MSBA 434:
Advanced Workshop on Machine Learning

Lecture 1: Deep Neural Networks

UCLA Anderson

2019

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- Over the last 10 years:
    - Backend Software Engineer
    - Data Warehouse Engineer
    - Data Analyst Contractor
    - Web App Developer
    - Game Developer

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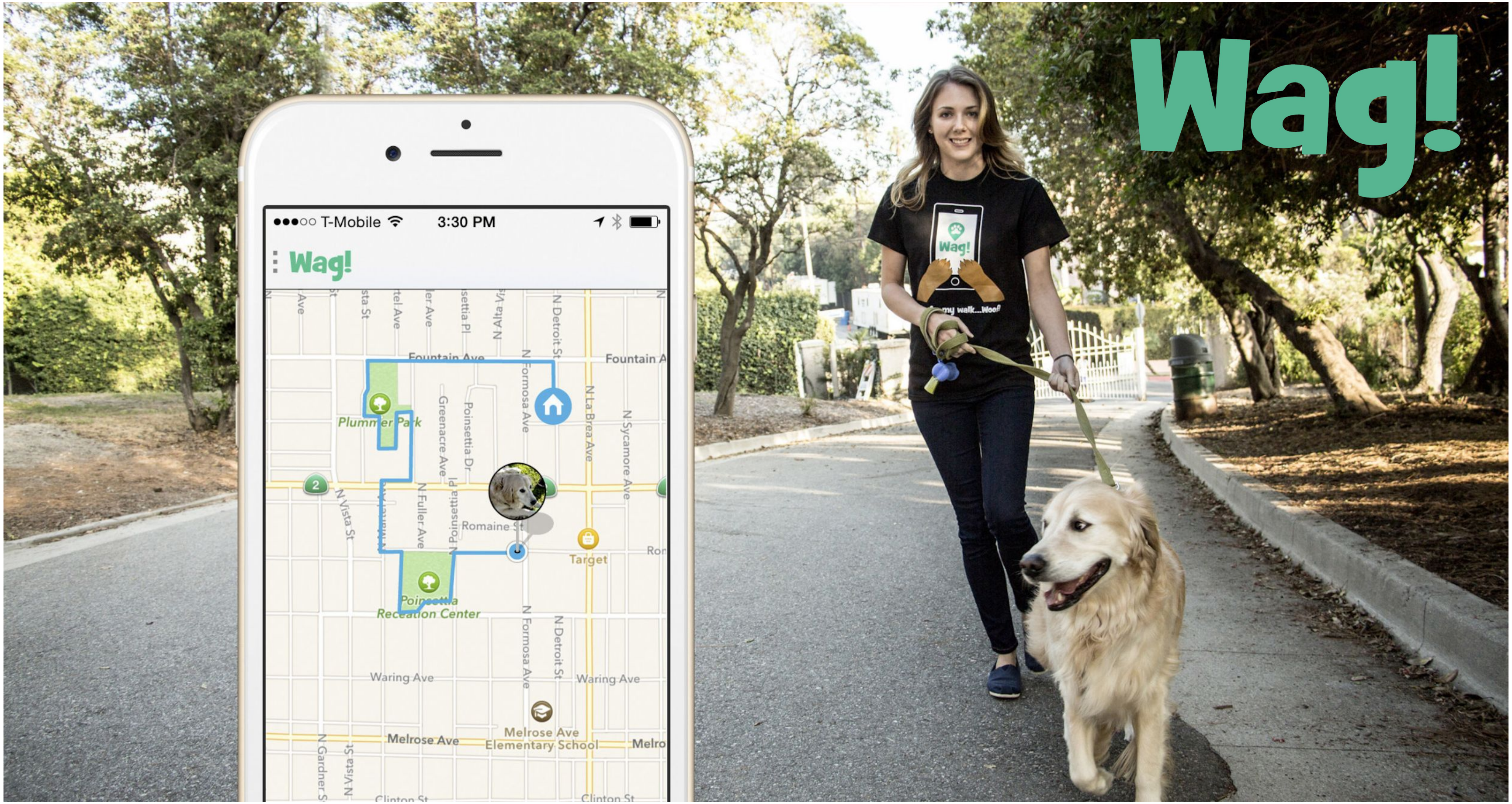
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N Sycamore Ave
Greenacre Ave
Poinsettia Dr
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N Gardner St
Clinton St

Course Overview

Date	Topic	Assignment Due
10/1	Deep Neural Networks	EOD 10/7
10/8	Convolutional Neural Networks	EOD 10/14
10/15	Recurrent Neural Networks	EOD 10/21
10/22	Generative Adversarial Networks	EOD 10/28
10/29	Ensemble Methods	EOD 11/12

Today’s Agenda

- Review of NN Theory and Practice
  - Model Training
  - Network Architecture
  - Optimization Algorithms
  - Regularization Methods
  - Training Pipelines
  - Optimization on Hyperparameter Space

- Autoencoders
  - Undercomplete
  - Sparse
  - Noisy

- Case Study: Denoising Images

Part 1

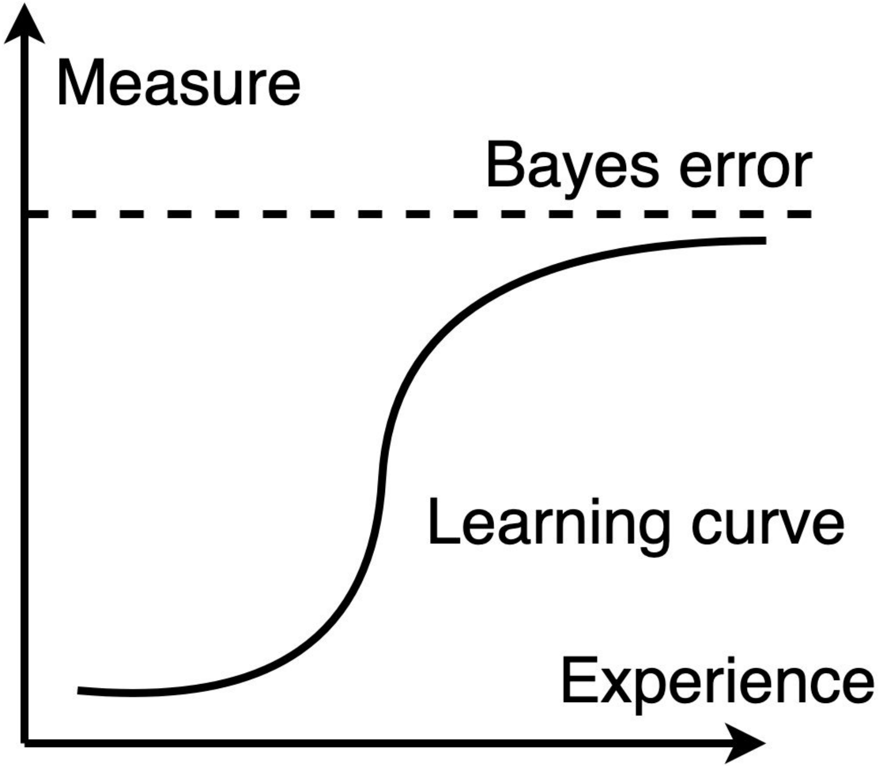
Review of NN Theory and Practice

What is Machine Learning?

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P,

if its performance at tasks in T, as measured by P, improves with experience E.

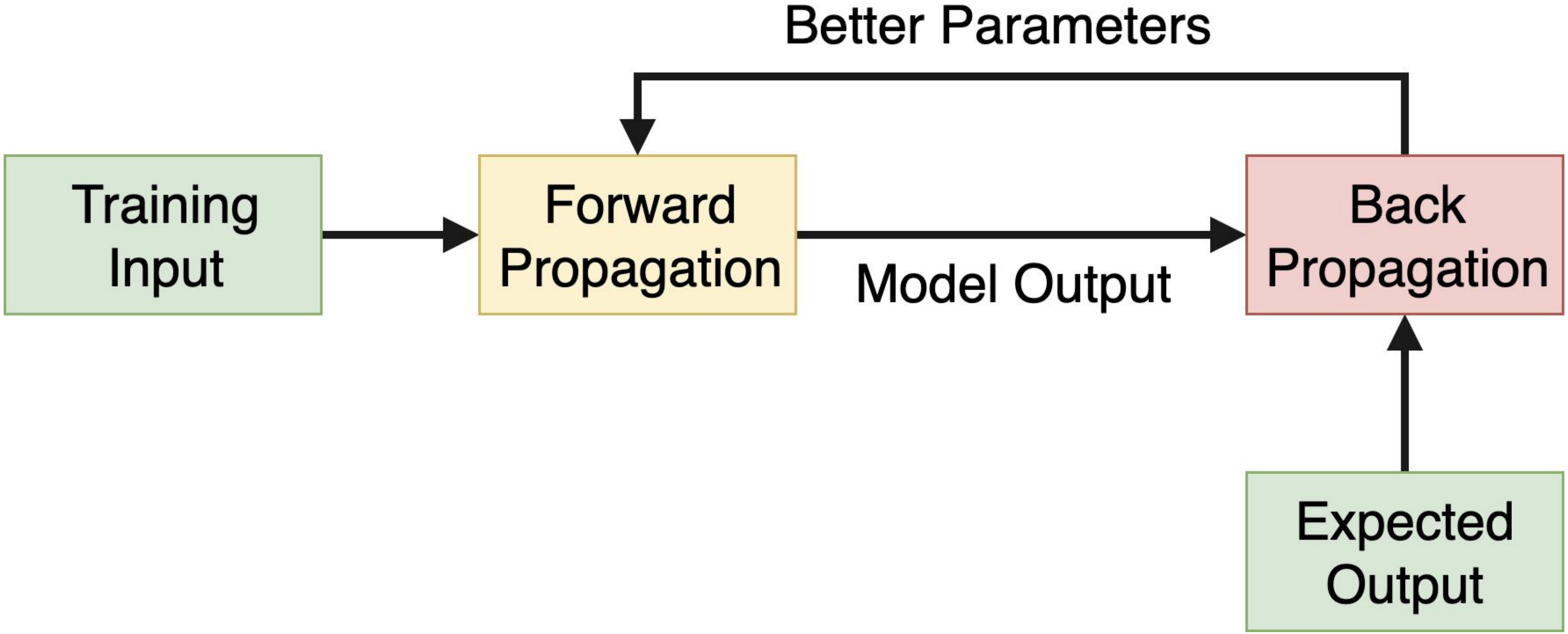
Source: Machine Learning, Tom Mitchell, McGraw Hill, 1997.



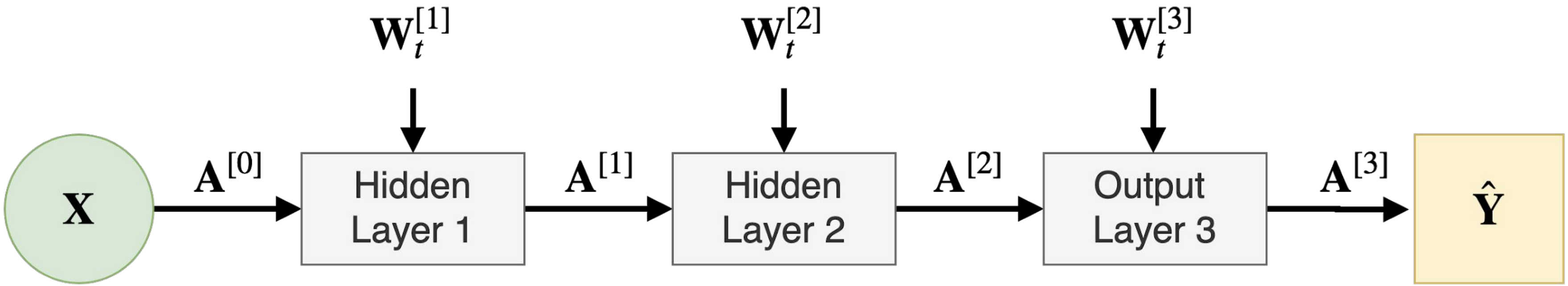
Managerial Economics of Machine Learning

Project Goal	Project Duration	Training Cost	Required Training
Design new architecture and train from scratch	Months	Expensive	Machine Learning Researcher
Use pre-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	Free	Automation Software Engineer

Training Iteration



Feedforward Architecture



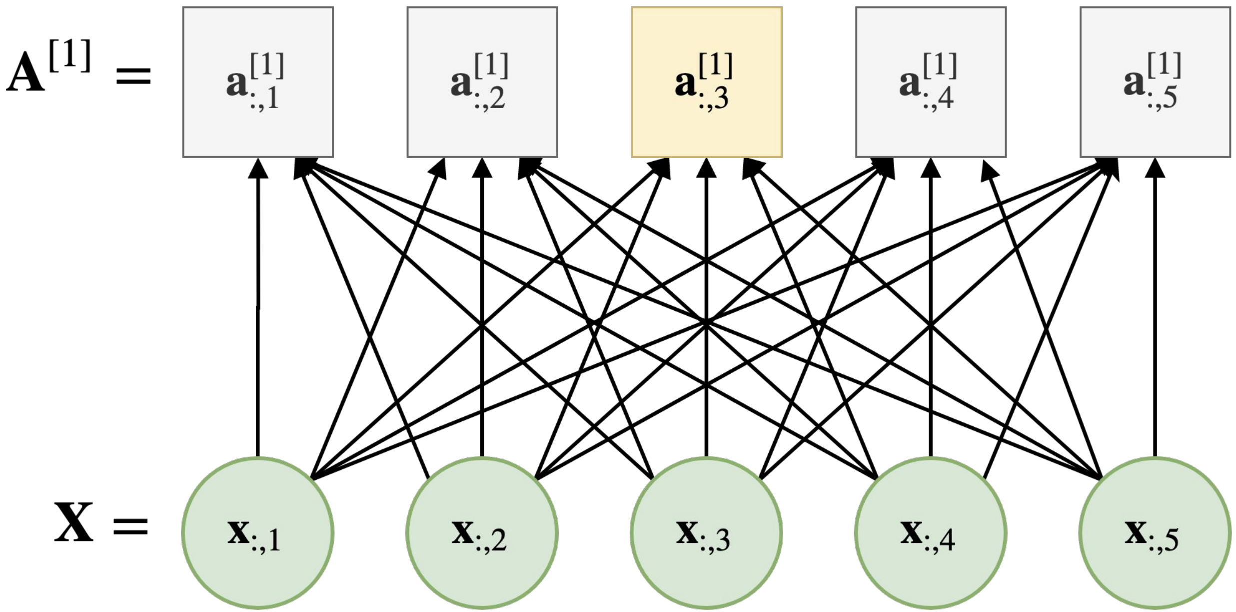
$\mathbf{X} = \mathbf{A}^{[0]}$ $\quad \hat{\mathbf{Y}} = \mathbf{A}^{[L]}$ $\quad L = 3$

Forward Propagation in a 3-Layer Feed-forward Network

FC: Single Neuron Activation

$$\mathbf{z}_{:,3}^{[1]} = \mathbf{X} \cdot \mathbf{w}_{3,:}^{[1]T} + b_3^{[1]}$$

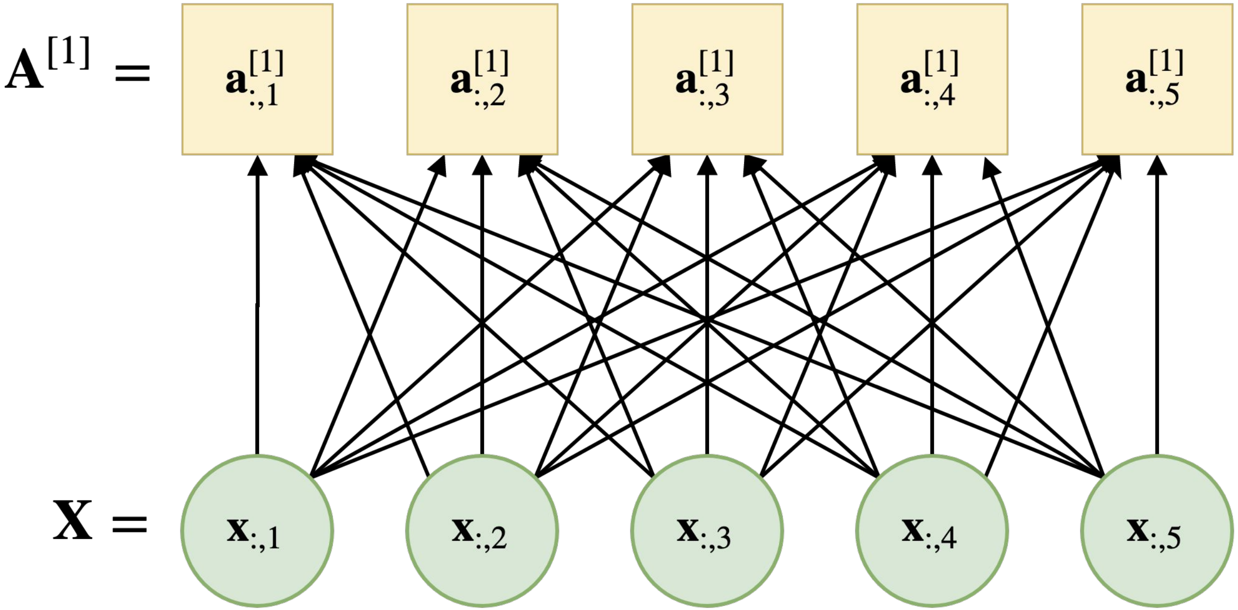
$$\mathbf{a}_{:,3}^{[1]} = f(\mathbf{z}_{:,3}^{[1]})$$



FC: Layer Activation

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

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



Fully Connected Layer

For input and activation matrices, row vectors are individual samples from the dataset.

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

Activation function is applied element-wise.

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

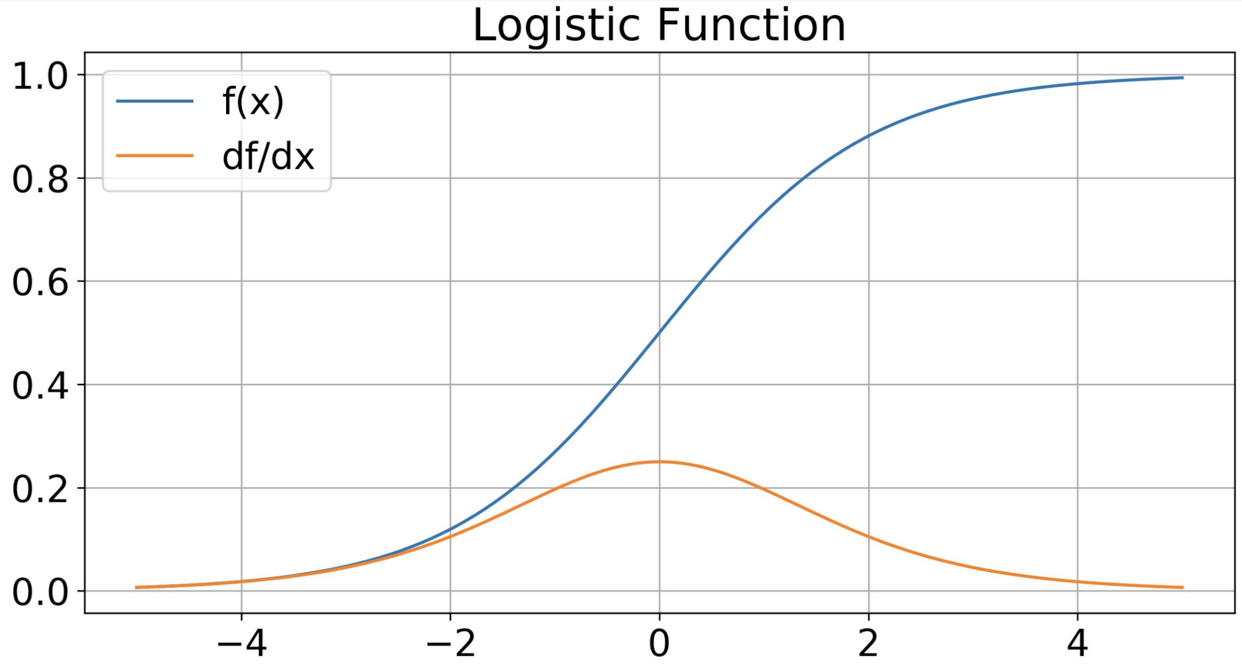
$$\mathbf{A}^{[l]} = f(\mathbf{Z}^{[l]})$$

See FullyConnectedLayer.ipynb for notation and linear algebra details.

