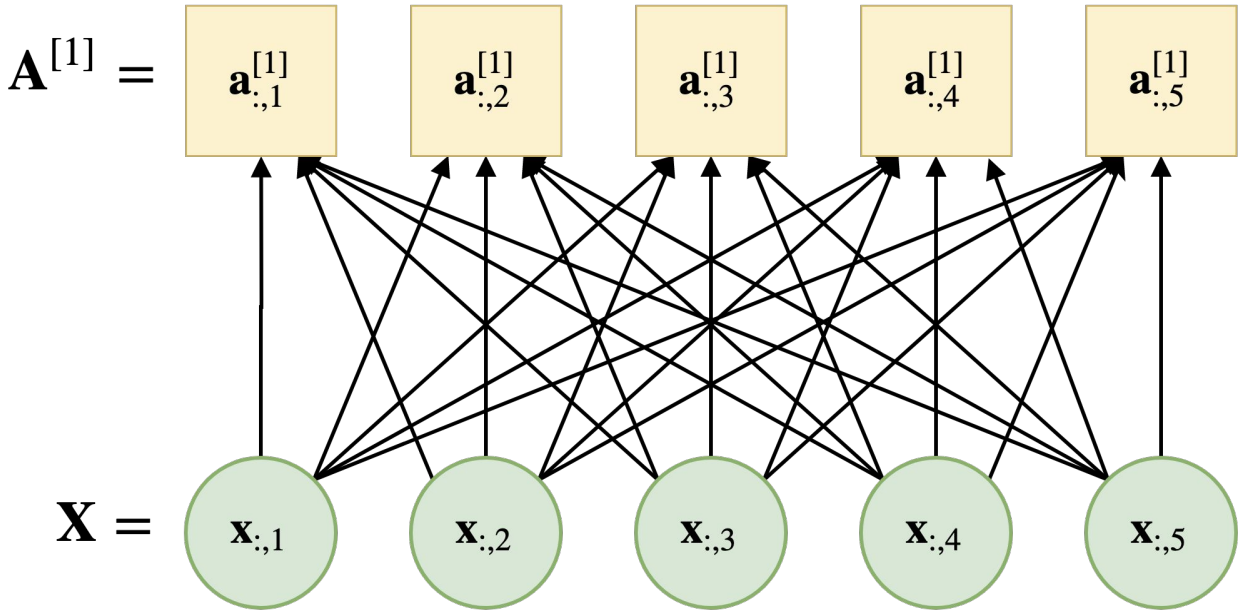
$$\mathbf{a}^{[1]}_{:,3} = f(\mathbf{z}^{[1]}_{:,3})$$



Dense Layer

$$\mathbf{Z}^{[1]} = \mathbf{X} \cdot \mathbf{W}^{[1]T} + \mathbf{b}^{[1]}$$

$$\mathbf{A}^{[1]} = f(\mathbf{Z}^{[1]})$$



See DenseLayer.ipynb for notation and linear algebra details.

Dense Layer: Linear Algebra

For input and activation matrices, row vectors are individual examples in the dataset.

For weight matrices, row vectors are individual neurons in the layer.

Activation function is applied element-wise.

$$\mathbf{Z}^{[l]} = \mathbf{A}^{[l-1]} \cdot \mathbf{W}^{[l]T} + \mathbf{b}^{[l]}$$

$$\mathbf{A}^{[l]} = f(\mathbf{Z}^{[l]})$$

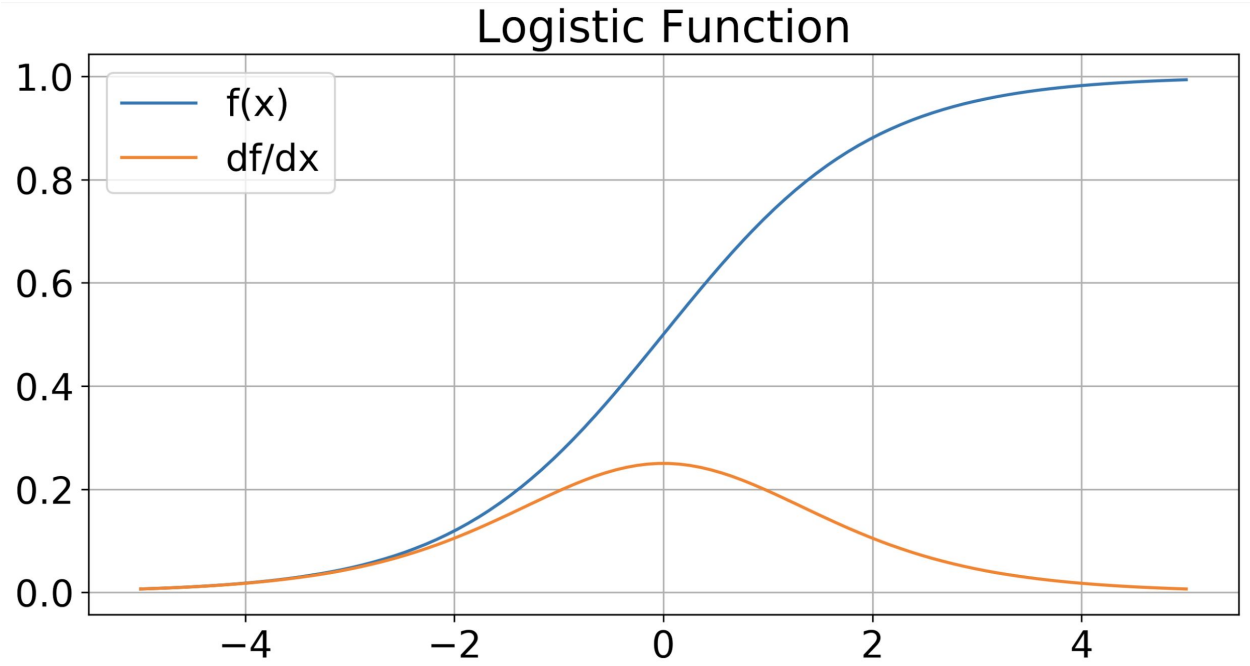
See DenseLayer.ipynb for notation and linear algebra details.

Logistic / Sigmoid

Range
Mean
Derivative

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

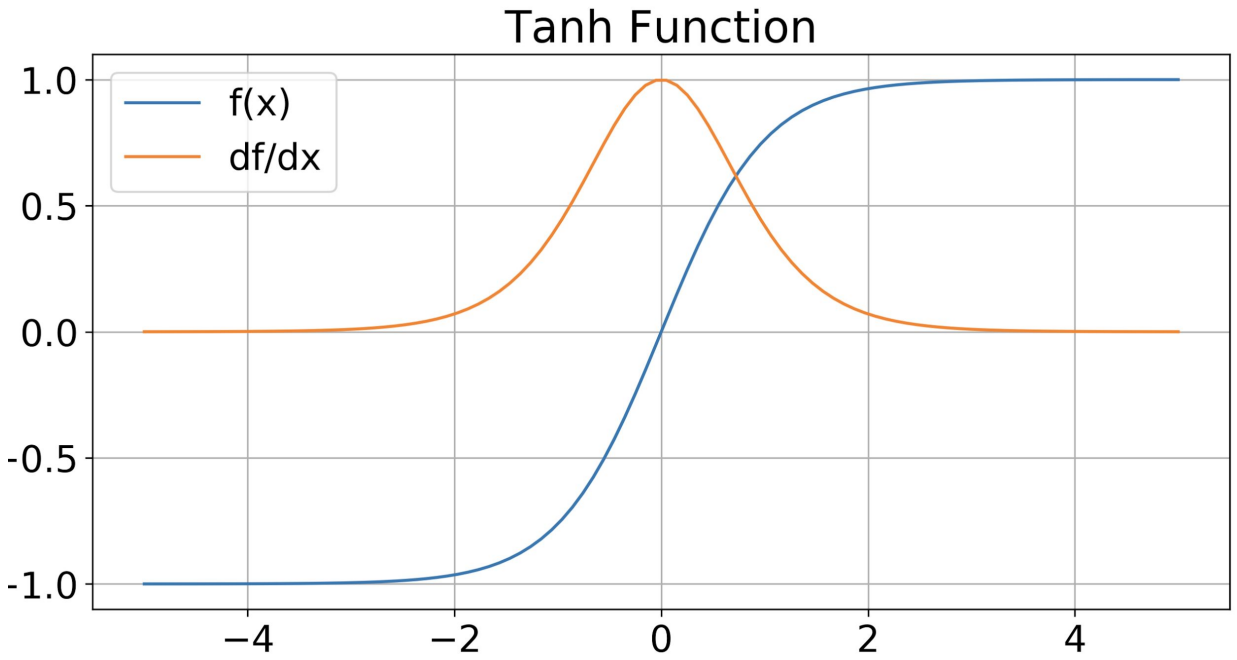
$$\frac{df}{dx} = \frac{e^x}{(e^x + 1)^2}$$



Hyperbolic Tangent

Range
Mean
Derivative

$$f(x) = 2L(2x) - 1$$
$$\frac{df}{dx} = 4L'(2x)$$

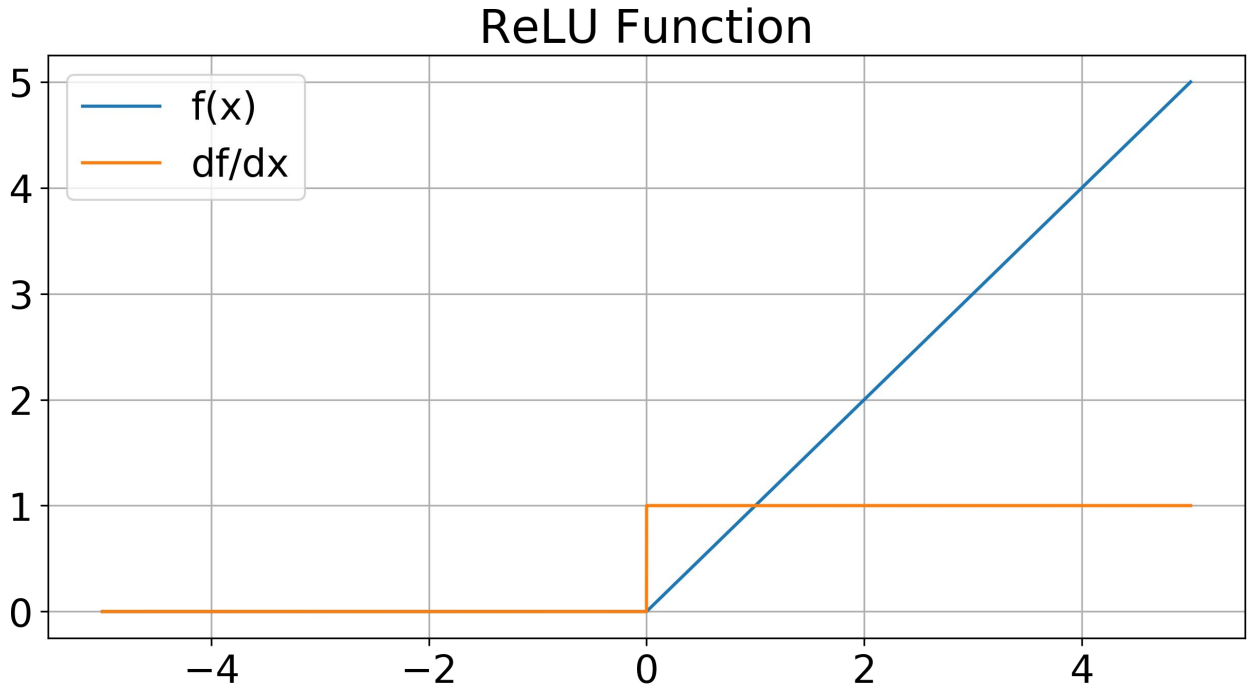


Rectified Linear Unit

Range
Mean
Derivative

$$f(x) = \begin{cases} x & \text{for } x \geq 0 \\ 0 & \text{for } x < 0 \end{cases}$$

$$\frac{df}{dx} = \begin{cases} 1 & \text{for } x > 0 \\ 0 & \text{for } x < 0 \\ \text{undefined} & \text{for } x = 0 \end{cases}$$



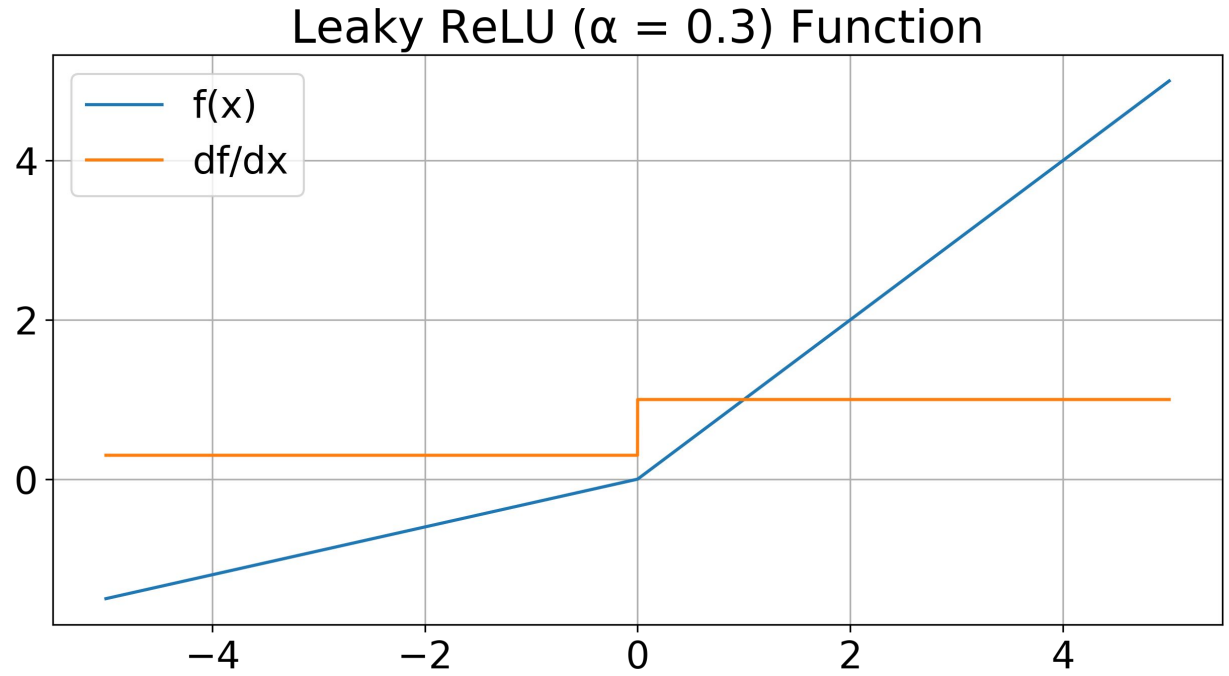
Glorot, X., et al. (2011)

Leaky ReLU

Range
Mean
Derivative

$$f(x) = \begin{cases} x & \text{for } x \geq 0 \\ \alpha x & \text{for } x < 0 \end{cases}$$

$$\frac{df}{dx} = \begin{cases} 1 & \text{for } x > 0 \\ \alpha & \text{for } x < 0 \\ \text{undefined} & \text{for } x = 0 \end{cases}$$

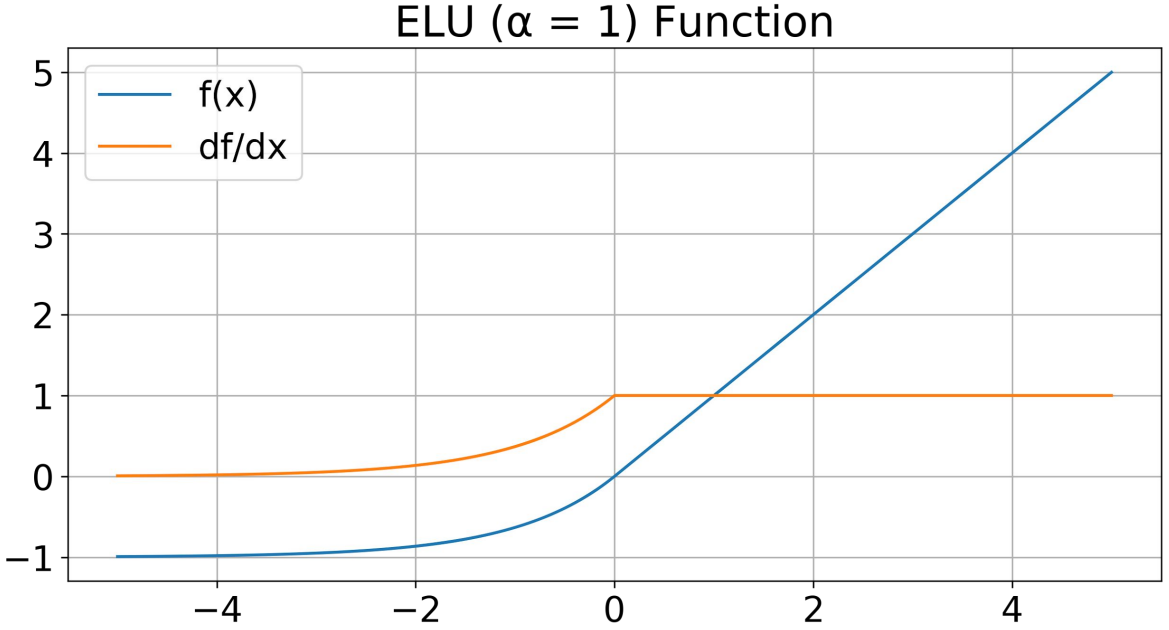


Exponential Linear Unit

Range
Mean
Derivative

$$f(x) = \begin{cases} x & \text{for } x \geq 0 \\ \alpha(e^x - 1) & \text{for } x < 0 \end{cases}$$

$$\frac{df}{dx} = \begin{cases} 1 & \text{for } x > 0 \\ \alpha e^x & \text{for } x < 0 \\ \text{undefined} & \text{for } x = 0 \end{cases}$$



Activation Functions

Range
Mean
Derivative

Function	Hidden Layer	Output Layer
Logistic	Mostly RNNs	Yes
ReLU	Yes	Yes
ELU	Yes	No, why?

Choice of activation functions in Hidden Layers is a hyper-parameter.
See ActivationFunctions.ipynb notebook for vectorized NumPy implementations.

Softmax Layer

Problem: multi-class classifier can't use independent logistic activation in output layer, because their sum won't add up to 1.

