

Advanced Workshop on Machine Learning

Lecture 1: Deep Neural Networks

Danylo Vashchilenko

- ML Engineer at AWS
- 4th year at UCLA Anderson



- Stockholm School of Economics (Riga)
- LinkedIn: linkedin.com/in/hellobanylo

Course Overview

Date	Topic	Assignment Due
9/26	(1) Review of Neural Networks (2) Autoencoders	EOD 10/2
10/3	Convolutional Neural Networks	EOD 10/9
10/10	Recurrent Neural Networks	EOD 10/16
10/17	Generative Adversarial Networks	EOD 10/23
10/24	Ensemble Methods	EOD 10/30

Course Resources

- Email: danylo.vashchilenko@anderson.ucla.edu
- Code: github.com/hellocanylo/ucla-deeplearning
-

Today's Agenda

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

Part 1

Review of NN Theory and Practice

Deep Learning Applications

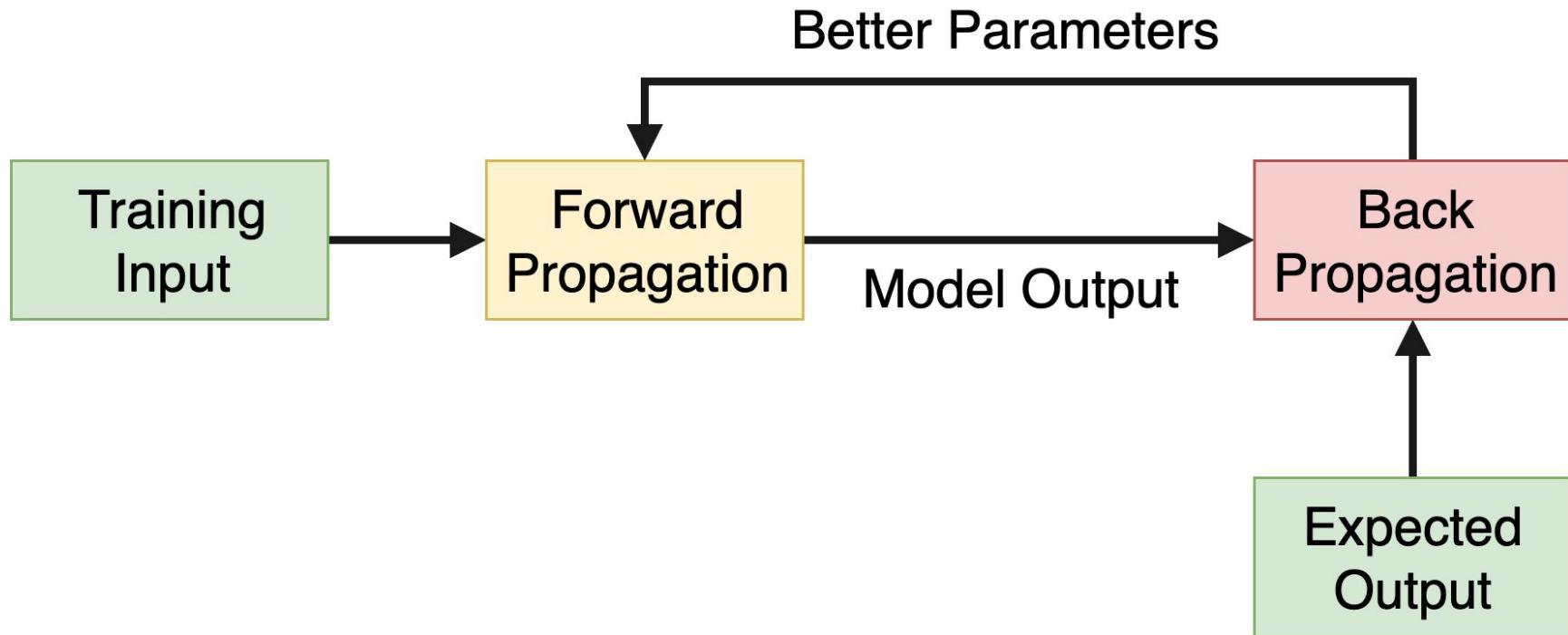
- Computer Vision
 - Image/Video Analysis and Generation
- Time-series Forecasting
- Natural Language Processing
 - Sentiment analysis
 - Text completion
 - Translation
- Sound Processing
 - Voice ↔ Text conversion
 - Voice assistants
- Game Theory (Reinforcement Learning)
 - Chess
 - Go
 - Pacman

Included in this course

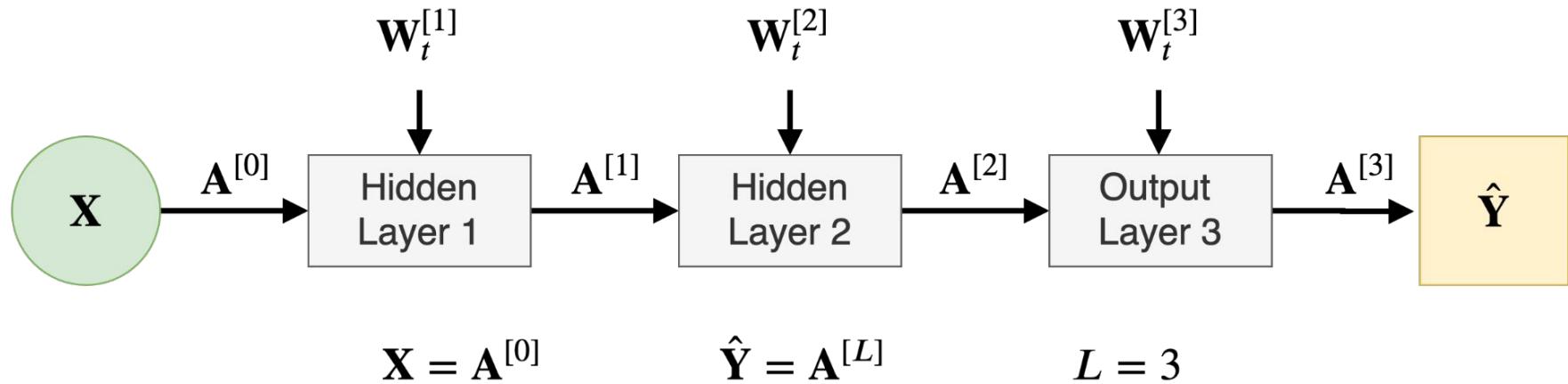
Managerial Economics of Deep Learning

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	Automation Software Engineer

Supervised Training Iteration



Feedforward Architecture



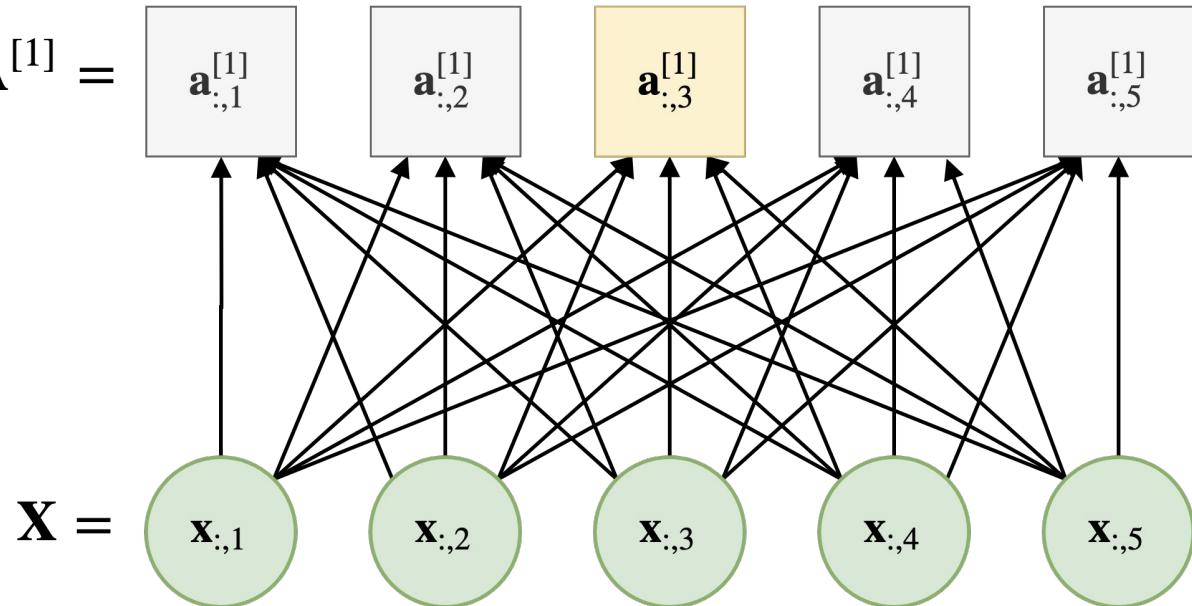
Forward Propagation in a 3-Layer **Feed-forward** Network

Fully Connected: Neuron Activation

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

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

$$\mathbf{A}^{[1]} =$$

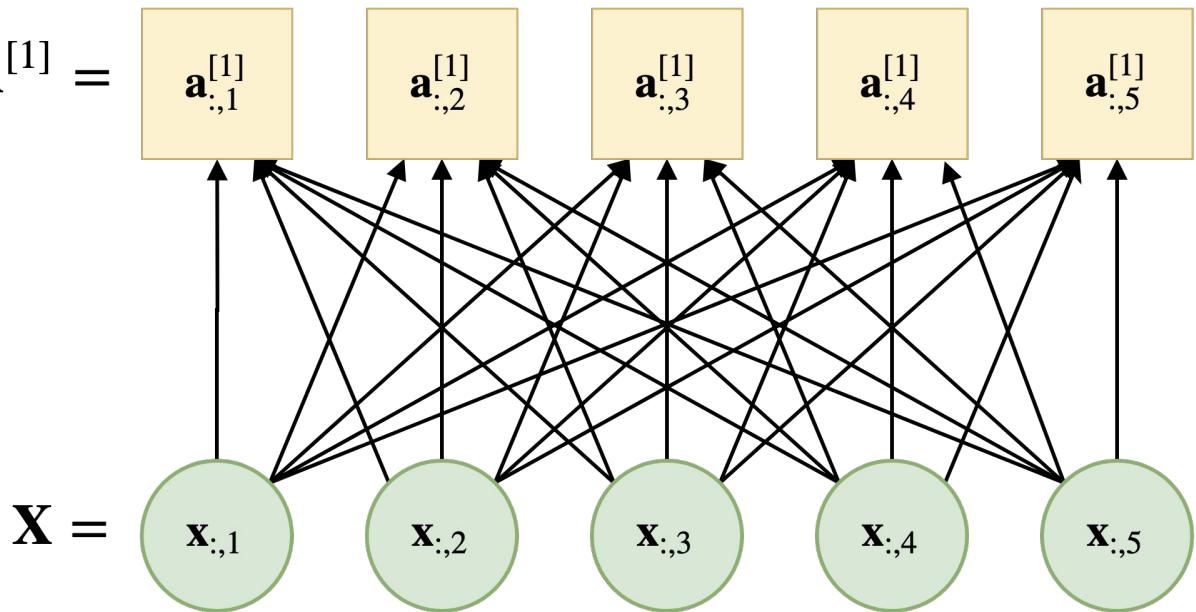


$$\mathbf{X} =$$

Fully Connected: Layer Activation

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

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



Fully Connected: 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**.

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

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

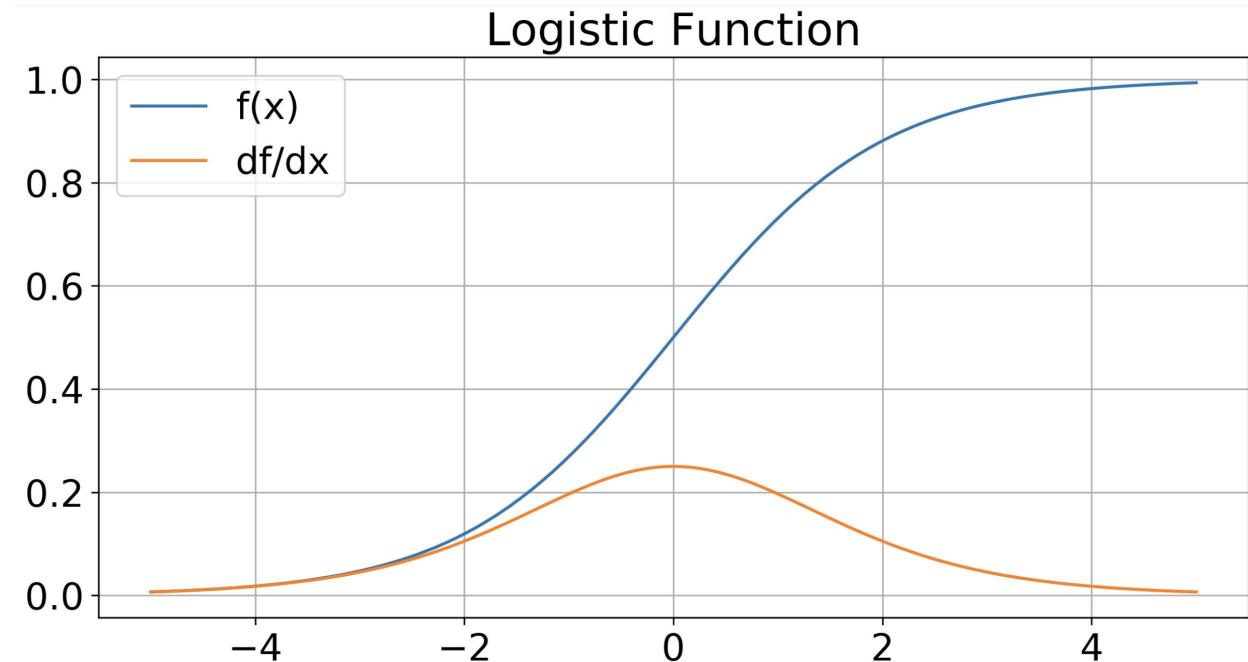
See **FullyConnectedLayer.ipynb** for notation and linear algebra details.