Logistic / Sigmoid

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

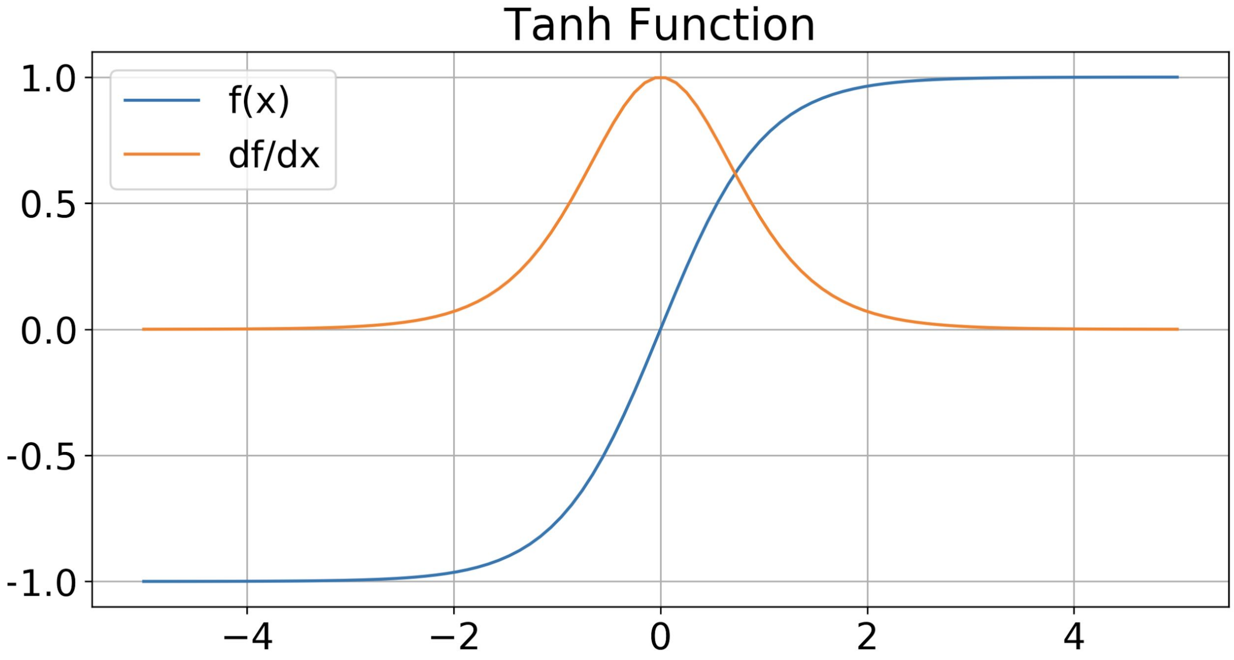
$$\frac{df}{dx} = \frac{e^x}{(e^x + 1)^2}$$



Hyperbolic Tangent

$$f(x) = 2L(2x) - 1$$

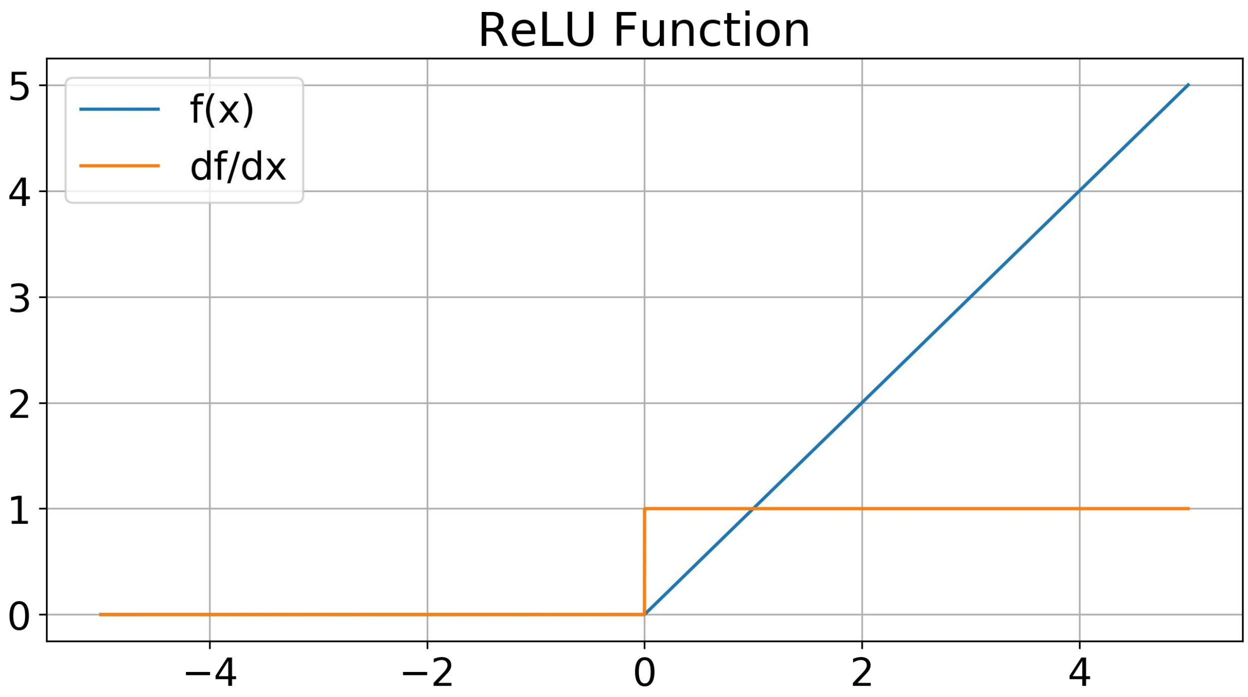
$$\frac{df}{dx} = 4L'(2x)$$



Rectified Linear Unit

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

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

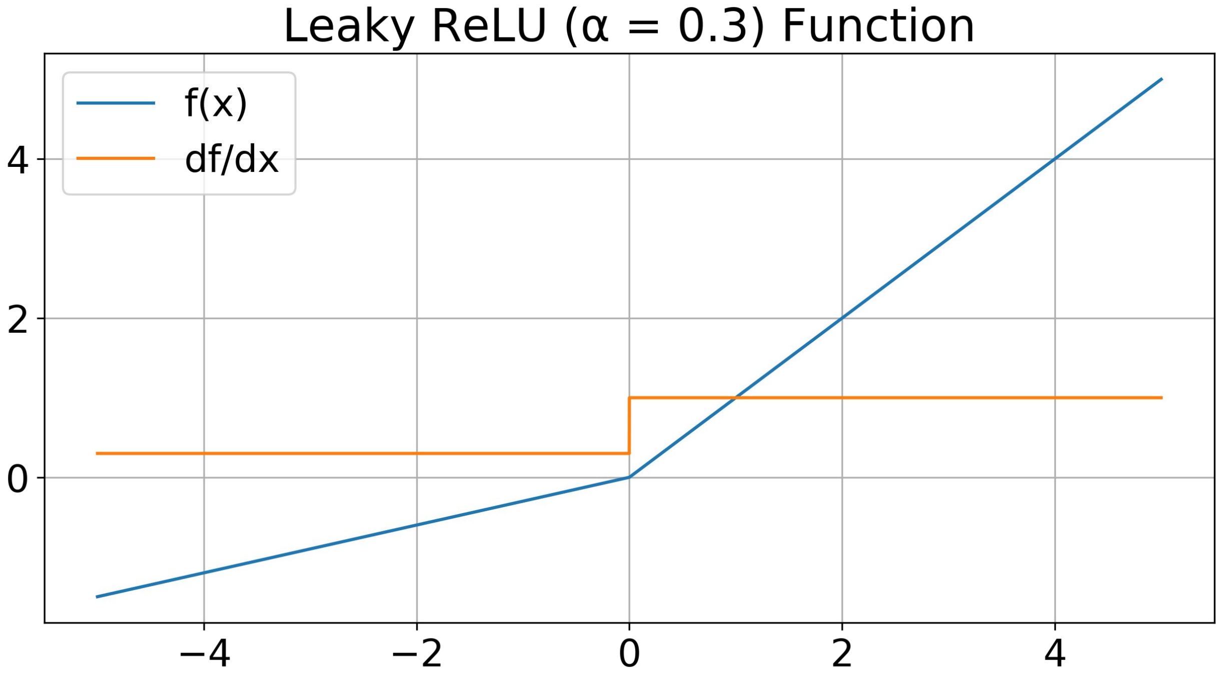


Glorot, X., et al. (2011)

Leaky ReLU

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

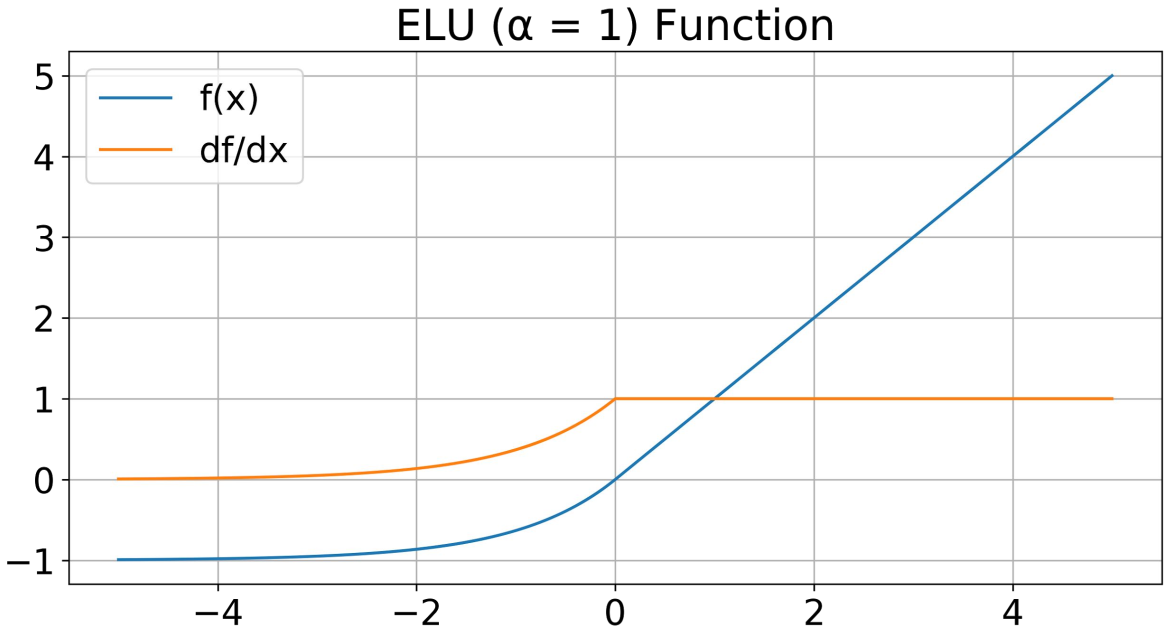
$$\frac{df}{dx} = \begin{cases} 1 & \text{for } x > 0 \\ \alpha & \text{for } x < 0 \\ \text{undefined} & \text{for } x = 0 \end{cases}$$



Exponential Linear Unit

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

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



Activation Functions

Function	Hidden Layer	Output Layer
Logistic	Mostly RNNs	Yes
Tanh	Mostly RNNs	Yes
ReLU	Yes	Yes
Leaky ReLU	Yes	No, why?
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.

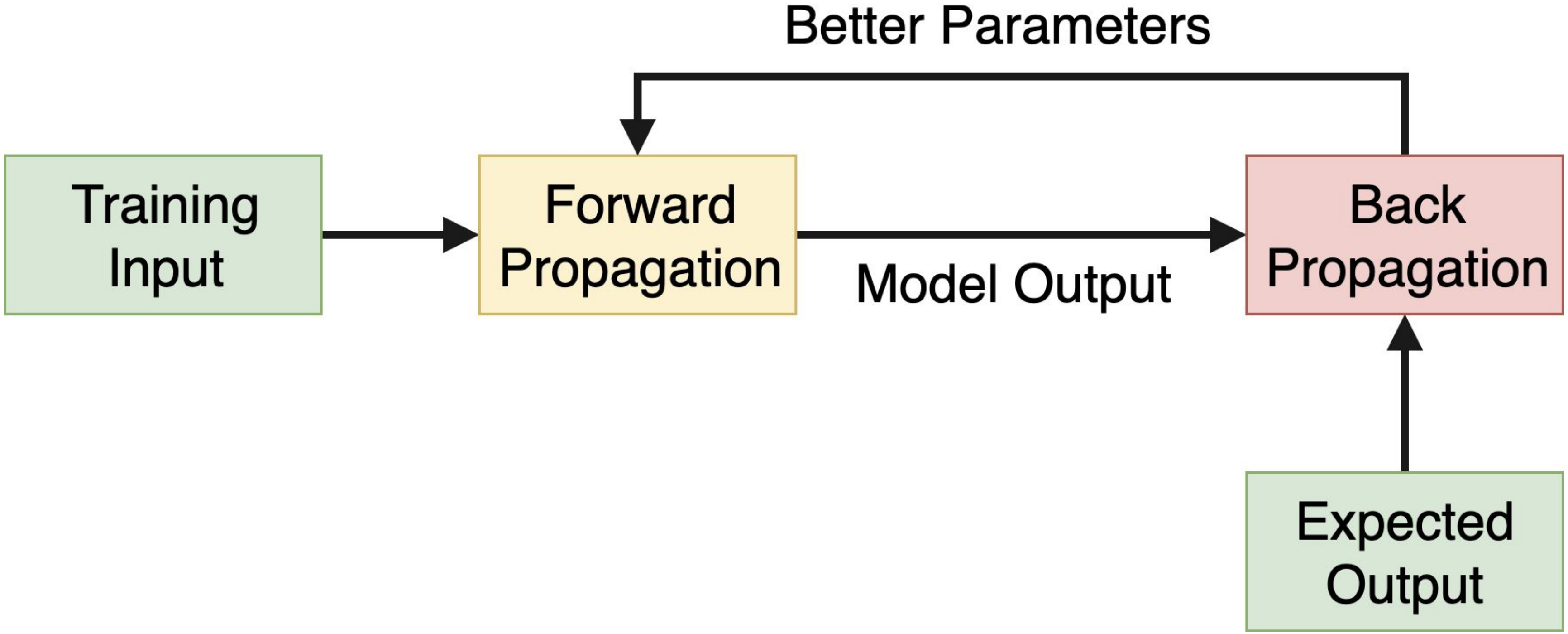
Solution:

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

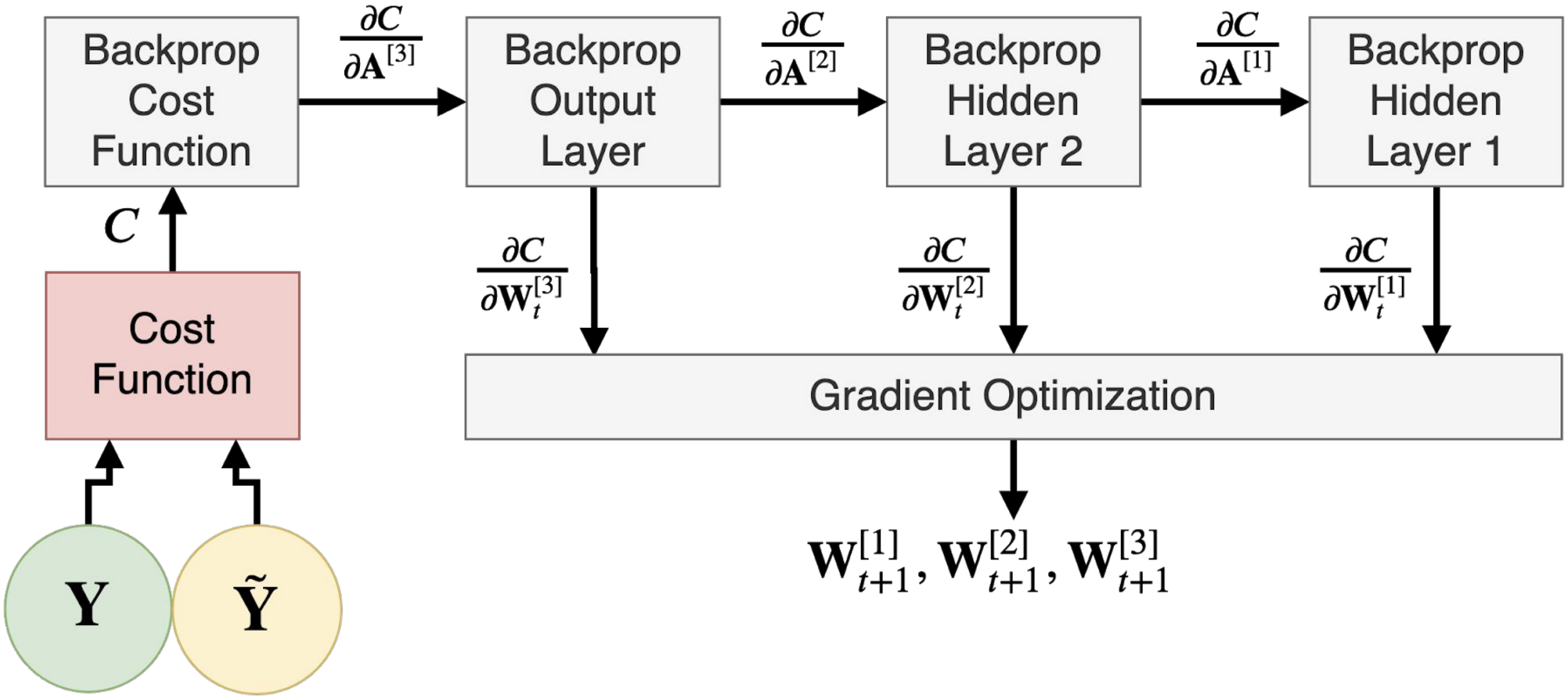
$$\mathbf{a}^{[l]}_{:,m} = \frac{\mathbf{z}^{[l]}_{:,m}}{\sum_{k=1}^{M} \mathbf{z}^{[l]}_{:,k}}$$

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

Training Iteration



Back Propagation in Feedforward Architecture



Regression Loss

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

Note that MAE is not differentiable at zero.

Total is cost is just an average loss across samples and features.

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

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

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

Classification Loss

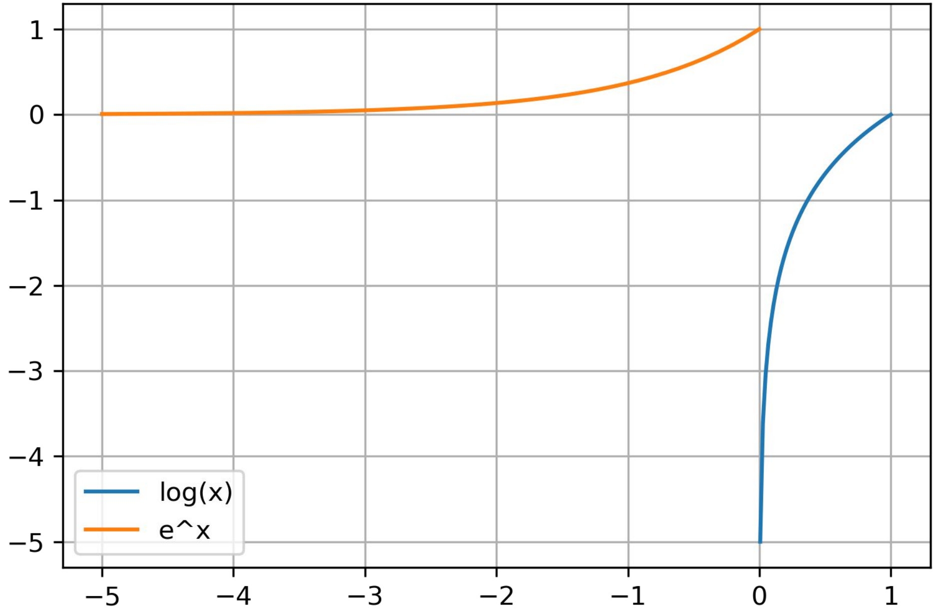
$$\text{Cost Function} \in ([0,1]^{S\times M}, [0,1]^{S\times M}) \to \mathbb{R}$$

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

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

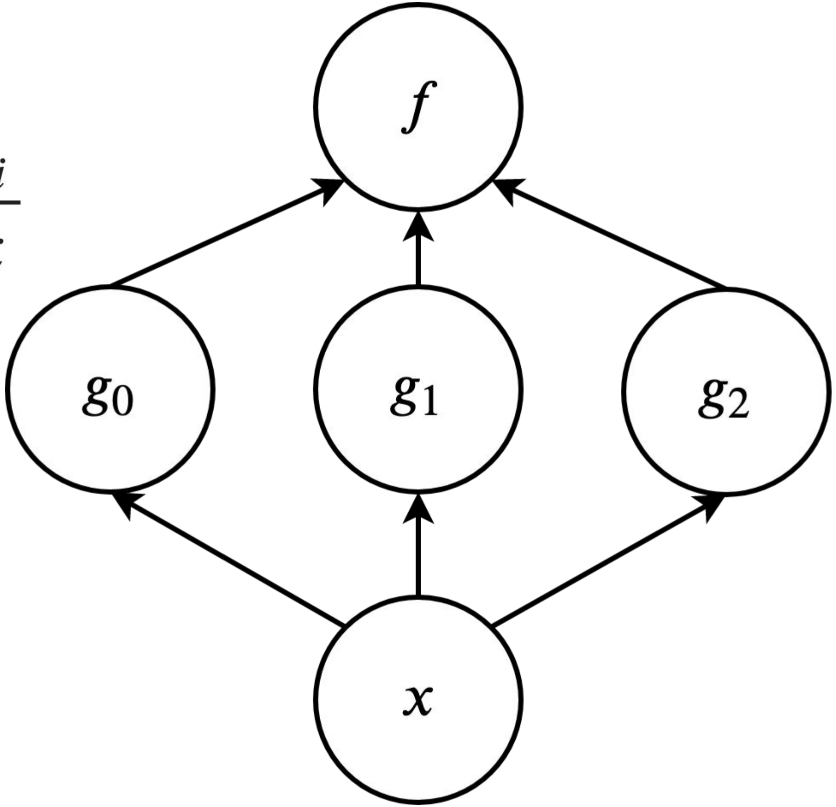
Cross entropy measures the difference between two probability distributions in an asymmetric way!

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



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 cost function with respect to every parameter.