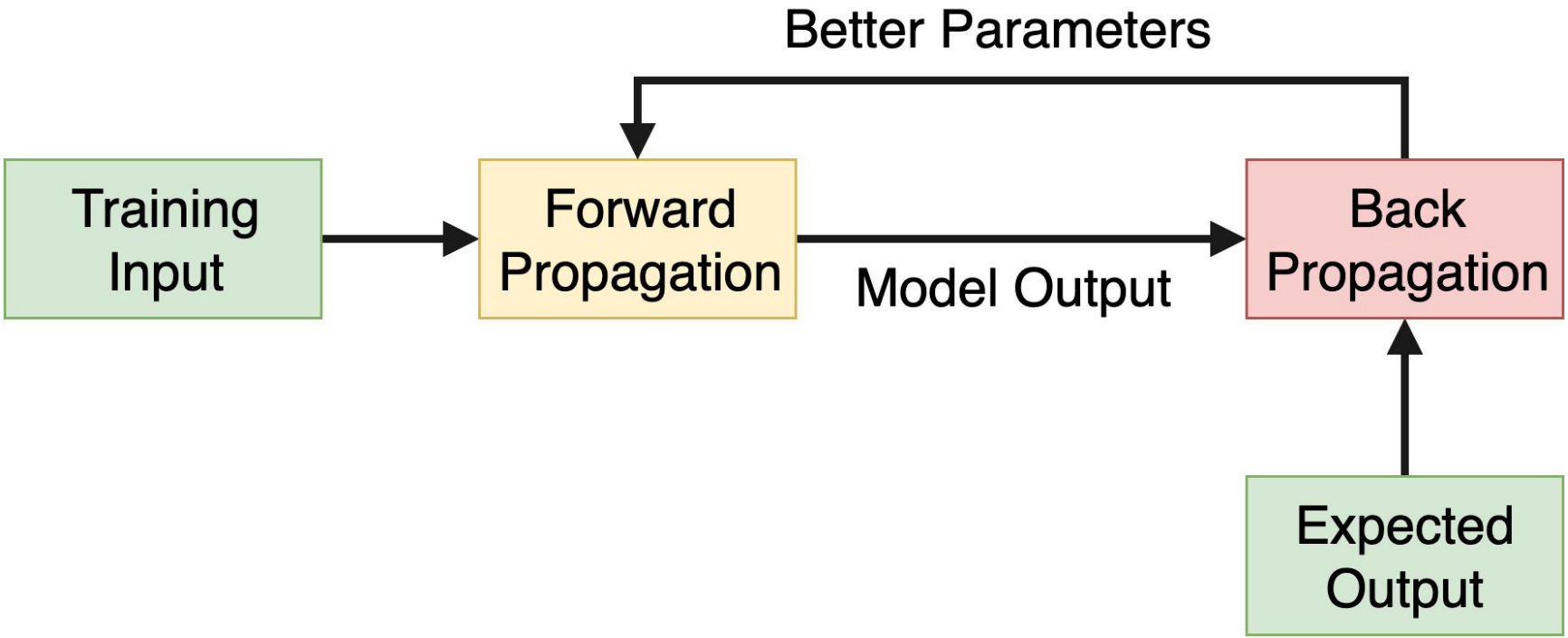
Solution:

$$\mathbf{z}^{[l]} = \exp(\mathbf{a}^{[l-1]})$$

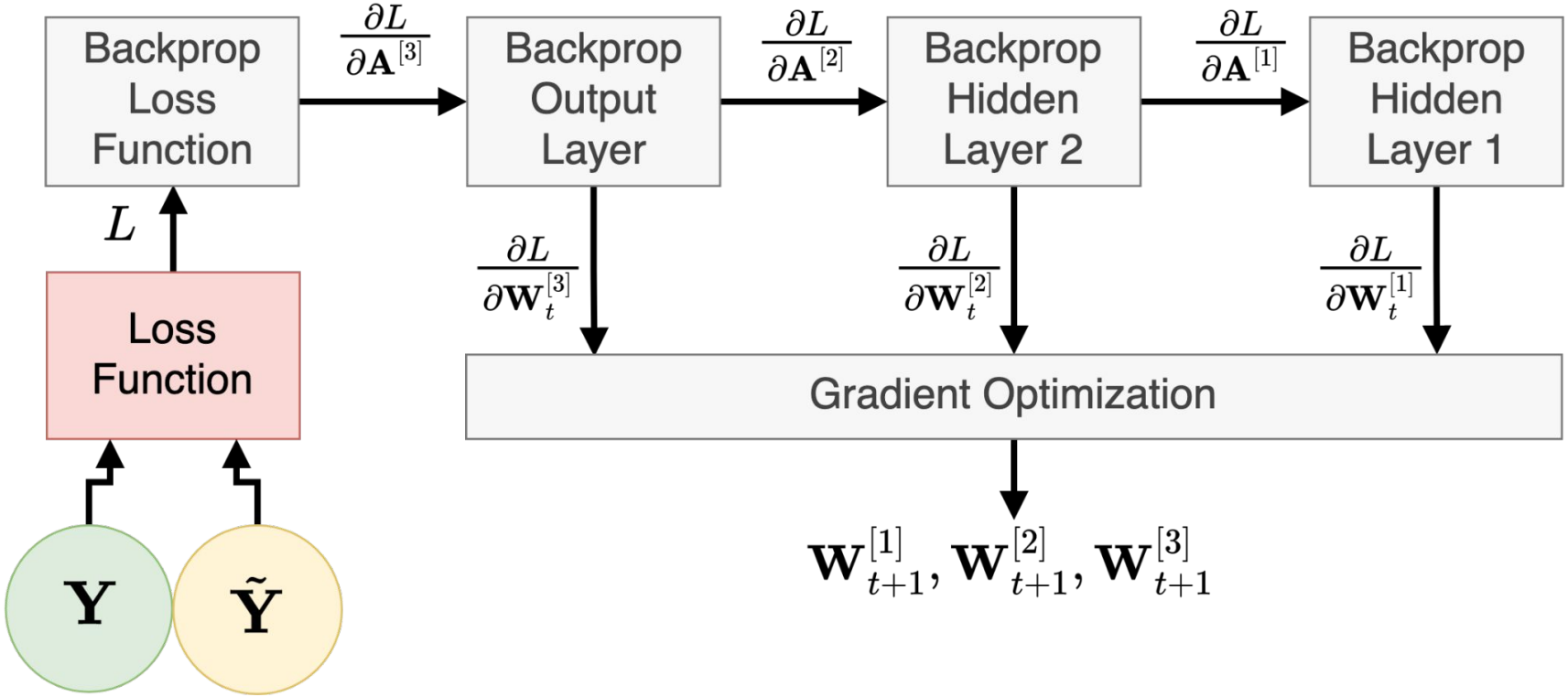
$$\mathbf{a}^{[l]}_{:,m} = \frac{\mathbf{z}^{[l]}_{:,m}}{\sum_{k=1}^{M} \mathbf{z}^{[l]}_{:,k}}$$

m	a[l-1]	z[l]	a[l]
0	-2	0.14	0.01
1	-1	0.37	0.03
2	0	1.00	0.09
3	1	2.72	0.23
4	2	7.39	0.64

Supervised Training Iteration



Back Propagation in Feedforward Architecture



Regression Loss

Regression loss is used when the output is real-valued.

Total loss is the average loss across examples and output dimensions.

$$\text{Loss Function} \in (\mathbb{R}^{S\times M}, \mathbb{R}^{S\times M}) \rightarrow \mathbb{R}$$

$$\text{Mean Absolute Error} = \frac{1}{SM}\sum_{s}^{S}\sum_{m}^{M}|y_{s,m} - \hat{y}_{s,m}|$$

$$\text{Mean Squared Error} = \frac{1}{SM}\sum_{s}^{S}\sum_{m}^{M}(y_{s,m} - \hat{y}_{s,m})^2$$

Classification Loss

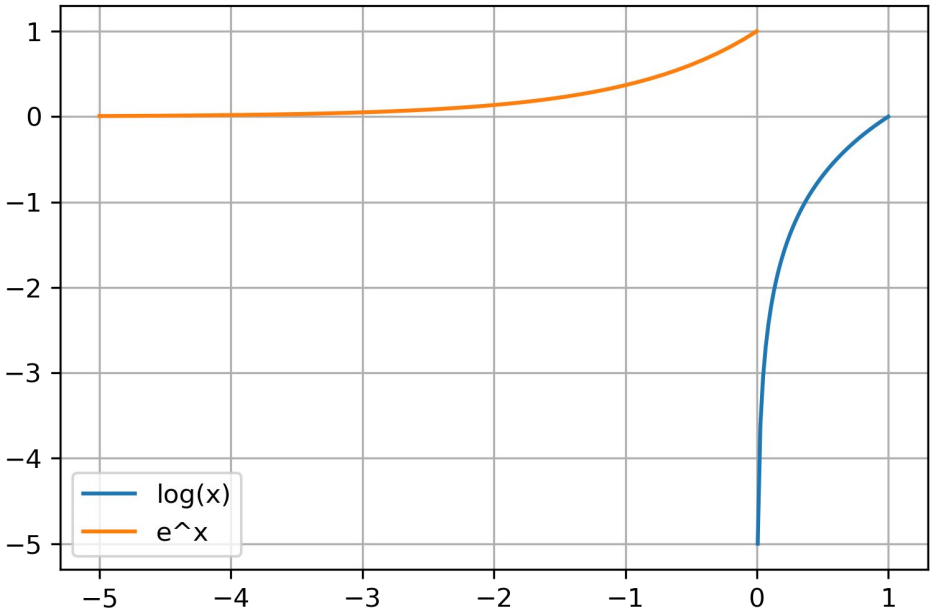
Classification loss is used when the output is in [0, 1] range.

Cross entropy measures the difference between two probability distributions in an asymmetric way!

Total is loss is just an average loss across samples and classes.

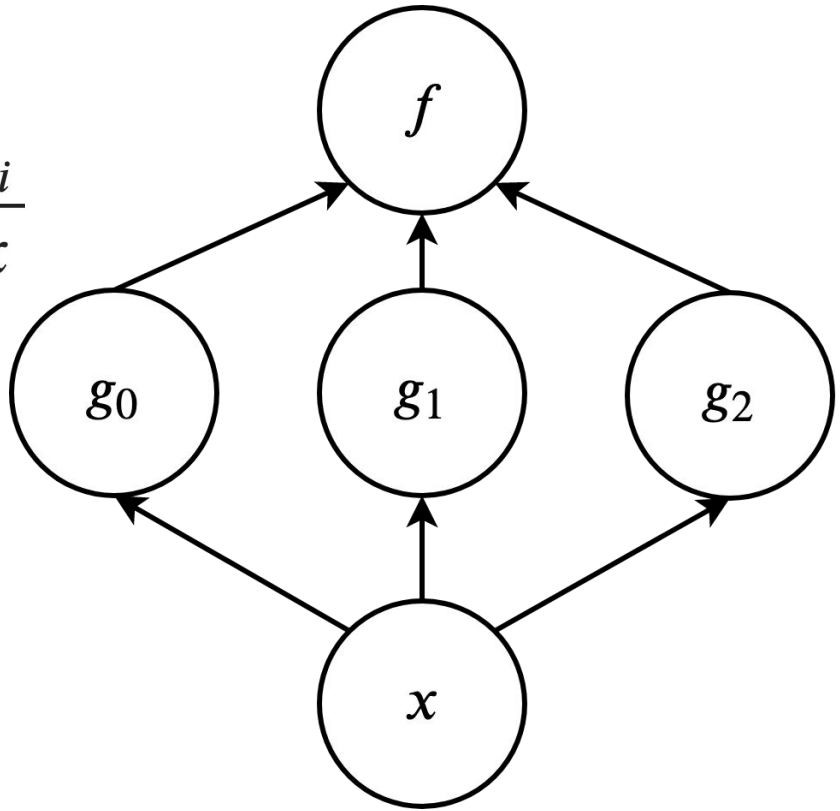
$$\text{Loss Function} \in ([0,1]^{S\times M}, [0,1]^{S\times M}) \rightarrow \mathbb{R}$$

$$\text{Cross Entropy} = -\frac{1}{SM}\sum_{s}^{S}\sum_{m}^{M} y_{s,m}\log(\hat{y}_{s,m})$$



Multivariate Chain Rule

$$\frac{\partial f(g_0(x), \ldots, g_n(x))}{\partial x} = \sum_i^n \frac{\partial f}{\partial g_i} \frac{\partial g_i}{\partial x}$$



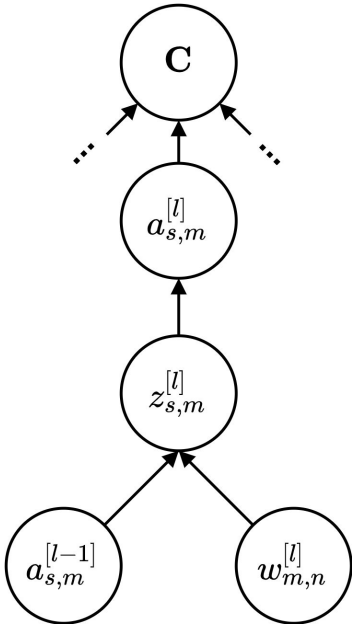
Since a neural network is a deep composition of simple differentiable functions, we can use the chain rule to calculate the derivative of the loss function with respect to every parameter.

Backpropagation in Fully Connected Layer

$$\frac{\partial a_{s,m}^{[l]}}{\partial z_{s,m}^{[l]}} = f'(z_{s,m}^{[l]}) \qquad \frac{\partial z_{s,m}^{[l]}}{\partial w_{m,n}^{[l]}} = a_{s,n}^{[l-1]}$$

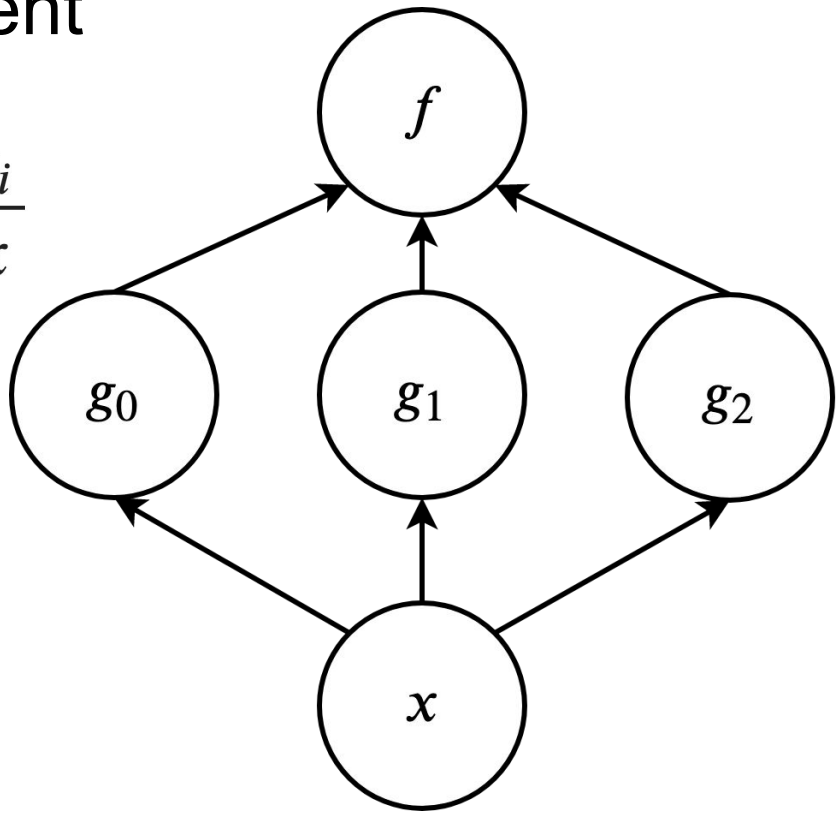
$$\frac{\partial C}{\partial w_{m,n}^{[l]}} = \sum_{s=1}^{S} \left[\frac{\partial C_s}{\partial a_{s,m}^{[l]}} * \frac{\partial a_{s,m}^{[l]}}{\partial z_{s,m}^{[l]}} * \frac{\partial z_{s,m}^{[l]}}{\partial w_{m,n}^{[l]}} \right]$$

$$\frac{\partial C}{\partial w_{m,n}^{[l]}} = \sum_{s=1}^{S} \left[\frac{\partial C_s}{\partial a_{s,m}^{[l]}} * f'(z_{s,m}^{[l]}) * a_{s,n}^{[l-1]} \right]$$



Exploding / Vanishing Gradient

$$\frac{\partial f(g_0(x), \ldots, g_n(x))}{\partial x} = \sum_i^n \frac{\partial f}{\partial g_i} \frac{\partial g_i}{\partial x}$$



Problem: Repeated multiplication makes gradients at the lower layers very large or very small.

Solution: Gradient clipping helps with the exploding gradient. Batch normalization helps with the vanishing gradient.

Batch Normalization

Problem

Make distribution of inputs to each layer have mean = 0 and standard deviation = 1.

Solution

1. During training, standardize hidden pre-activations within a batch.
2. Add trainable parameters to rescale via optimization.
3. During inference, use the training dataset statistics and learned parameters.

$$\mathbf{u}^{[l]} = \frac{1}{S}\sum_{s=1}^{S} \mathbf{z}_{s,:}^{[l]}$$

$$\mathbf{v}^{[l]} = \frac{1}{S}\sum_{s=1}^{S} (\mathbf{z}_{s,:}^{[l]} - \mathbf{u}^{[l]})^2$$

$$\mathbf{z}^{[l]} \leftarrow \frac{\mathbf{z}^{[l]} - \mathbf{u}}{\sqrt{\mathbf{v}^{[l]} + \epsilon}}$$

$$\mathbf{z}^{[l]} \leftarrow \mathbf{z}^{[l]} \odot \tilde{\mathbf{v}}^{[l]} + \tilde{\mathbf{u}}$$

Ioffe S., Szegedy C., (2015)

See BatchNormalization.ipynb for details, NumPy, and Keras implementations.

Batch Normalization of … ?

If the activation function is not zero-centered, prefer:

1. Dot product + bias
2. Activation function
3. Batch normalization

If the activation function is zero-centered, also try:

1. Dot product + bias
2. Batch normalization
3. Activation function

See BatchNormalization.ipynb for details, NumPy, and Keras implementations.

Parameter Initialization

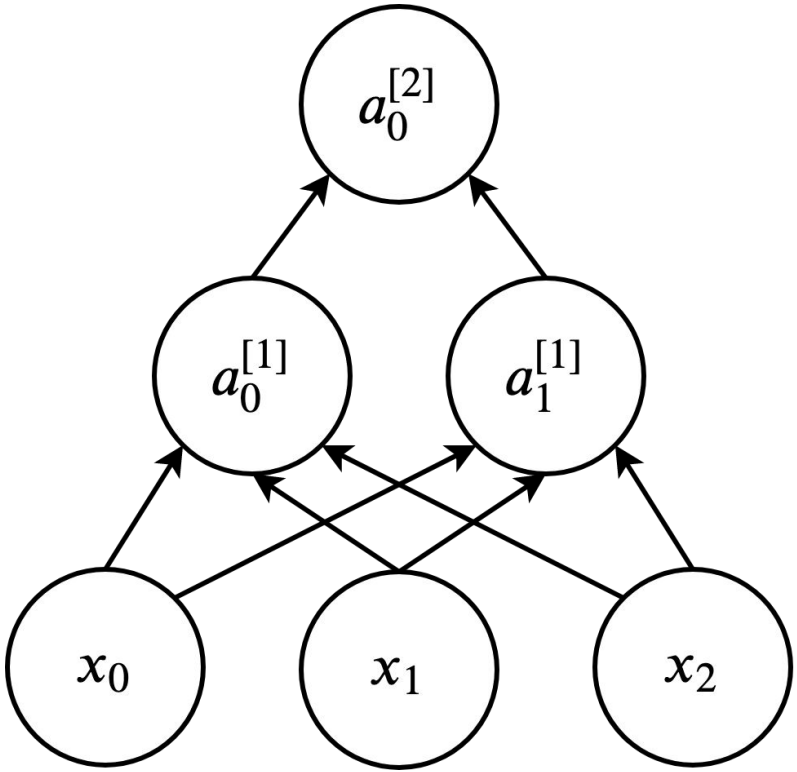
Problem

Initializing every weight identically will prevent any learning due to gradient symmetry.

$$\forall g, h:$$

$$\mathbf{w}_{g,:}^{[l]} = \mathbf{w}_{h,:}^{[l]}$$

$$b_g^{[l]} = b_h^{[l]}$$



Parameter Initialization

- Xavier Glorot, and Yoshua Bengio (2010)
  - Makes variance of activation and gradient between layers similar
  - Derivation constraints the variance of the distribution, not its shape

$$W_i \sim U\left(-\sqrt{\frac{6}{n_{in}+n_{out}}}, \sqrt{\frac{6}{n_{in}+n_{out}}}\right)$$

$$n_{in}(n_{out}) = \text{count of input (output) connections}$$

See WeightInitialization.ipynb for details, and Keras implementations.