Range
Mean
Derivative

Logistic / Sigmoid

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

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

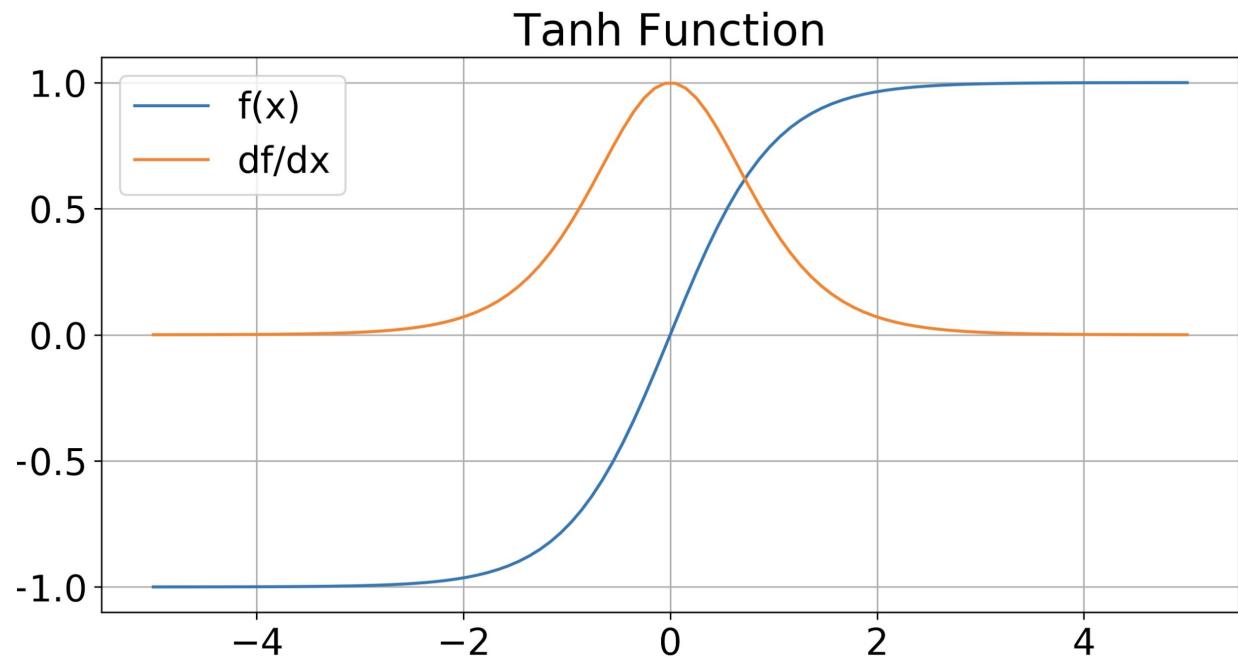


Range
Mean
Derivative

Hyperbolic Tangent

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

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

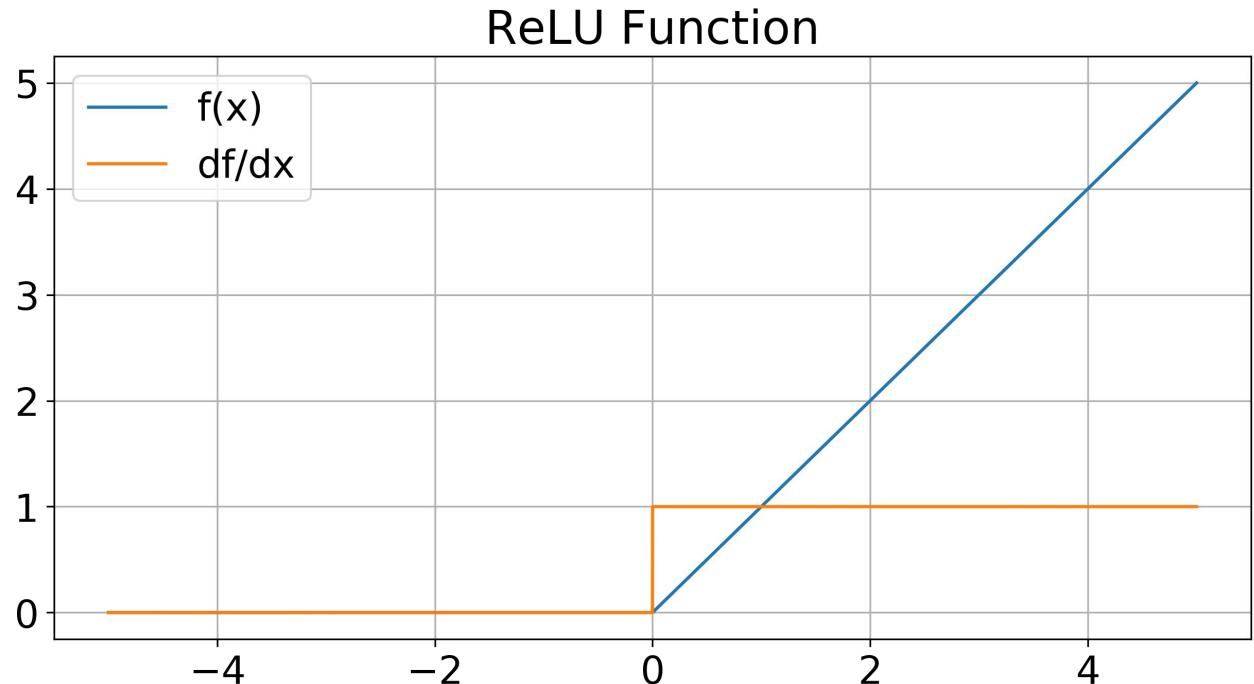


Range
Mean
Derivative

Rectified Linear Unit

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

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

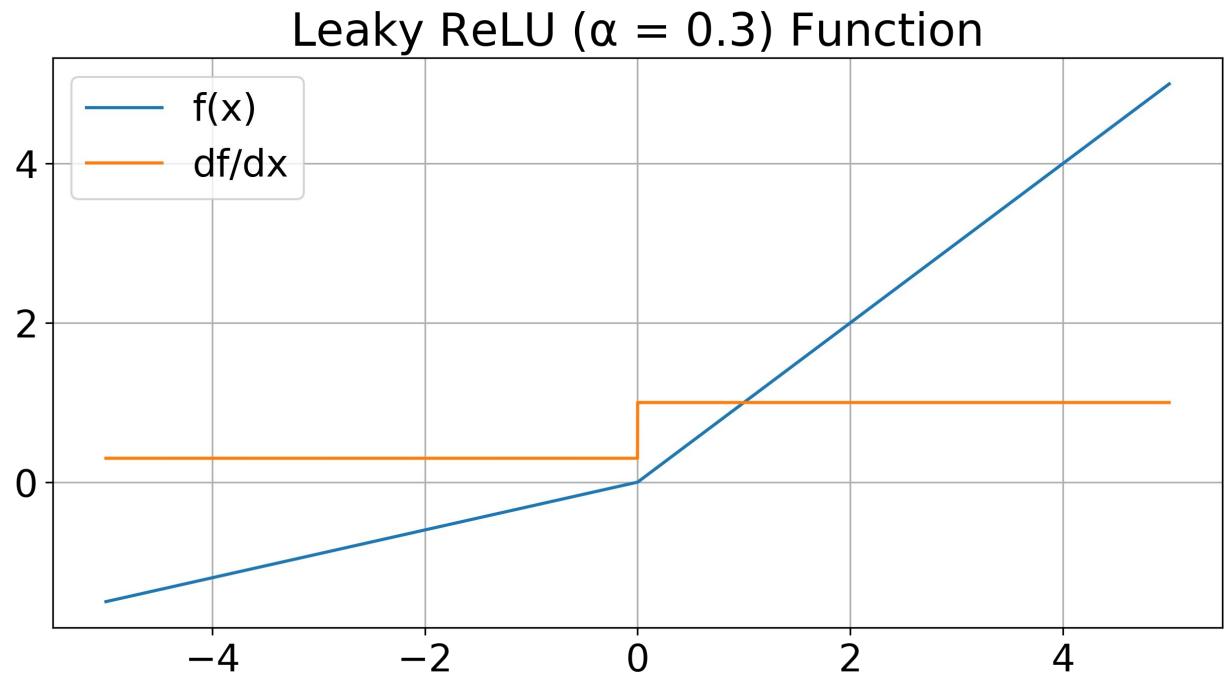


Range
Mean
Derivative

Leaky ReLU

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

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

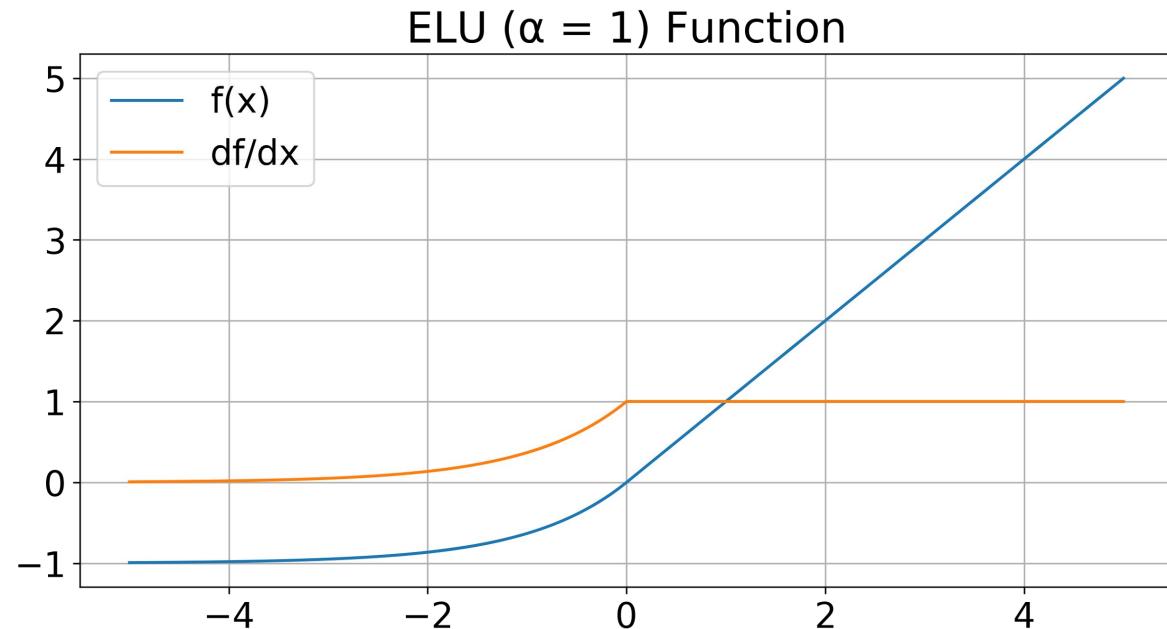


Range
Mean
Derivative

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

Range
Mean
Derivative

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.

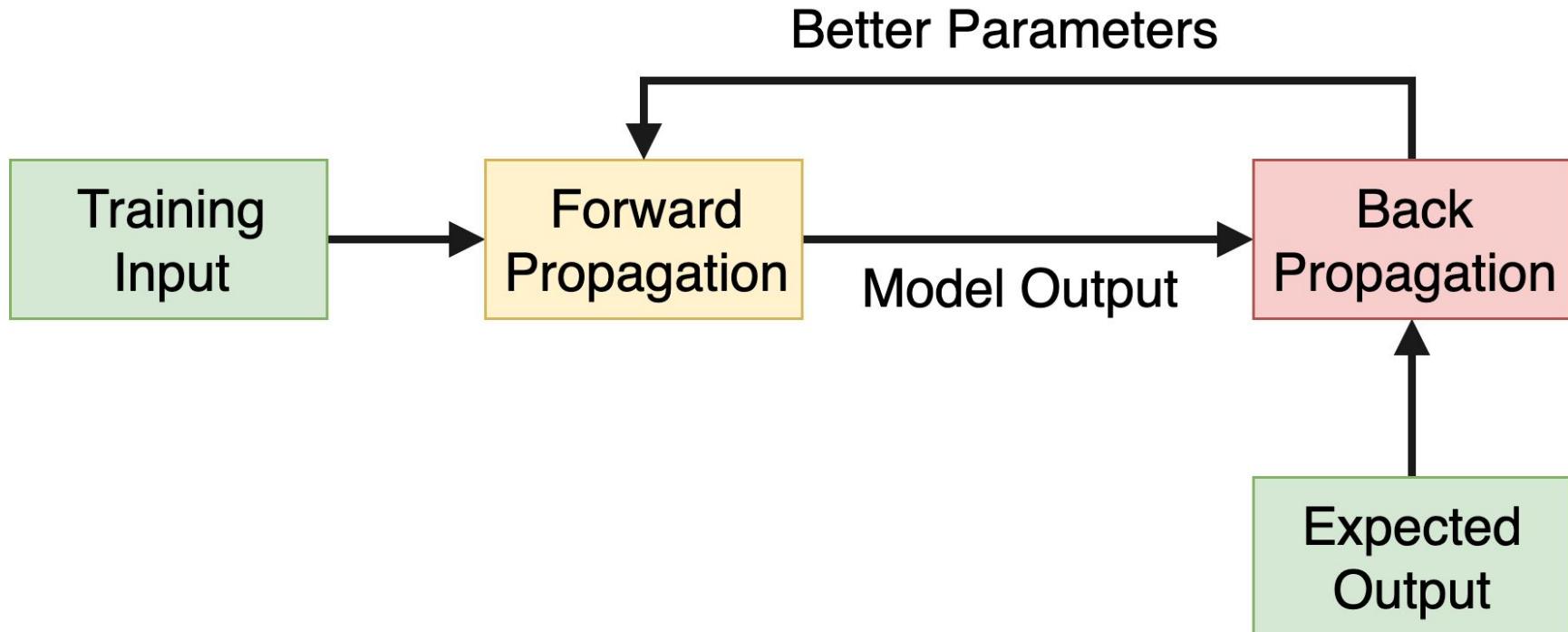
Solution:

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

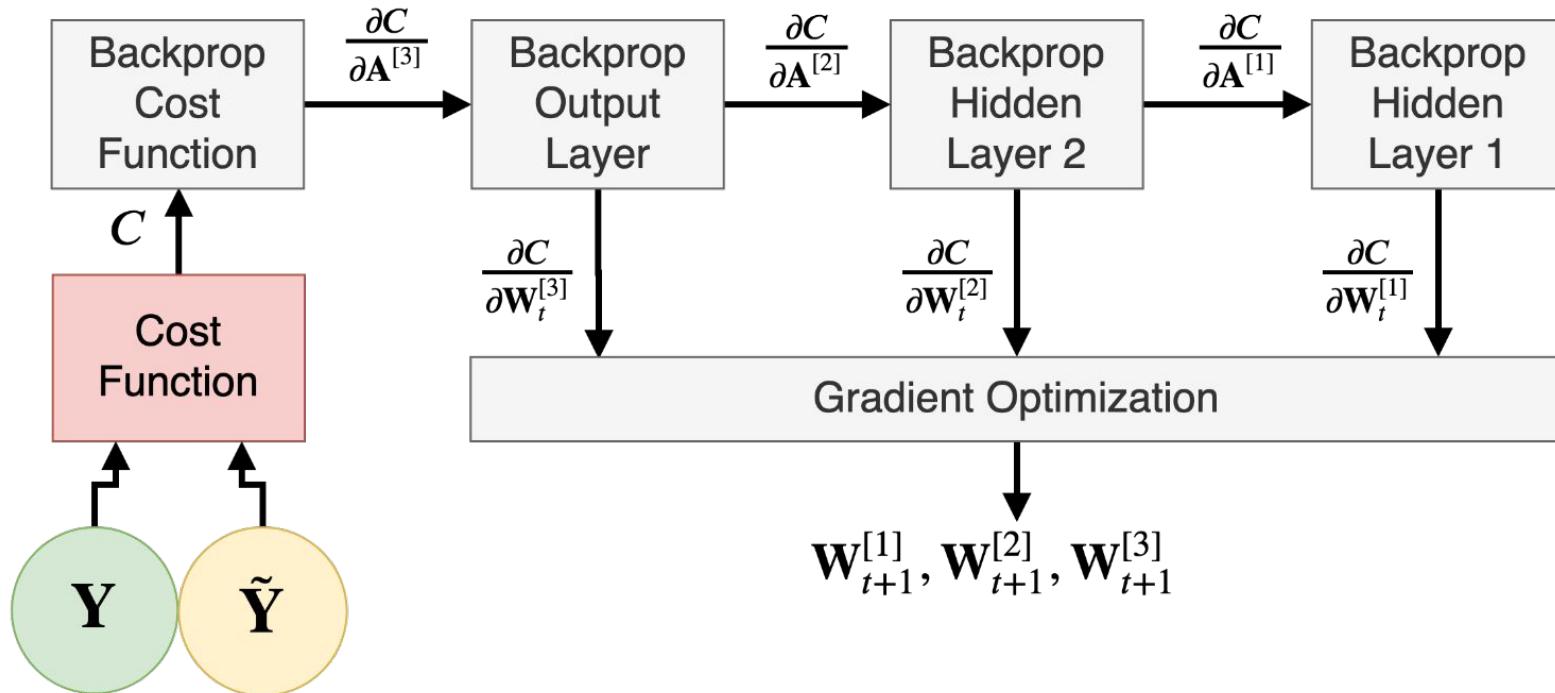
$$\mathbf{a}_{:,m}^{[l]} = \frac{\mathbf{z}_{:,m}^{[l]}}{\sum_{k=1}^M \mathbf{z}_{:,k}^{[l]}}$$

	$\mathbf{a}^{[l-1]}$	$\mathbf{z}^{[l]}$	$\mathbf{a}^{[l]}$
m			
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**.

Note that MAE is not differentiable at zero.

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

Cost 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

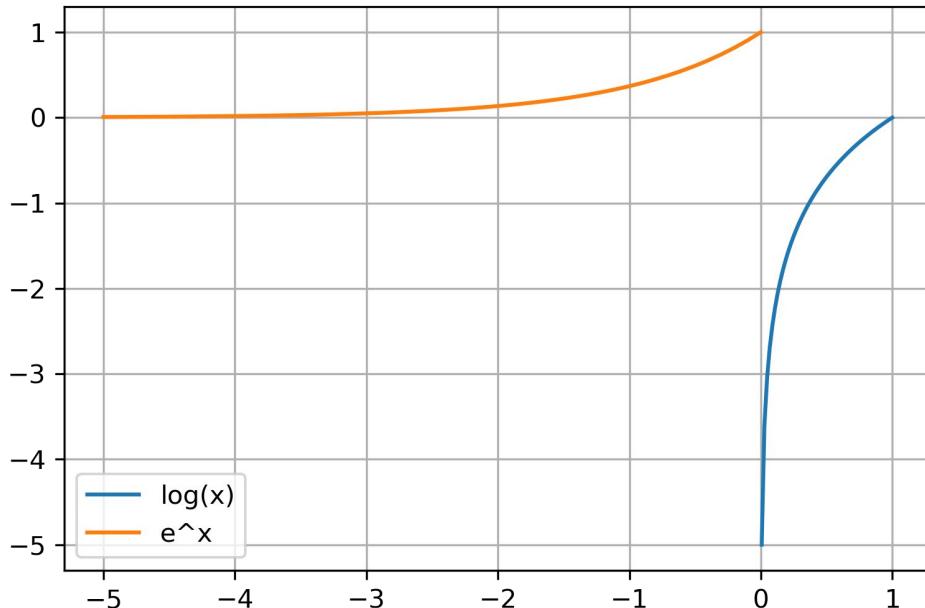
Classification loss is used when the **output is in $[0, 1]$** range.