Backpropagation in Fully Connected Layer

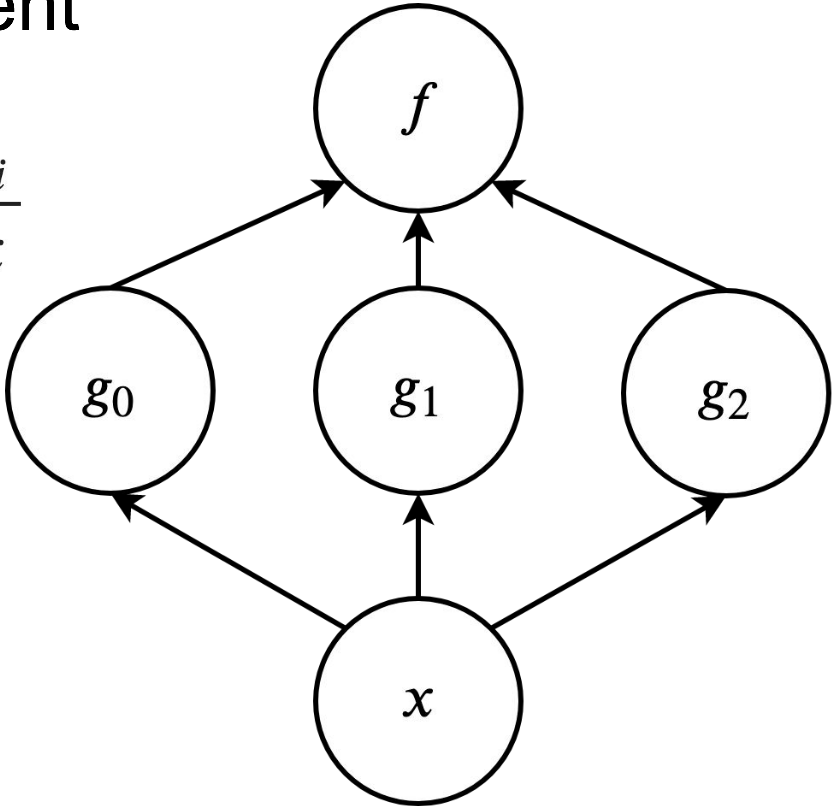
$$\frac{\partial a_{s,m}^{[l]}}{\partial z_{s,m}^{[l]}} = f'(z_{s,m}^{[l]}) \qquad \frac{\partial z_{s,m}^{[l]}}{\partial w_{m,n}^{[l]}} = a_{s,n}^{[l-1]}$$

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

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

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 undo standardization 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)

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 discussion, NumPy, and Keras implementations.

Parameter Initialization

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

$$\forall g, h :$$

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

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

$$z_{s,g}^{[l]} = \mathbf{a}_{s,:}^{[l-1]} \cdot \mathbf{w}_{g,:}^{[l]T} + b_g^{[l]}$$

$$z_{s,h}^{[l]} = \mathbf{a}_{s,:}^{[l-1]} \cdot \mathbf{w}_{h,:}^{[l]T} + b_h^{[l]}$$

$$z_{s,g}^{[l]} = z_{s,h}^{[l]}$$

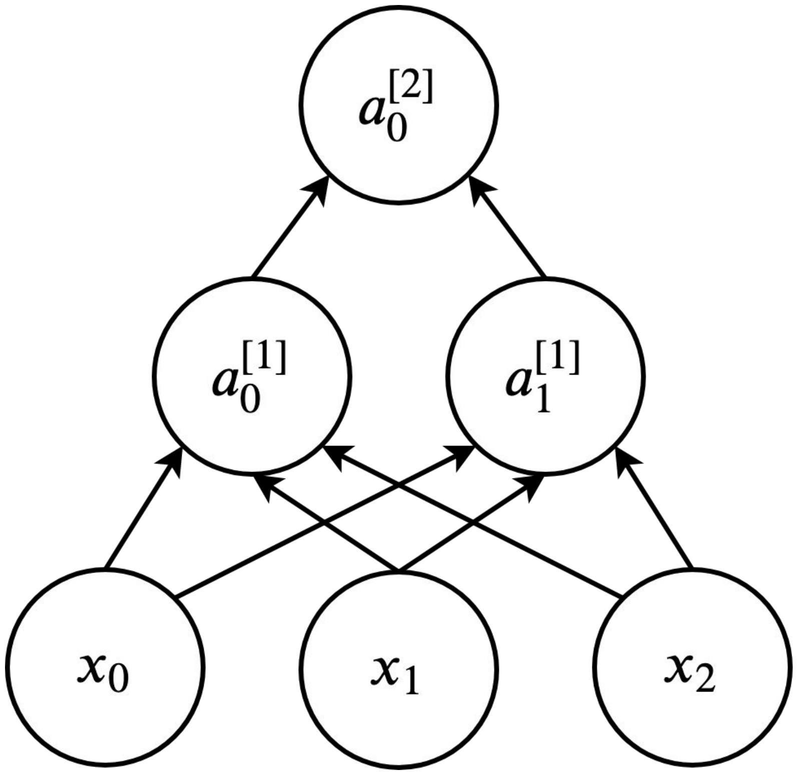
$$a_{s,g}^{[l]} = f(z_{s,g}^{[l]}) = f(z_{s,h}^{[l]}) = a_{s,h}^{[l]}$$

Parameter Initialization

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

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

$$\frac{\partial C_s}{\partial w_{g,n}^{[l]}} = \frac{\partial C_s}{\partial w_{h,n}^{[l]}}$$



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 discussion, and Keras implementations.

Parameter Initialization

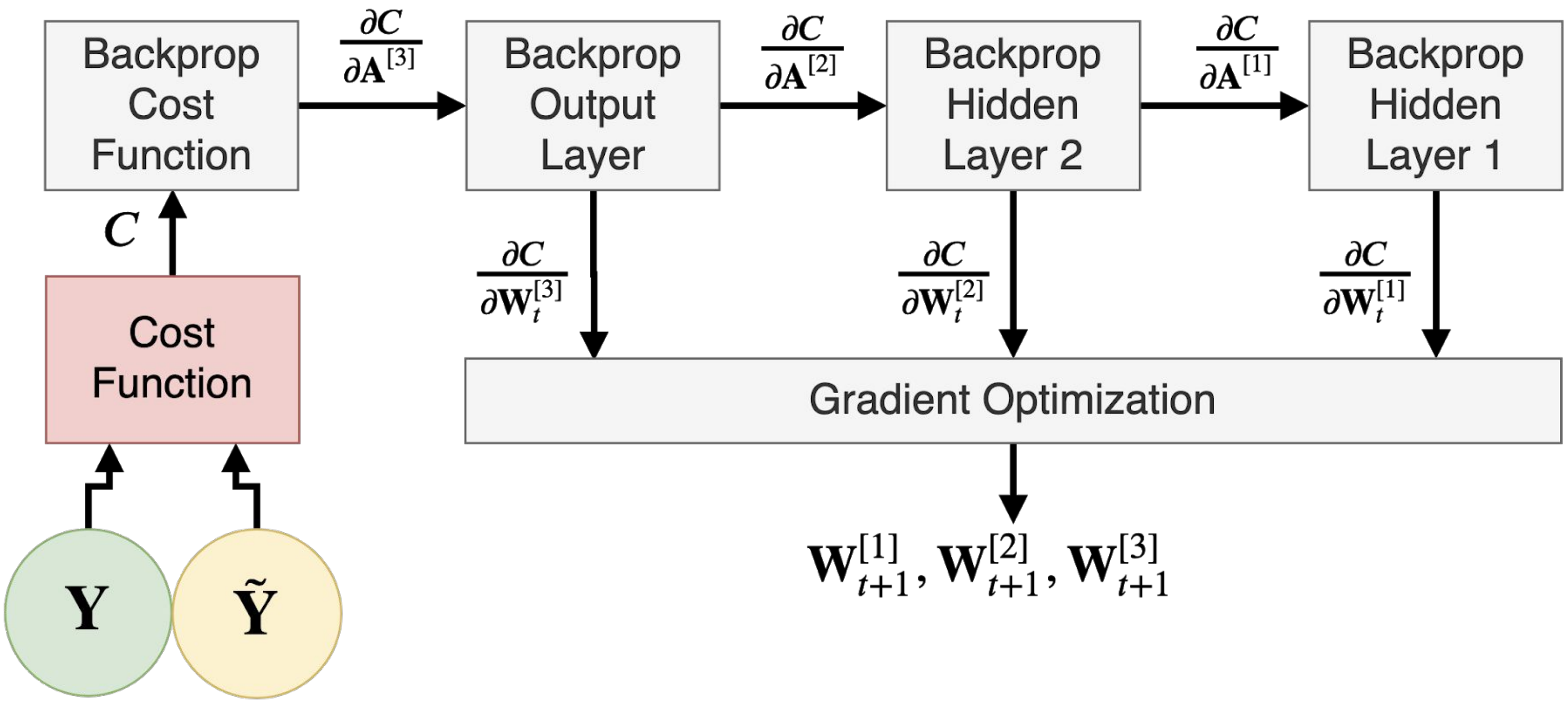
- He, K., Zhang, X., Ren, S., and Sun, J., (2015)
  - Makes variance of activation and gradient between layers similar
  - Derivation constraints the variance of the distribution, not its shape

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

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

See WeightInitialization.ipynb for discussion, and Keras implementations.

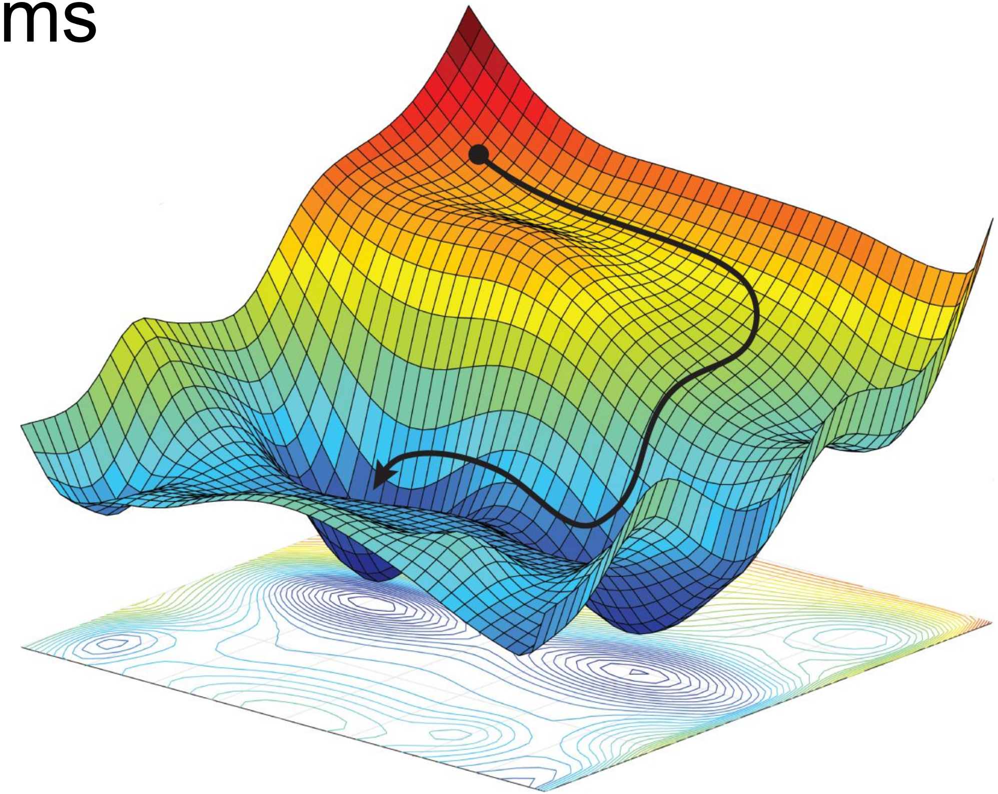
Back Propagation in Feedforward Architecture



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

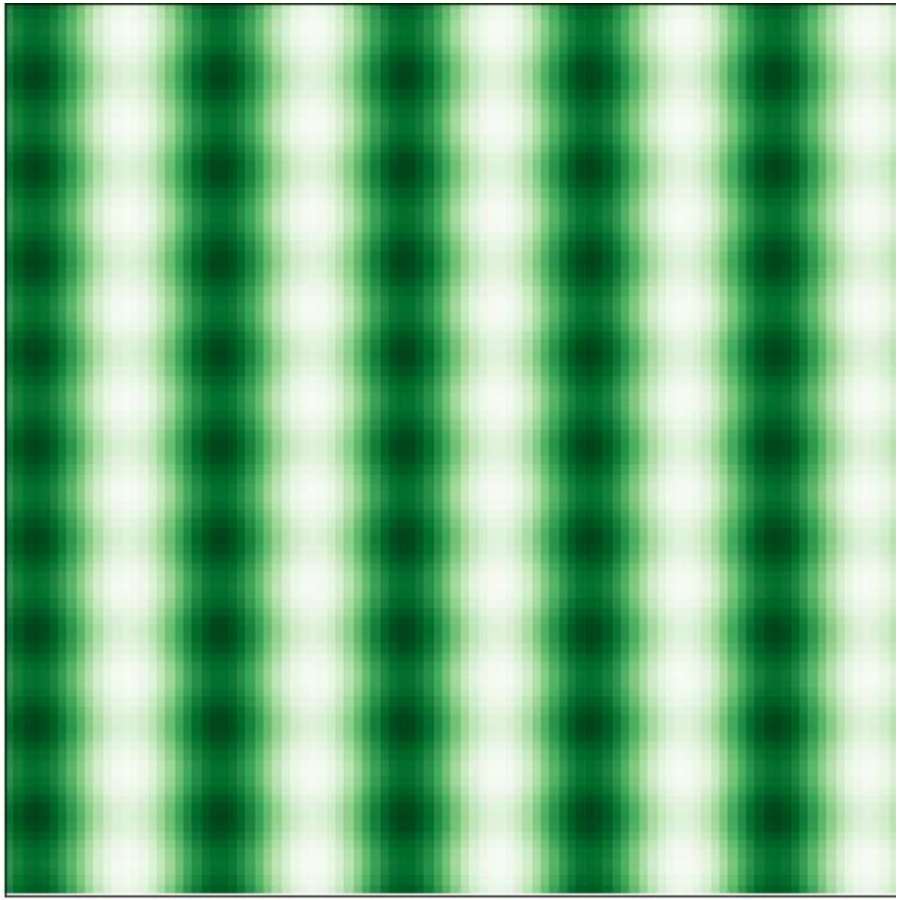
$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \nabla_{\mathbf{W}_t}$$

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

Three flavors:

- Stochastic (n = 1)
- Batch (n = N)
- **Mini-batch (1 < n < N)**

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

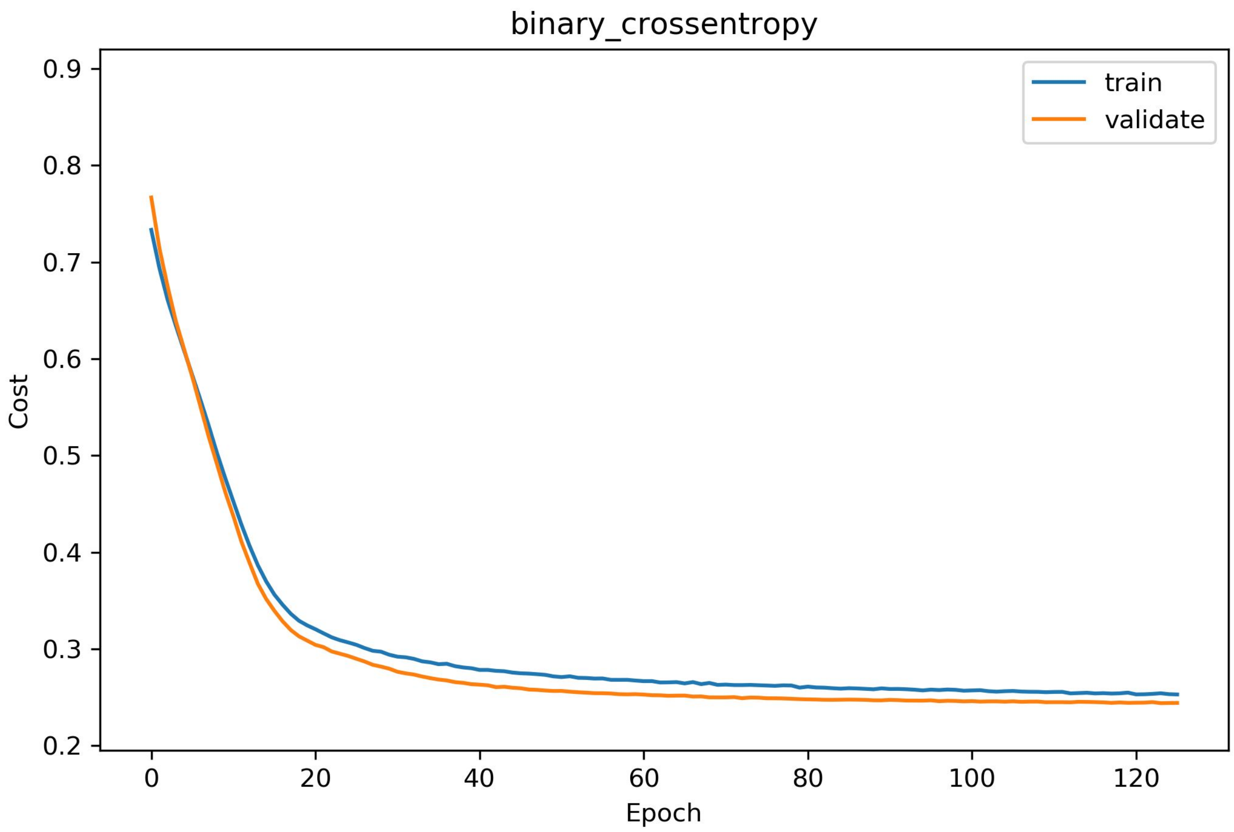


$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

Convergence of Learning Curve

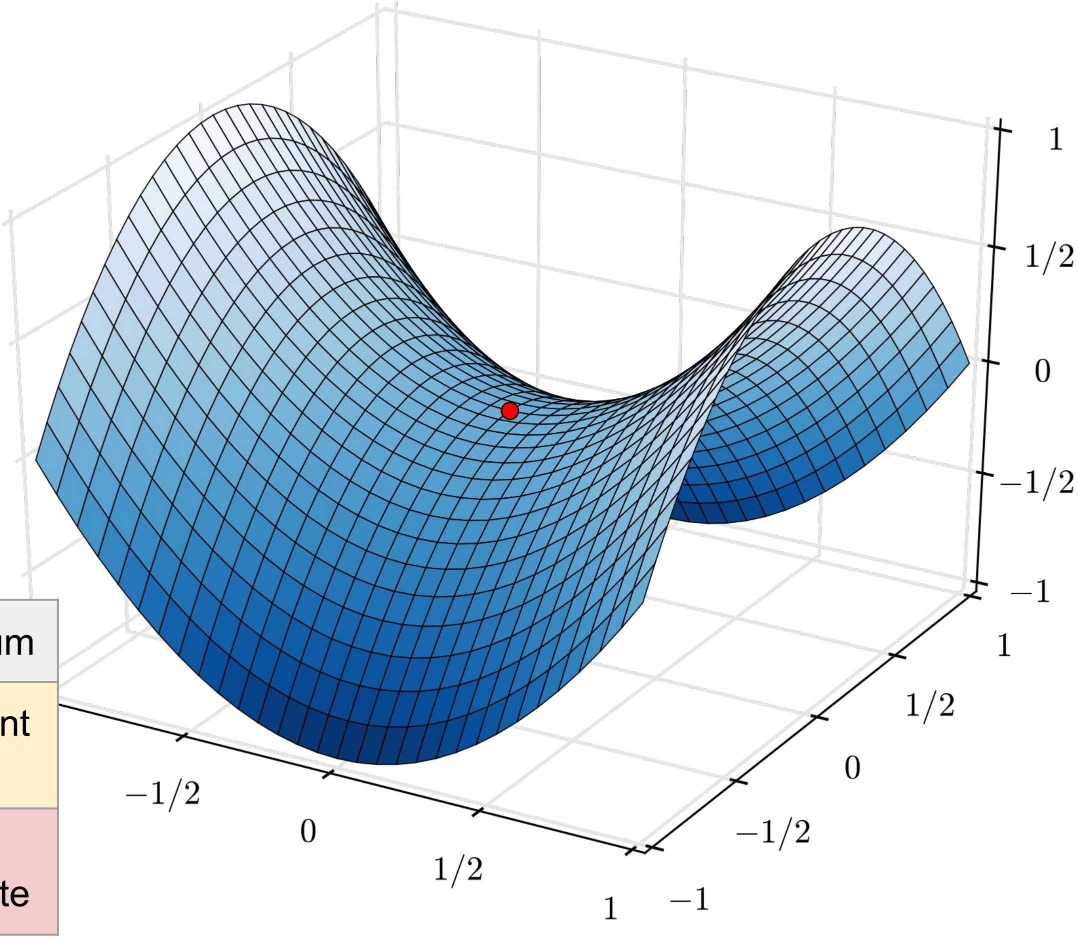
Typically, you want to continue training until it the training cost as a function of time converges.

But if the learning curve converges, did the model find its optimal parameters?