Parameter Initialization

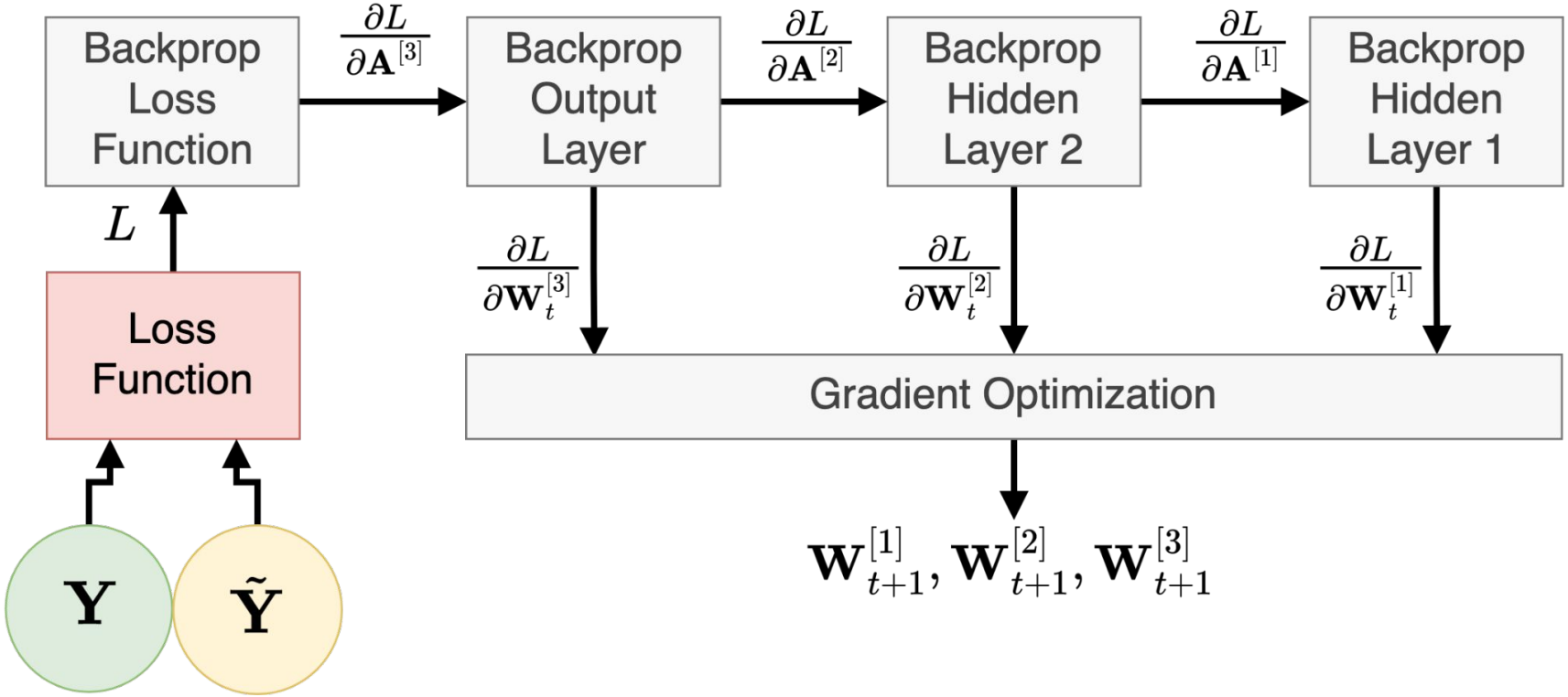
- He, K., Zhang, X., Ren, S., and Sun, J., (2015)
    - Makes variance of activation and gradient between layers similar
    - Derivation constraints the variance of the distribution, not its shape

$$W_i \sim N\left(0, \sqrt{\frac{2}{n_{in}}}\right)$$

$$n_{in} = \text{count of input connections}$$

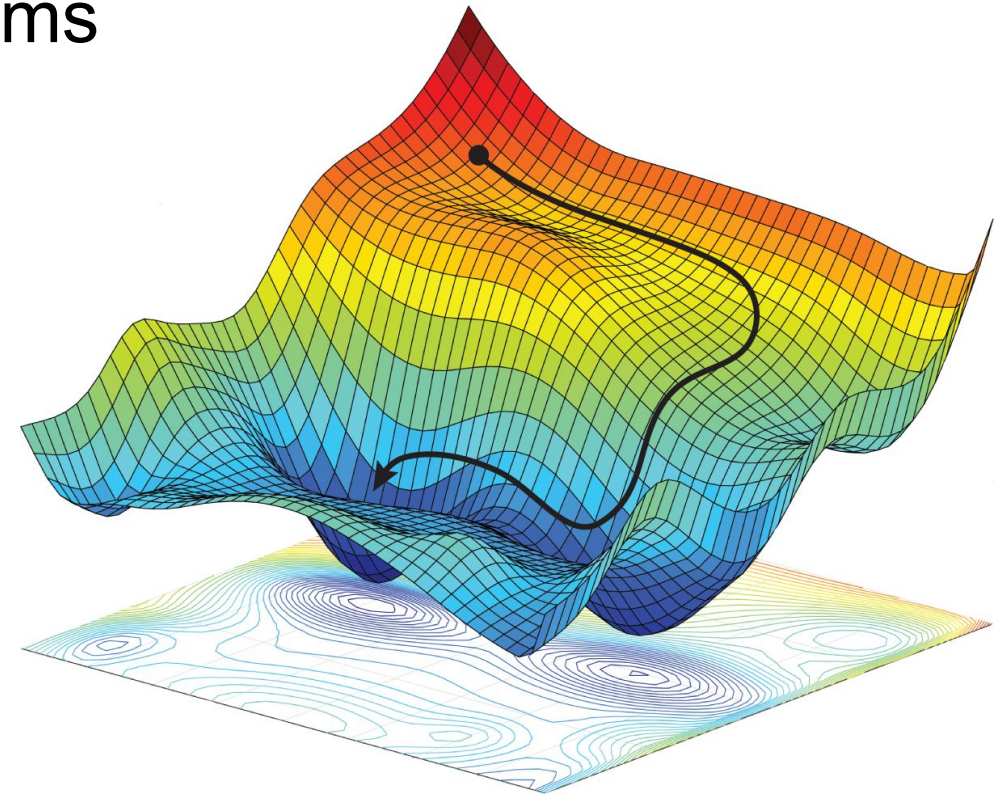
See WeightInitialization.ipynb for details, and Keras implementations.

Back Propagation in Feedforward Architecture



Optimization Algorithms

- Gradient Descent
  - Batch
  - Stochastic
  - Mini-batch
- Gradient Descent with Improvements:
  - Momentum
  - RMSprop
  - Adam



Source: Stochastic Gradient/Mirror Descent: Minimax Optimality and Implicit Regularization (Azizan, N. & Hassibi, B., 2018)

Gradient Descent

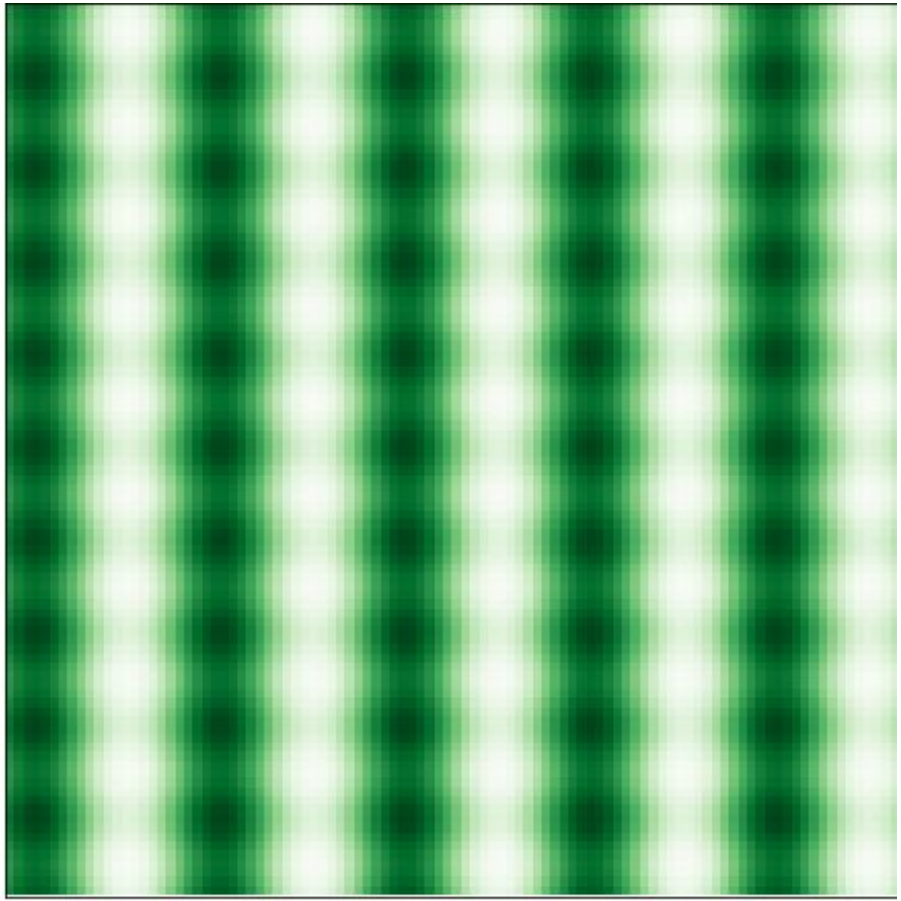
$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \nabla_{\mathbf{W}_t}$$

$$\nabla_{\mathbf{W}_t} = \frac{\partial L(\mathbf{W}_t)}{\partial \mathbf{W}_t}$$

Three flavors:

- Stochastic (n = 1)
- Full-batch (n = S)
- Mini-batch (1 < n < S)

See GradientDescent.ipynb for details, NumPy, Tensorflow, and Keras implementations.

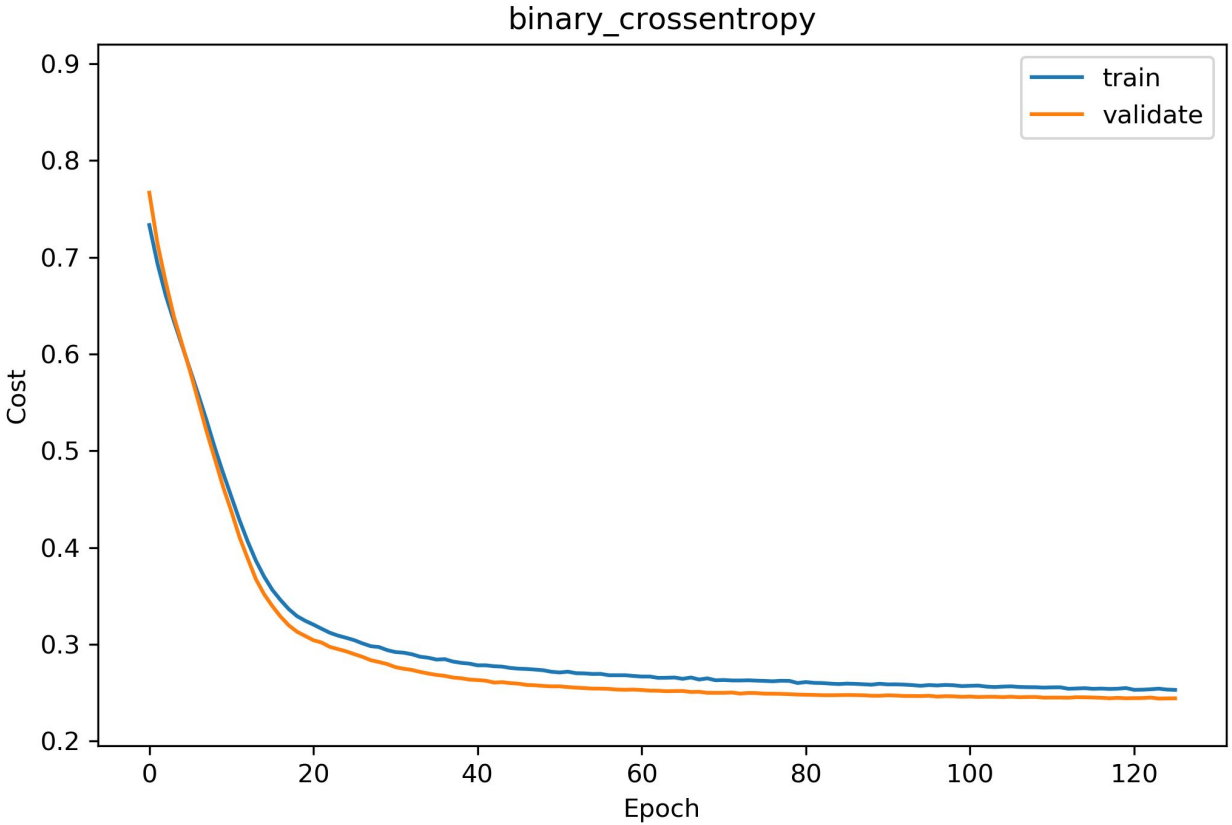


$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

Convergence of Learning Curve

Typically, you want to continue training until it the training loss as a function of time converges.

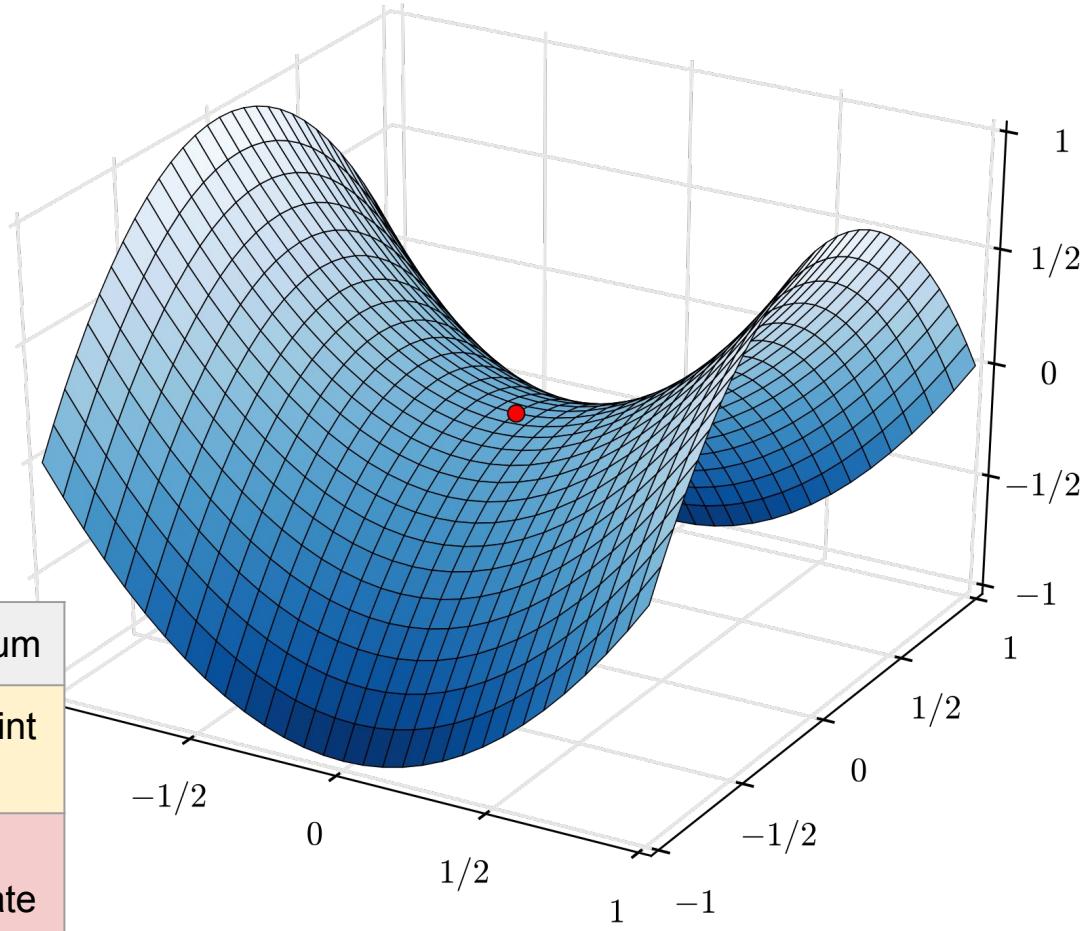
But if the learning curve converges, did the algorithm find the function's global minimum?



Saddle Point

Gradient vector is zero but the point is not a local extremum.