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

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

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

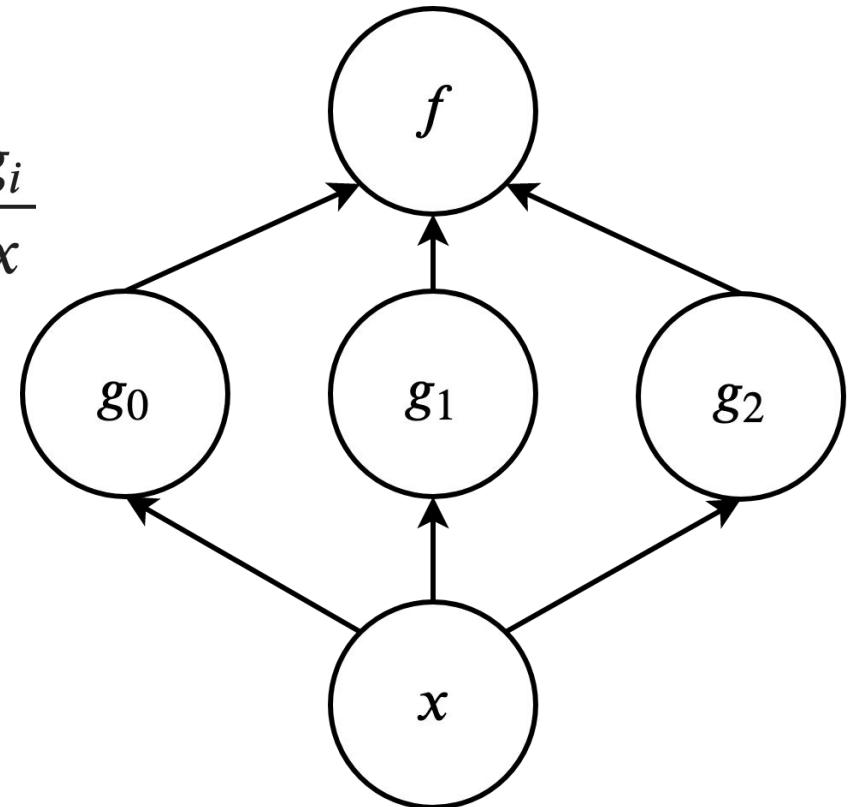
$$\text{Cross Entropy} = -\frac{1}{SM} \sum_s^S \sum_m^M y_{s,m} \log(\hat{y}_{s,m})$$



Multivariate Chain Rule

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

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.

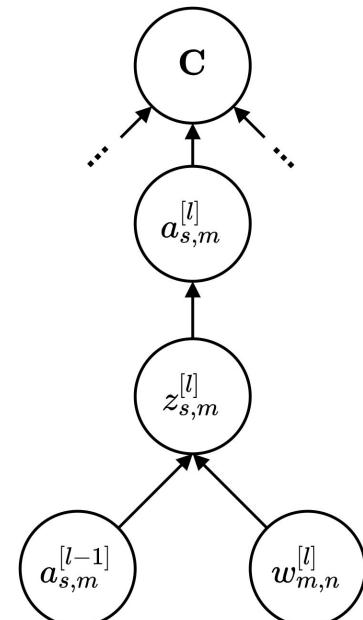


Backpropagation in Fully Connected Layer

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

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

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

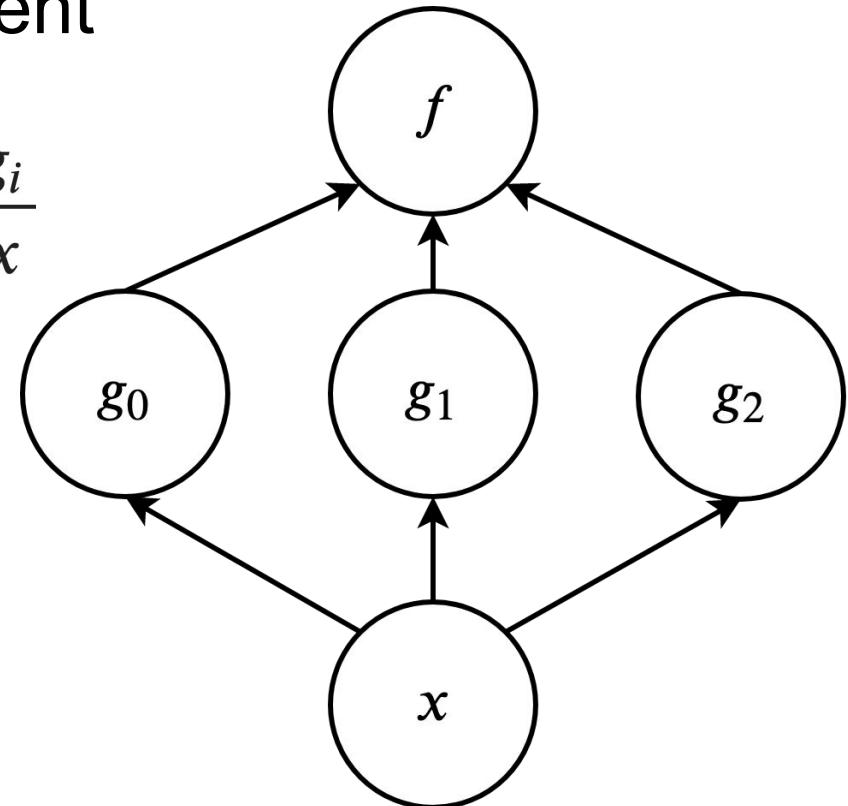


Exploding / Vanishing Gradient

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

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.

$\forall g, h :$

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

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

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

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

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

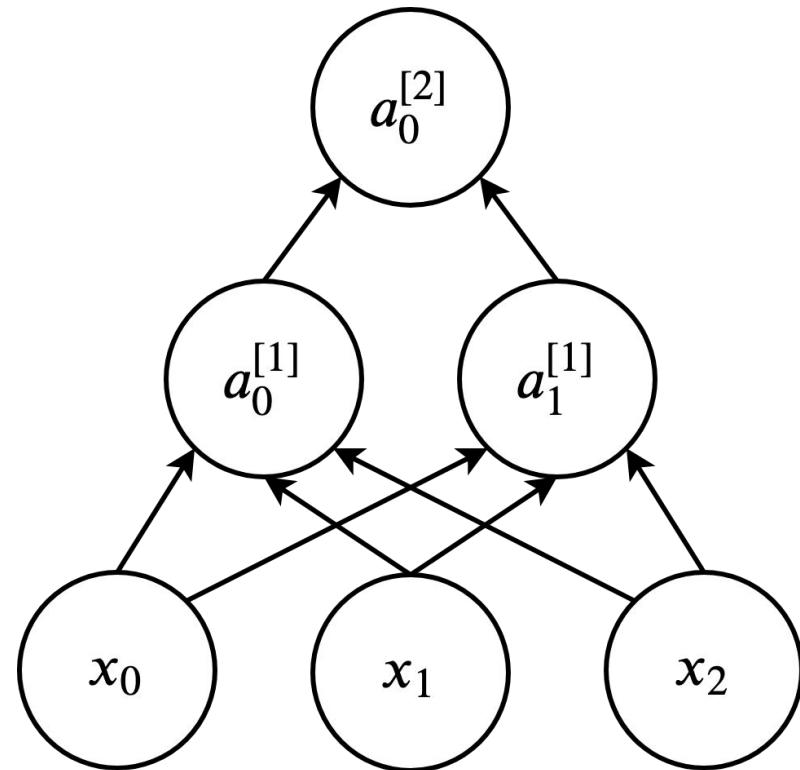
$$a_{s,g}^{[l]} = f(z_{s,g}^{[l]}) = f(z_{s,h}^{[l]}) = a_{s,h}^{[l]}$$

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

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

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

See [WeightInitialization.ipynb](#) for discussion, and Keras implementations.

Parameter Initialization

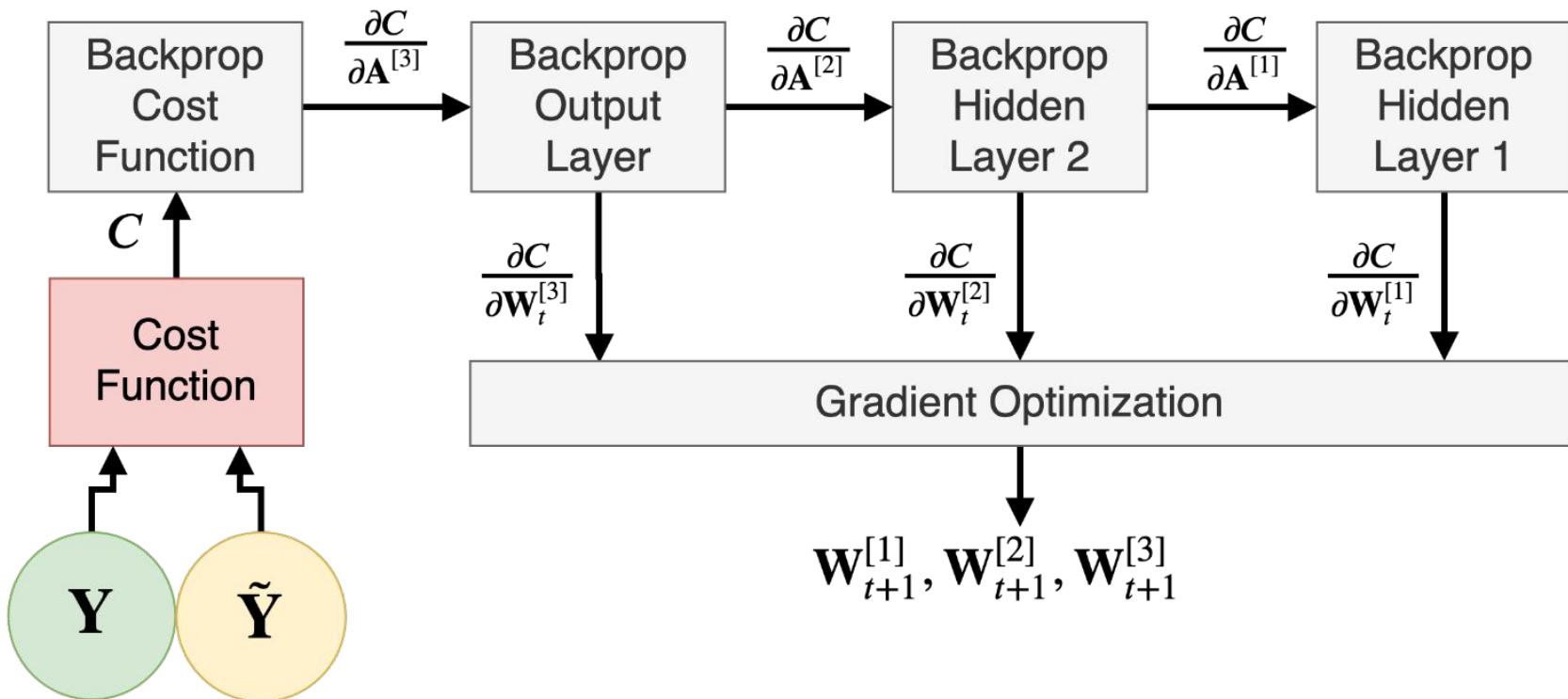
- He, K., Zhang, X., Ren, S., and Sun, J., (2015)
 - Makes variance of activation and gradient between layers similar
 - Derivation constraints the variance of the distribution, not its shape

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

n_{in} = count of input connections

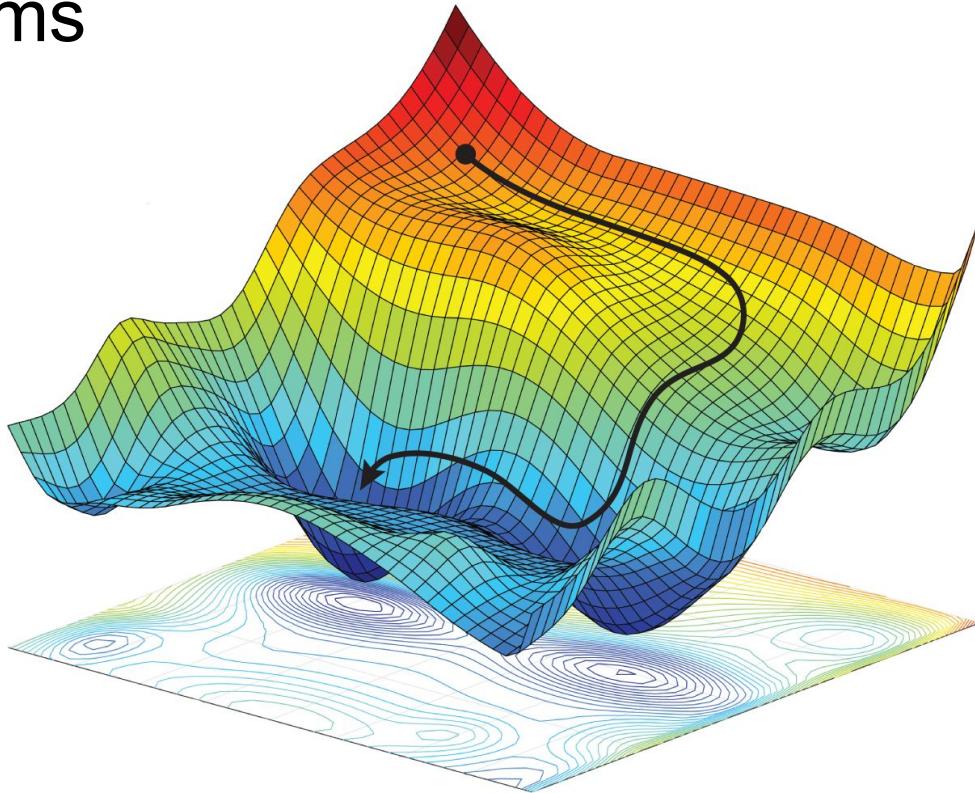
See [WeightInitialization.ipynb](#) for discussion, and Keras implementations.

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

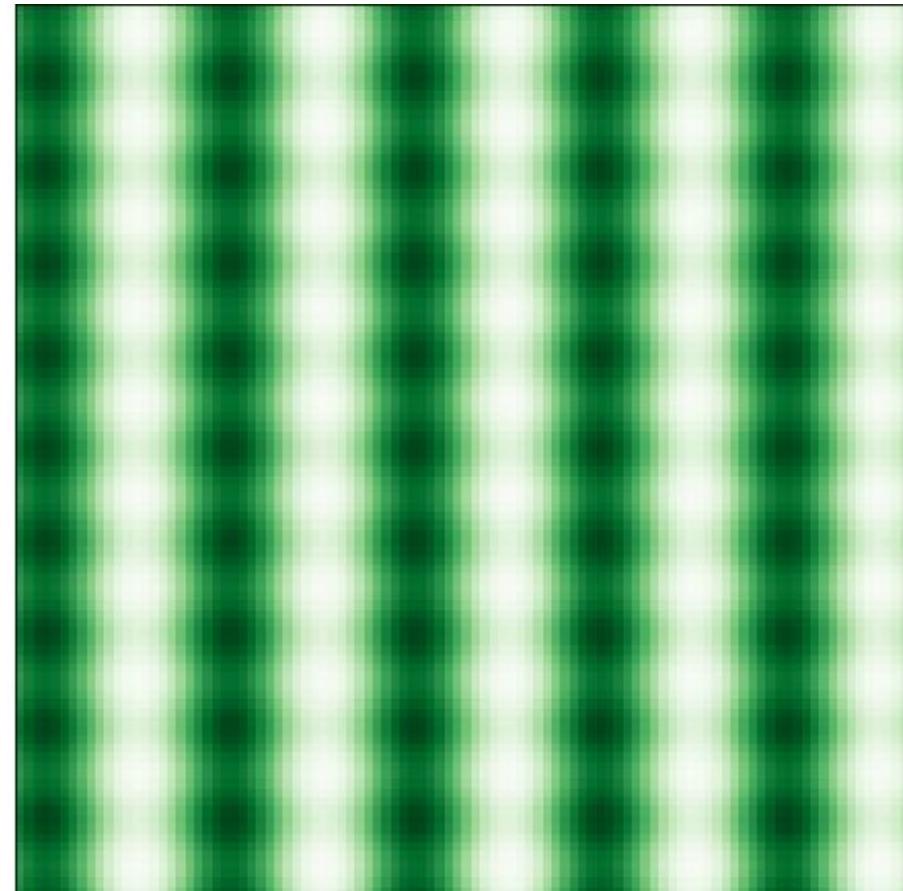
$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \nabla_{\mathbf{W}_t}$$

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

Three flavors:

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

See [GradientDescent.ipynb](#) for discussion,
NumPy, Tensorflow, and Keras
implementations.