Saddle Point

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



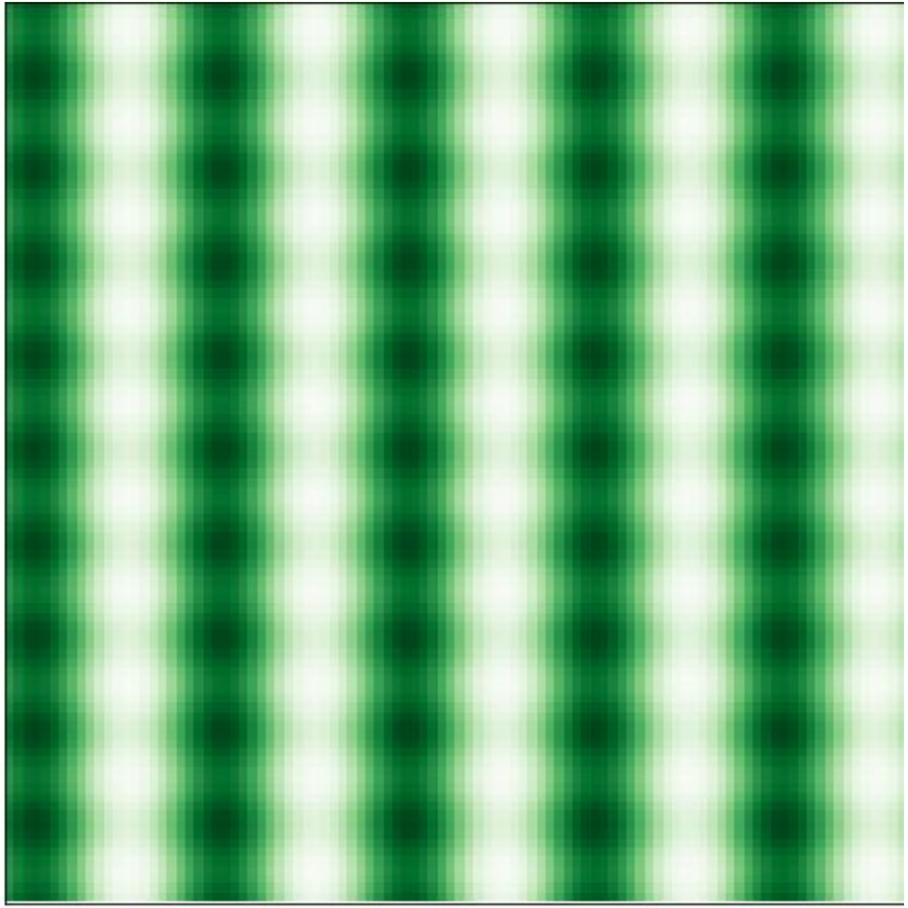
Dimension	X: minimum	X: maximum
Y: minimum	Local minimum	Saddle point
Y: maximum	Saddle point	Too high learning rate

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)



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

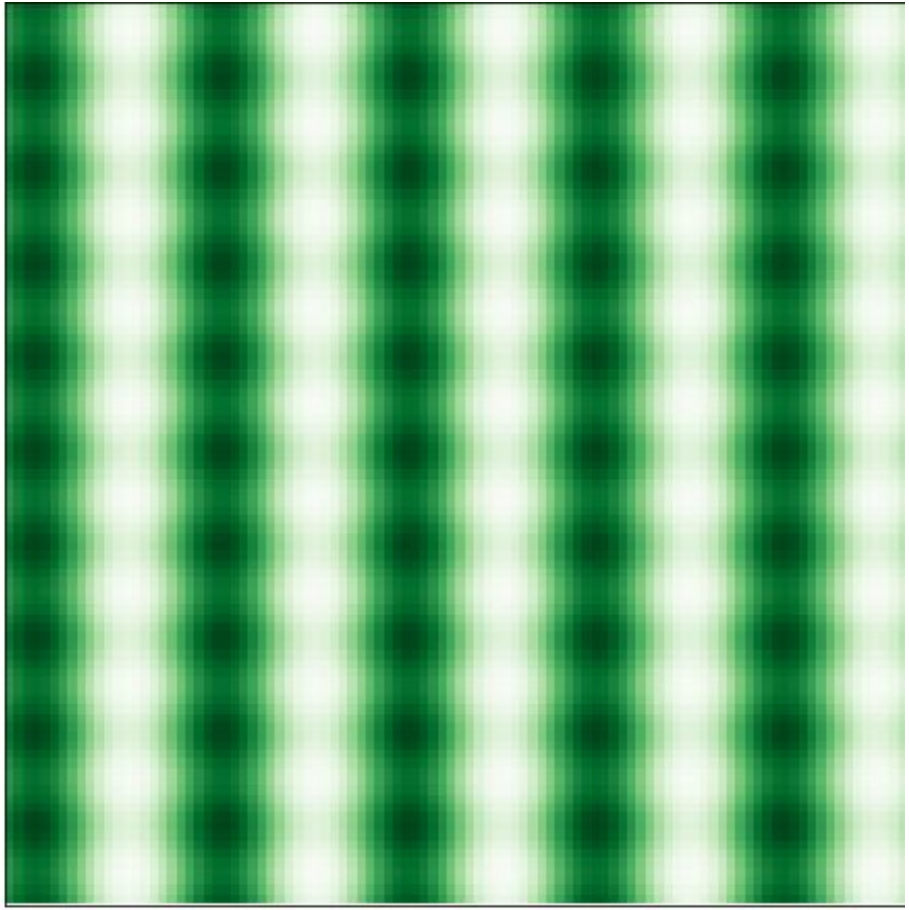
RMSprop

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

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

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

Unpublished work by Geoffrey Hinton.



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

Adam

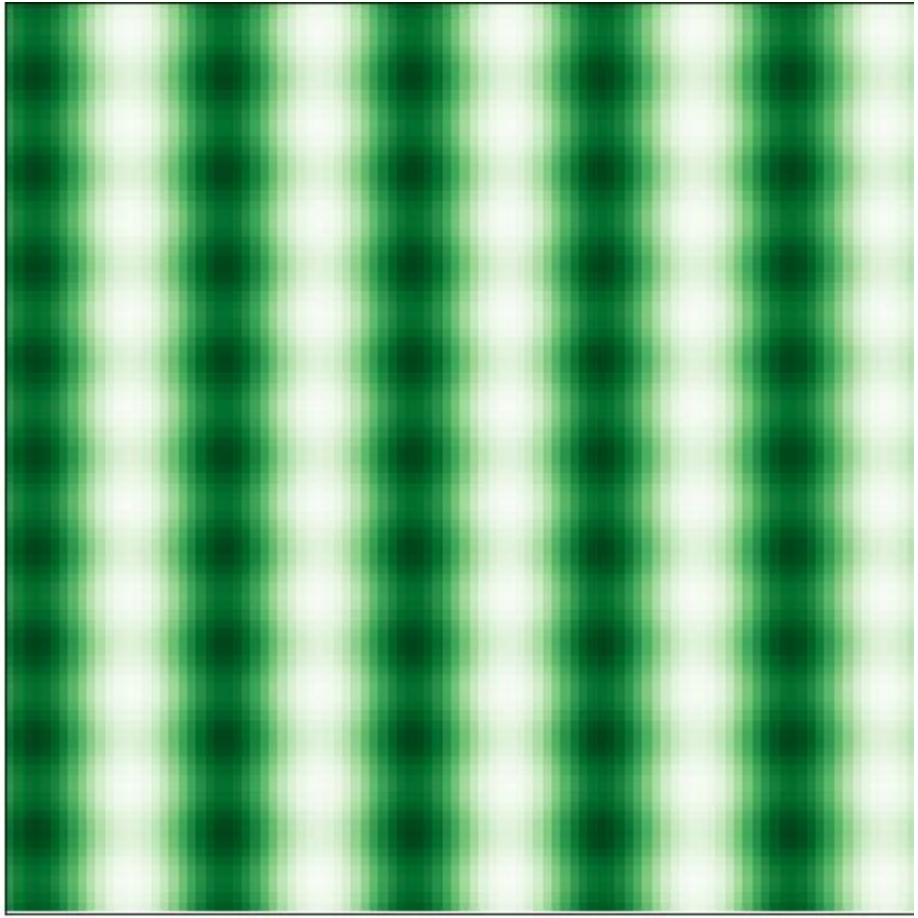
$$\mathbf{V}_{t+1} = \beta \mathbf{V}_t + (1-\beta)\nabla_{\mathbf{W}_t}$$

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

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

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

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



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

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

Learning is not Memorization

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

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

- No Free Lunch Theorem

Model Evaluation

Before you train anything, the dataset is split into:

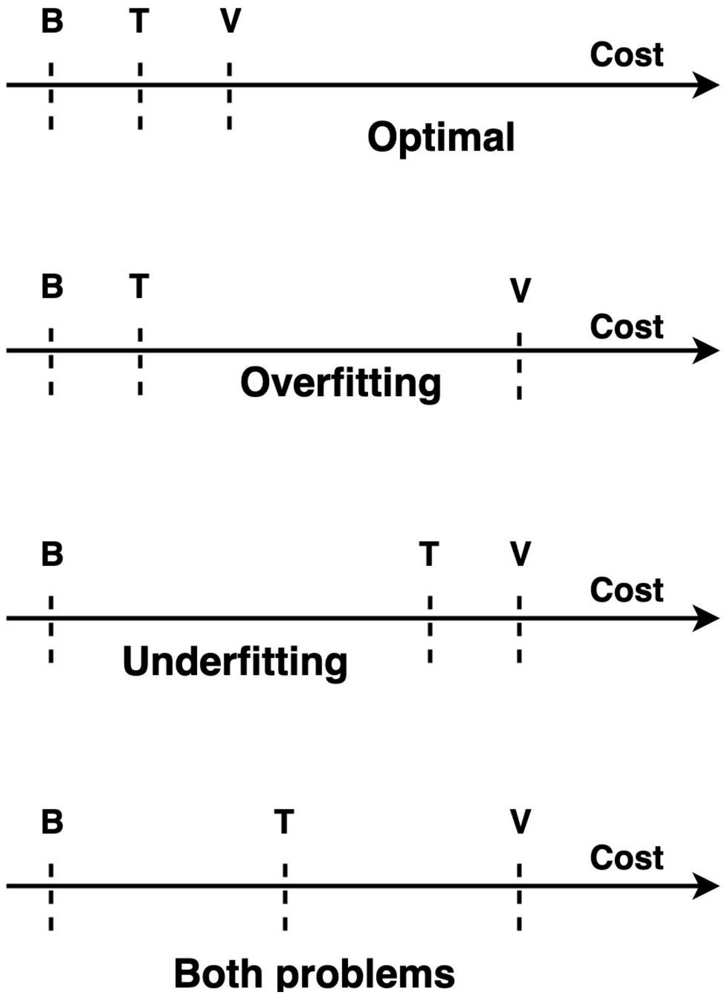
- Training dataset (~80%)
- Validation dataset (~10%)
- Testing dataset (~10%)

Why do we need three datasets?

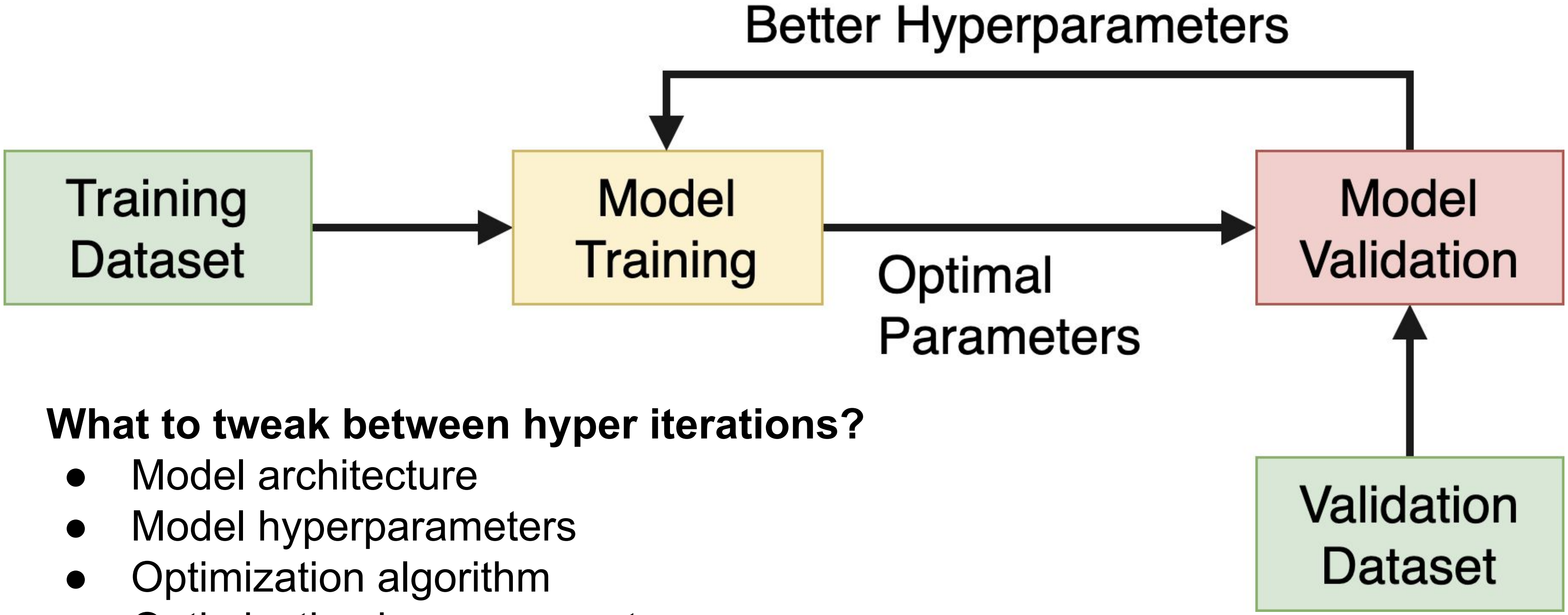
	Learn from...	Verify on...
Parameters	Training dataset	Validation dataset
Hyperparameters	Validation dataset	Testing dataset

Generalization Inference

Scenario	Suggestions
Optimal	Write a research paper
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 (except for the paper)



Hyper Training Iteration

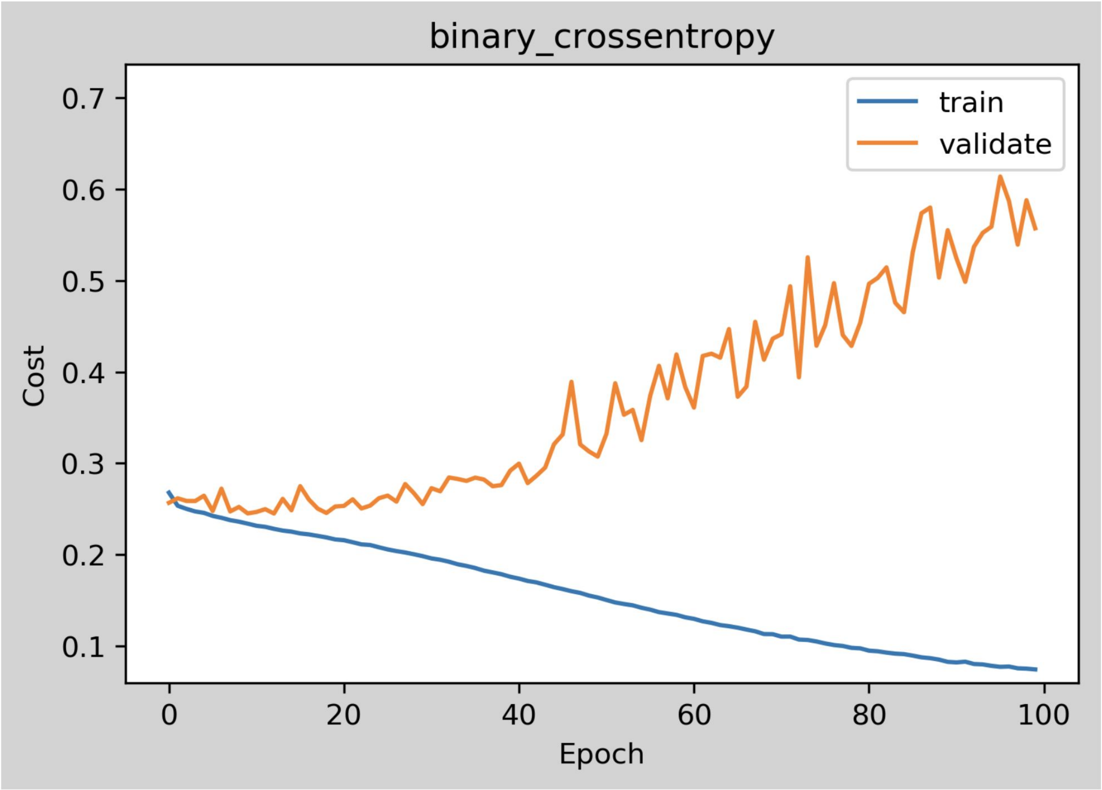


What to tweak between hyper iterations?

- 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.



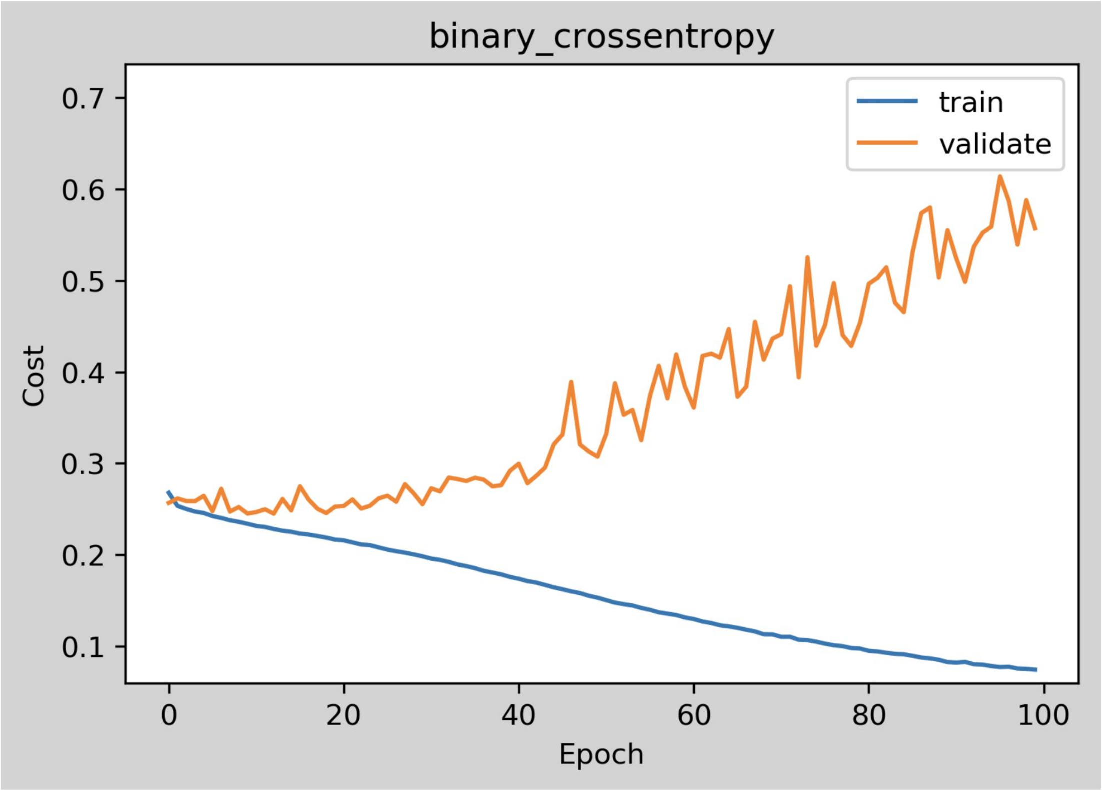
Regularization

Problem

Reduce overfitting via preference for simpler models.

Solutions

- L1 Norm
- L2 Norm



Regularization via Vector Norms

$$\mathrm{Cost}\Big(\mathbf{Y}, \hat{\mathbf{Y}}, \mathbf{W}\Big) = \text{Supervised Cost}(\mathbf{Y}, \hat{\mathbf{Y}}) + \alpha * \text{Regularization Cost}(\mathbf{W})$$

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

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

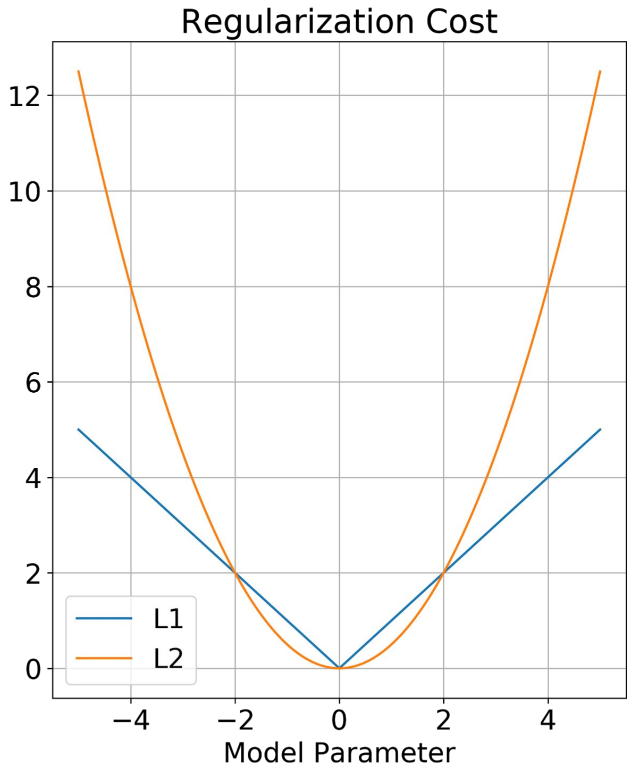
$$\mathrm{L}_2(\mathbf{W}) = \frac{1}{2} \sum_i^n w_i^2$$

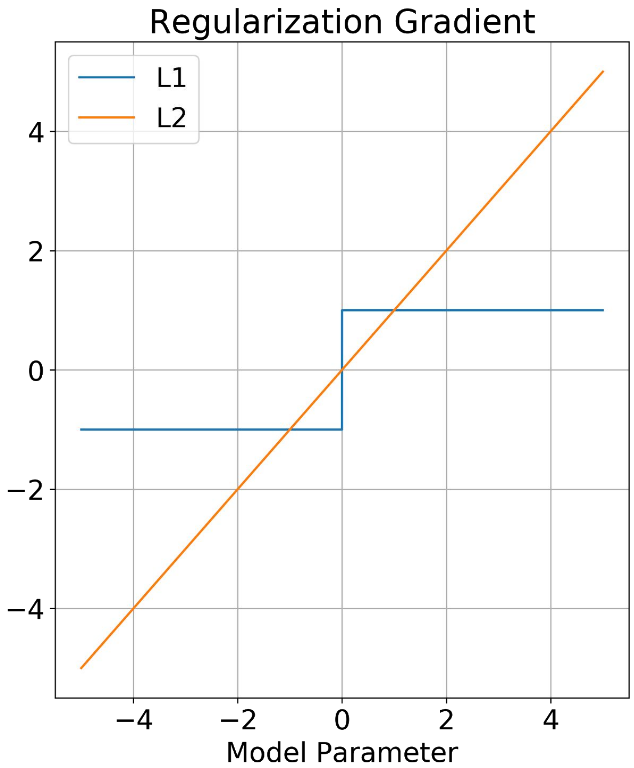
$$\frac{d\mathrm{L}_2}{dw_i} = w_i$$

Comparison of L1 and L2 Norms

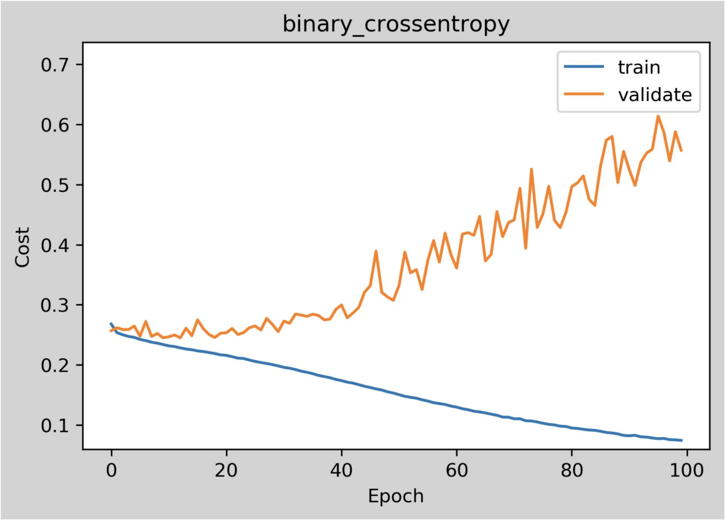
L1 is more likely to prefer a sparse parameter matrix.