Dimension	X: minimum	X: maximum
Y: minimum	Local minimum	Saddle point
Y: maximum	Saddle point	Too high learning rate

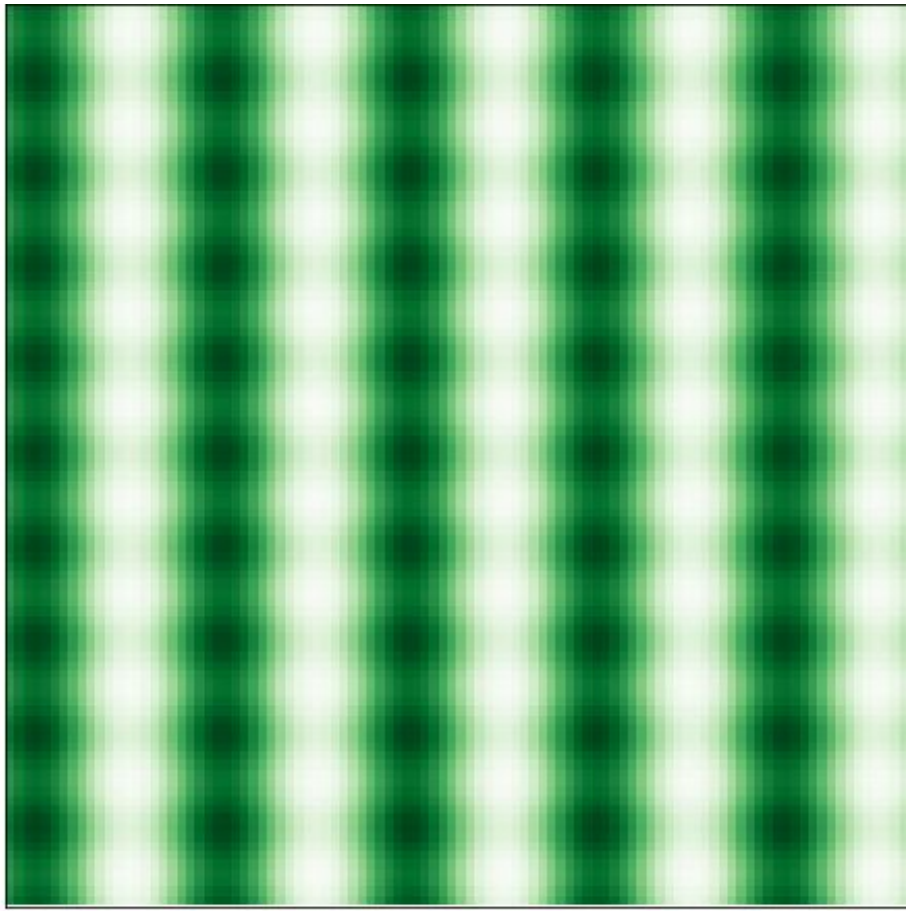


Momentum

$$\mathbf{V}_{t+1} = \beta \mathbf{V}_t + (1 - \beta) \nabla_{\mathbf{W}_t}$$
$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \mathbf{V}_{t+1}$$

Constant β is typically = 0.9, but should be optimized as a hyperparameter.

Qian, G. (1999)



$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

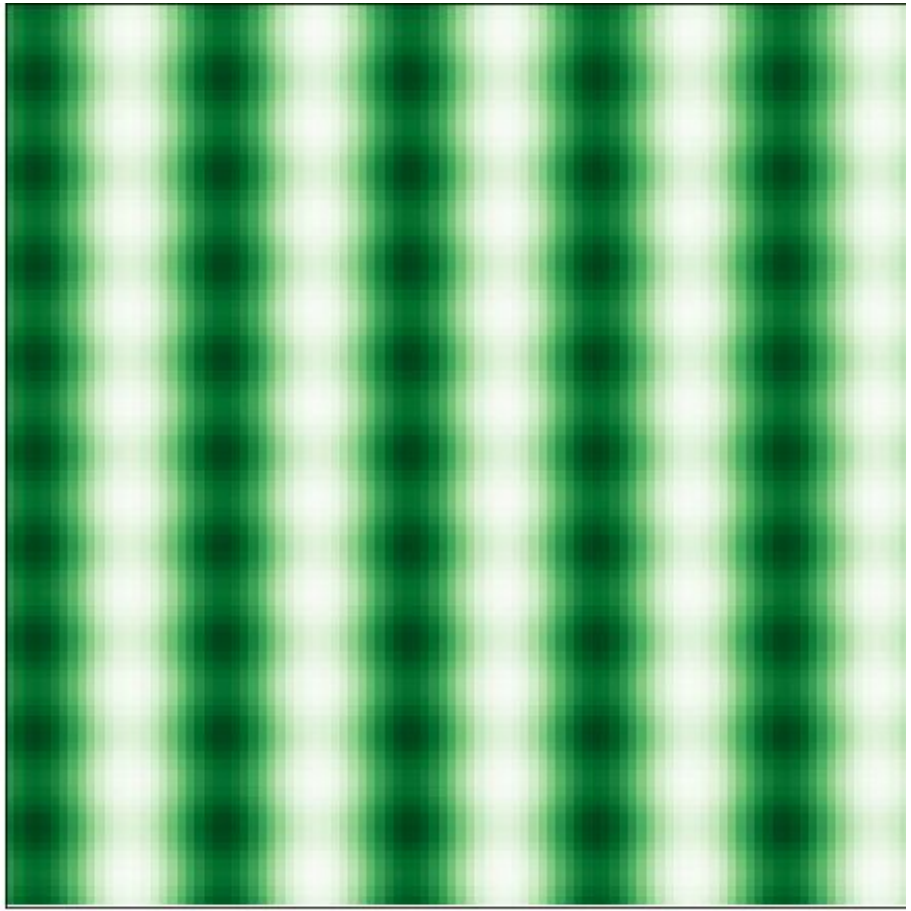
RMSprop

$$\mathbf{S}_{t+1} = \gamma \mathbf{S}_t + (1-\gamma)(\nabla_{\mathbf{W}_t})^2$$

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \frac{\nabla_{\mathbf{W}_t}}{\sqrt{\mathbf{S}_{t+1}}}$$

Constant γ is typically = 0.9, but should be optimized as a hyperparameter.

Unpublished work by Geoffrey Hinton.



$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

Adam

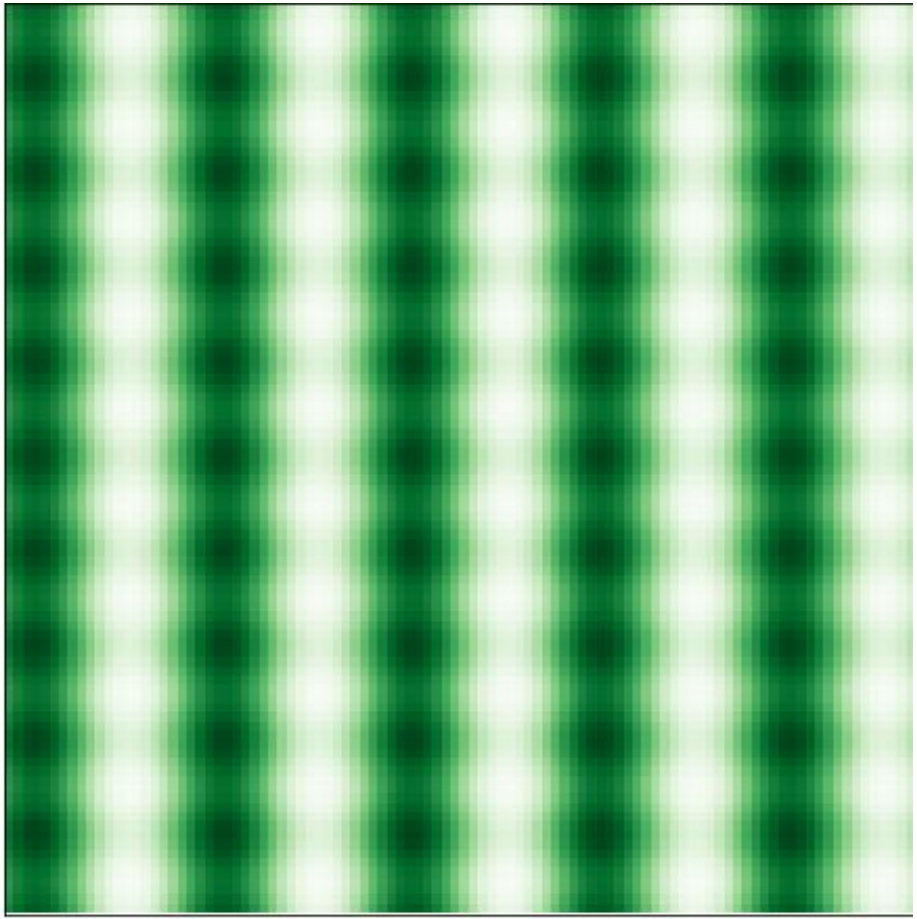
$$\mathbf{V}_{t+1} = \beta \mathbf{V}_t + (1-\beta)\nabla_{\mathbf{W}_t}$$

$$\mathbf{S}_{t+1} = \gamma \mathbf{S}_t + (1-\gamma)(\nabla_{\mathbf{W}_t})^2$$

$$\tilde{\mathbf{V}}_{t+1} = \frac{\mathbf{V}_{t+1}}{(1-\beta^t)}$$

$$\tilde{\mathbf{S}}_{t+1} = \frac{\mathbf{S}_{t+1}}{(1-\gamma^t)}$$

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \frac{\tilde{\mathbf{V}}_{t+1}}{\sqrt{\tilde{\mathbf{S}}_{t+1}}}$$



$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

Kingma, D., and Ba, J. (2015)

Learning = Memorization + Generalization

- Any learning requires a prior belief on how to generalize from training instances to unseen instances.

- Verify any learning on data that was not used during parameter optimization.

- No Free Lunch Theorem

Model Evaluation

Before you train anything, the dataset is split into:

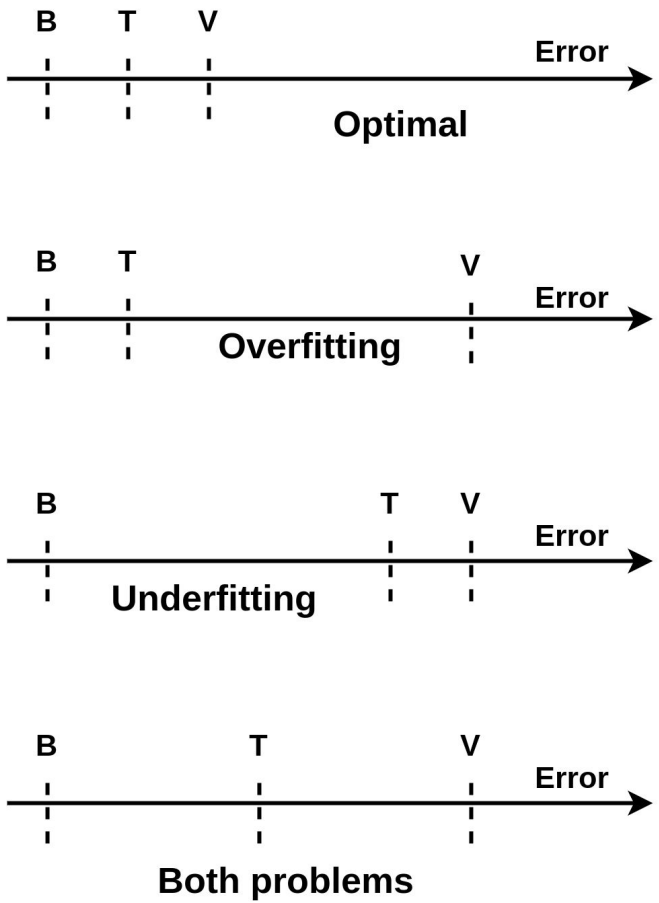
- Training segment (~80%)
- Validation segment (~10%)
- Testing segment (~10%)

What?	How?	Learn from...	Verify on...
Parameters	Gradient Descent	Training segment	Validation segment
Hyperparameters	Manual, semi-auto, or AutoML	Validation segment	Testing segment

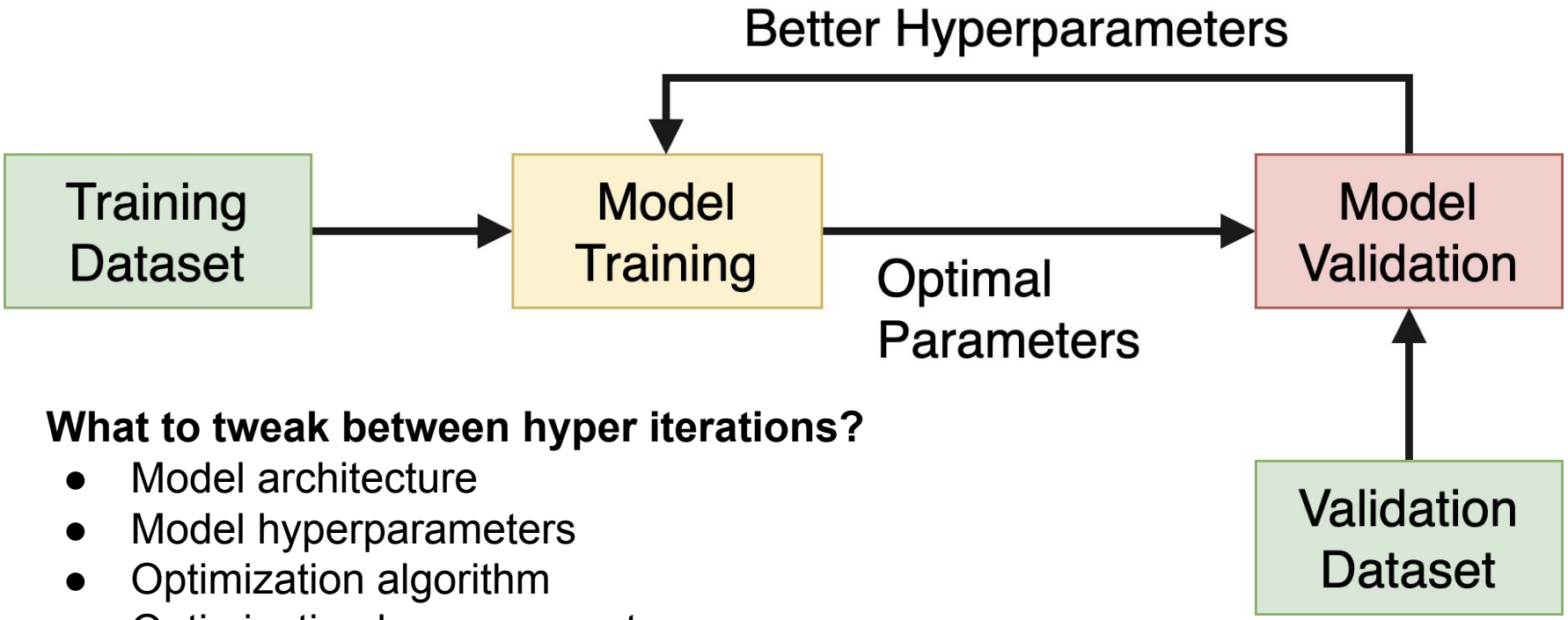
Generalization Inference

B = benchmark, T = training, V = validation

Scenario	Suggestions
Overfitting	● Collect more data ● Augment existing data ● Early stopping ● Decrease model capacity ● Increase regularization
Underfitting	● Change architecture ● Increase model capacity ● Reduce regularization
Both problems	All of the above



Hyper Training Iteration



What to tweak between hyper iterations?

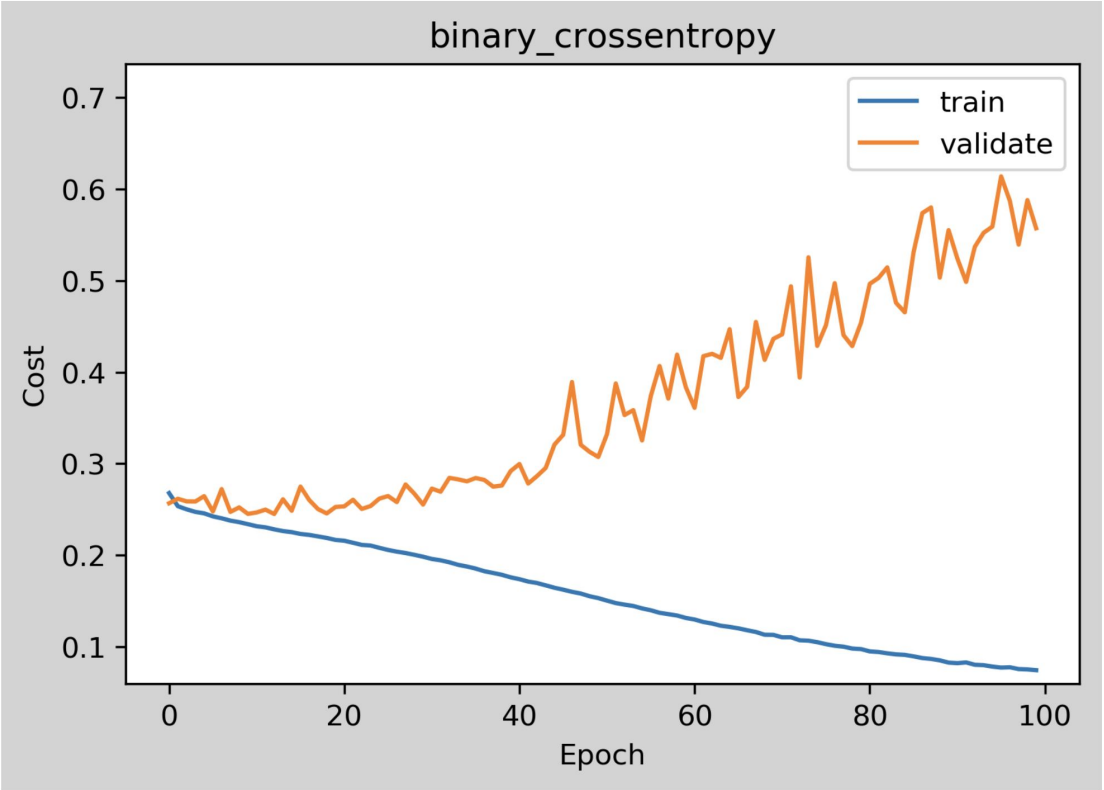
- Model architecture
- Model hyperparameters
- Optimization algorithm
- Optimization hyperparameters

Maximum Overfit

1. Train a model that overfits the training dataset as much as possible.

2. Confirm the training metrics are satisfactory.

3. Introduce regularization to improve the validation metrics.



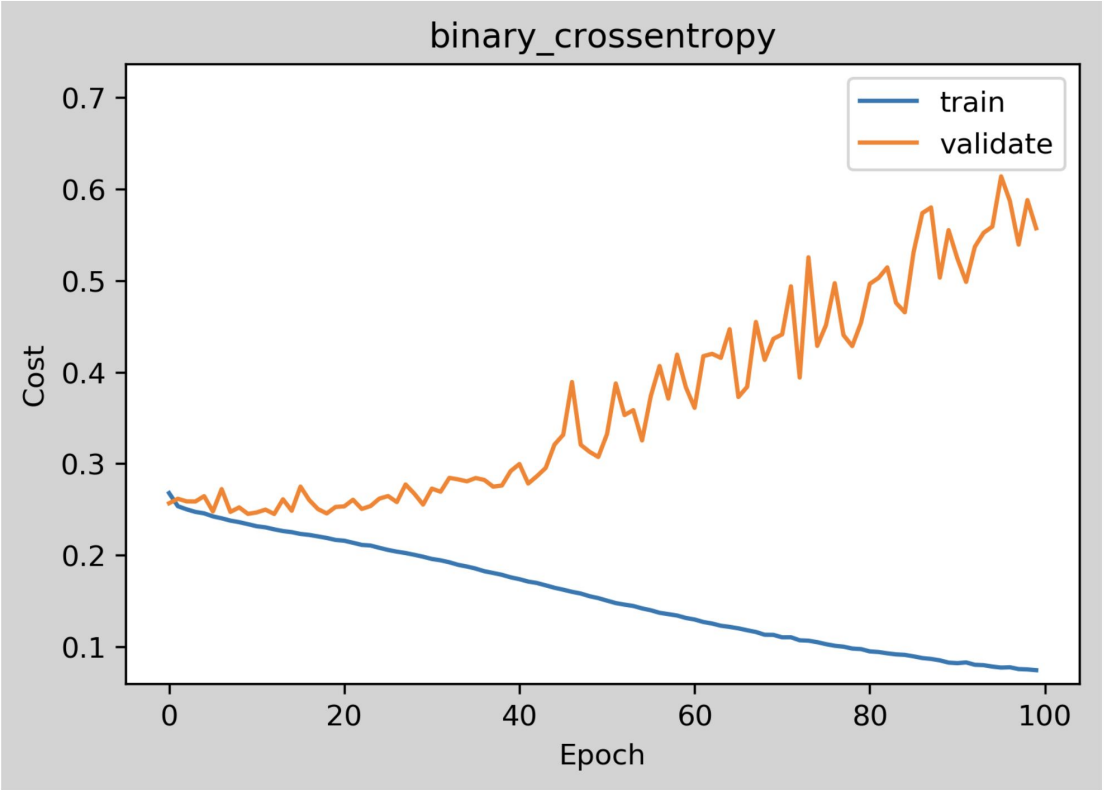
Regularization

Problem

Reduce overfitting via preference for simpler models.