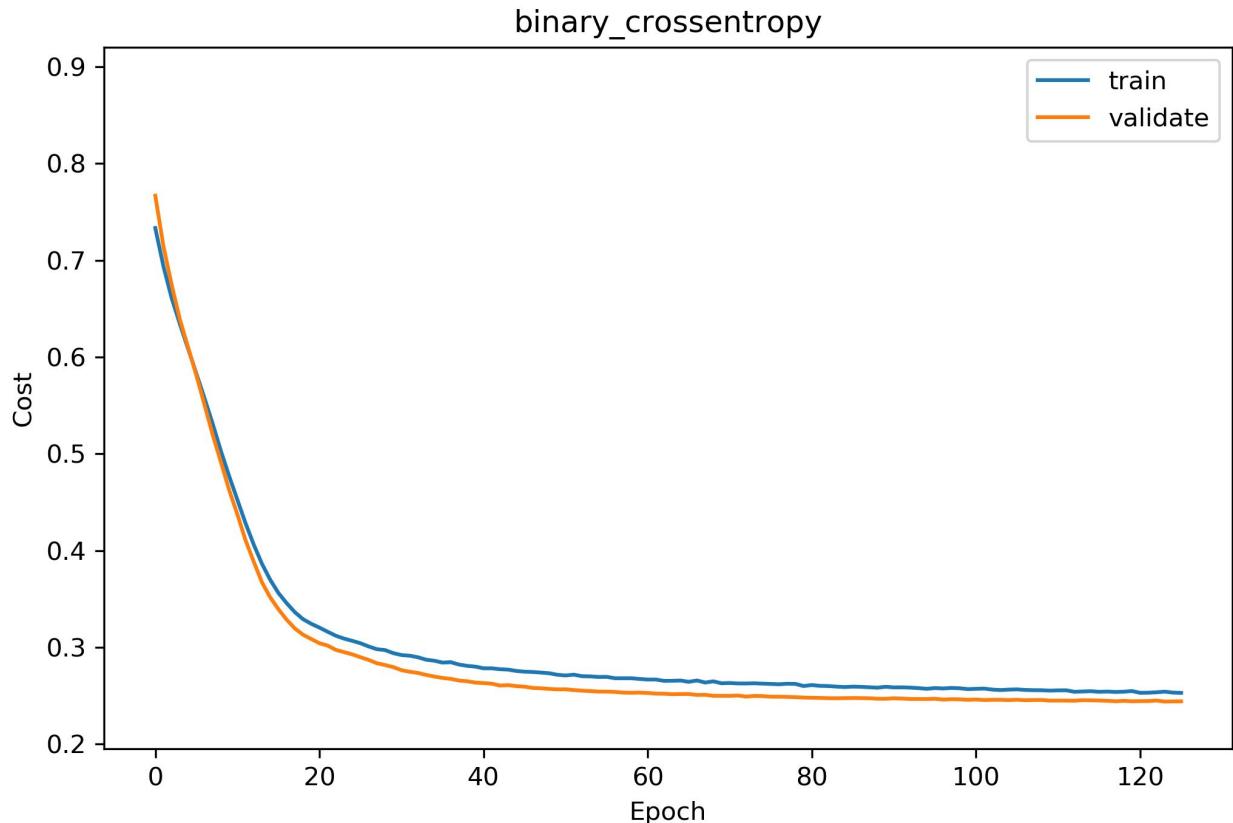


$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

Convergence of Learning Curve

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

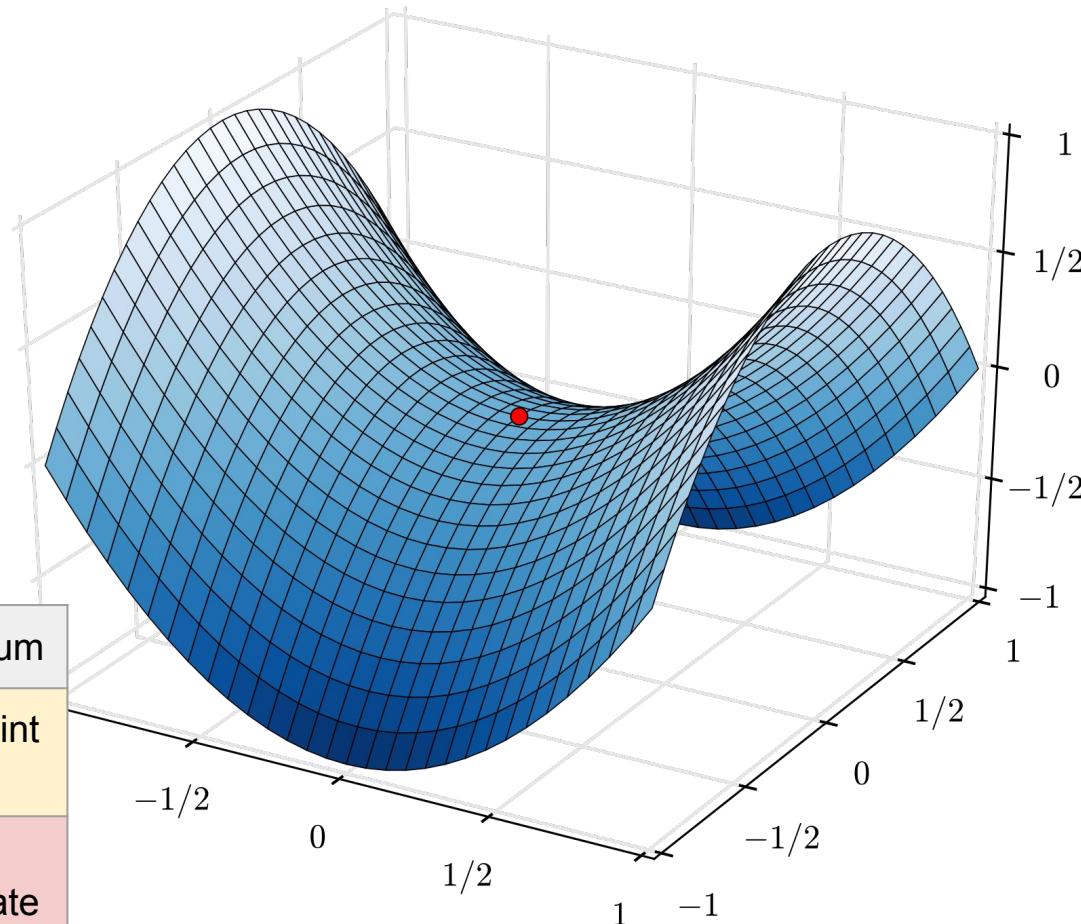
But if the learning curve converges, **did the algorithm find the function's global minimum?**



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

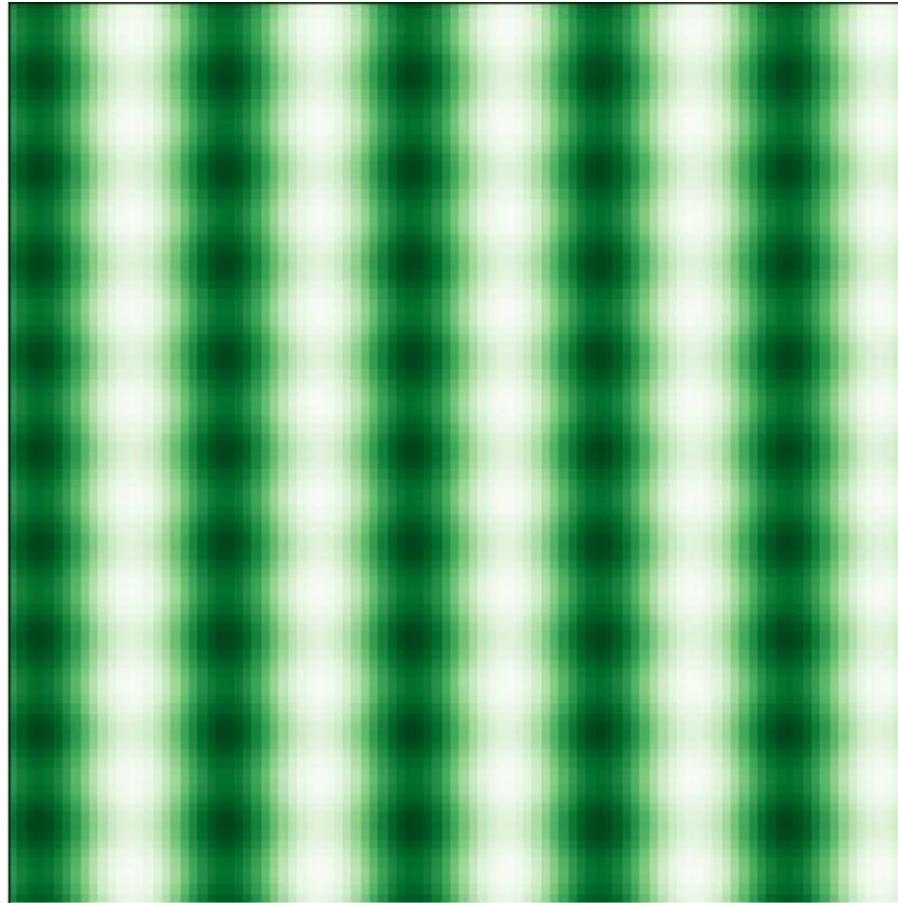


Momentum

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

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

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



Qian, G. (1999)

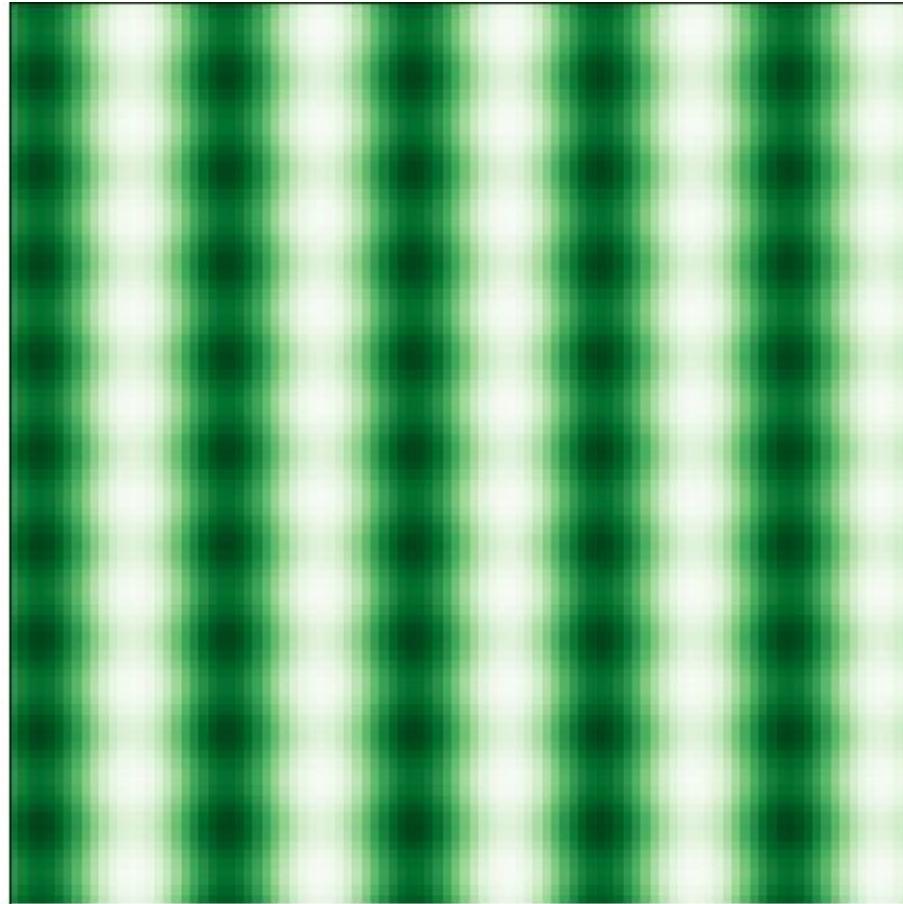
$$S(\mathbf{x}) = 3\sin(x_0) + \sin(x_1)^2$$

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

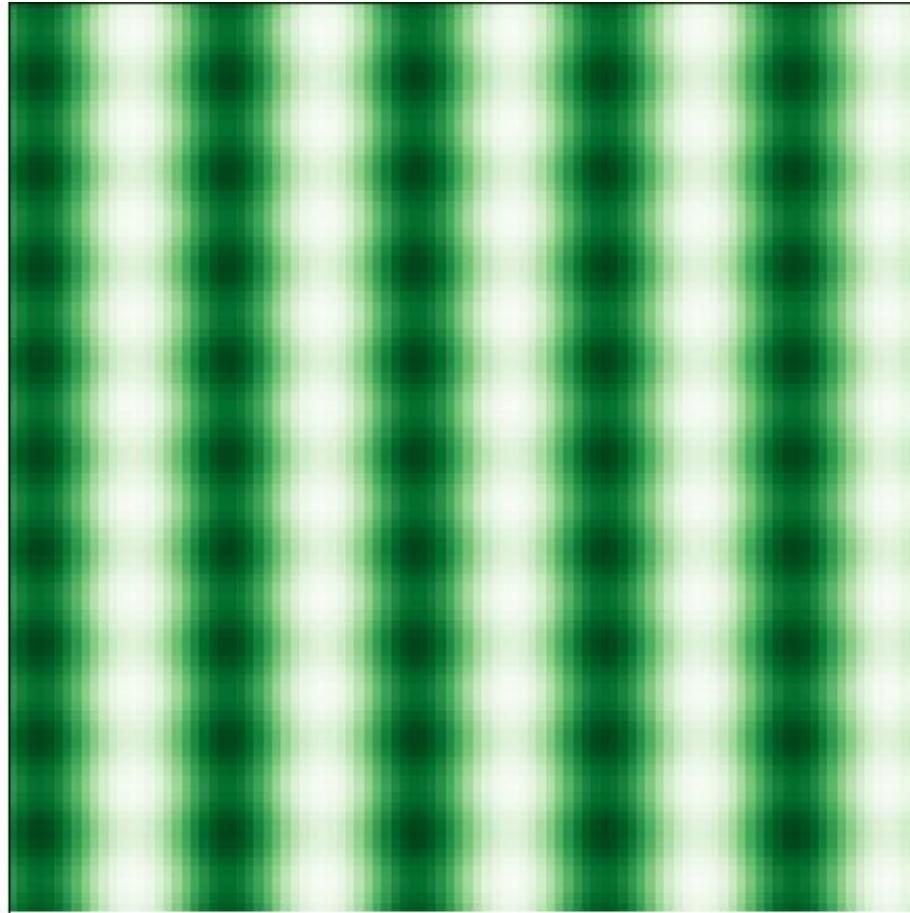
$$\mathbf{V}_{t+1} = \beta \mathbf{V}_t + (1 - \beta) \nabla_{\mathbf{W}_t}$$

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

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

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

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



Learning = Memorization + Generalization

- Any learning requires a prior 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:

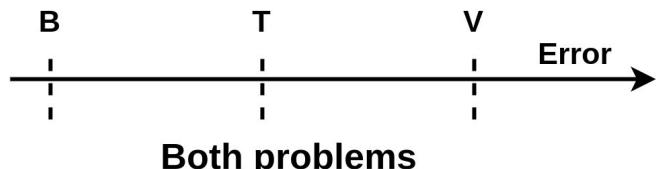
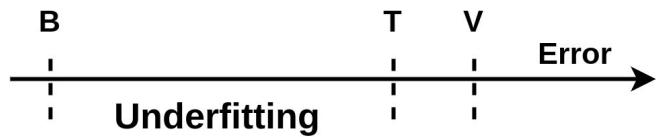
- Training segment (~80%)
- Validation segment (~10%)
- Testing segment (~10%)