L2 is more likely to remove extremely large parameters.

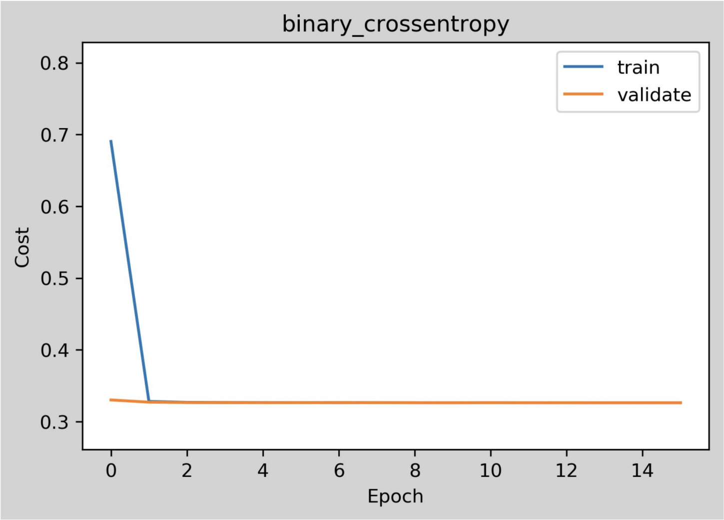




Effect of Regularization Cost

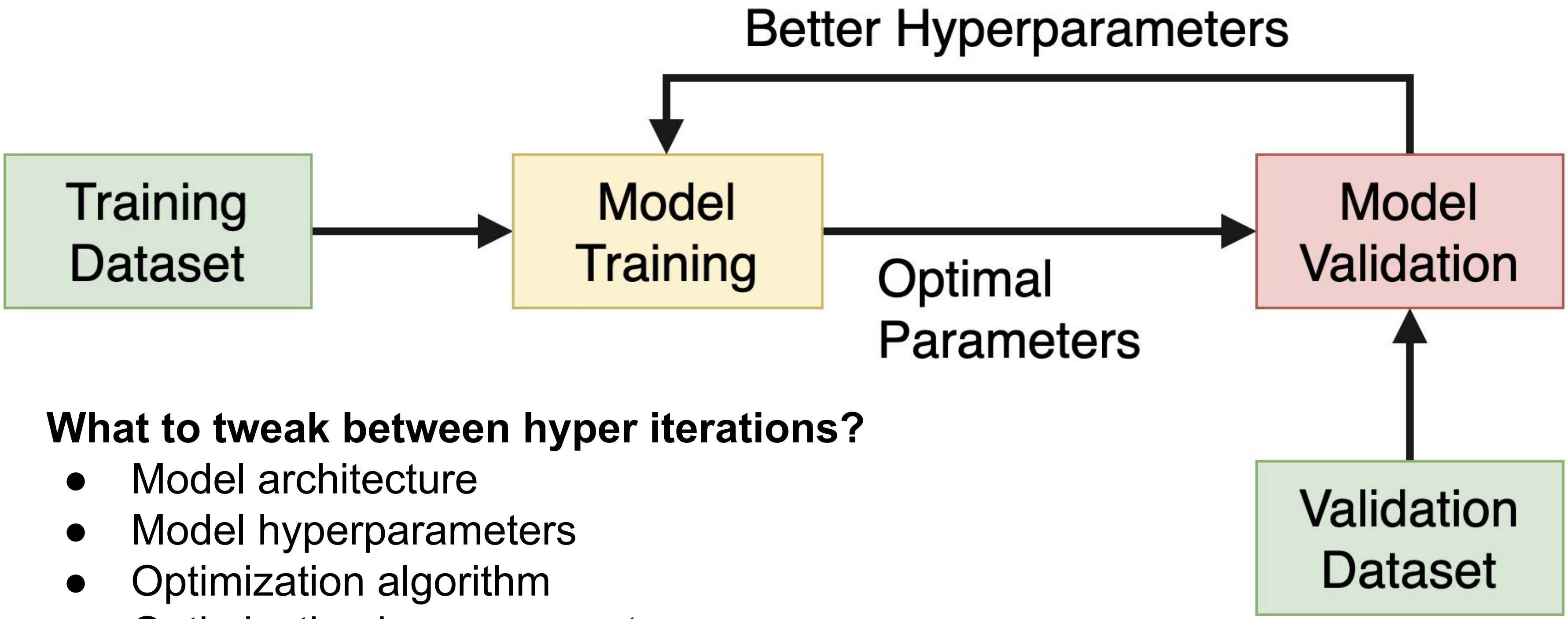


L2 Regularization Factor = 0.00



L2 Regularization Factor = 0.05

Hyper Training Iteration



What to tweak between hyper iterations?

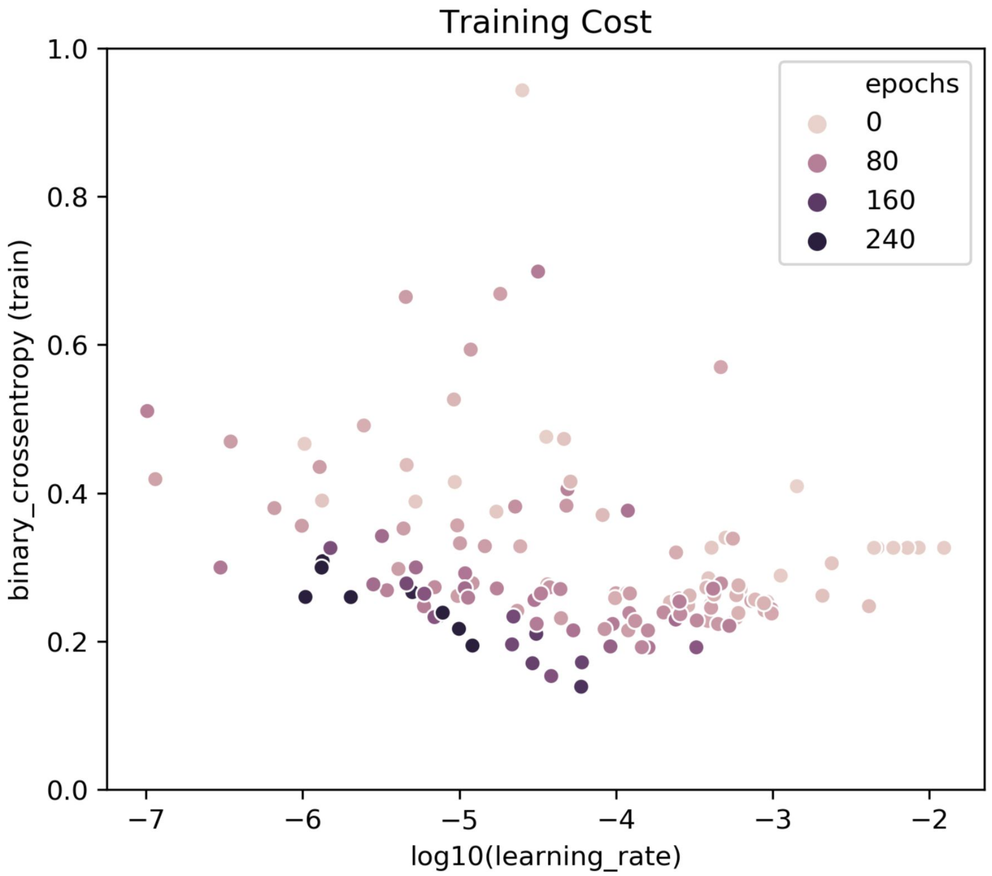
- Model architecture
- Model hyperparameters
- Optimization algorithm
- Optimization hyperparameters

Tuning Learning Rate

Sample from uniform distribution, but use exponential scale for ratios.

Narrow down after reviewing enough training jobs.

Some hyperparameters can be judged on partial dataset before learning curve convergences.

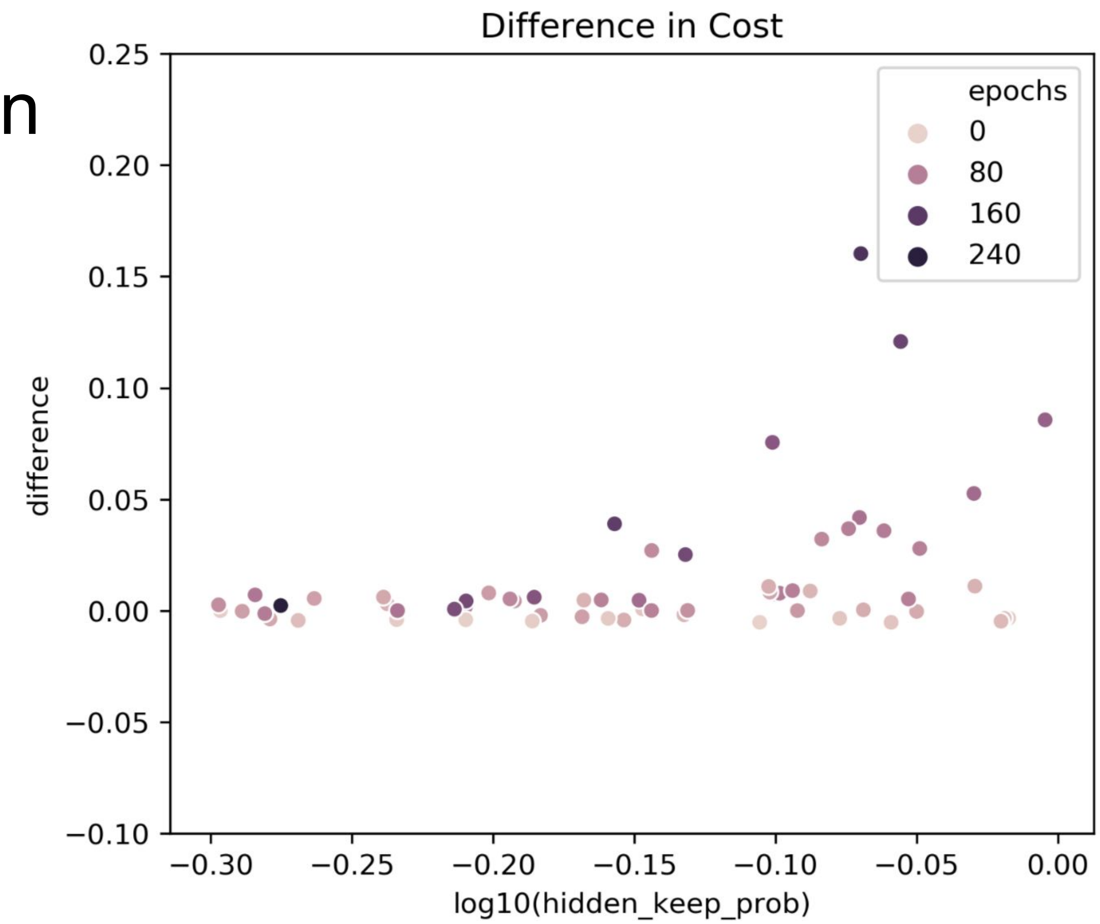


Tuning Regularization

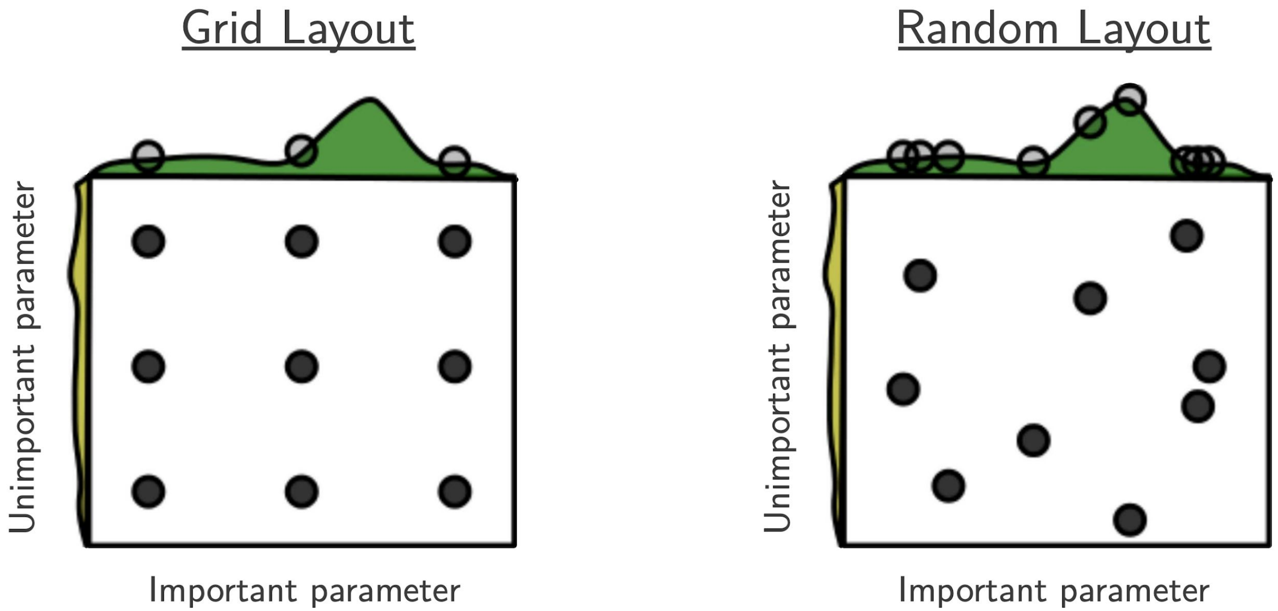
Regularization hyperparams need to be judged on the validation/training cost gap.

Plot the hyperparam vs the validation/training cost gap.

Identify maximum level of regularization that keeps the gap from exploding.

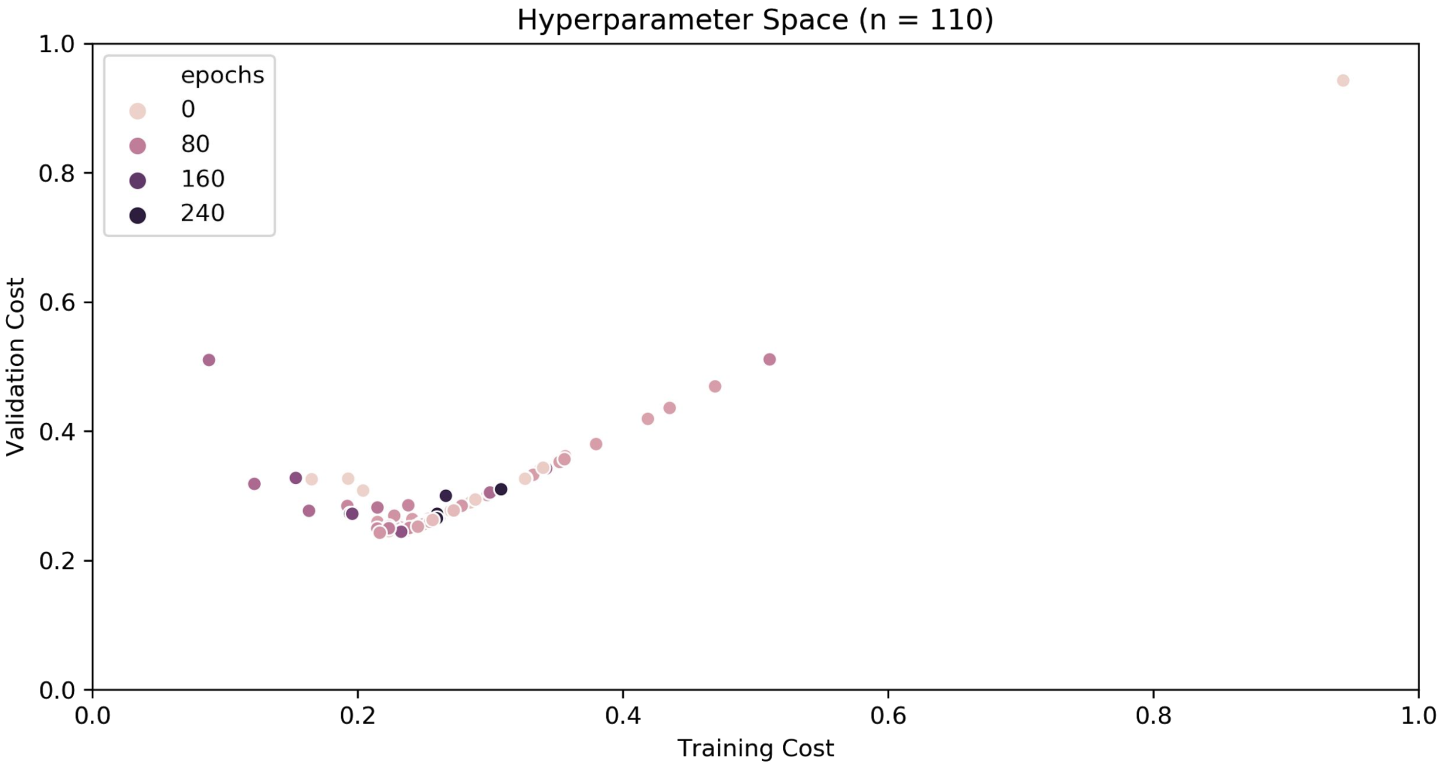


Grid Search vs Random Search

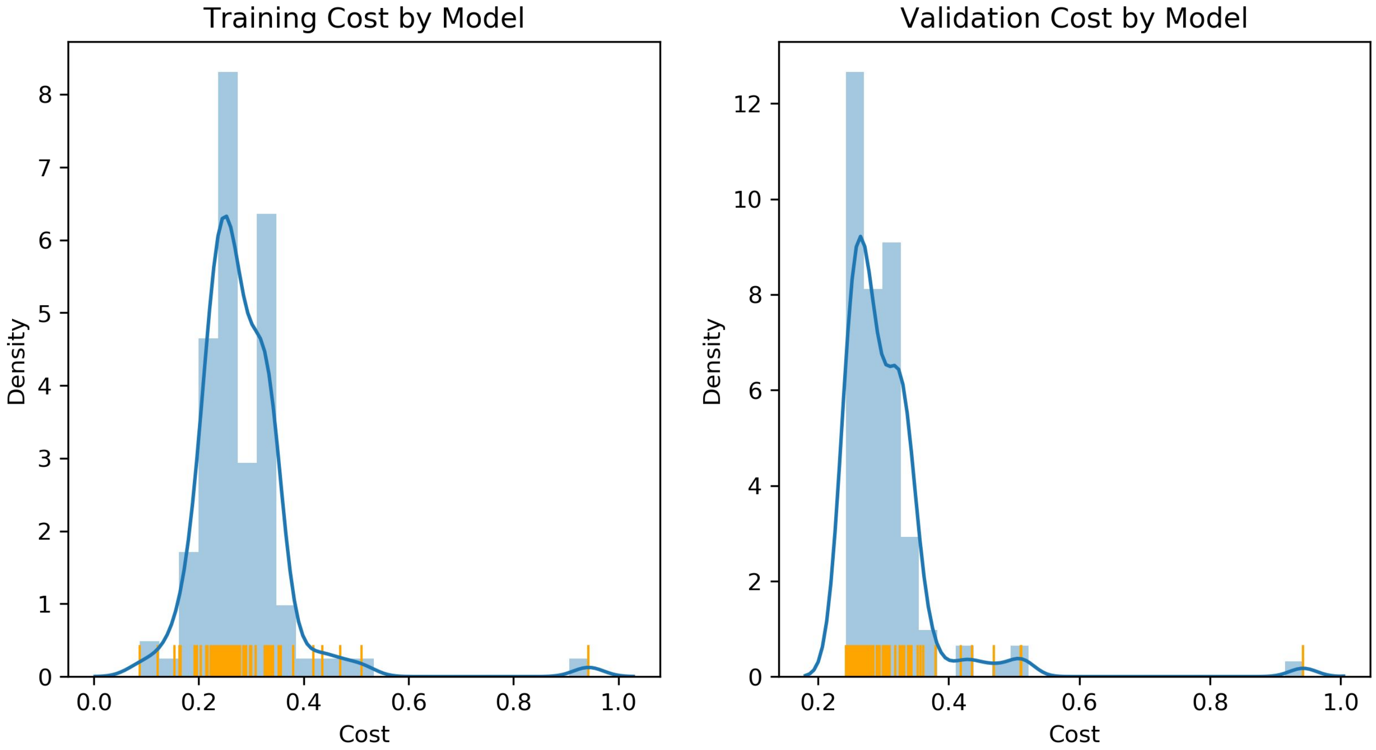


Source: Random Search for Hyper-Parameter Optimization (Bergstra, J. & Bengio, Y., 2012)