Solutions

- L1 Norm
- L2 Norm



Regularization via Vector Norms

$$\text{Loss}\left(\mathbf{Y}, \hat{\mathbf{Y}}, \mathbf{W}\right) = \text{Supervised Loss}(\mathbf{Y}, \hat{\mathbf{Y}}) + \alpha * \text{Regularization Loss}(\mathbf{W})$$

$$\mathrm{L}_1(\mathbf{W}) = \sum_i^n |w_i|$$

$$\mathrm{L}_2(\mathbf{W}) = \frac{1}{2} \sum_i^n w_i^2$$

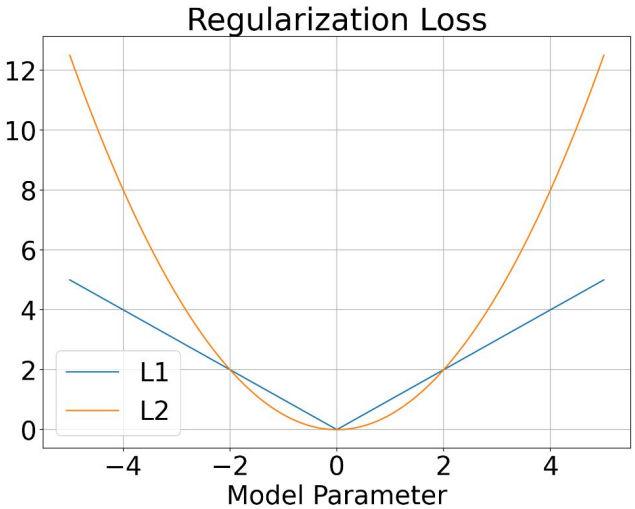
$$\frac{d\mathrm{L}_1}{dw_i} = \begin{cases} 1 & \text{if } w_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

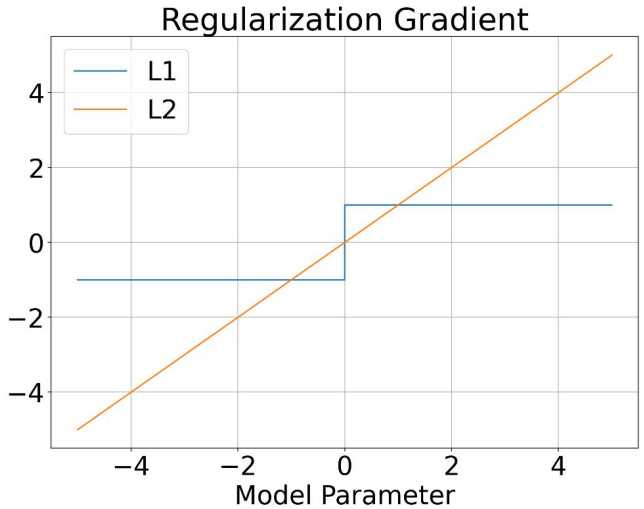
$$\frac{d\mathrm{L}_2}{dw_i} = w_i$$

Comparison of L1 and L2 Norms

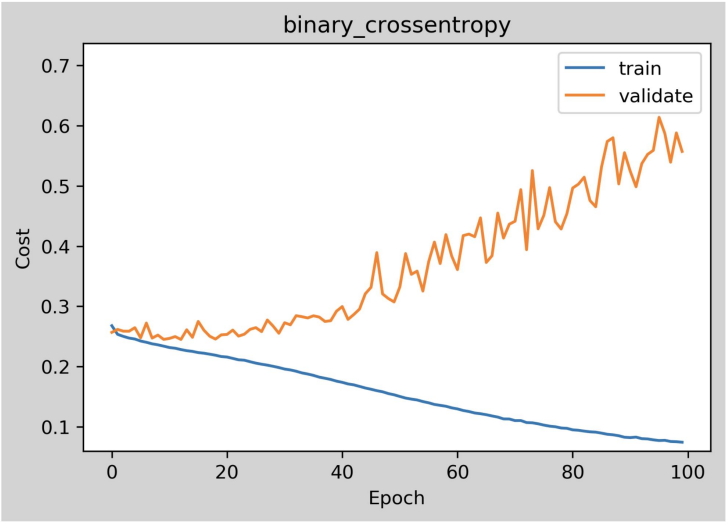
L1 is more likely to prefer a sparse parameter matrix.

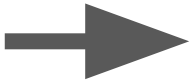
L2 is more likely to remove extremely large parameters.

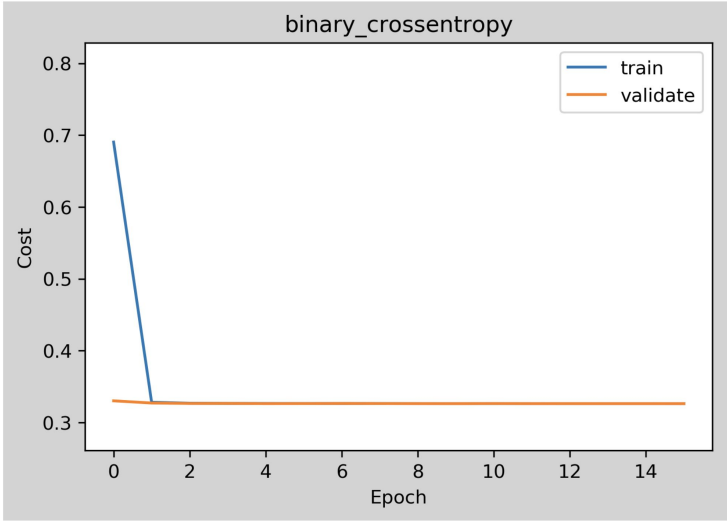




Effect of Regularization Loss



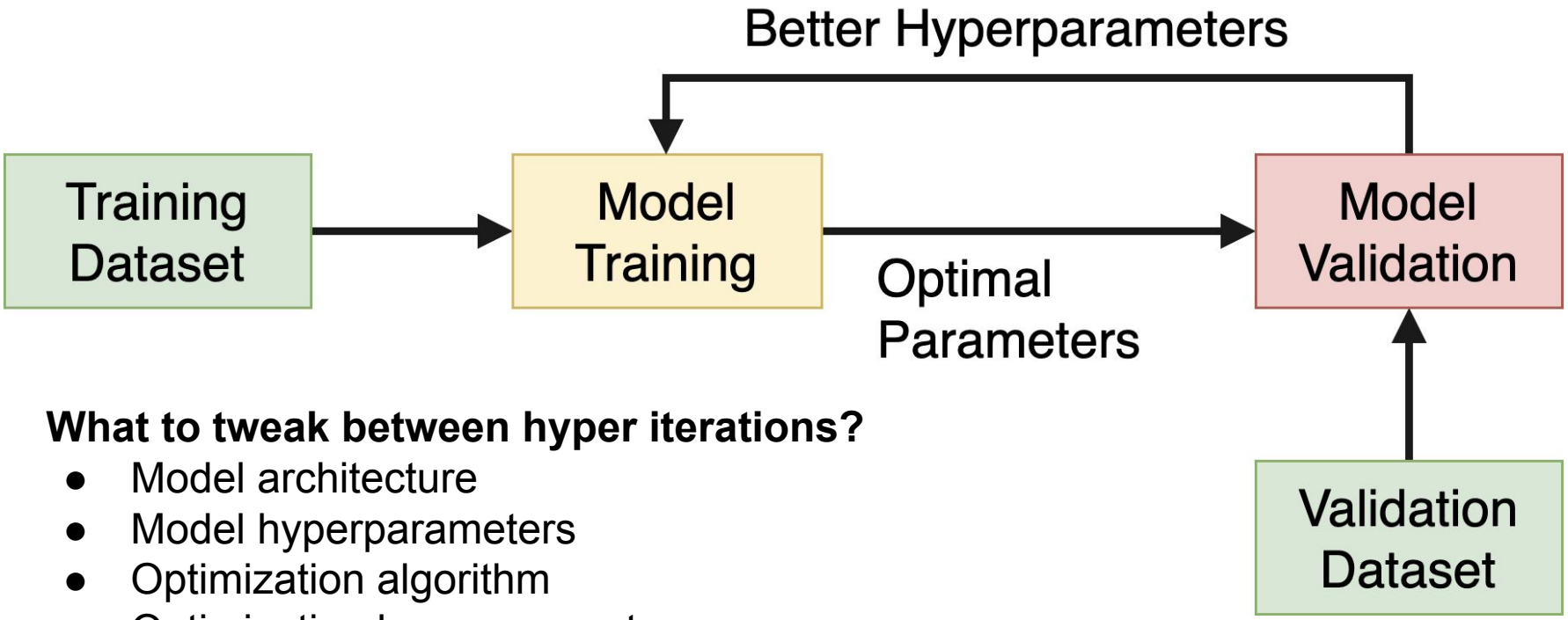




L2 Regularization Factor = 0.00

L2 Regularization Factor = 0.05

Hyper Training Iteration



What to tweak between hyper iterations?

- Model architecture
- Model hyperparameters
- Optimization algorithm
- Optimization hyperparameters

TensorFlow

- Why graph-based computation?
  - Distributed computation
    - Between CPUs/GPUs
    - Between servers
  - Easy backpropagation

- Pre-trained models
  - https://www.tensorflow.org/hub
  - https://keras.io/applications

Part 2

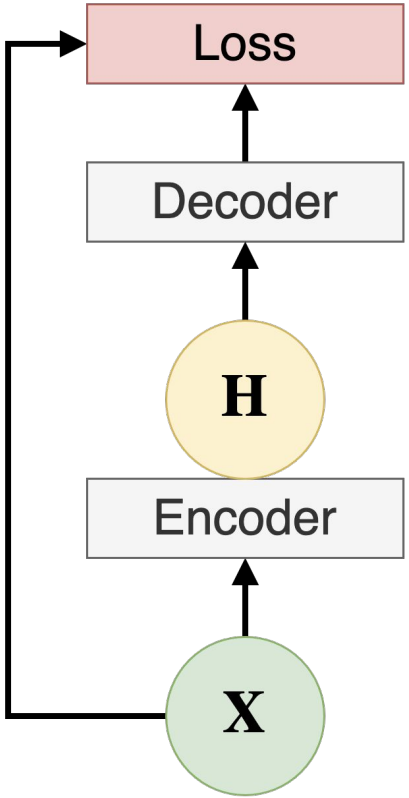
Autoencoders

(Image by a Stable Diffusion model)

Autoencoders

Problem
Extract useful representation of the data without explicitly specifying how to do it.

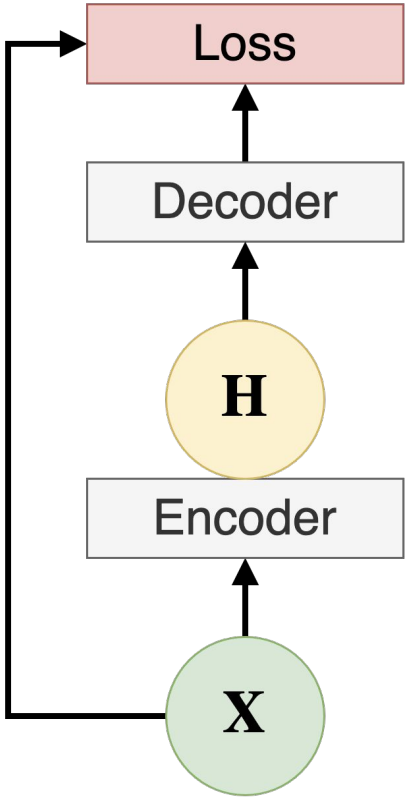
Solution
Train a network to reconstruct the input under various restrictions.



Undercomplete Autoencoders

Problem
Prevent the network from copying the input to the latent representation.

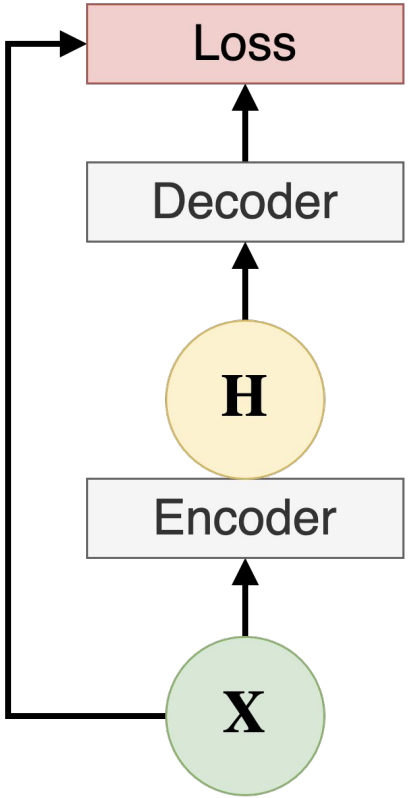
Solution
Reduce dimensionality of the latent representation.



Use Case: Dimensionality Reduction

Problem
Reduce the compute and storage requirements without losing important information.

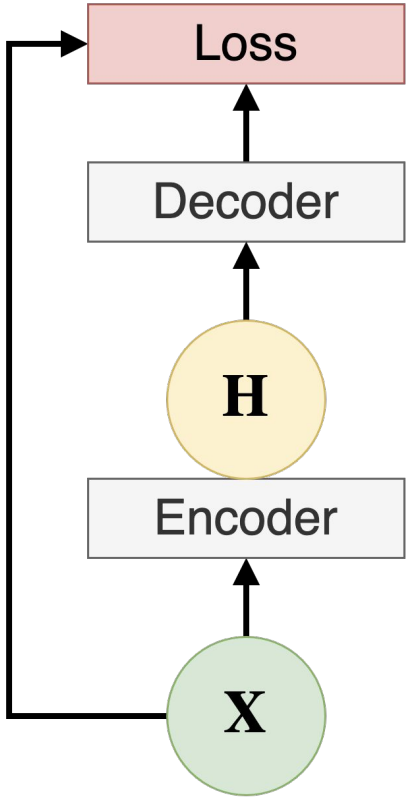
Solution
Use the latent representation of the data.



Use Case: Anomaly Detection

Problem
Detect inputs that are very different from normal inputs (e.g. anomalies).

Solution
Use the reconstruction loss as the estimate of the anomaly score.



Borghesi, A., et al. (2018)

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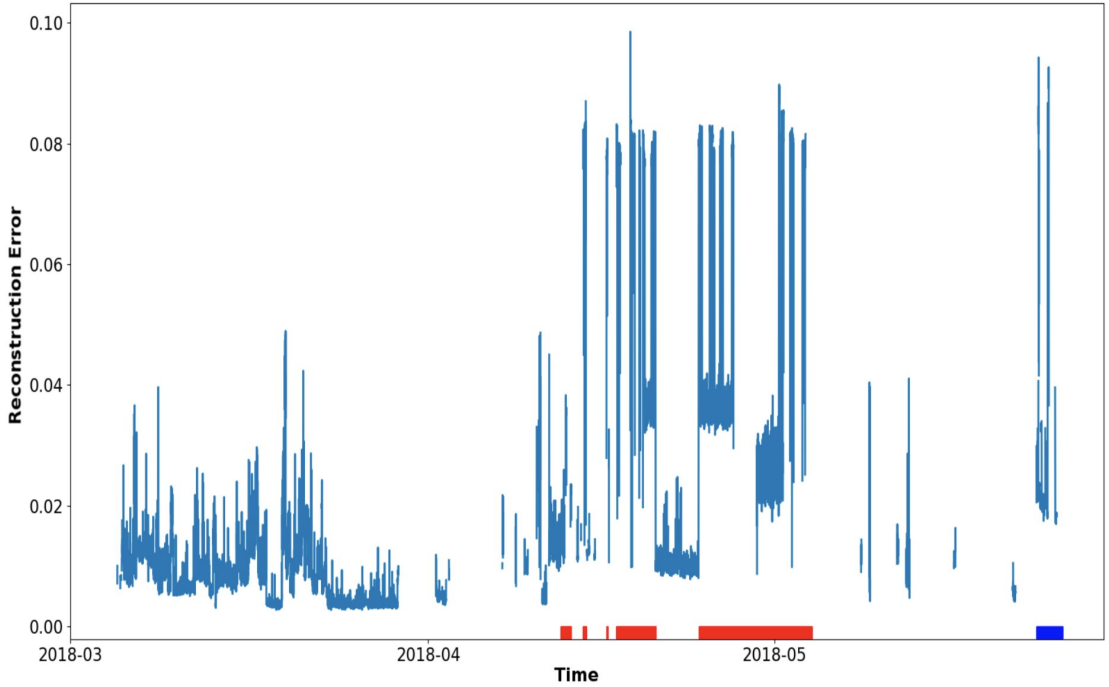
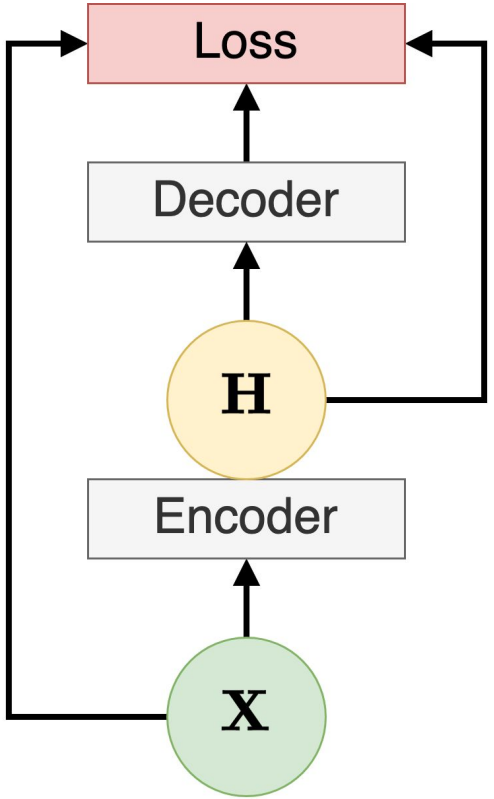


Borghesi, A., et al. (2018)

Sparse Autoencoders

Problem
Prevent the network from copying the input to the latent representation.