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

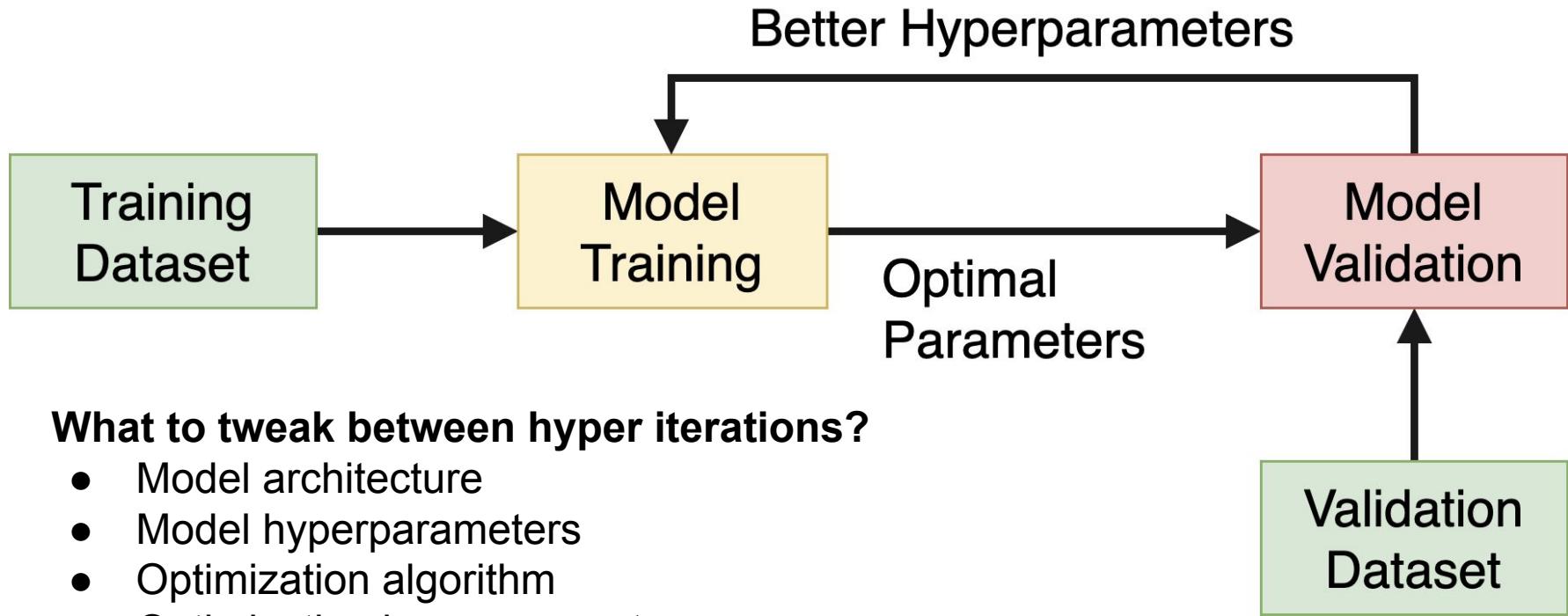
Generalization Inference

B = benchmark, T = training, V = validation

Scenario	Suggestions
Overfitting	<ul style="list-style-type: none">• Collect more data• Augment existing data• Early stopping• Decrease model capacity• Increase regularization
Underfitting	<ul style="list-style-type: none">• Change architecture• Increase model capacity• Reduce regularization
Both problems	All of the above

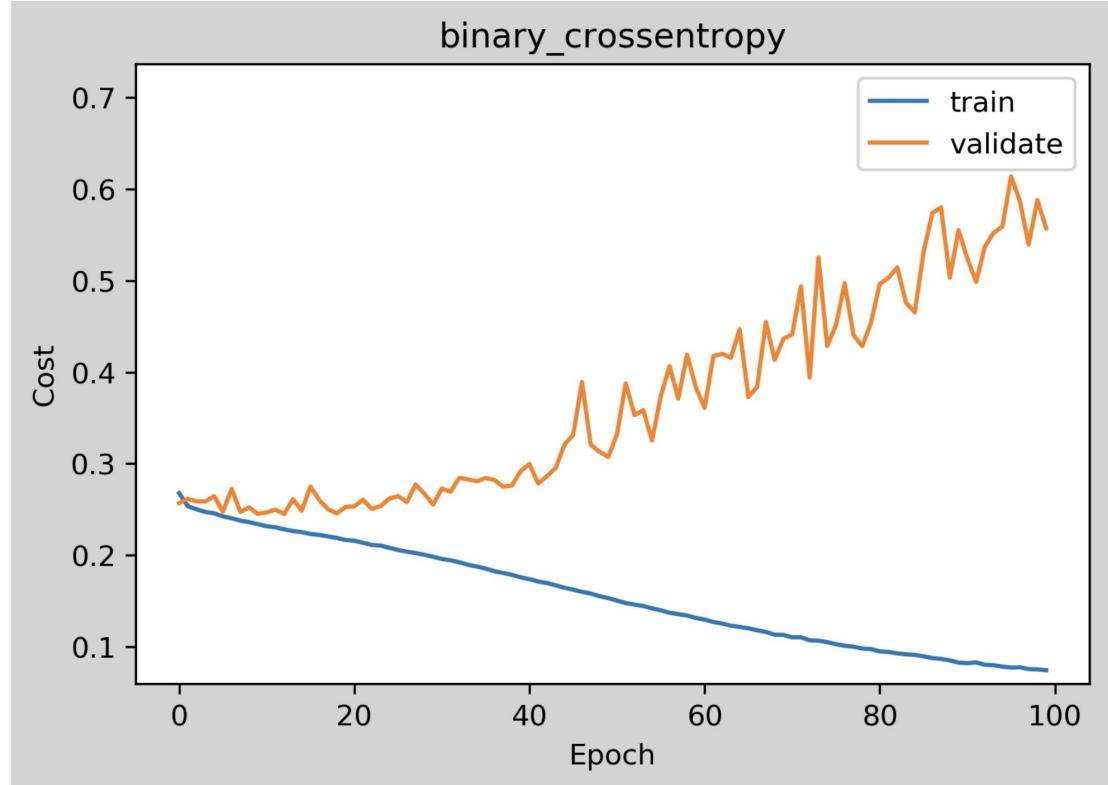


Hyper Training Iteration



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.



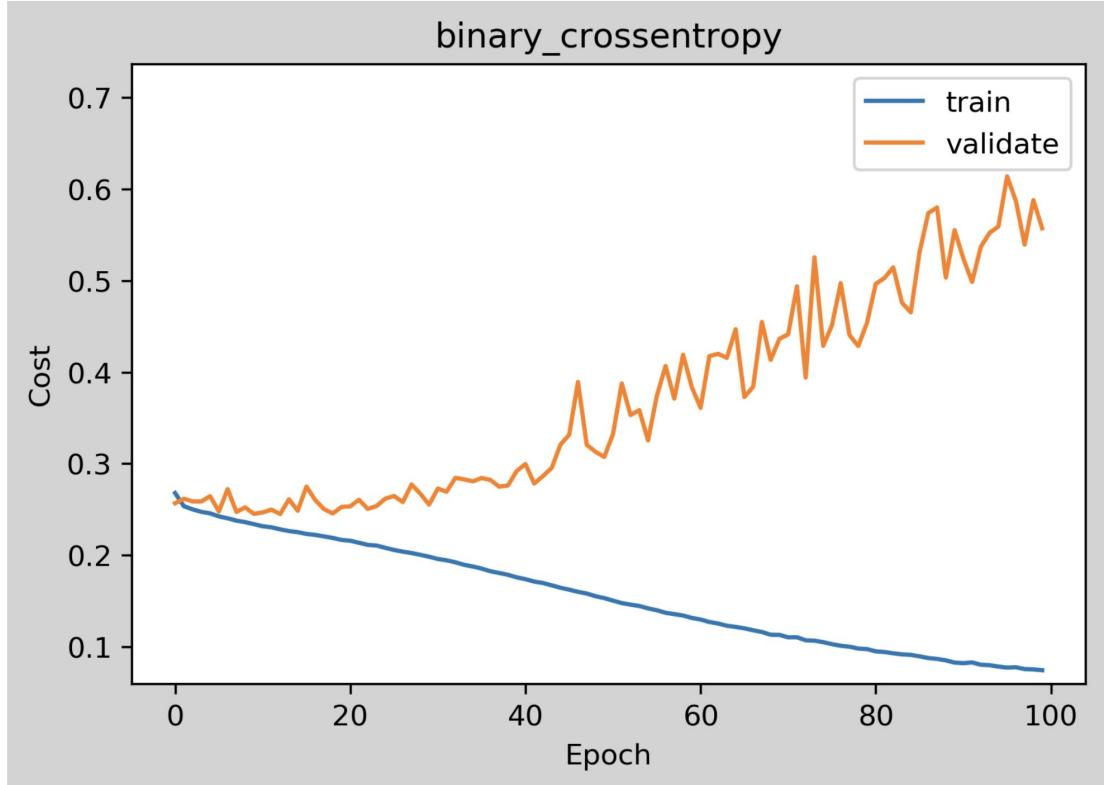
Regularization

Problem

Reduce overfitting via
**preference for simpler
models.**

Solutions

- L1 Norm
- L2 Norm



Regularization via Vector Norms

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

$$L_1(\mathbf{W}) = \sum_i^n |w_i|$$

$$\frac{dL_1}{dw_i} = \begin{cases} 1 & \text{if } w_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

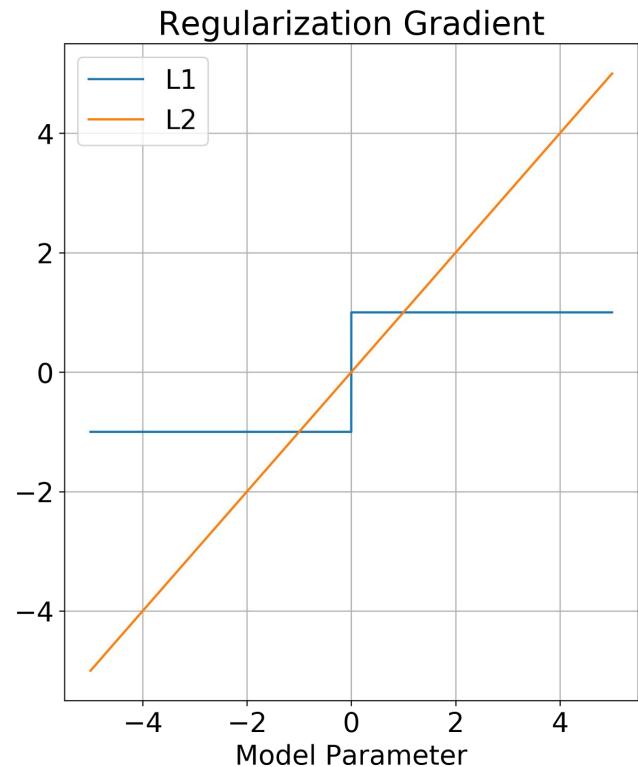
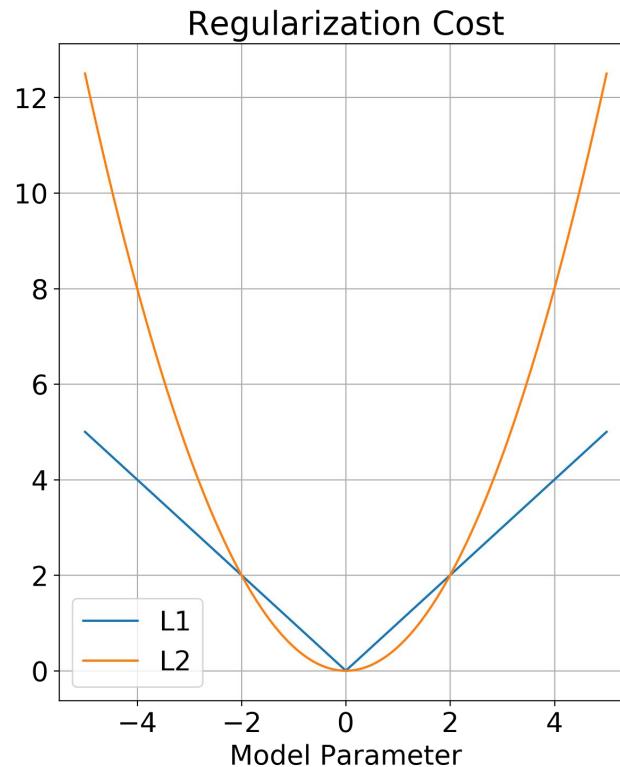
$$L_2(\mathbf{W}) = \frac{1}{2} \sum_i^n w_i^2$$

$$\frac{dL_2}{dw_i} = w_i$$

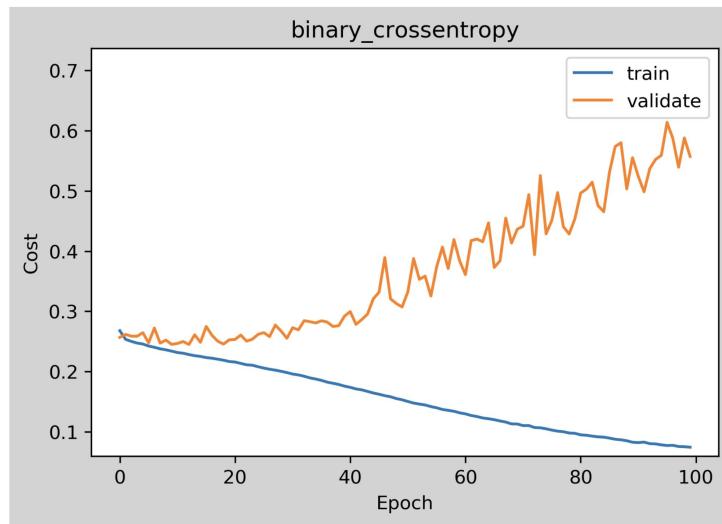
Comparison of L1 and L2 Norms

L1 is more likely to prefer a sparse parameter matrix.

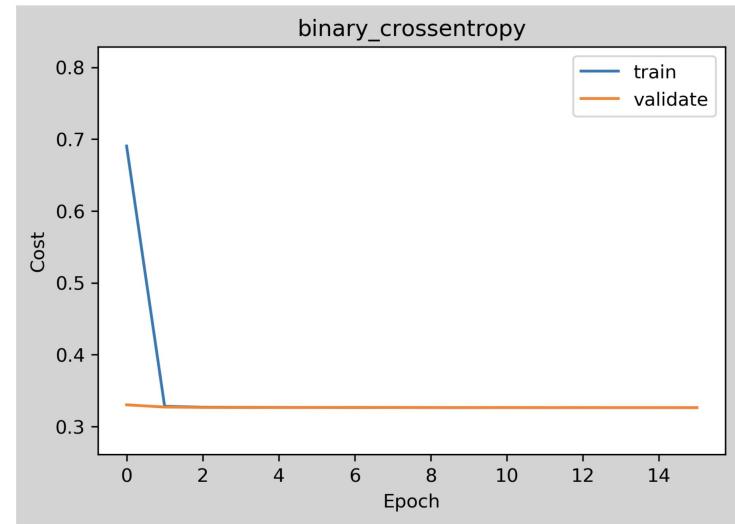
L2 is more likely to remove extremely large parameters.



Effect of Regularization Cost

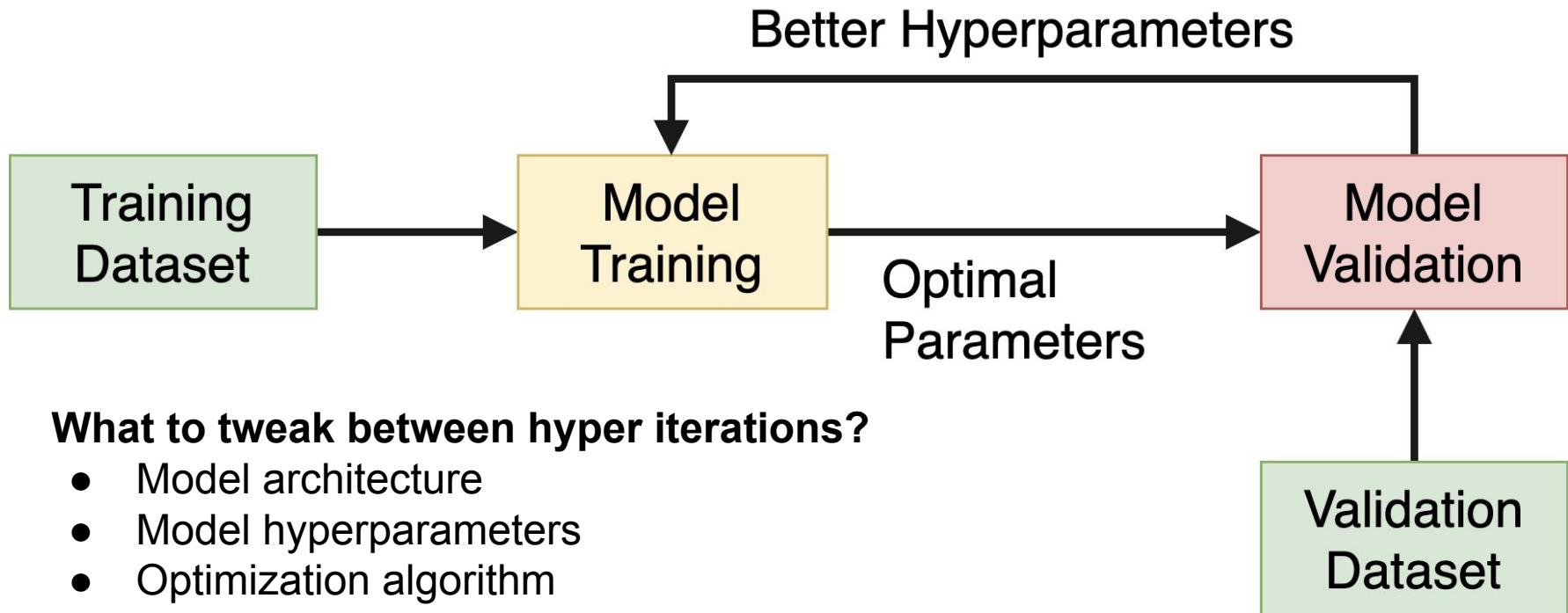


L2 Regularization Factor = 0.00



L2 Regularization Factor = 0.05

Hyper Training Iteration



What to tweak between hyper iterations?