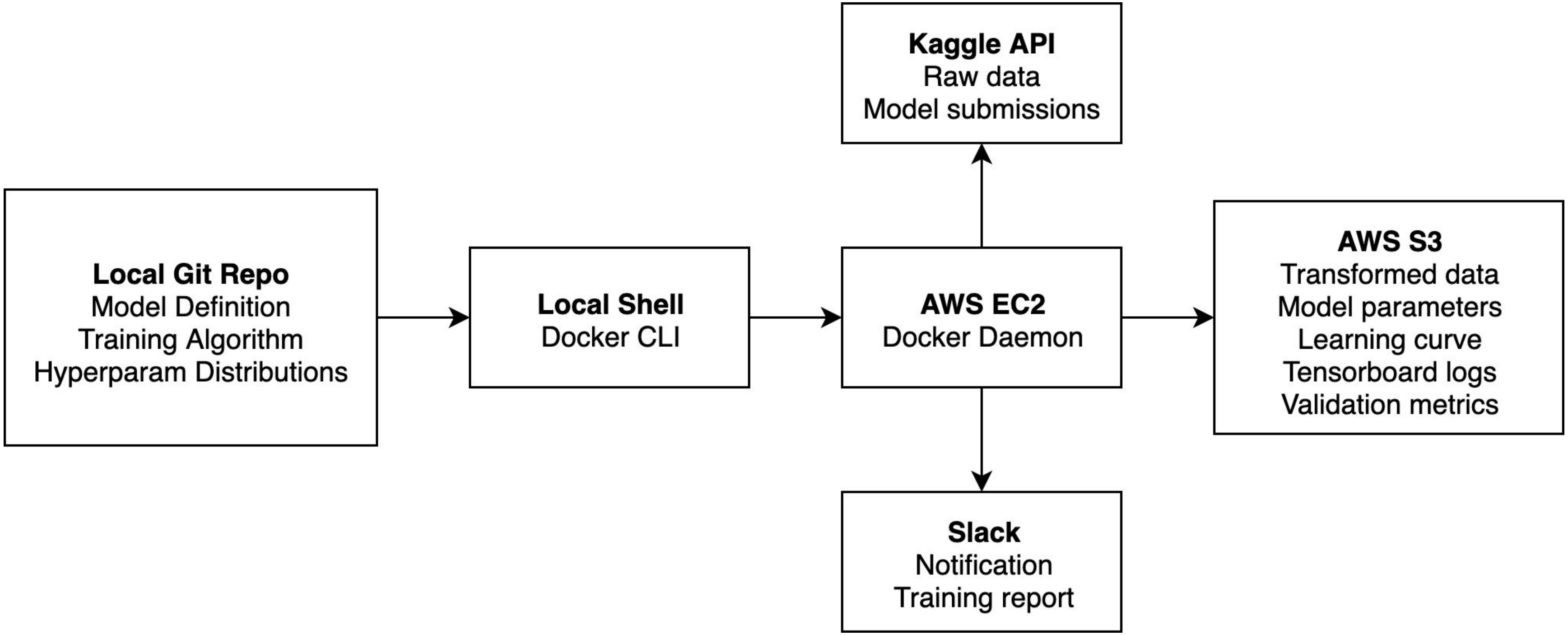
Exploring Hyperparam Space



Exploring Hyperparam Space



Cloud Infrastructure



TensorFlow / Keras

- 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
- Excellent community
  - http://playground.tensorflow.org

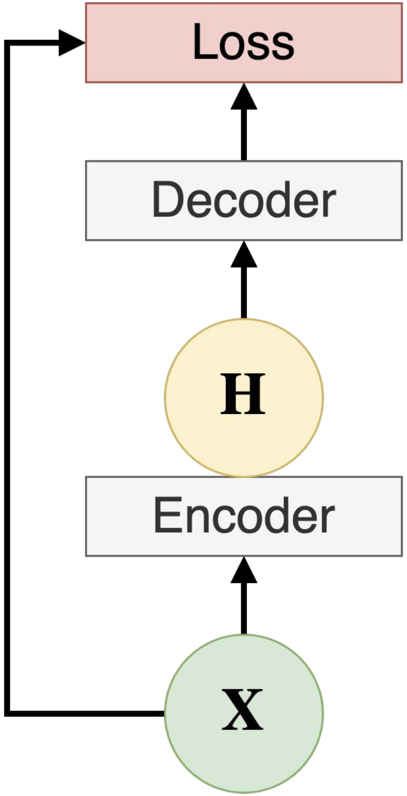
Part 2

Autoencoders

Autoencoders

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

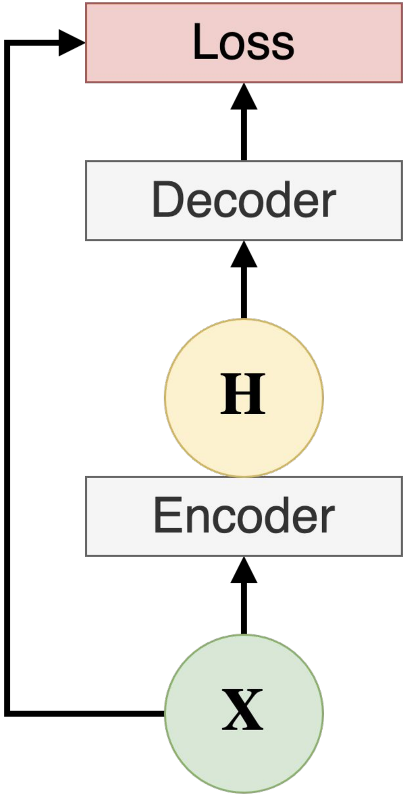
Solution
Train a network to reconstruct the input under various restrictions.



Undercomplete Autoencoders

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

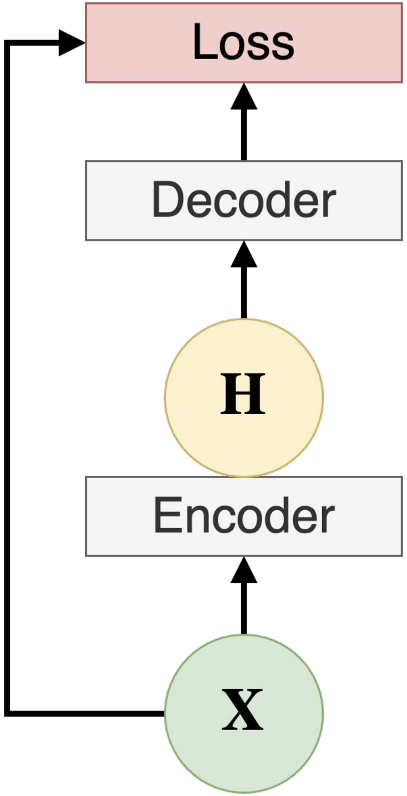
Solution
Reduce dimensionality of the latent representation.



Use Case: Dimensionality Reduction

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

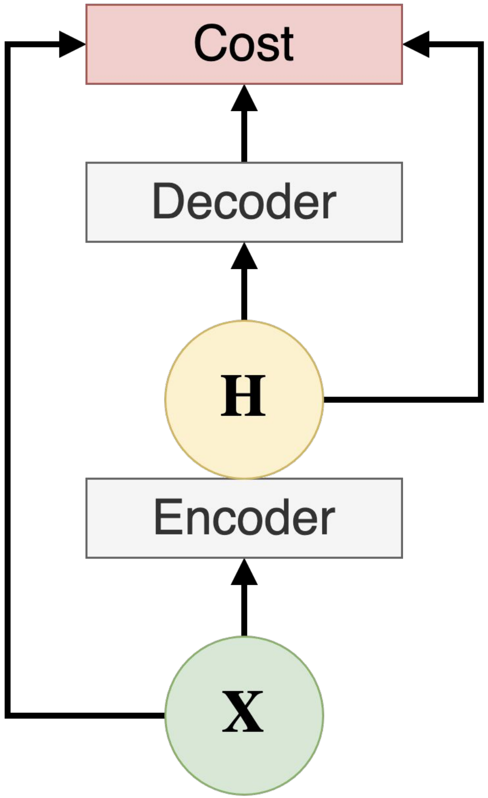
Solution
Use the latent representation of the data.



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.

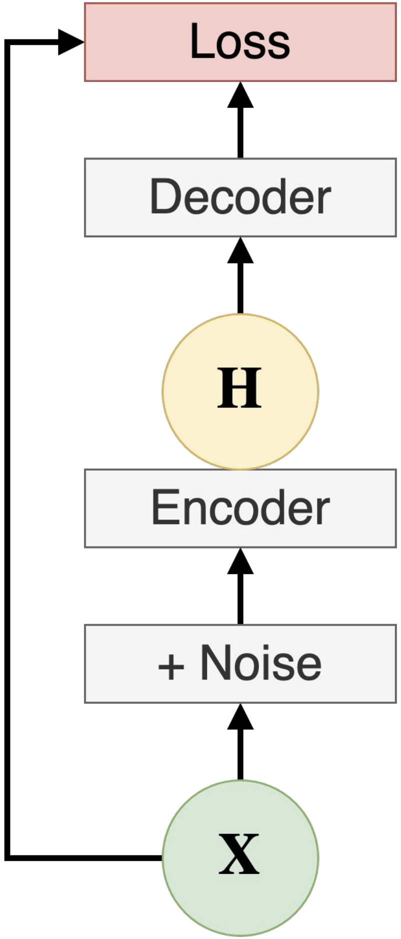


Denoising Autoencoders

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

Solution
Add random noise to the input, while optimizing MSE against the clean input.

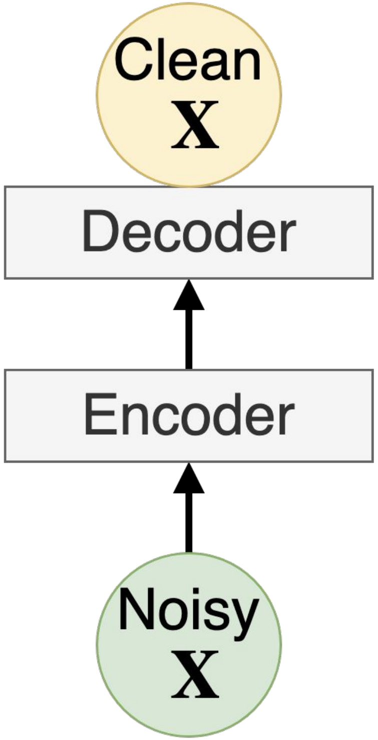
Vincent, P., et al. (2008)



Use Case: Image Denoising

Problem
Remove noise from the image without explicitly describing properties of the noise.

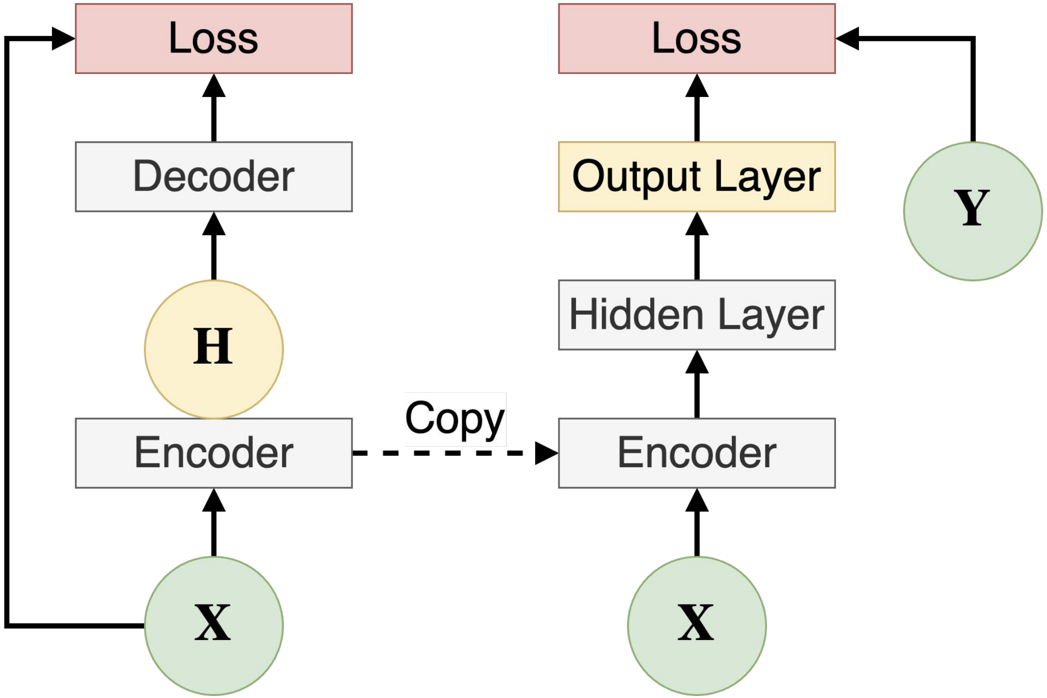
Solution
Feed a noisy image through an autoencoder, even if not trained on noisy data.



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.



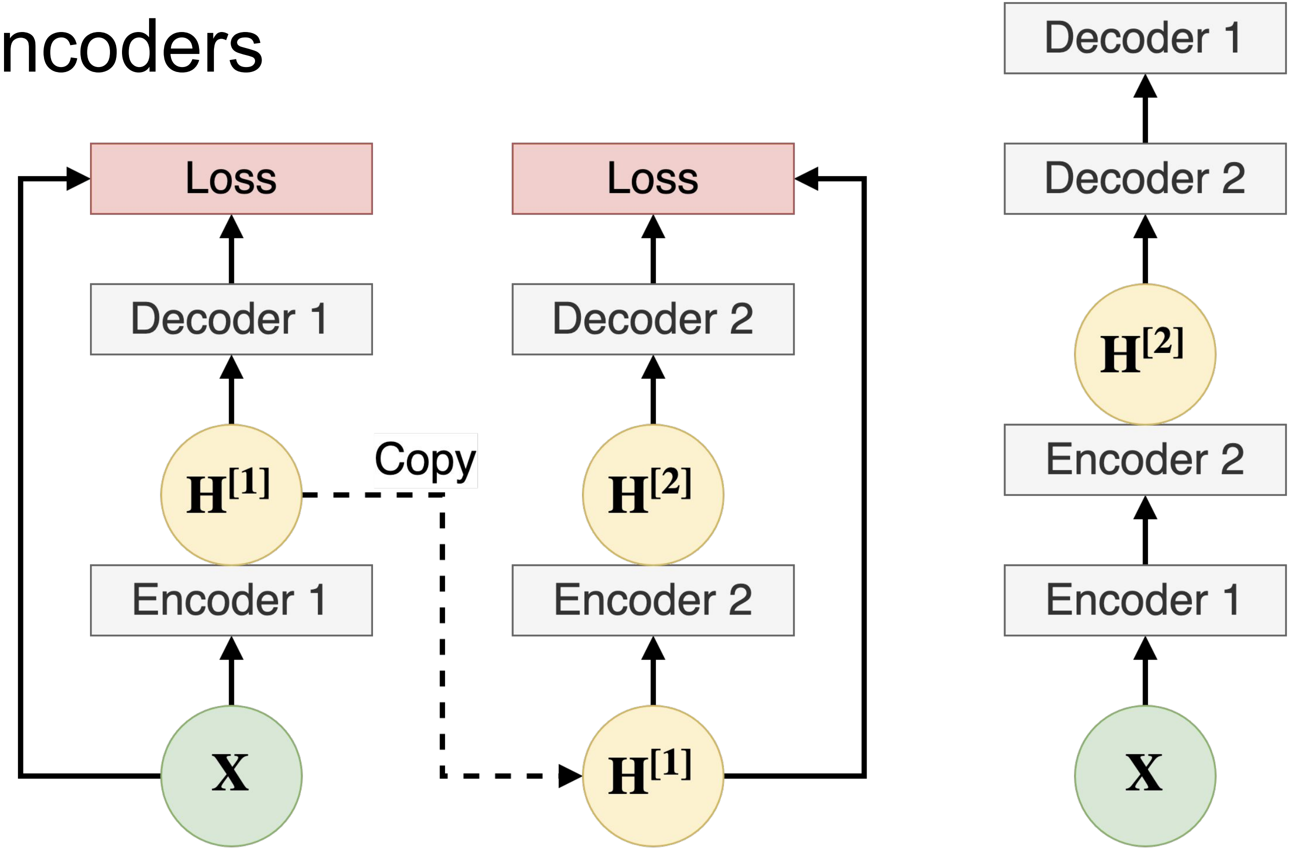
Bengio, Y., et al. (2007)

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

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Initialize a network with parameters that are better than random.

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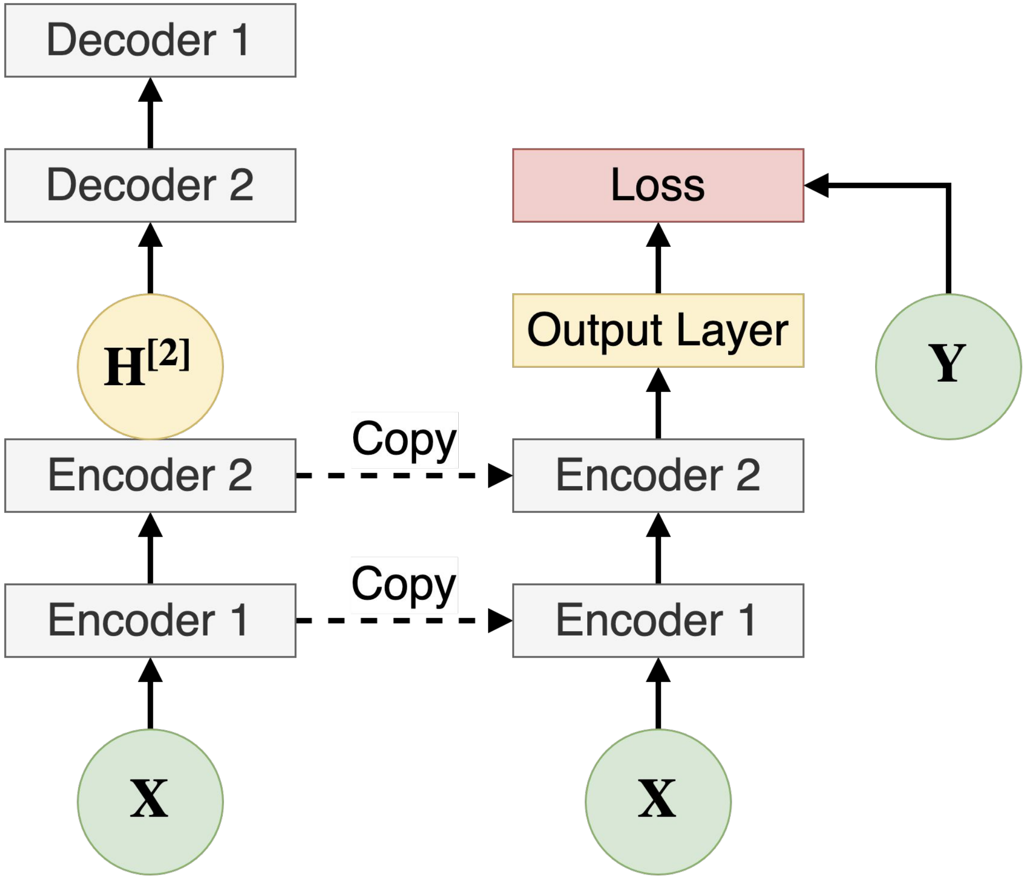
Use pre-trained stacked encoder layers as the bottom of the network.



Bengio, Y., et al. (2007)

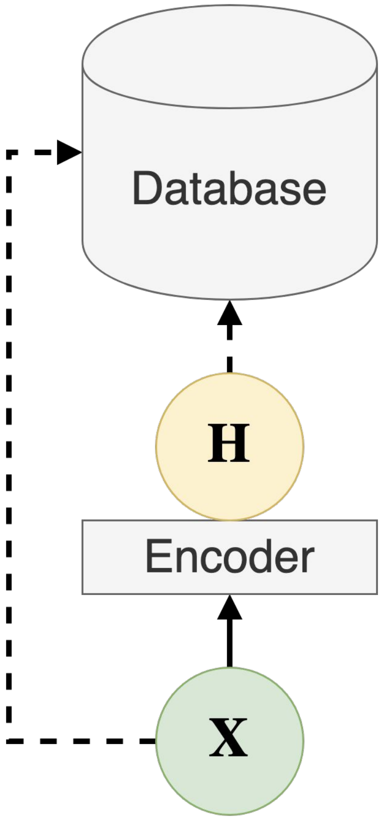
Use Case: Semantic Hashing

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)

Step 1: Store Records



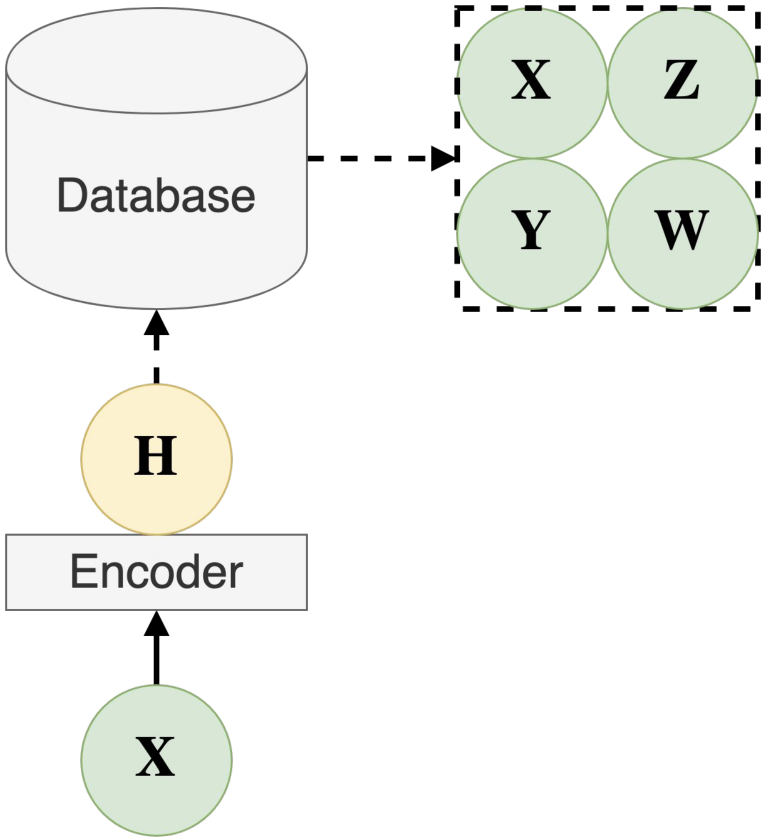
Use Case: Semantic Hashing

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)

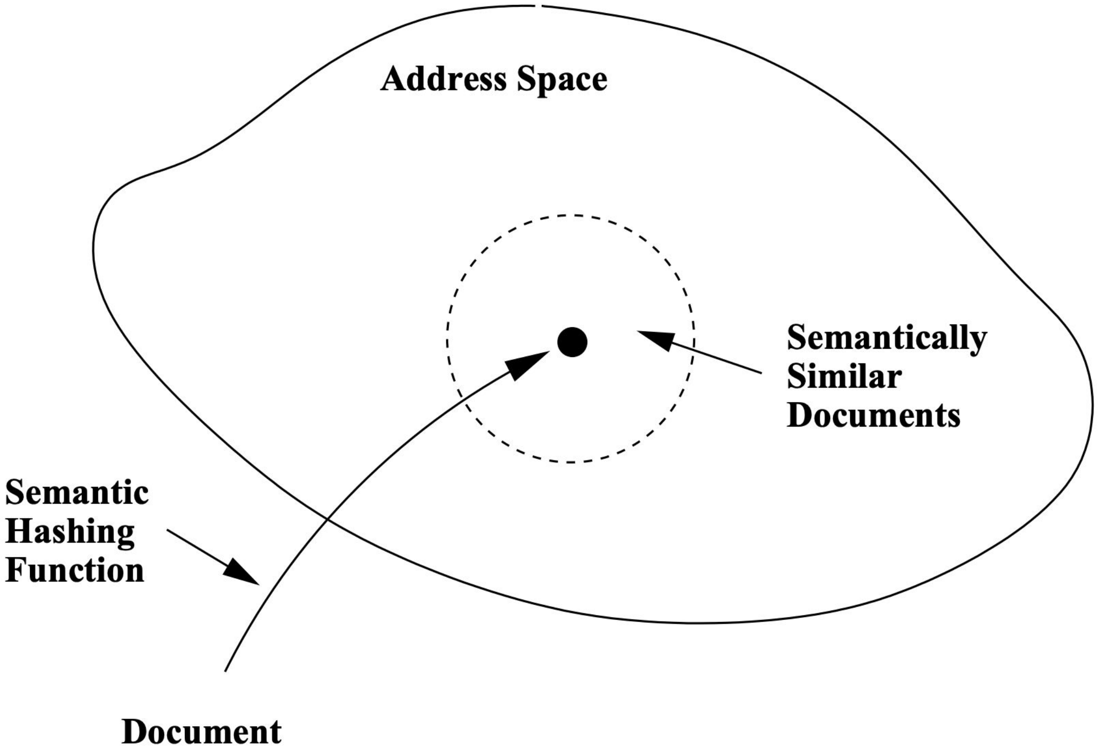
Step 2: Retrieve Records



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.