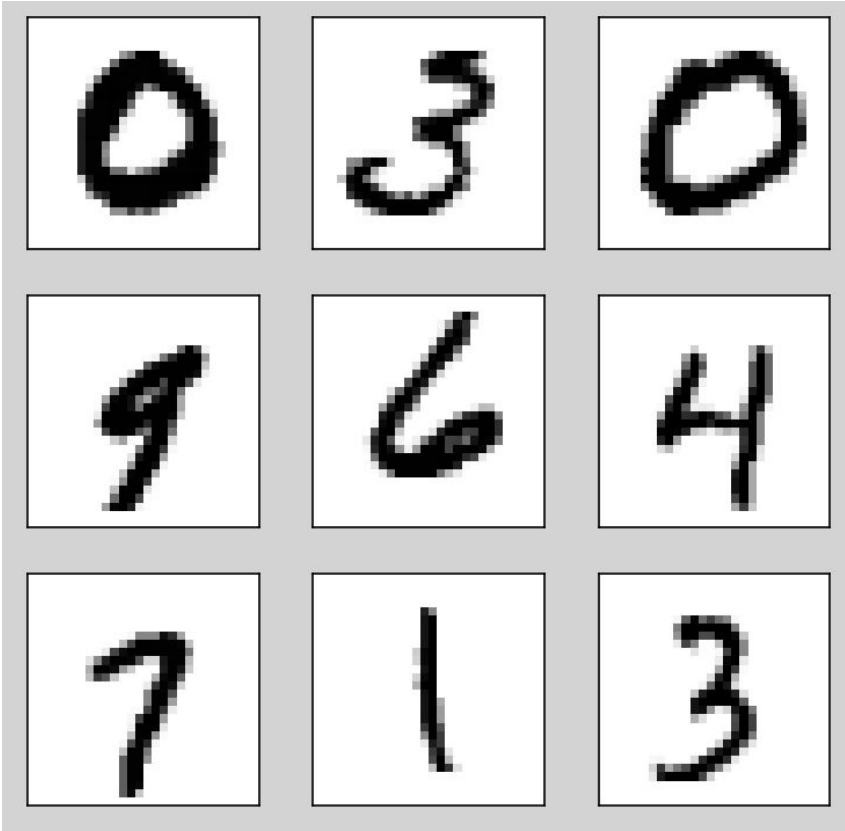
Solution
Add L1 penalty on the latent representation (not the weights) to the total cost.



Case Study: MNIST

- Dataset
  - 70K images of handwritten digits
  - Each image is 28 x 28 in [0, 1] (grayscale)

- Dimensionality Reduction Task
  - Reduce the dimensions from 784 to ???
  - Scored with MSE of the reconstructions against the original images



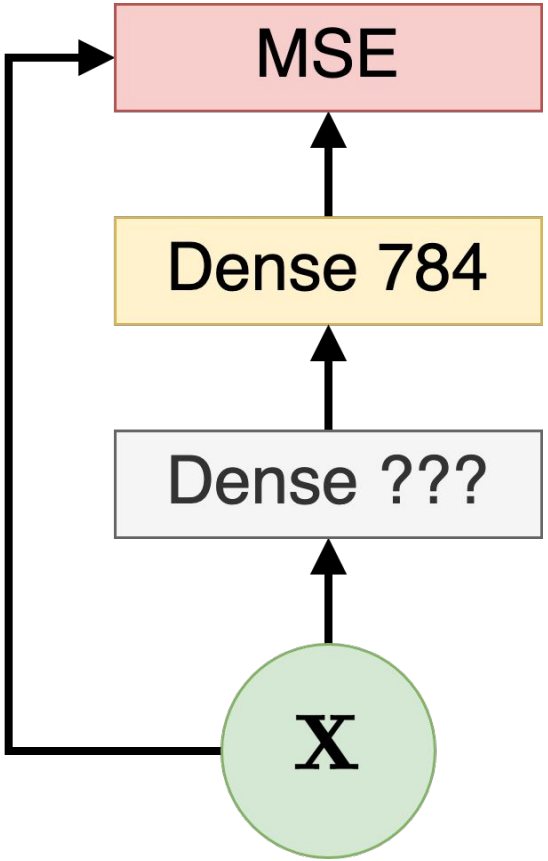
Model: Training

Undercomplete Autoencoder

Encoder Width
???

Encoder Depth
1 layer

Activation
ELU



Hyperparam Search: Greedy Strategy

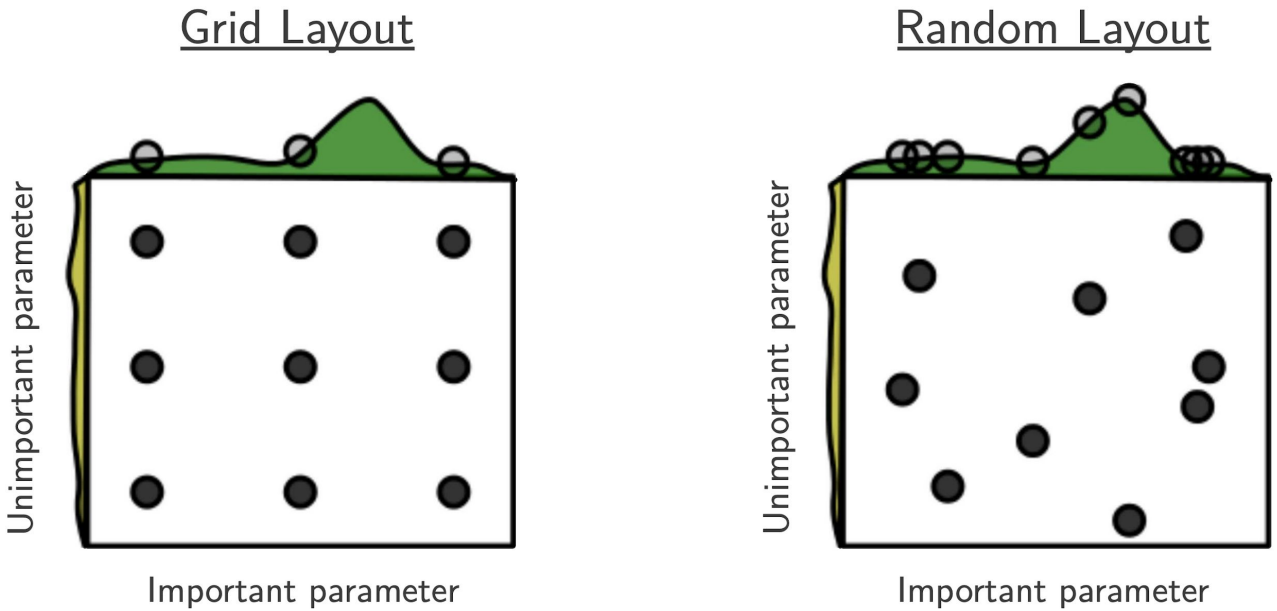
Sequence of hyperparam search:

1. Learning rate
2. Encoder width
3. Initialization seed
4. Final training

Pros: easy to implement

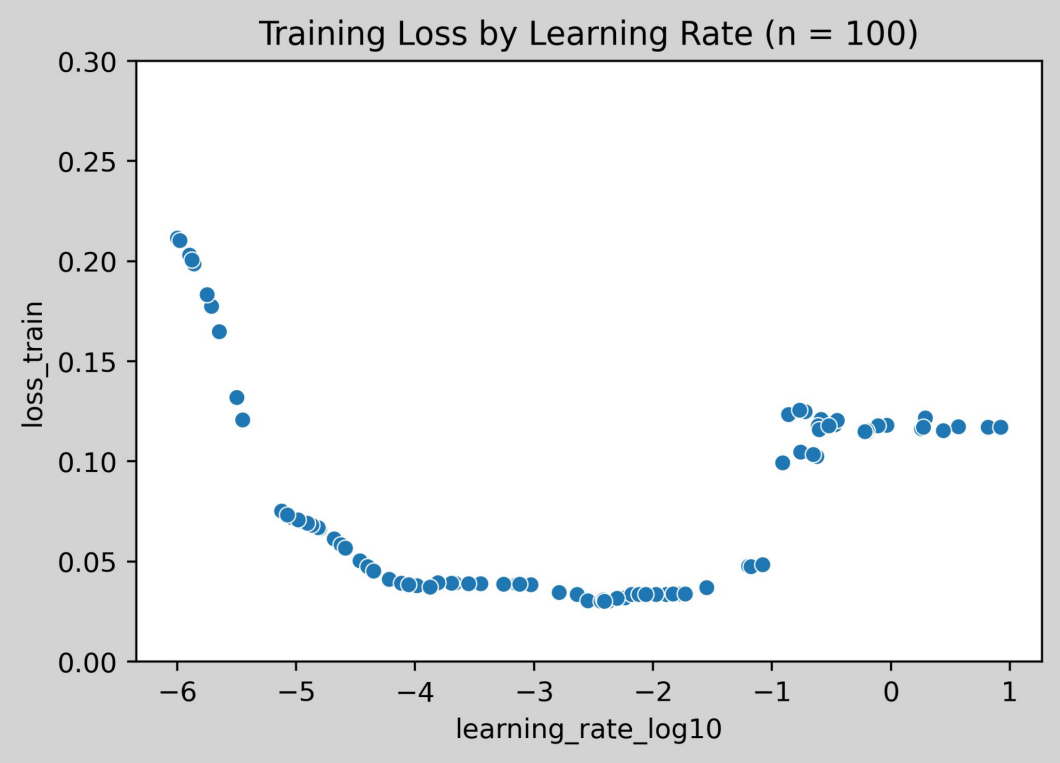
Cons: sequence needs to be carefully ordered

Grid Search vs Random Search



Source: Random Search for Hyper-Parameter Optimization (Bergstra, J. & Bengio, Y., 2012)

Hyperparam Search: Learning Rate



Iteration

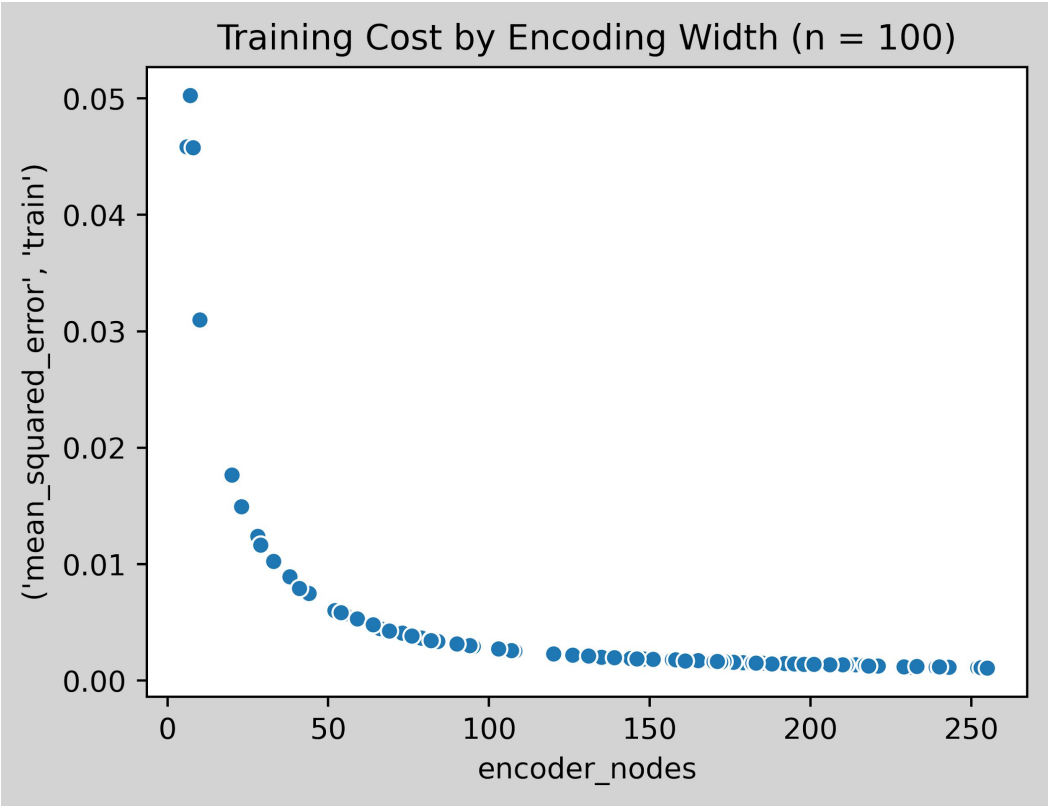
1. t ~ Uniform(-6, 1)
2. Learning Rate = 10 ** t
3. Train for 20 epochs

Repeat to train 100 models

Conclusion

Optimal initial learning rate = 10 ** -2.5

Hyperparam Search: Encoding Width



Iteration

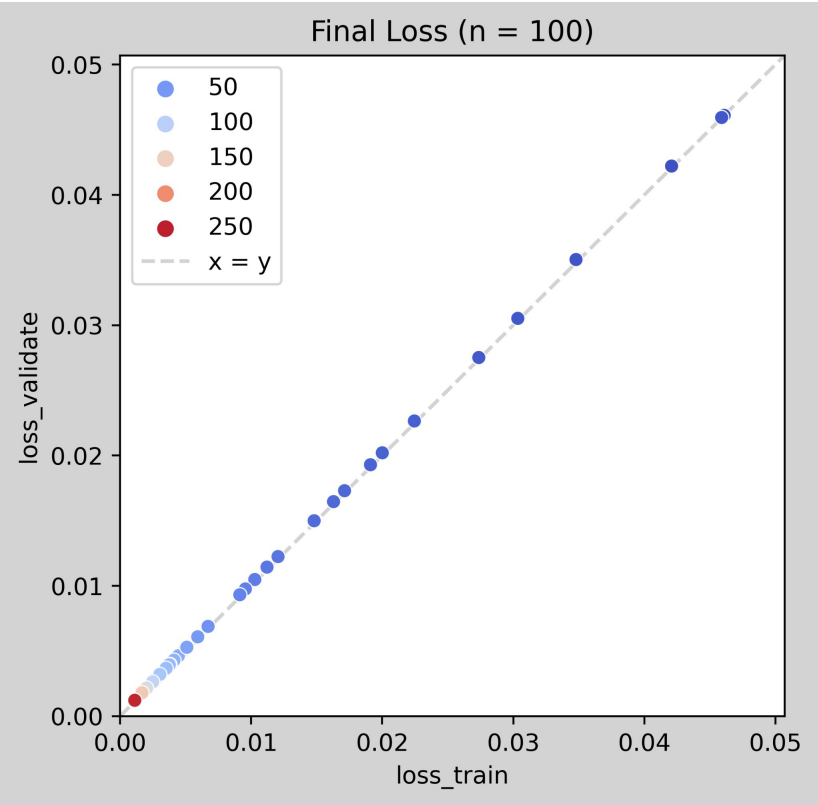
1. Width ~ Uniform(4, 256)
2. Train for 20 epochs

Repeat to train 100 models

Conclusion

Reconstruction error levels out at ~100 nodes.

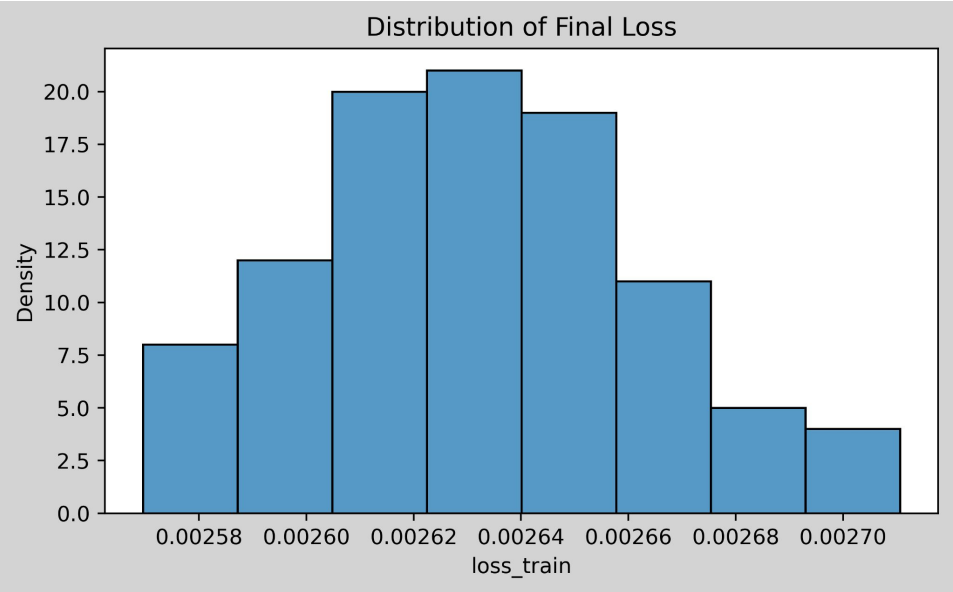
Hyperparam Search: Encoding Width



Autoencoder can overfit if the decoder is reproducing training examples without using the encoded representation.

Conclusion
No overfitting under 256 nodes.

Hyperparam Search: Weight Initialization



Iteration

1. Seed ~ Uniform(0, 2 ** 32 -1)
2. Weights ~ Glorot Uniform
3. Train for 20 epochs

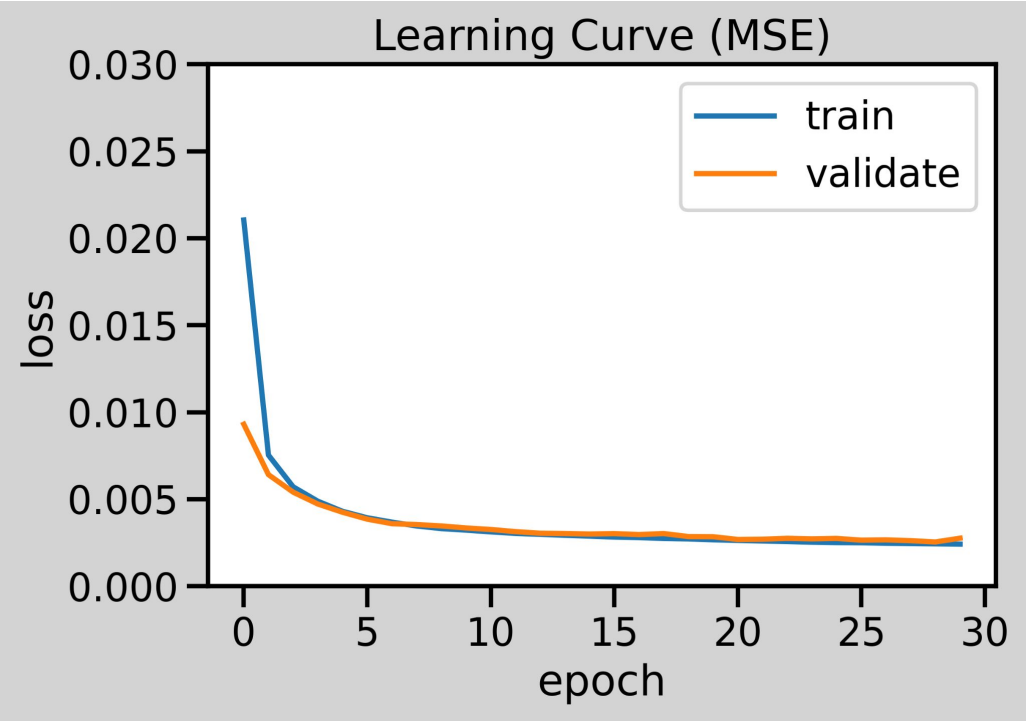
Repeat for 100 models

Inference

Choice of initial weights does not seem to matter much in this case.