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

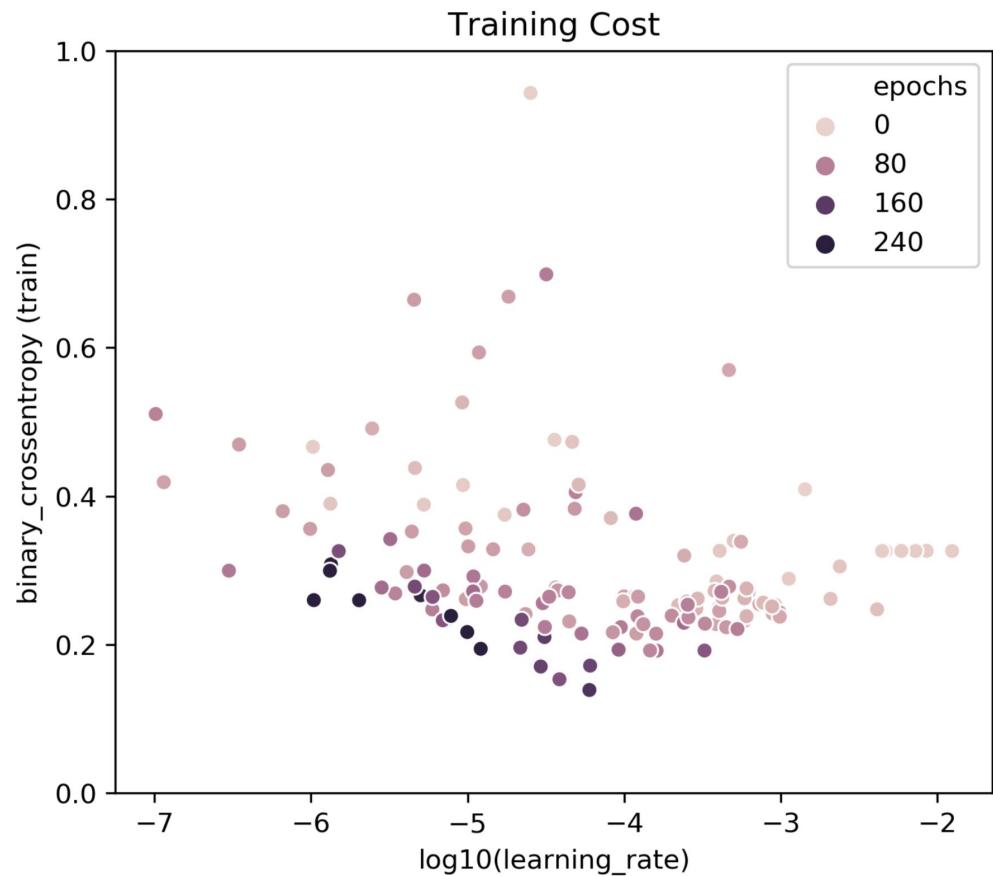
Validation
Dataset

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**.

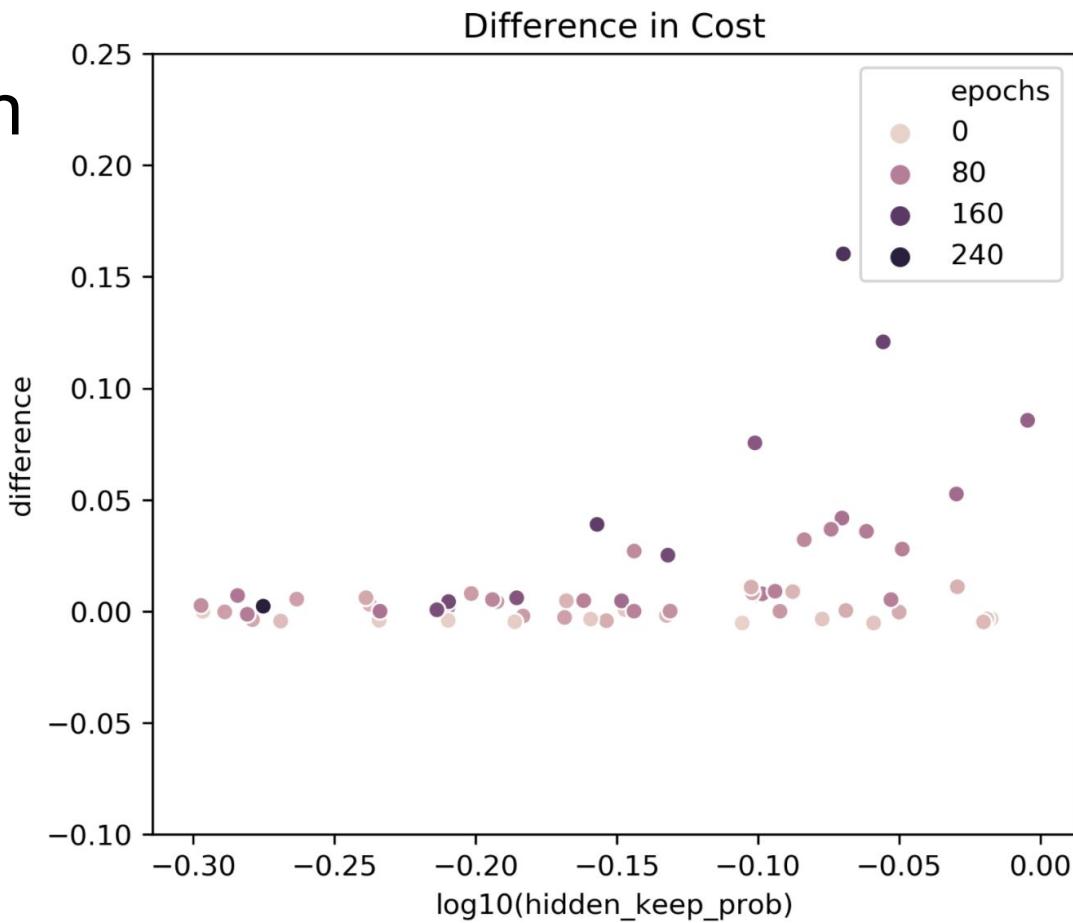


Tuning Regularization

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

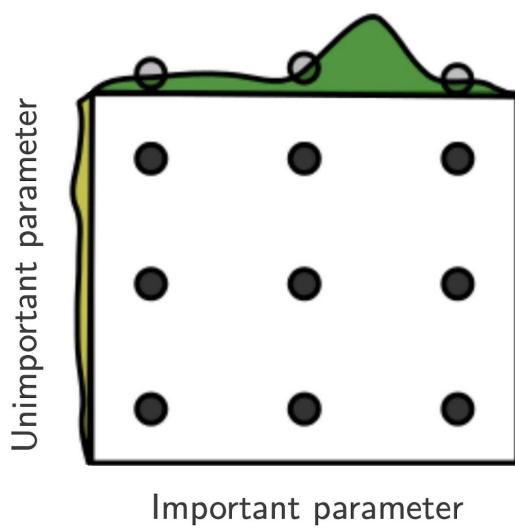
Plot the hyperparam vs the validation/training cost gap.

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

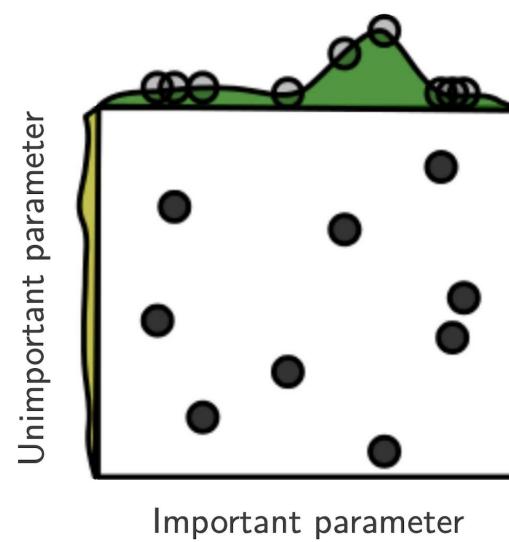


Grid Search vs Random Search

Grid Layout



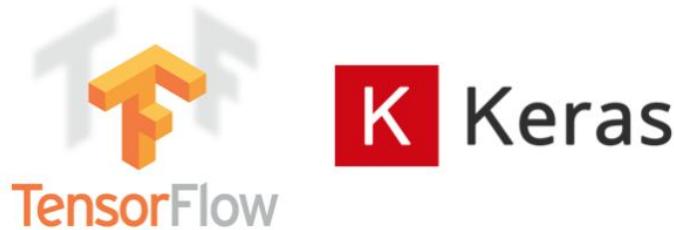
Random Layout



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

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



Part 2

Autoencoders

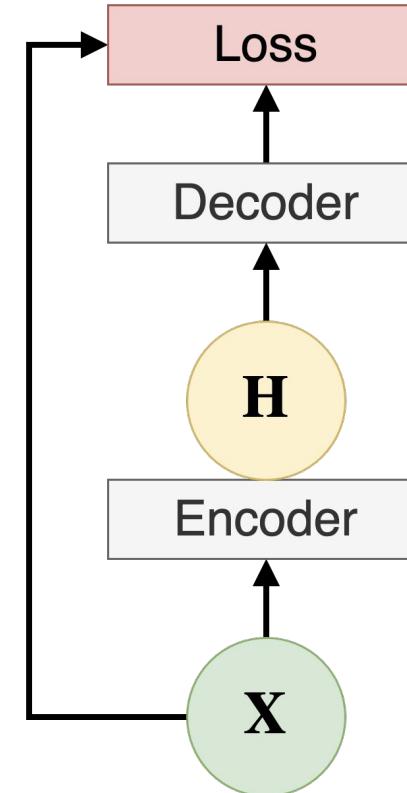
Autoencoders

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**.



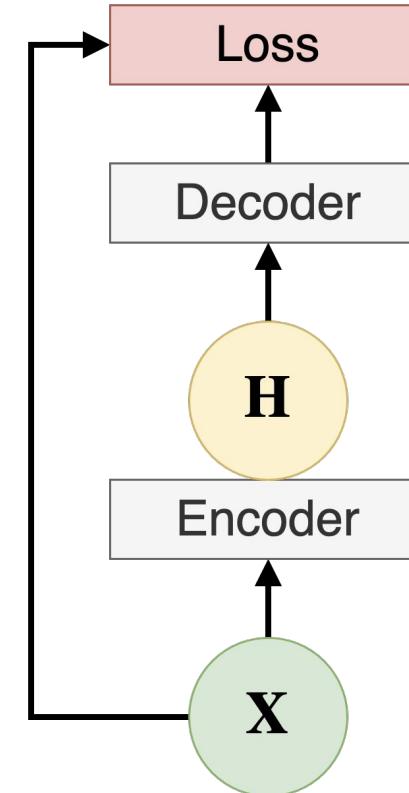
Undercomplete Autoencoders

Problem

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

Solution

Reduce **dimensionality** of the latent representation.



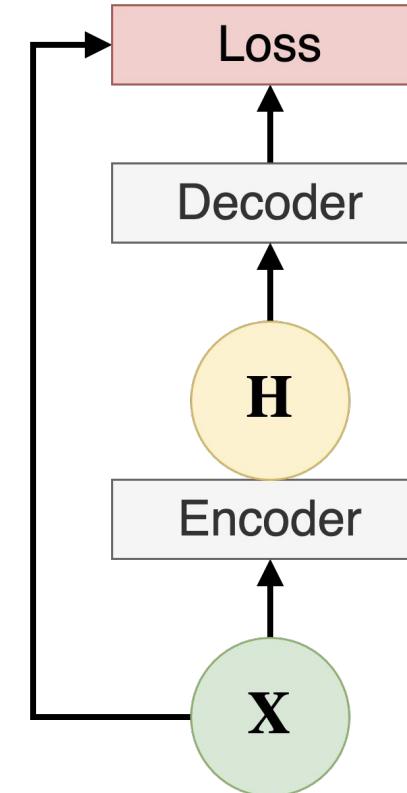
Use Case: Dimensionality Reduction

Problem

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

Solution

Use the **latent representation** of the data.



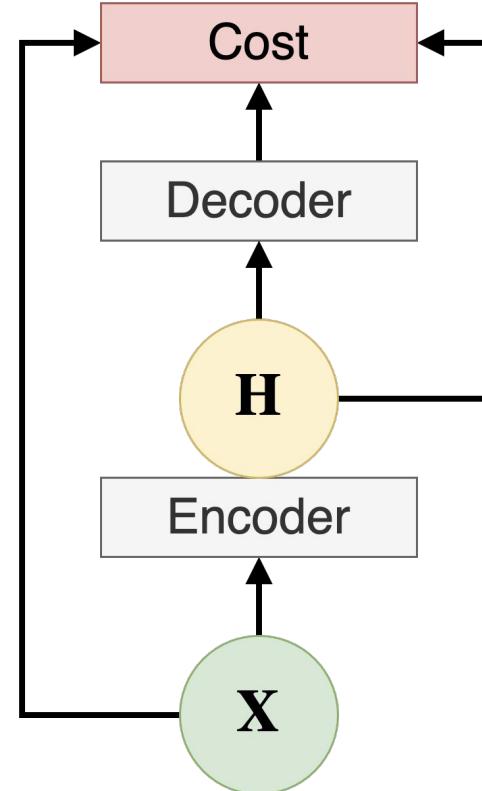
Sparse Autoencoders

Problem

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

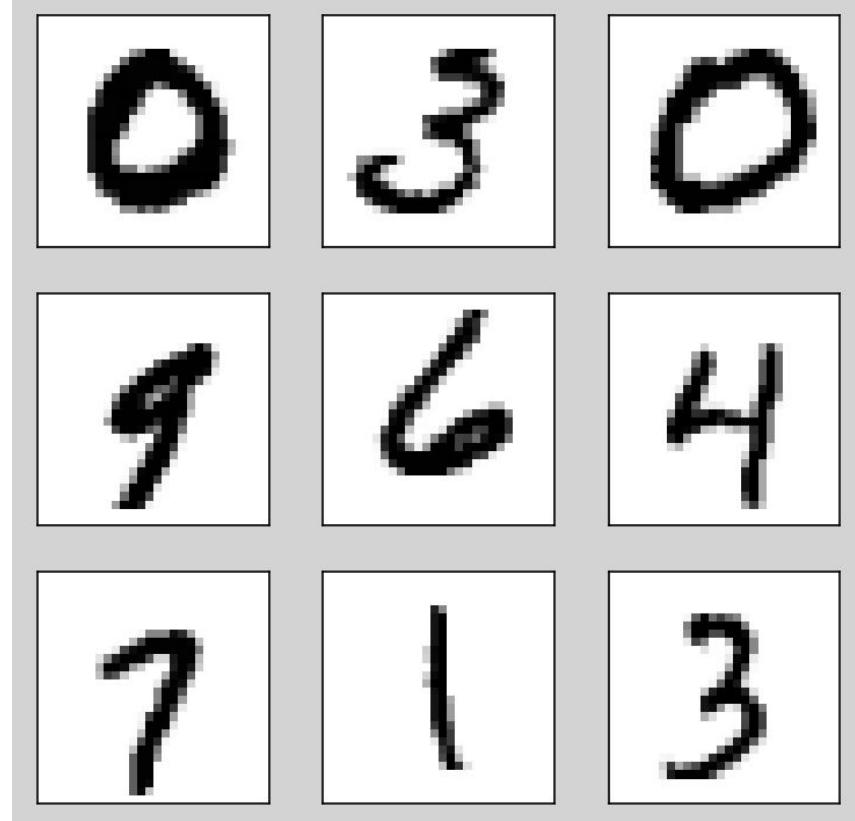
Solution

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



Case Study: MNIST

- Dataset
 - 70K images of handwritten digits
 - Each image is 28×28 in $[0, 1]$ (grayscale)
- Dimensionality Reduction Task
 - Reduce the dimensions from 784 to ???
 - Scored with MSE of the reconstructions against the original images



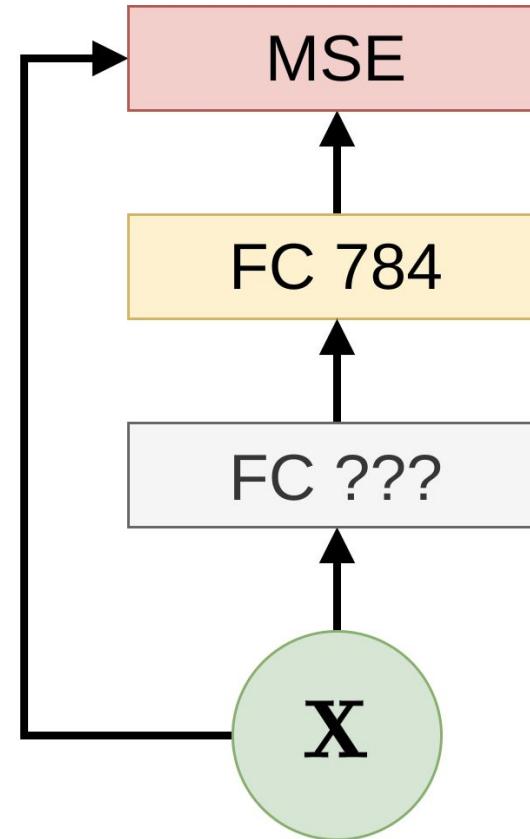
Model: Training

**Undercomplete
Autoencoder**

Encoder Width
???