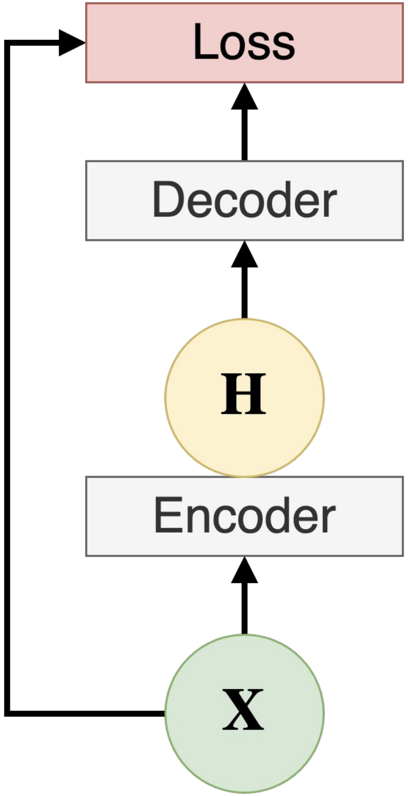
Salakhutdinov, R., and Hinton, G. (2007)

Use Case:
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.

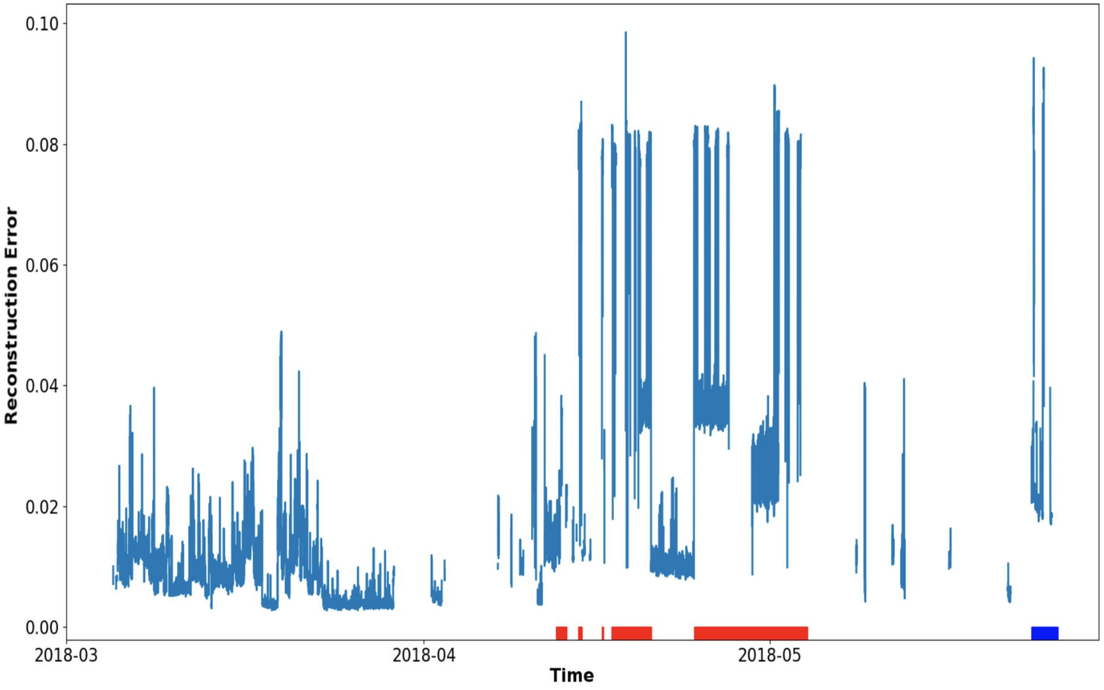
Borghesi, A., et al. (2018)



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.

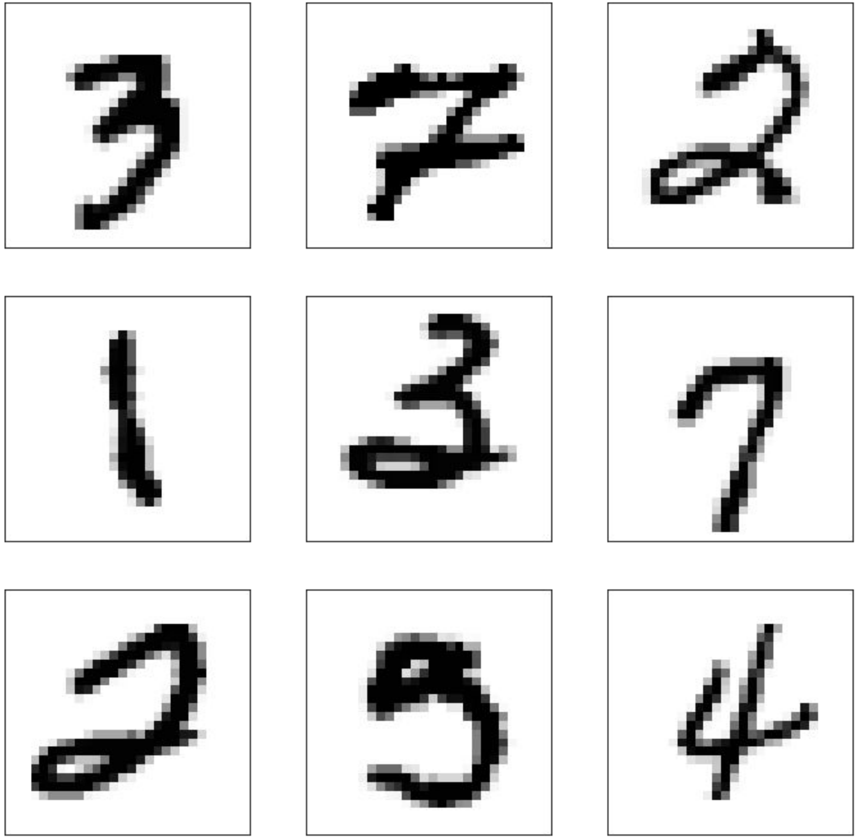


Borghesi, A., et al. (2018)

Case Study: MNIST

- Dataset
  - 70K images of handwritten digits
  - Each image is 28 x 28 in [0, 1] (grayscale)
  - Augmented with Normal(0, 0.1)

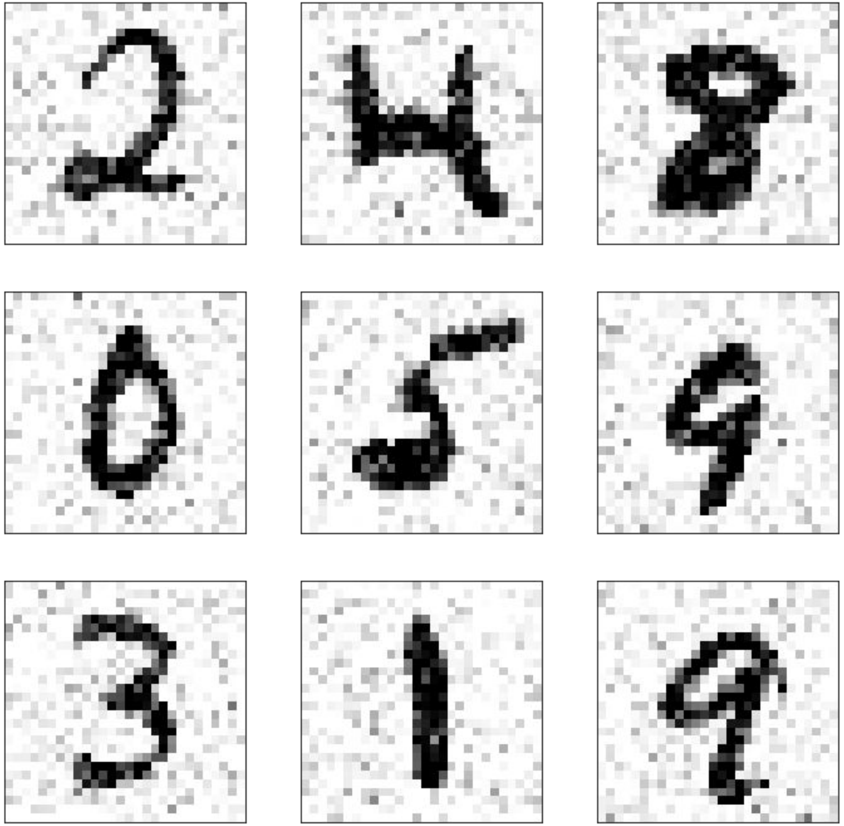
- Denoising Task
  - Remove noise from the images
  - Scored with MSE against original images



Gaussian Noise

- Dataset
  - 70K images of handwritten digits
  - Each image is 28 x 28 in [0, 1] (grayscale)
  - Augmented with Normal(0, 0.1)

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



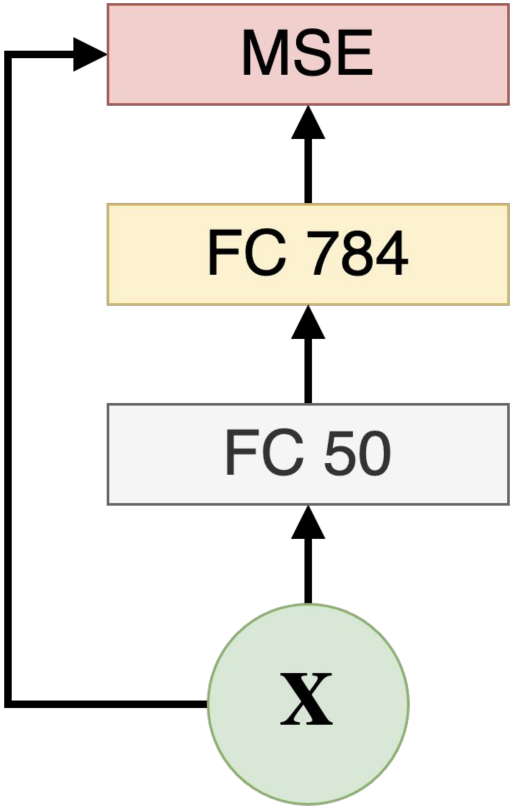
Model: Training

Undercomplete Autoencoder

Encoding Width
50 nodes

Encoder Depth
1 layer

Activation
ELU



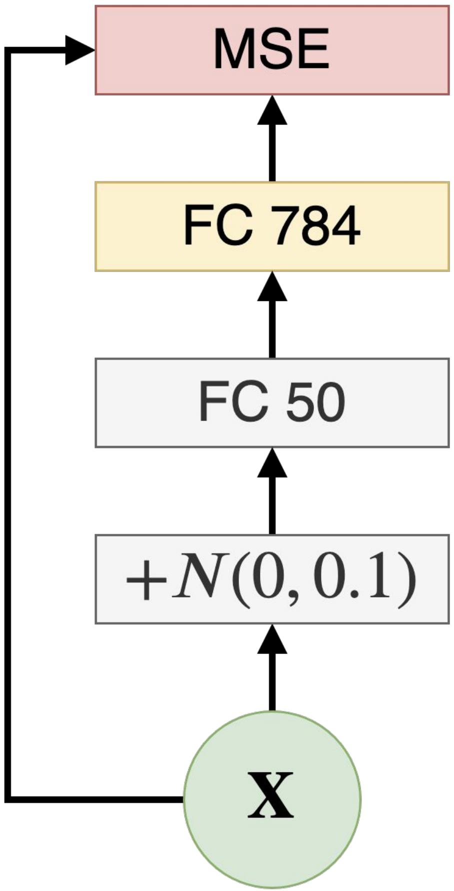
Model: Testing

Undercomplete Autoencoder

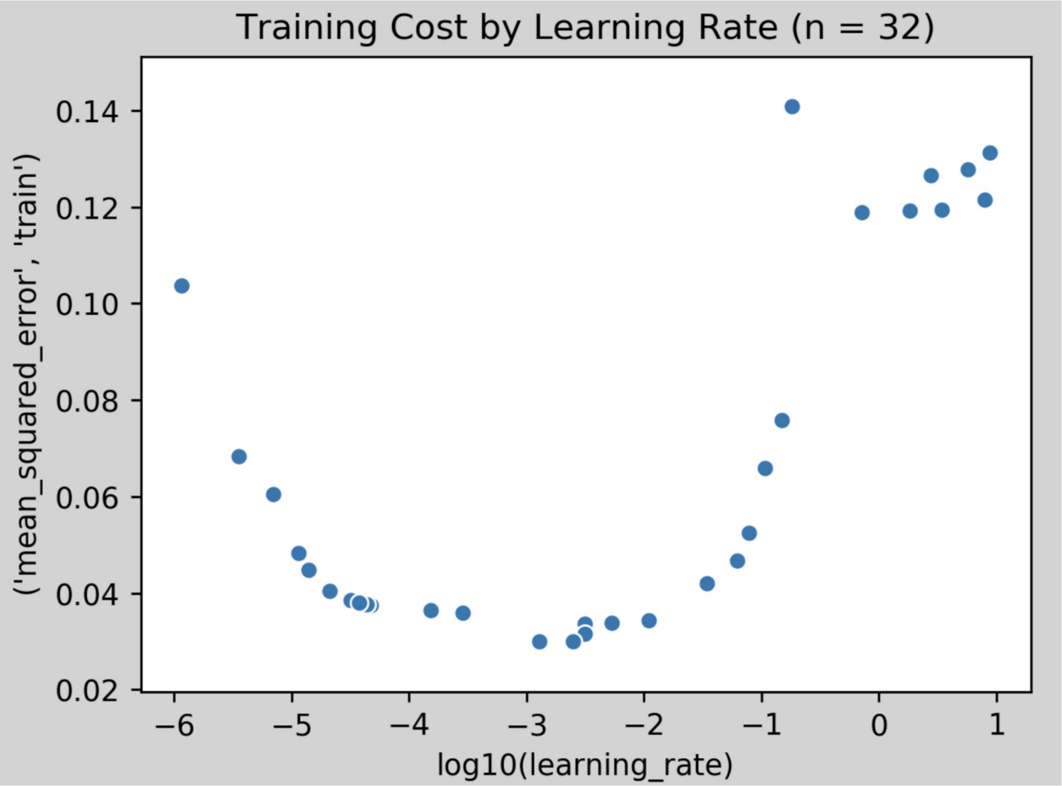
Encoding Width
50 nodes

Encoder Depth
1 layer

Activation
ELU



Hyperparam Search: Learning Rate



Iteration

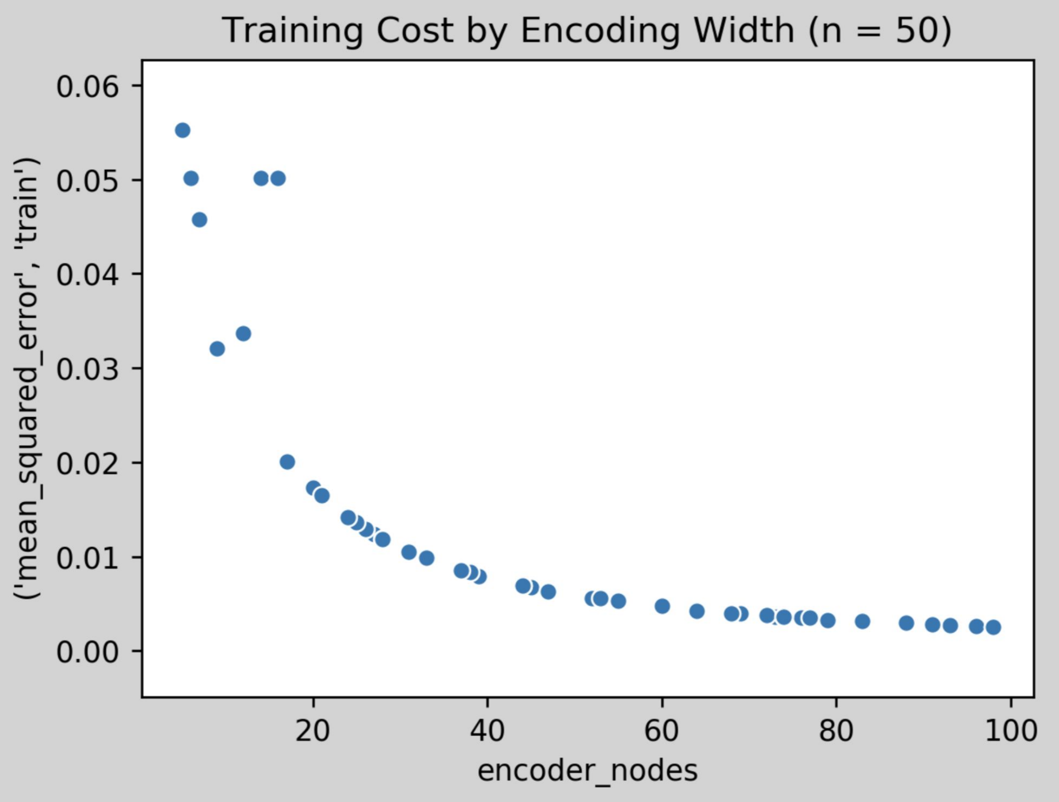
1. t ~ Uniform(-6, 1)
2. Learning Rate = 10 ** t
3. Train for 20 epochs

Repeat to train 32 models

Inference

Optimal initial learning rate of 10 ** -3

Hyperparam Search: Encoding Width



Iteration

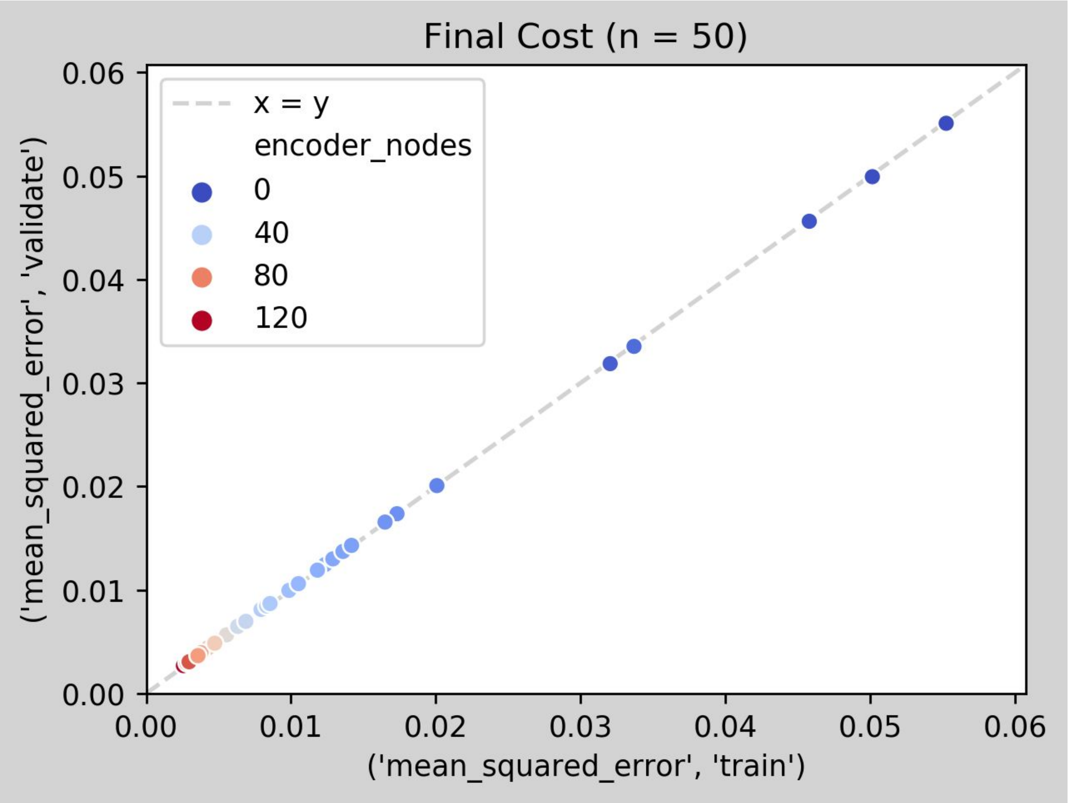
1. Nodes ~ Uniform(5, 100)
2. Train for 20 epochs

Repeat to train 32 models

Inference

Higher encoding dimensionality lowers reconstruction loss, but levels out at 60 nodes.