Use seed with the lowest log loss.

Final Training



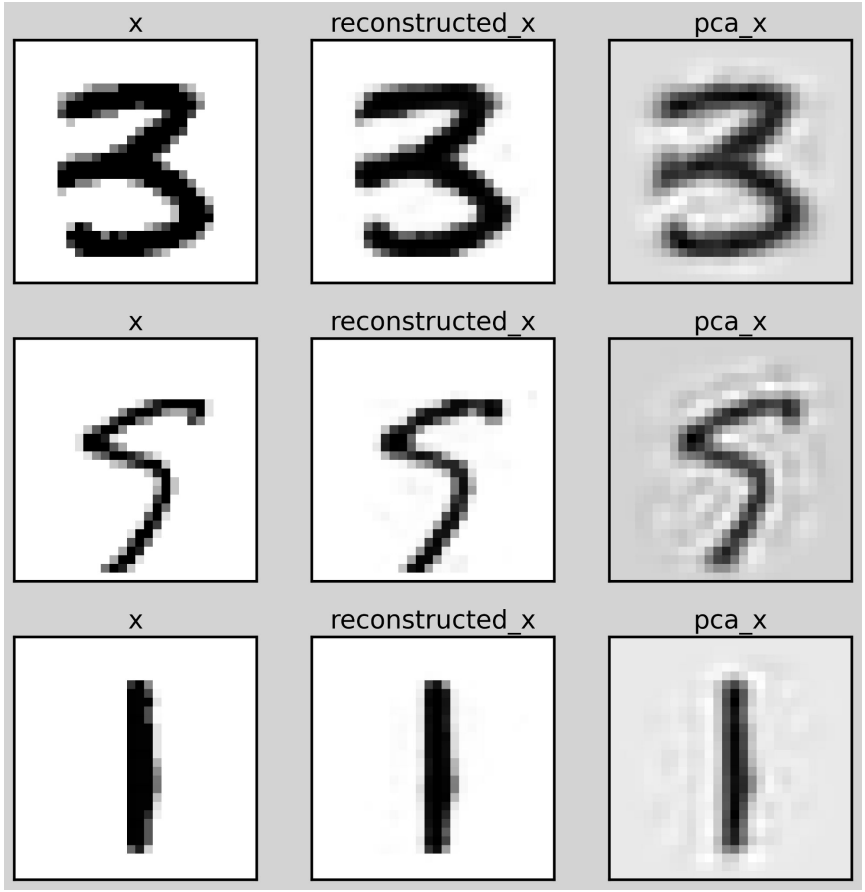
Hyperparams
Optimizer = Adam
Batch Size = 128
Learning Rate = 10 ** -2.5
Encoder width = 100
Initialization seed = 2366951942
Epochs = Early stopping triggered after 28 epochs

Conclusion
Learning curve converged towards MSE = 0.003

Image Examples

Images reconstructed by Autoencoder appear to be almost identical to the original images.

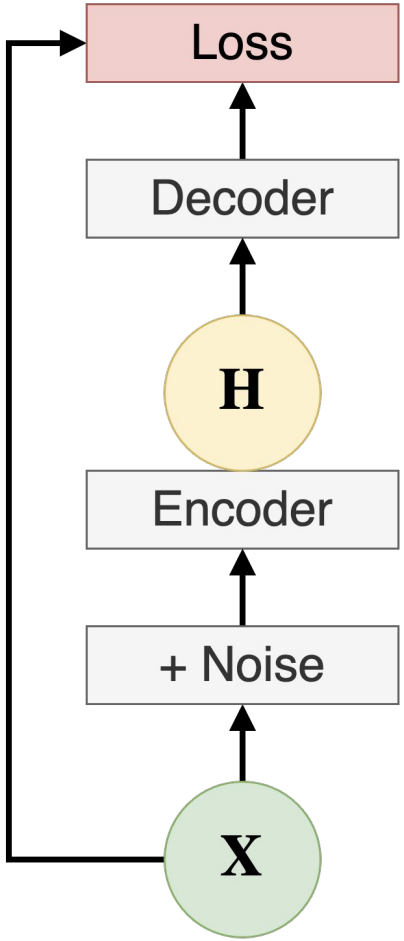
Model	Training Task	MSE
Undercomplete AE	Reconstruction	0.0024
PCA (n = 100)	Reconstruction	0.0056



Denoising Autoencoders: Training

Problem
Remove noise from the input given its distribution.

Solution
Add random noise to the input, while minimizing difference with the clean input.

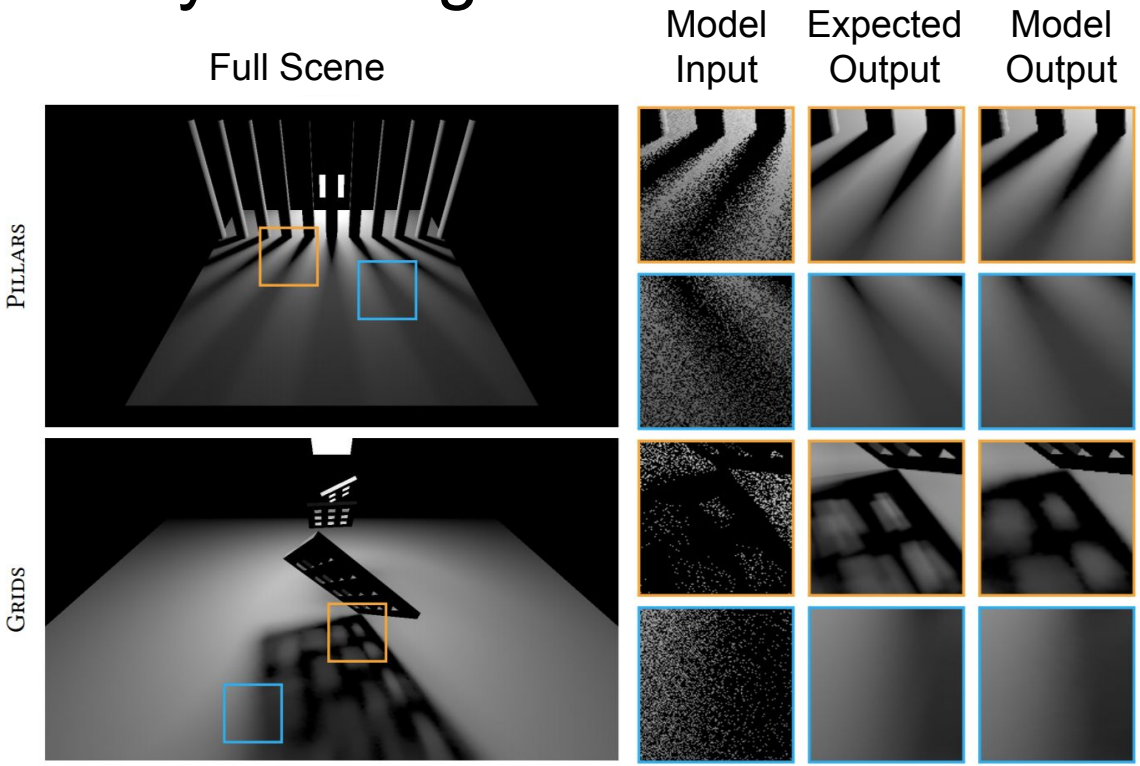


Vincent, P., et al. (2008)

Case Study: NVIDIA Ray Tracing

Ray Tracing engine produces noisy images if not given enough time to run.

Denoising autoencoder removes noise faster than the Ray Tracing engine would take to achieve the same quality.



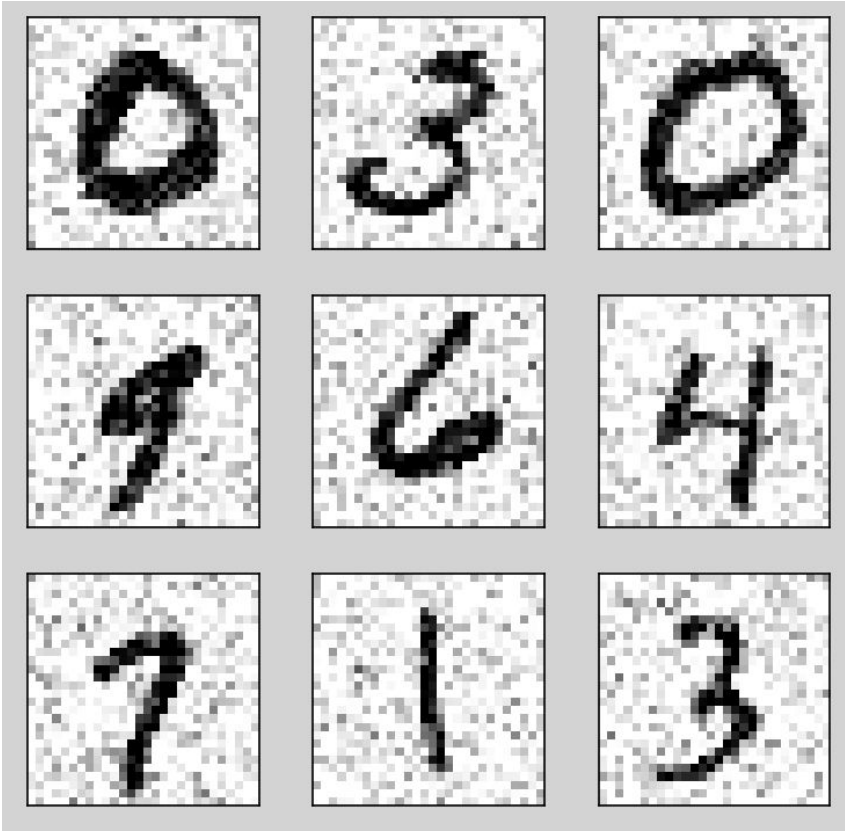
Schied, C., et al. (2017)

Case Study: NVIDIA Ray Tracing

Case Study: MNIST

- Dataset
  - 70K images of handwritten digits
  - Each image is 28 x 28 in [0, 1] (grayscale)
  - Augmented with Gaussian(0, 0.2)

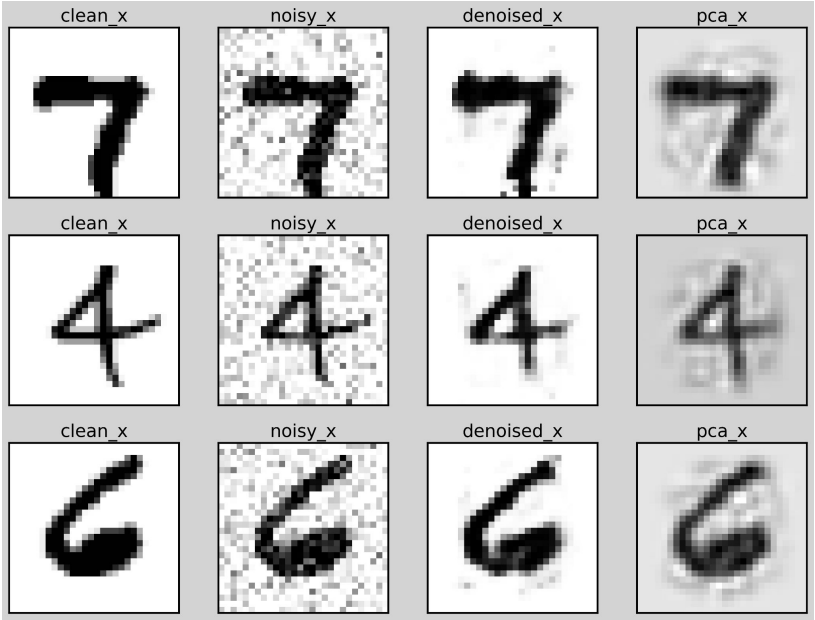
- Denoising Task
  - Remove noise from the images
  - Scored with MSE against original images



Undercomplete Autoencoder?

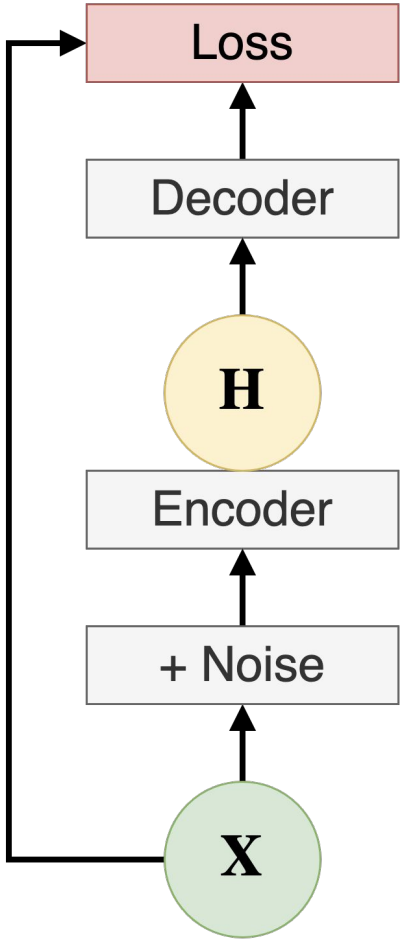
Undercomplete autoencoder can also be used for denoising even though the noise distribution was not specified either implicitly or explicitly during training.

Model	Training Task	Inference Task	MSE
Undercomplete Autoencoder	Reconstruction	Reconstruction	0.0024
		Denoising	0.0117
PCA (n = 100)	Reconstruction	Denoising	0.0106

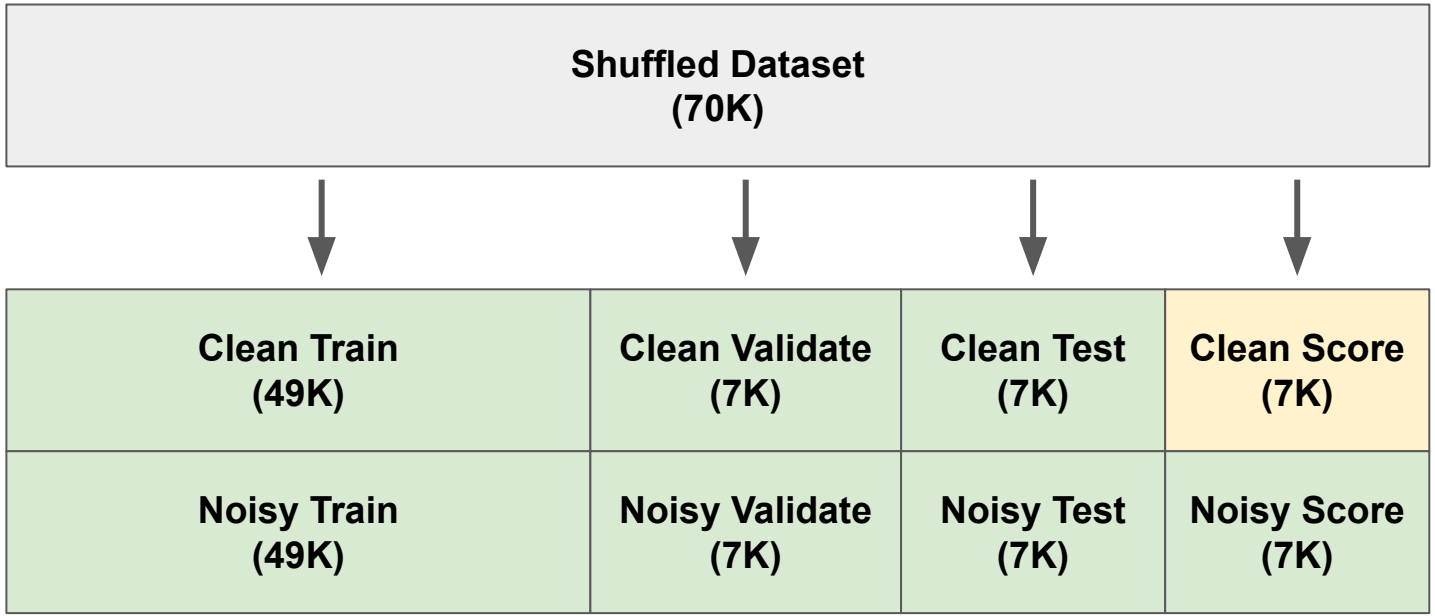


Assignment #1

- Train an Autoencoder
  - Architecture: undercomplete and/or sparse
  - **Training mode: denoising**
- Scored on Denoising Task
  - Methodology on the next slides
- Augmented MNIST Dataset
  - Noise ~ Normal(0, 0.2)
  - Shape = 70K x 28 x 28
  - Data Type = float32 in [0, 1]
  - File Type = Parquet



Assignment Dataset



Solution Methodology

- Read the Jupyter notebooks
- Must implement denoising training mode
- Try different Autoencoder architectures:
  - undercomplete
  - sparse
  - or both
- Try different encoder width / depth
- Try different optimizers
- Try different learning rates
- Try learning rate decay

What’s in the assignment template?

	Model Architecture	Training Task	Inference Task
Assignment template	Undercomplete	Reconstruction	Anomaly Detection
Your assignment	Up to you	Denoising	Denoising

Demo

AssignmentTemplate.ipynb

Assignment Deliverables

1. Jupyter notebook and/or Python script
    a. Data preprocessing
    b. Construction and training of the final model
    c. Inference on the Noisy Score dataset
2. Final model definition
    a. Keras serialization in JSON format
3. Final model parameters
    a. Keras serialization in H5 format
4. Denoised images from the Noisy Score dataset
    a. Shape = 7K x 784
    b. Data Type = float64 in [0, 1]
    c. File Type = Parquet

Assignment Grading

- Due EOD 10/8
  - Zero points for late submissions
  - Zero points for incomplete submissions
  - Zero points for non-denoising training mode

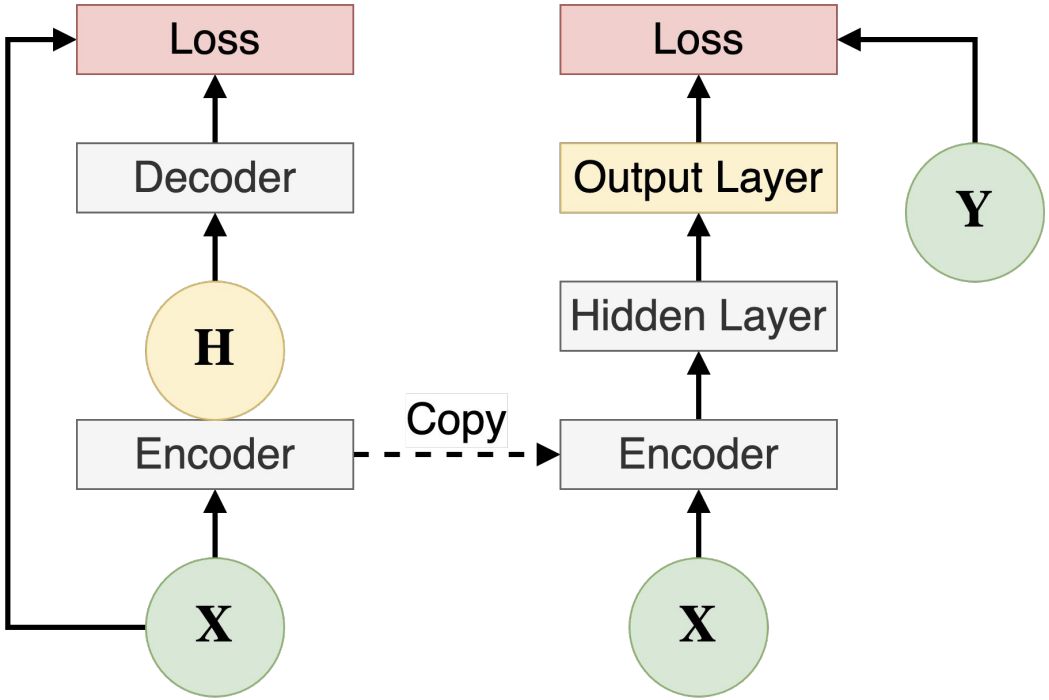
- Maximum points = 20
  - 10 points if MSE (Denoised vs Clean) on Score Dataset < 0.02
  - 10 points proportional to percentile of MSE on Score Dataset relative to the class
  - In 2019, the average MSE was 0.0120

- Compute Environments
  - AWS SageMaker Studio

Unsupervised Pre-training

Problem
Initialize a network with parameters that are better than random.