Encoder Depth
1 layer

Activation
ELU



Hyperparam Search: Greedy Strategy

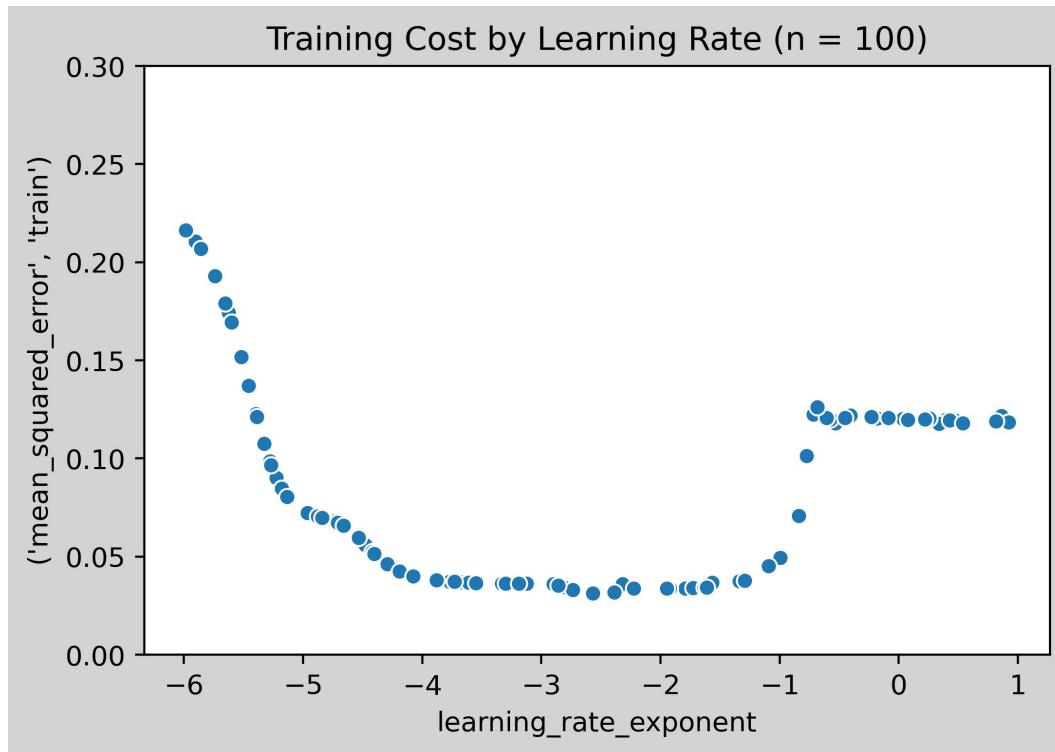
Sequence of hyperparam search:

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

Pros: easy to implement

Cons: sequence needs to be carefully ordered

Hyperparam Search: Learning Rate



Iteration

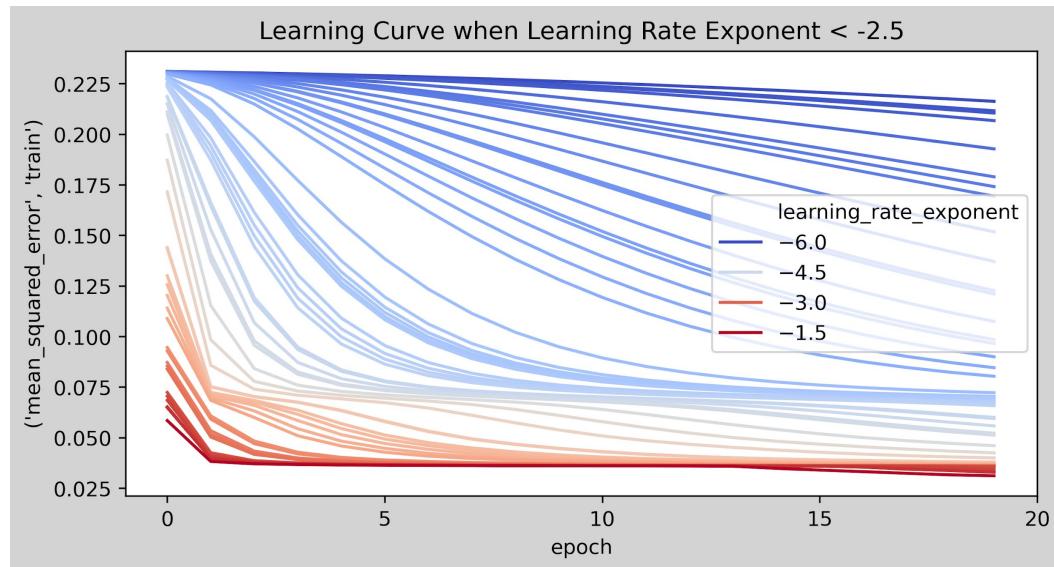
1. $t \sim \text{Uniform}(-6, 1)$
2. Learning Rate = $10^{** t}$
3. Train for 20 epochs

Repeat to train 100 models

Conclusion

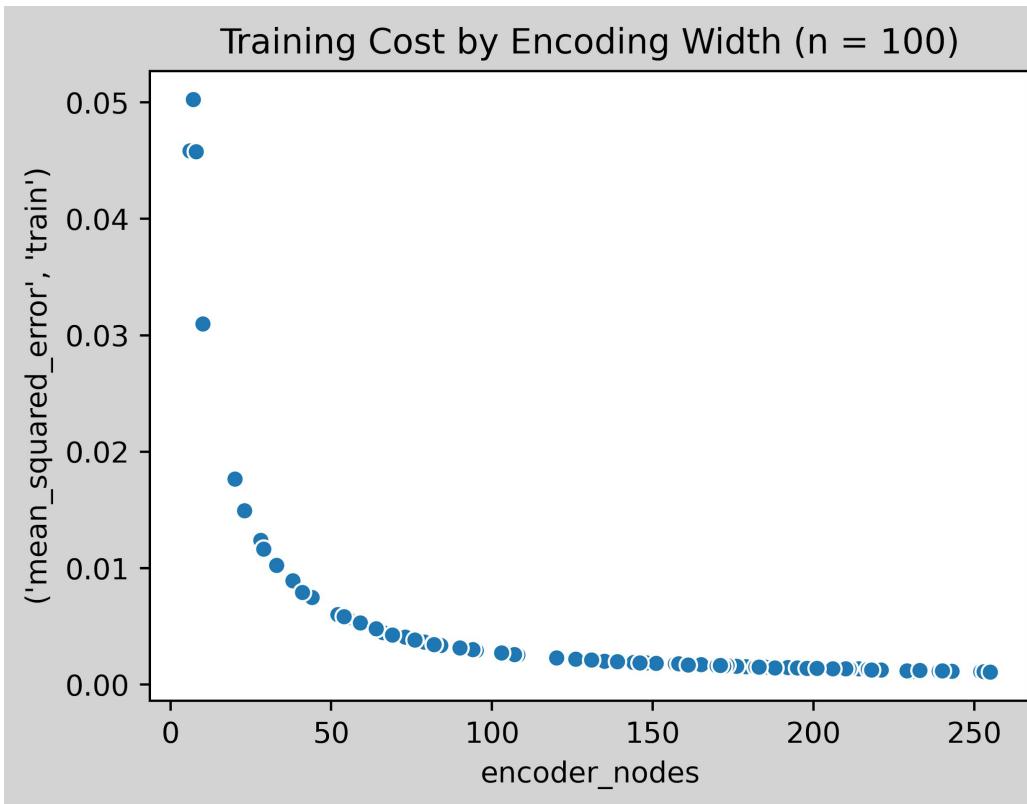
Optimal initial learning rate =
 $10^{** -2.5}$

Hyperparam Search: Learning Rate



Learning curves with learning rate **below/above optimal** are more flat.

Hyperparam Search: Encoding Width



Iteration

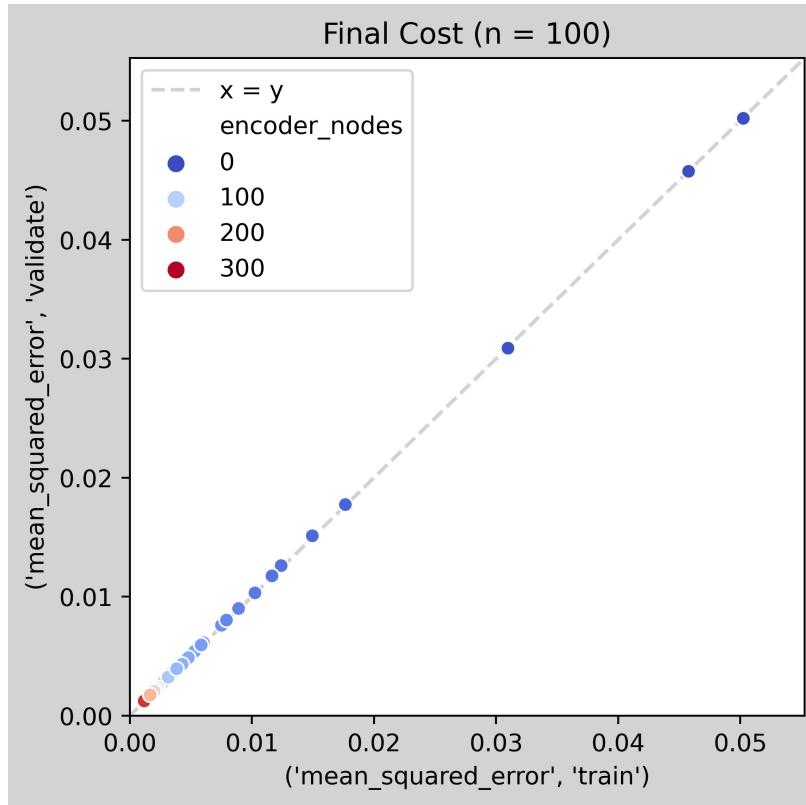
1. Width ~ Uniform(4, 256)
2. Train for 20 epochs

Repeat to train 100 models

Conclusion

Reconstruction error levels out at ~100 nodes.

Hyperparam Search: Encoding Width

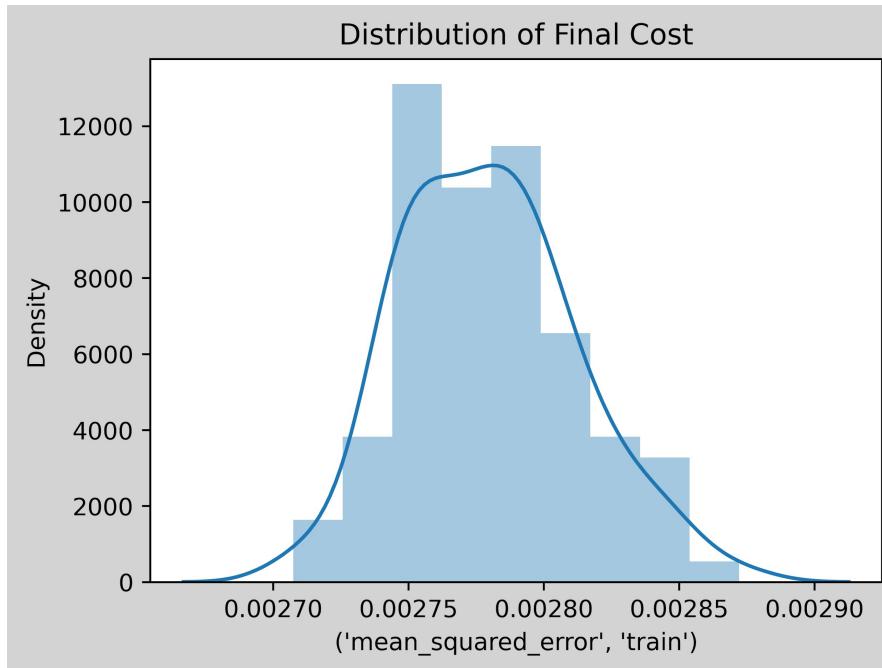


Autoencoder **can overfit if the decoder is reproducing training examples** without using the encoded representation.

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

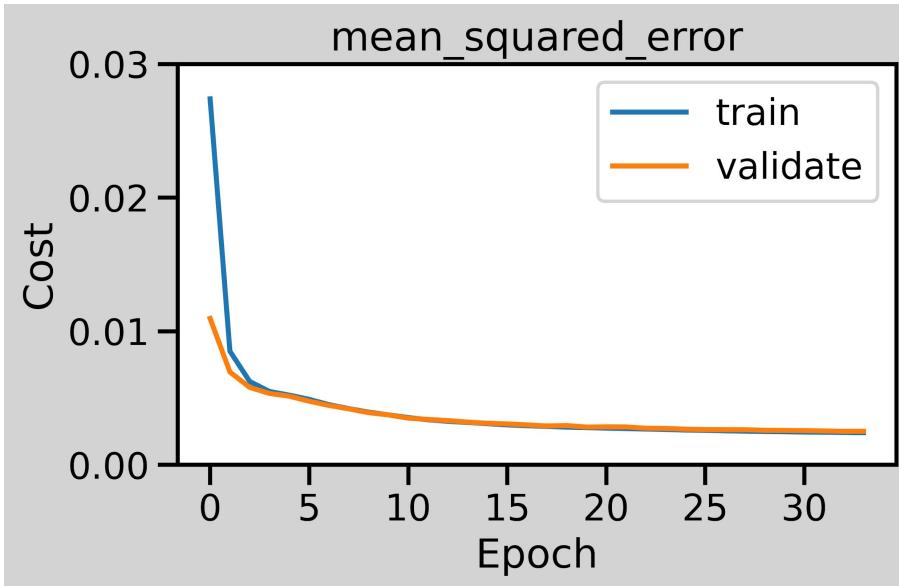
Repeat for 100 models

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 34 epochs

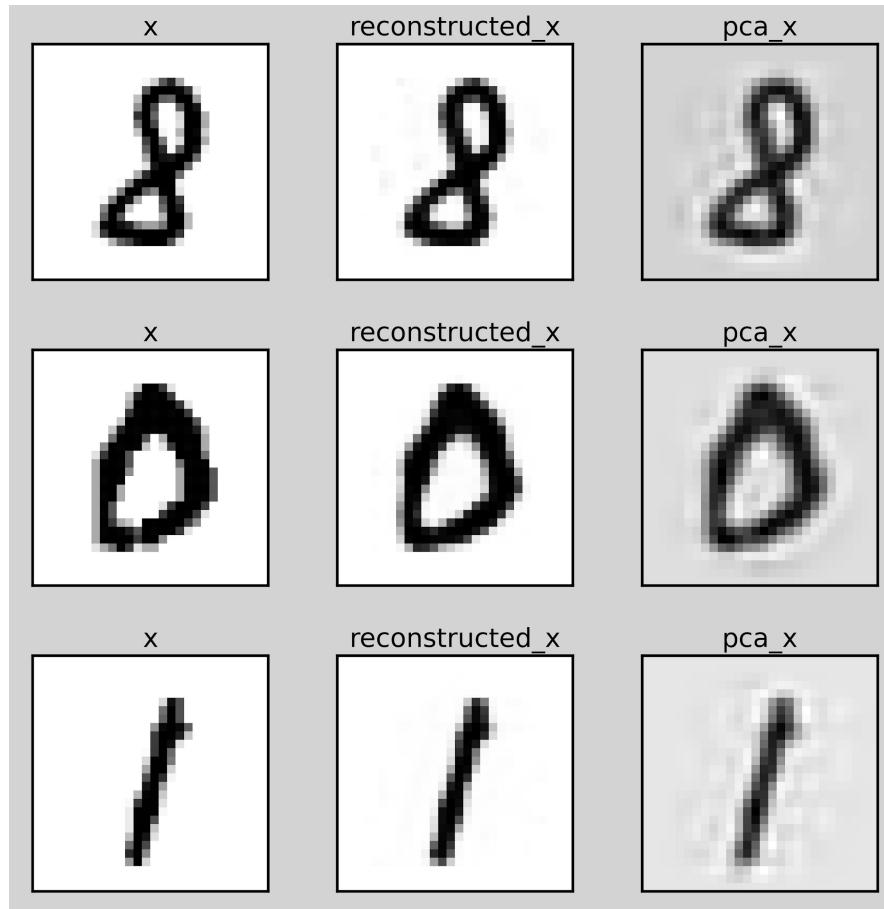
Conclusion

Learning curve converged
towards MSE = 0.0024

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	Reconstruction	0.0057



Denoising Autoencoders: Training

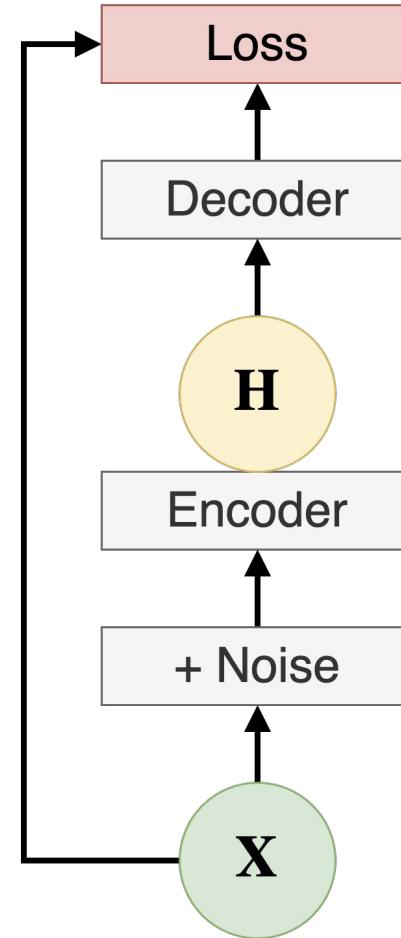
Problem

Remove noise from the input given its distribution.