Hyperparam Search: Encoding Width



Iteration

1. Nodes ~ Uniform(5, 100)
2. Train for 20 epochs

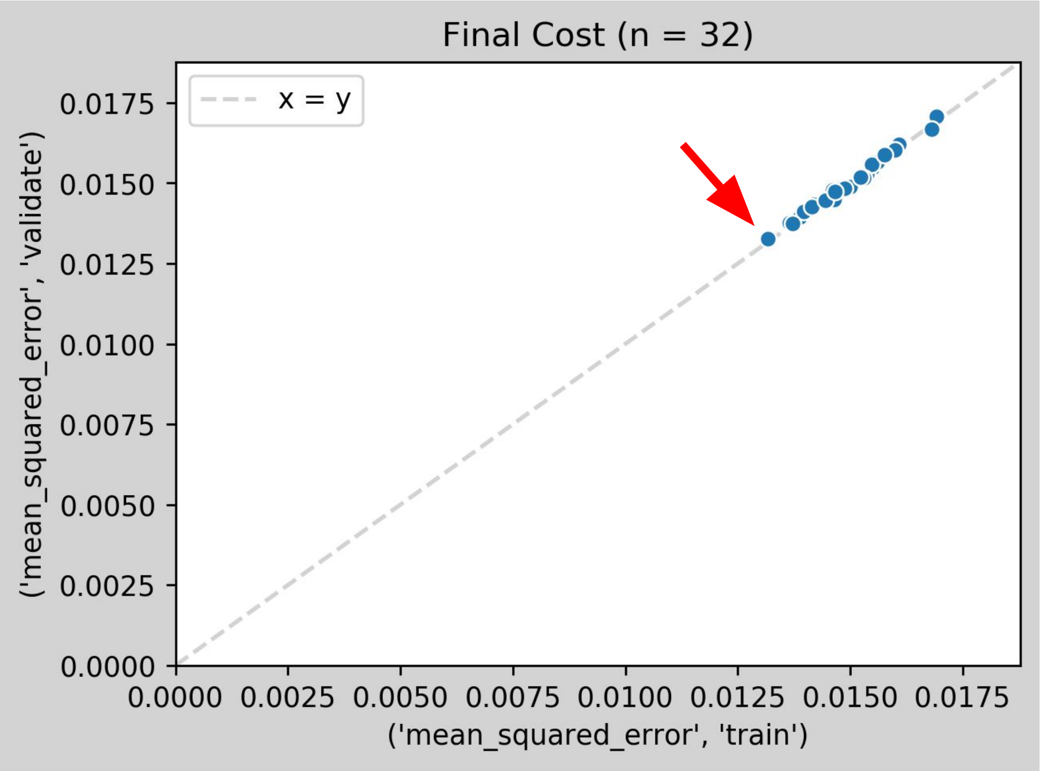
Repeat to train 32 models

Inference

Higher encoding dimensionality lowers reconstruction loss.

No overfitting under 100 nodes.

Hyperparam Search: Weight Initialization



Iteration

1. Pick random seed
2. Weights ~ Glorot Uniform
3. Train for 20 epochs

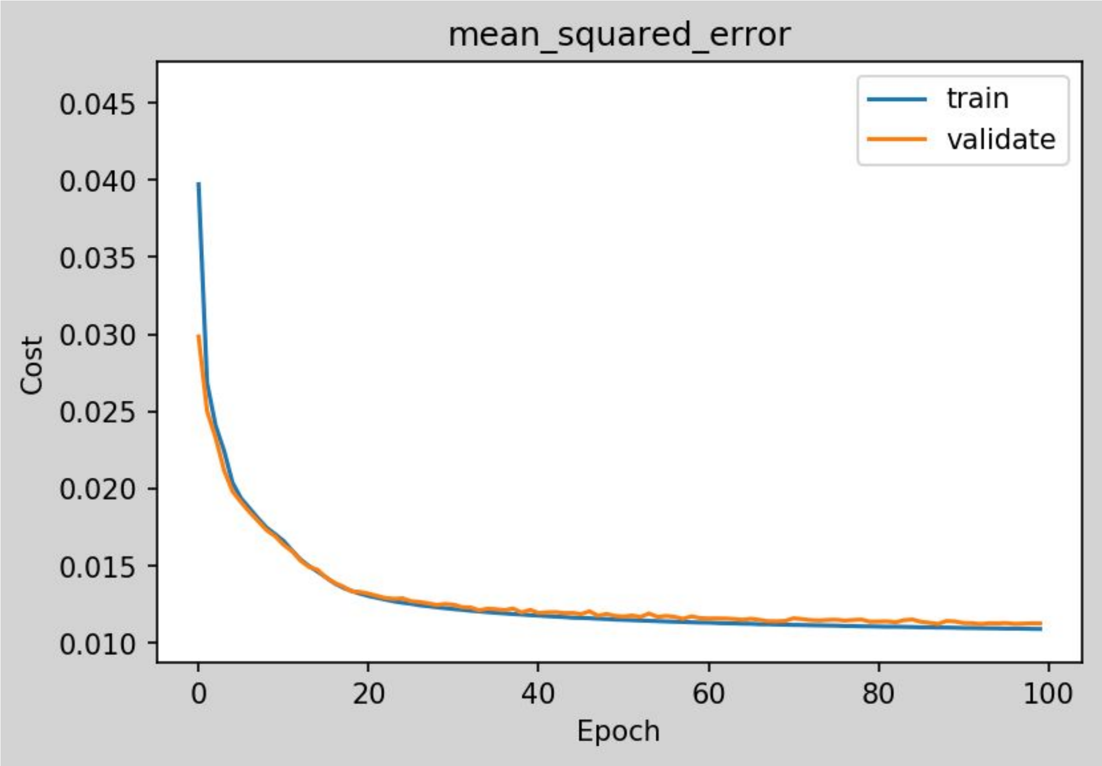
Repeat for 32 models

Inference

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

Use seed with the lowest MSE.

Final Training



Hyperparams
Optimizer: Adam
Batch Size: 32
Learning Rate: 10 ** -3
Epochs: 100

Inference
Learning stops at around 60 epochs. MSE is unlikely to go below 0.01 without additional tuning.

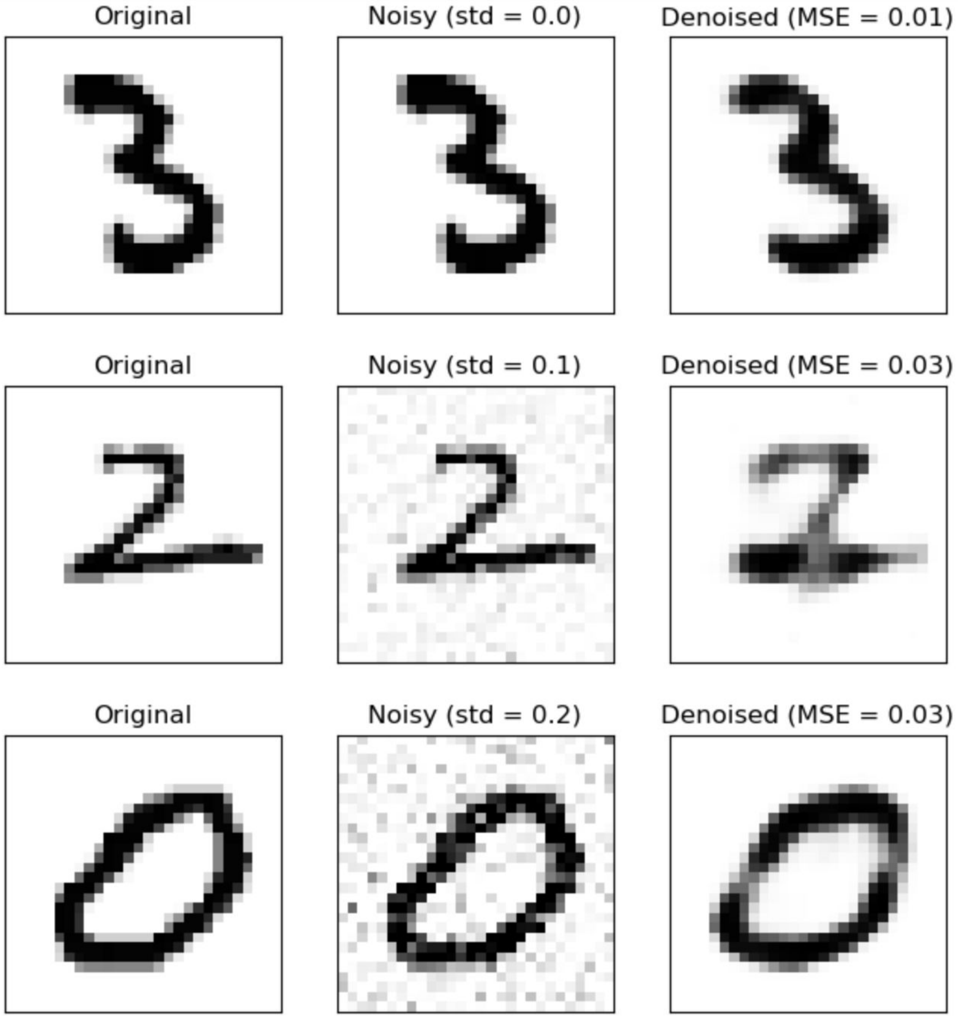
Image Examples

Reconstruction Task

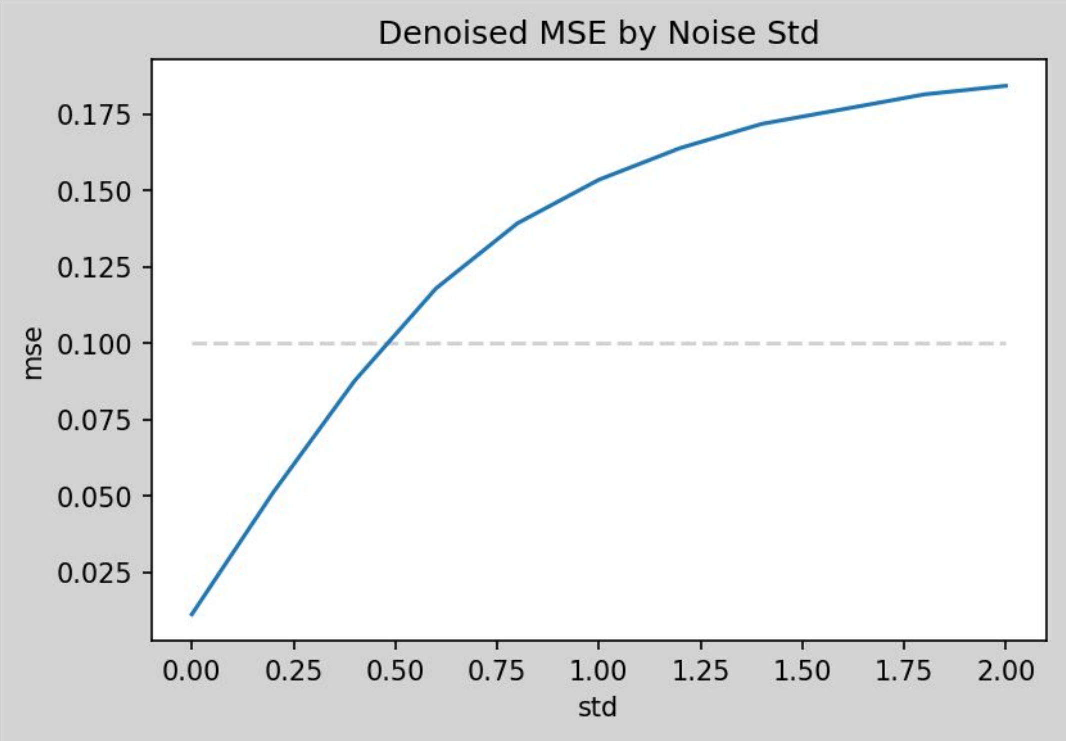
- Training MSE = 0.01
- Validation MSE = 0.01

Denoising Task (Std = 0.1)

- Training MSE = 0.03
- Validation MSE = 0.03



Model Report



Reconstruction Task

- Training MSE = 0.01
- Validation MSE = 0.01

Denoising Task (Std = 0.1)

- Training MSE = 0.03
- Validation MSE = 0.03

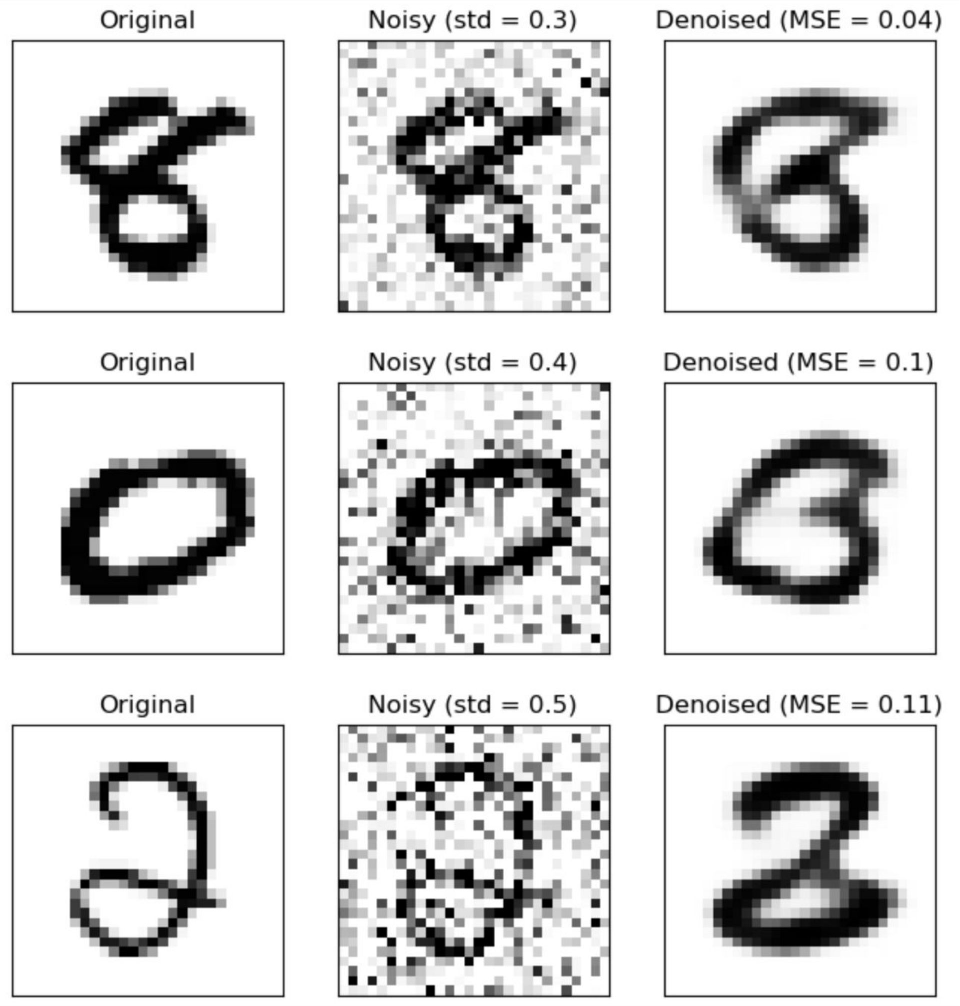
Model Report

Reconstruction Task

- Training MSE = 0.01
- Validation MSE = 0.01

Denoising Task (Std = 0.1)

- Training MSE = 0.03
- Validation MSE = 0.03

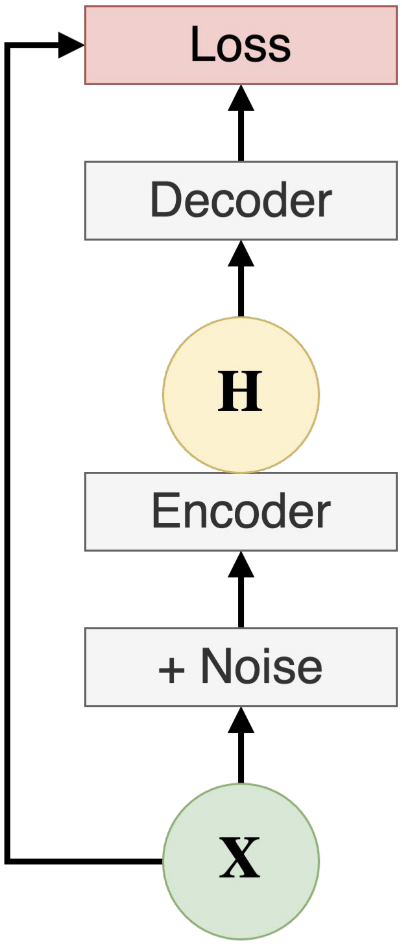


Assignment #1

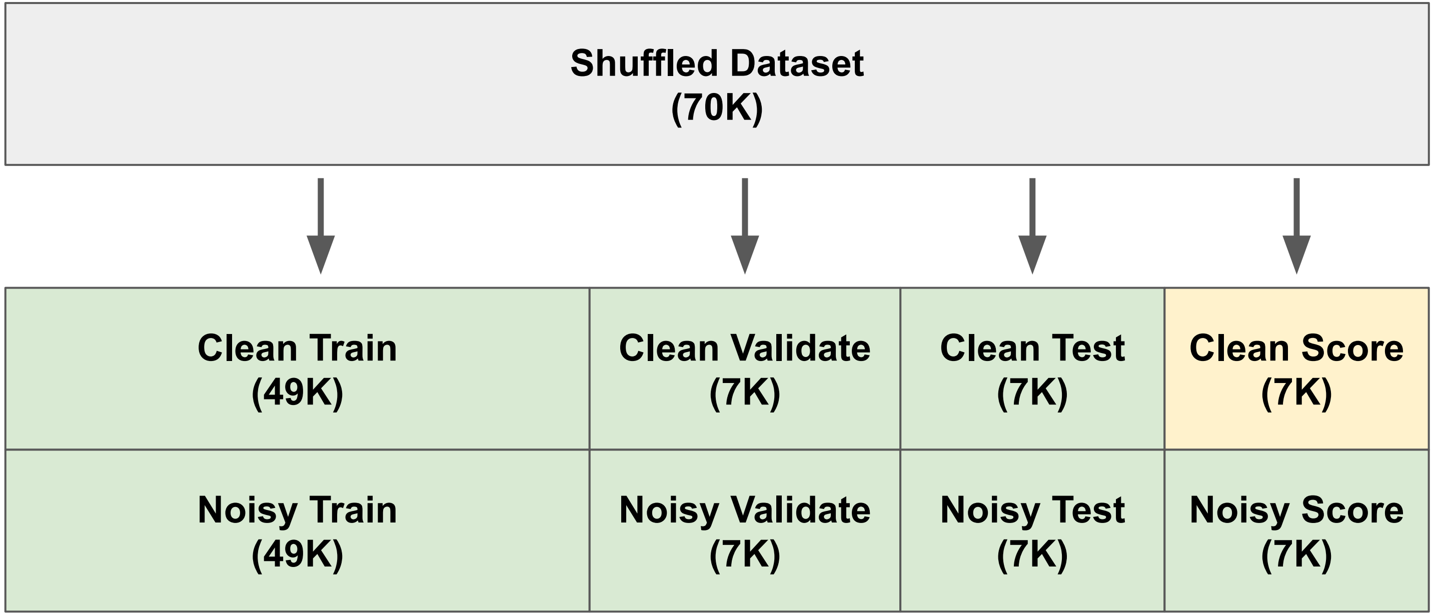
- Train an Autoencoder
  - Sparse, denoising, or both

- Scored on Denoising Task
  - Testing methodology on the right

- Augmented MNIST Dataset
  - Noise ~ Normal(0, 0.2)
  - Shape = 70K x 28 x 28
  - Data Type = float64 in [0, 1]
  - File Type = Parquet



Assignment Dataset



Assignment Methodology

- Read the Jupyter notebooks
- Try different Autoencoder constraints
  - NOT ONLY Undercomplete
  - add SPARSITY cost
  - add DENOISING training regime
  - or add both
- Try different encoder width / depth
- Try different optimizers
- Try different learning rates
- Try stacking multiple layers

Demo

UndercompleteAutoencoder.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 28 x 28
    b. Data Type = float64 in [0, 1]
    c. File Type = Parquet

Assignment Grading

- Due EOD 10/7
  - Zero points for late submissions
  - Zero points for incomplete submissions
  - Zero points for undercomplete-only autoencoders

- Maximum points = 20
  - 10 points if MSE (Denoised vs Clean) on Score Dataset < 0.03
  - 10 points proportional to percentile of MSE on Score Dataset relative to the class

- Compute Environments
  - Your laptop (Anaconda + Jupyter)
  - Google Colab
  - AWS SageMaker Notebook

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. Stochastic Gradient/Mirror Descent: Minimax Optimality and Implicit Regularization (Azizan, N. & Hassibi, B., 2018)
13. Understanding the difficulty of training deep feedforward neural networks (Glorot, X., and Bengio Y., 2010)

Thanks

+ Q&A Time