Solution
Use pre-trained encoder layer as the bottom of the network.



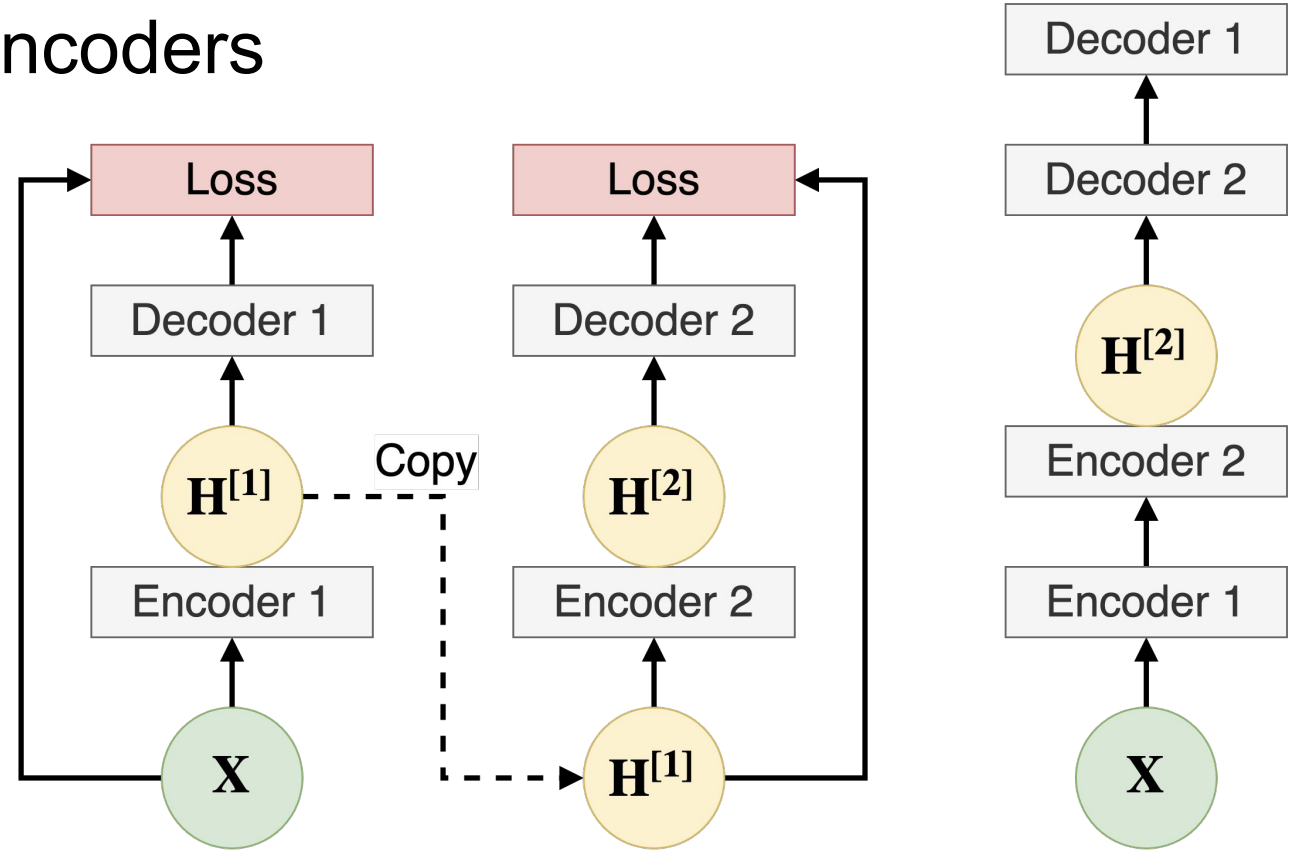
Bengio, Y., et al. (2007)

Stacked Autoencoders

Deep autoencoders are typically trained in greedy layer-wise procedure.

Layers trained one at a time, starting with the outermost.

Finally, they are stacked into a single autoencoder.

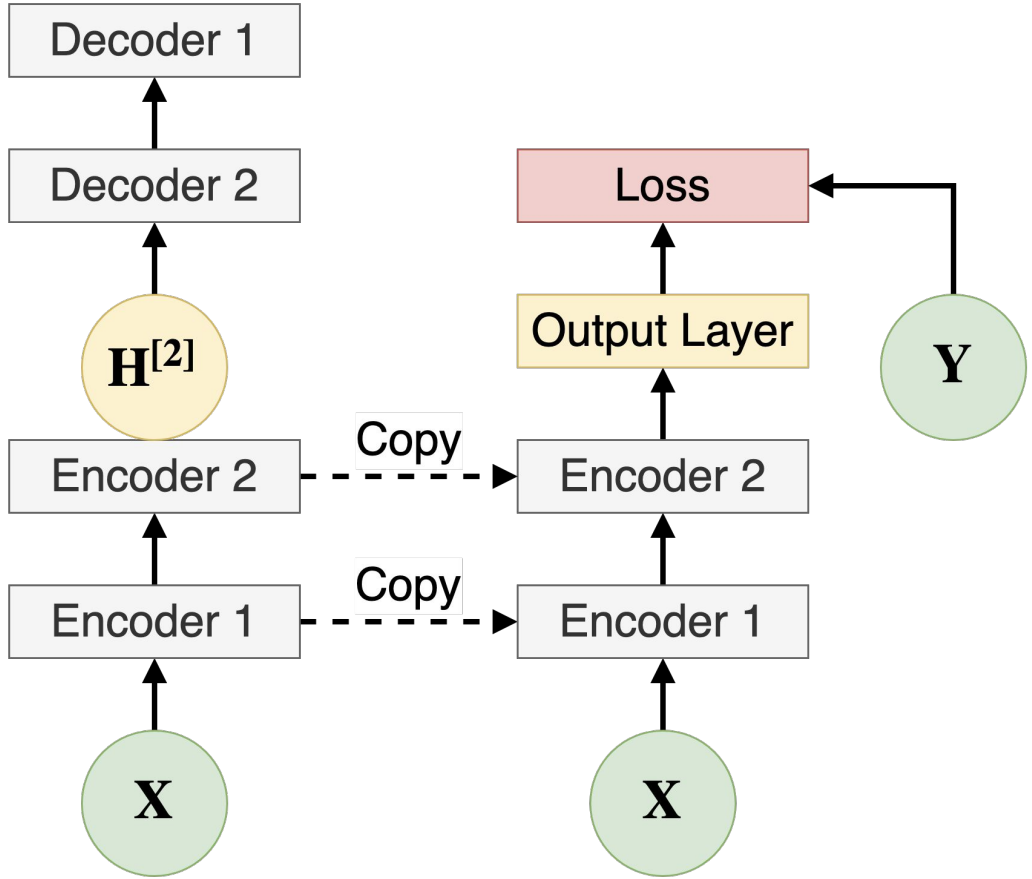


Bengio, Y., et al. (2007)

Deep Unsupervised Pre-training

Problem
Initialize a network with parameters that are better than random.

Solution
Use pre-trained stacked encoder layers as the bottom of the network.

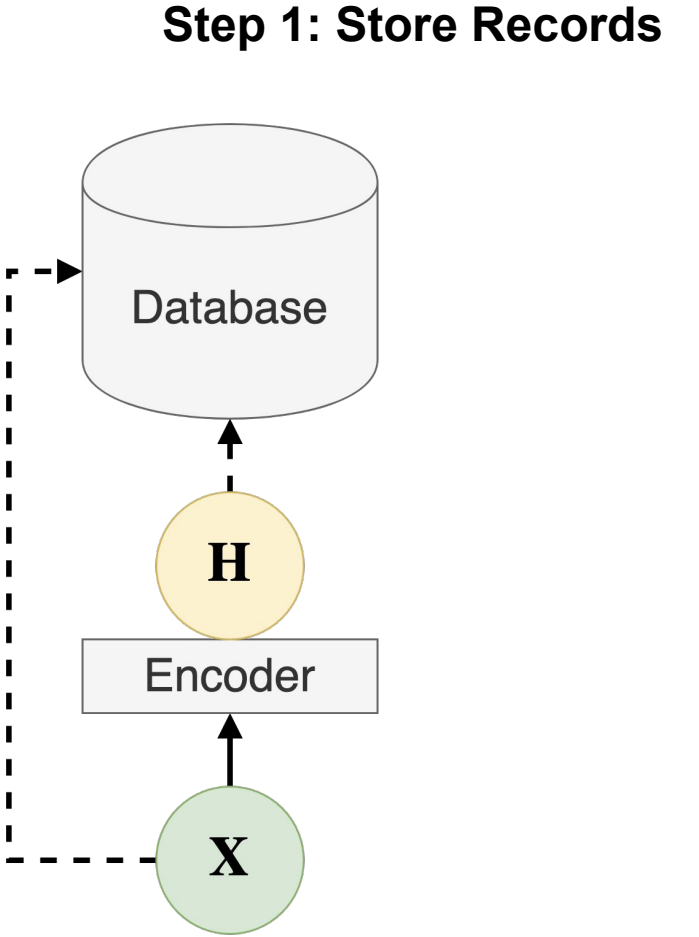


Bengio, Y., et al. (2007)

Use Case: Semantic Hashing

Problem
Find entries similar to the query input from a very large dataset.

Solution
Use the latent representation as the key in a database.

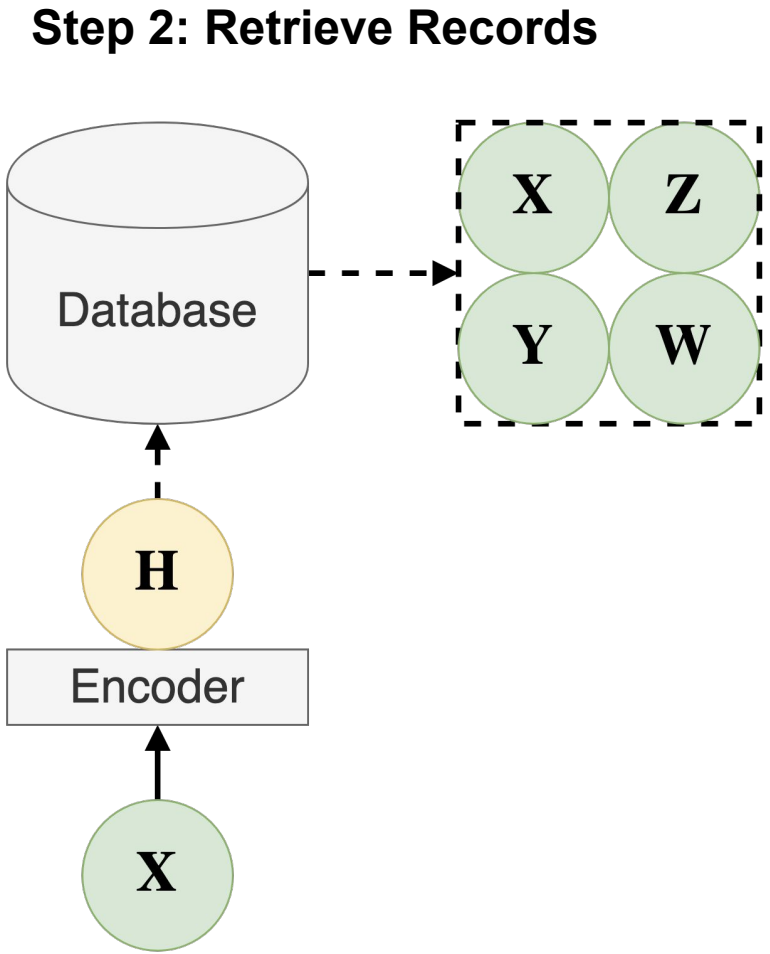


Salakhutdinov, R., and Hinton, G. (2007)

Use Case: Semantic Hashing

Problem
Find entries similar to the query input from a very large dataset.

Solution
Use the latent representation as the key in a database.



Salakhutdinov, R., and Hinton, G. (2007)

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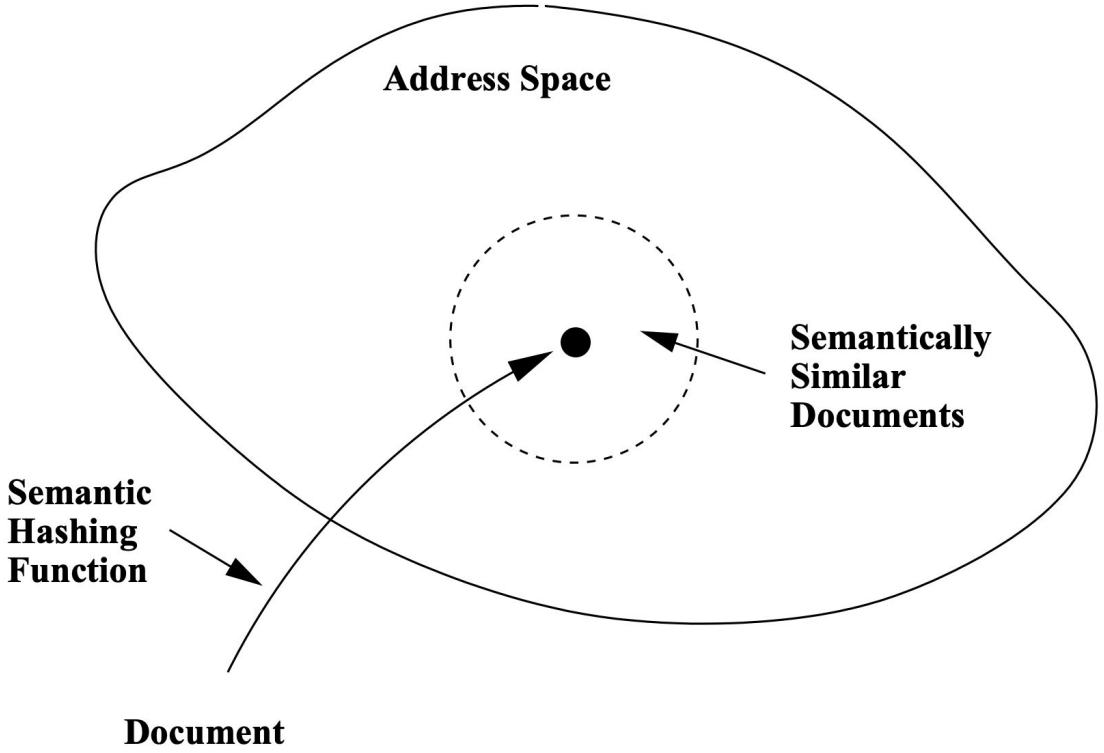
Solution
Use the latent representation as the key in a database.



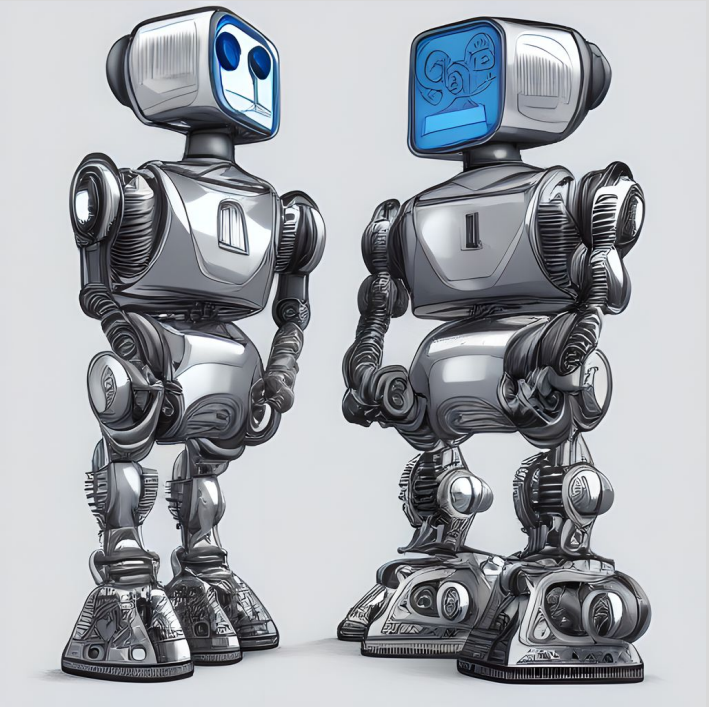
Salakhutdinov, R., and Hinton, G. (2007)

References

1. Adam: A Method for Stochastic Optimization (Kingma, D., and Ba, J., 2017)
2. Anomaly Detection using Autoencoders in High Performance Computing Systems (Borghesi, A., and Bartolini, A., 2018)
3. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (Ioffe S., Szegedy C., 2015).
4. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification (He, K., et al., 2015)
5. **Deep Learning (Goodfellow, I., Bengio, Y, and Courville, A., 2016)**
6. Extracting and Composing Robust Features with Denoising Autoencoders (Vincent, P., et al., 2008)
7. Greedy Layer-Wise Training of Deep Networks (Bengio, Y., et al., 2007)
8. Machine Learning (Mitchell, T., and Hill, M., 1997)
9. On the Momentum Term in Gradient Descent Learning Algorithms (Qian, N., 1999)
10. Random Search for Hyper-Parameter Optimization (Bergstra, J. & Bengio, Y., 2012)
11. Semantic Hashing (Salakhutdinov, R., and Hinton, G., et al., 2007)
12. Spatiotemporal Variance-Guided Filtering: Real-Time Reconstruction for Path-Traced Global Illumination (Schied, C., et al., 2017)
13. Stochastic Gradient/Mirror Descent: Minimax Optimality and Implicit Regularization (Azizan, N. & Hassibi, B., 2018)
14. Understanding the difficulty of training deep feedforward neural networks (Glorot, X., and Bengio Y., 2010)

Thanks

+ Q&A Time



(Image by a Stable Diffusion model)