Solution

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

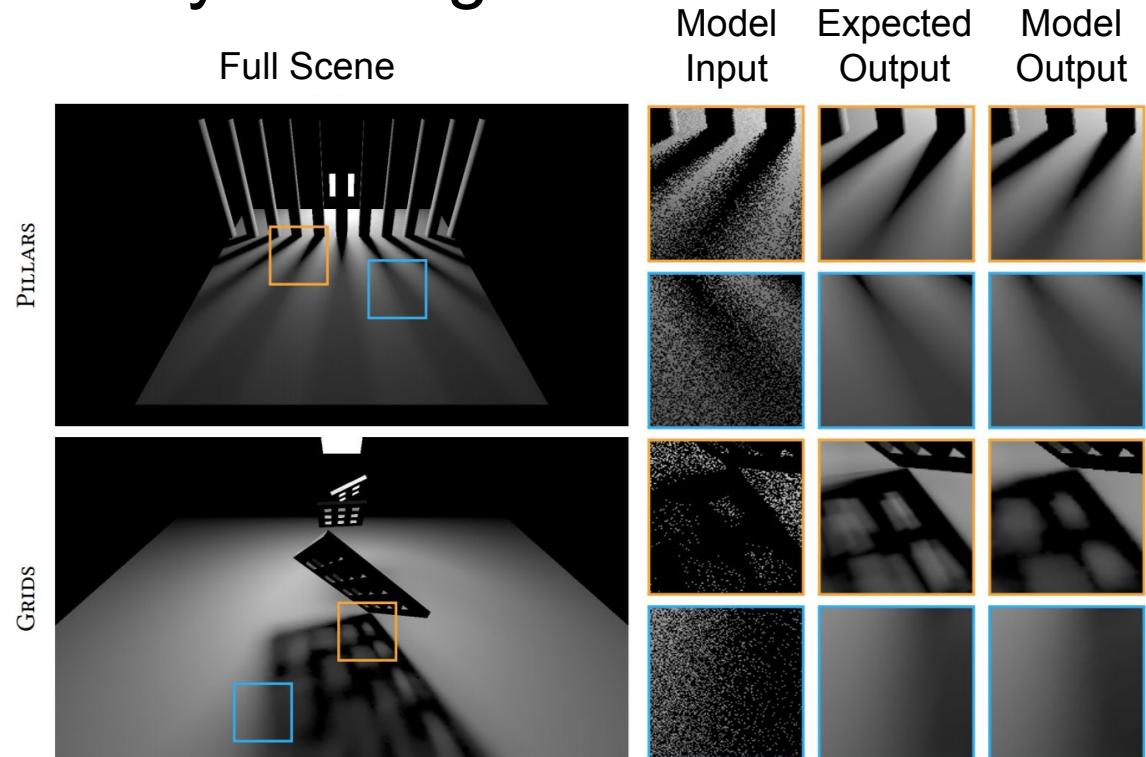
Vincent, P., et al. (2008)



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.

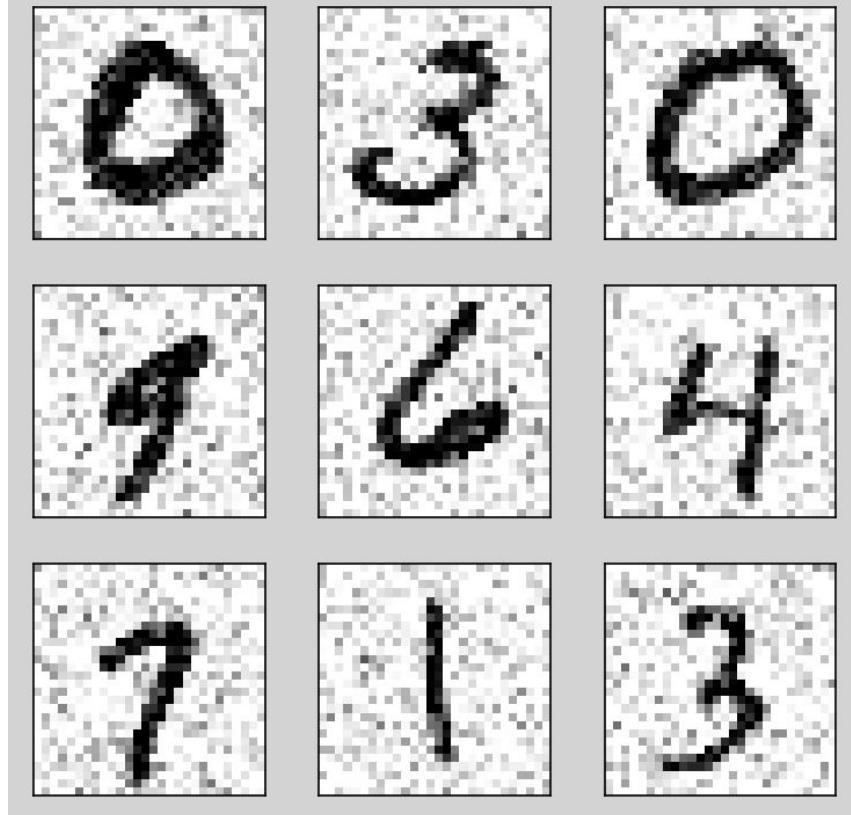


Case Study: NVIDIA Ray Tracing



Case Study: MNIST

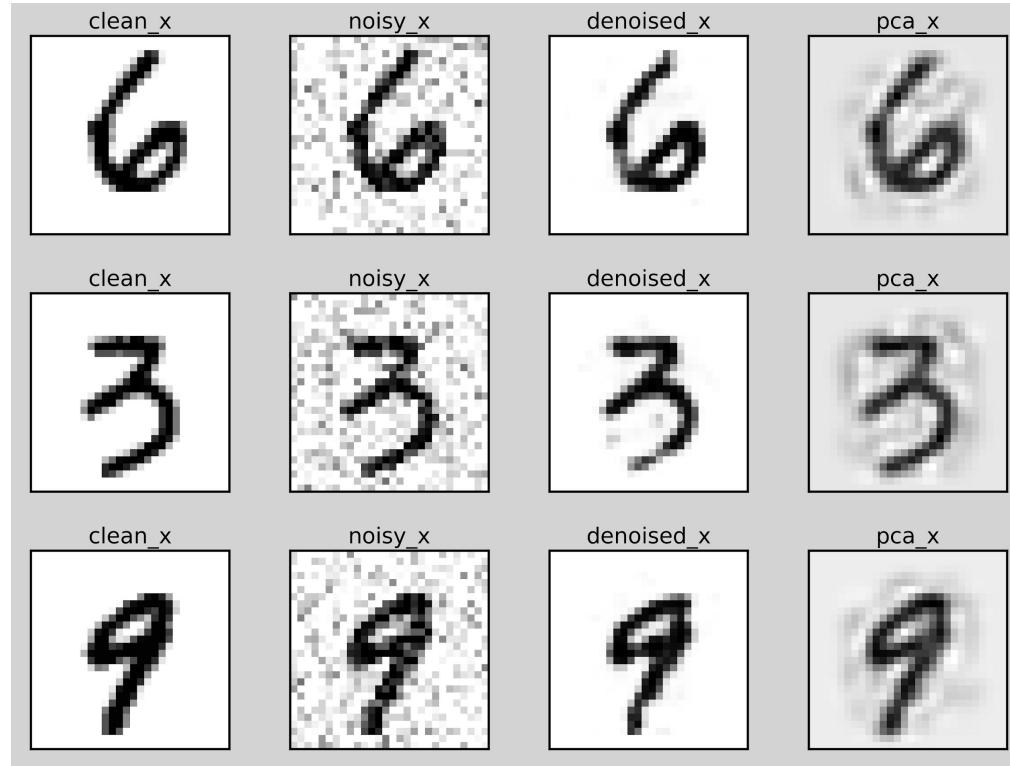
- Dataset
 - 70K images of handwritten digits
 - Each image is 28×28 in $[0, 1]$ (grayscale)
 - Augmented with $\text{Gaussian}(0, 0.2)$
- Denoising Task
 - Remove noise from the images
 - Scored with MSE against original images



Undercomplete Autoencoder?

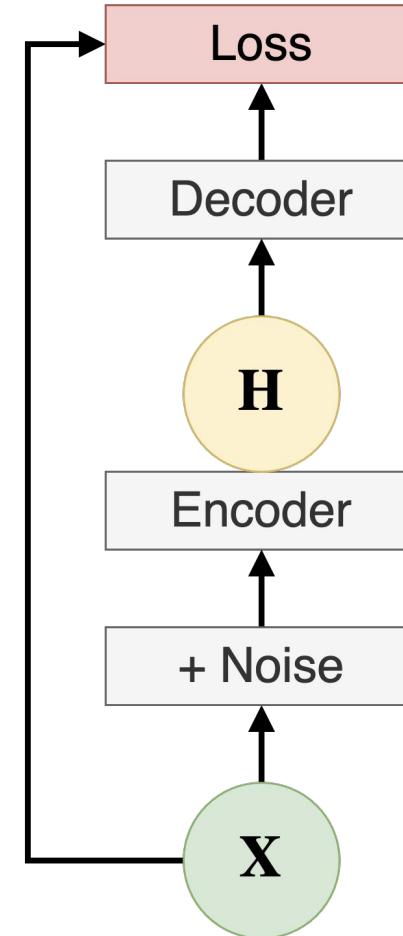
Undercomplete autoencoder can also be used for denoising even though **the noise distribution was not specified** either implicitly or explicitly during training.

Model	Inference Task	MSE
Undercomplete AE	Reconstruction	0.0024
Undercomplete AE	Denoising	0.0123
PCA	Denoising	0.0107

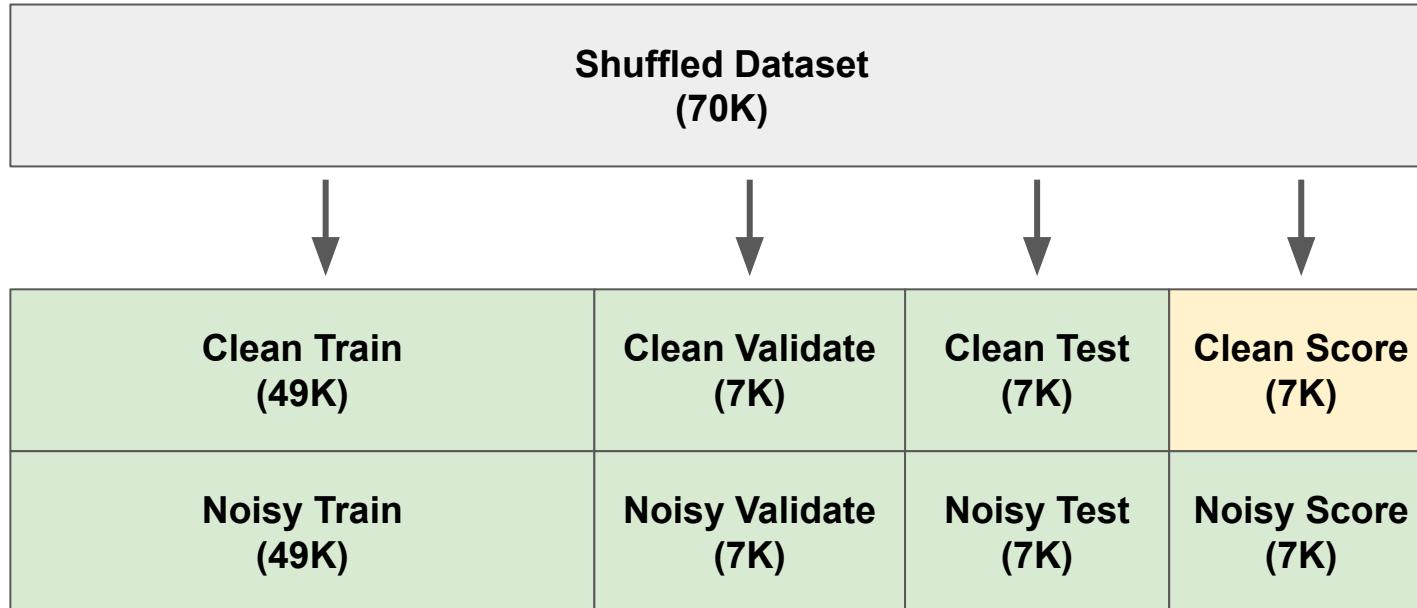


Assignment #1

- Train an Autoencoder
 - Architecture: undercomplete and/or sparse
 - **Training mode: denoising**
- Scored on Denoising Task
 - Methodology on the next slides
- Augmented MNIST Dataset
 - Noise $\sim \text{Normal}(0, 0.2)$
 - 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

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 784
 - b. Data Type = float64 in [0, 1]
 - c. File Type = Parquet

Assignment Grading

- Due EOD 10/4
 - 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
 - My best MSE was 0.004, but I know it can be even lower
- Compute Environments
 - Your laptop (Docker + Jupyter)
 - AWS SageMaker Notebook

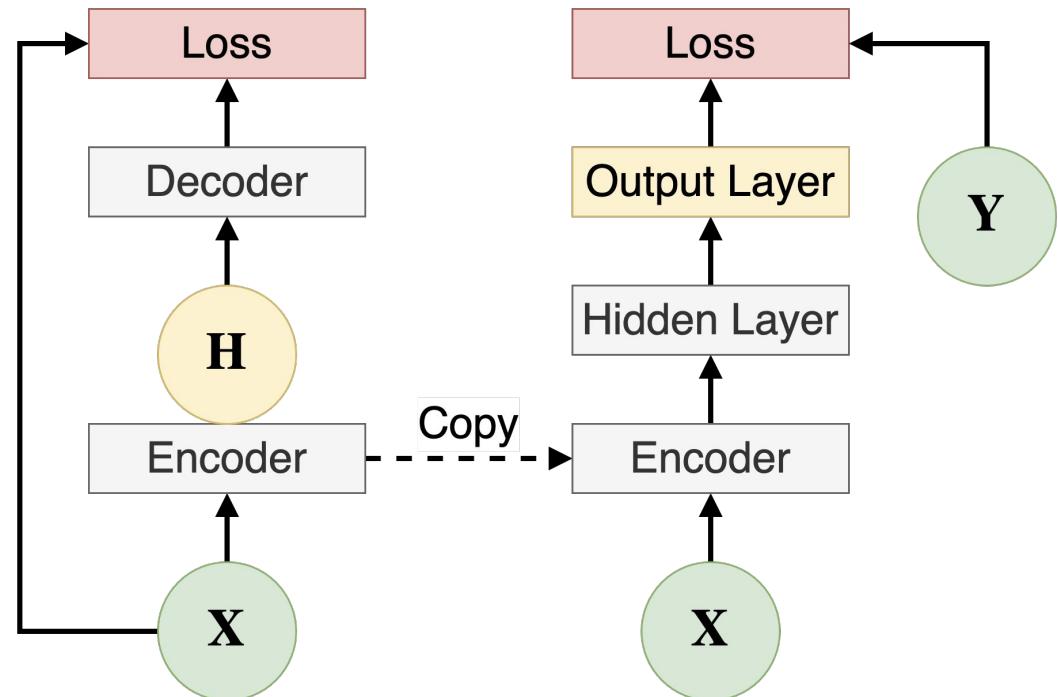
Unsupervised Pre-training

Problem

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

Solution

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

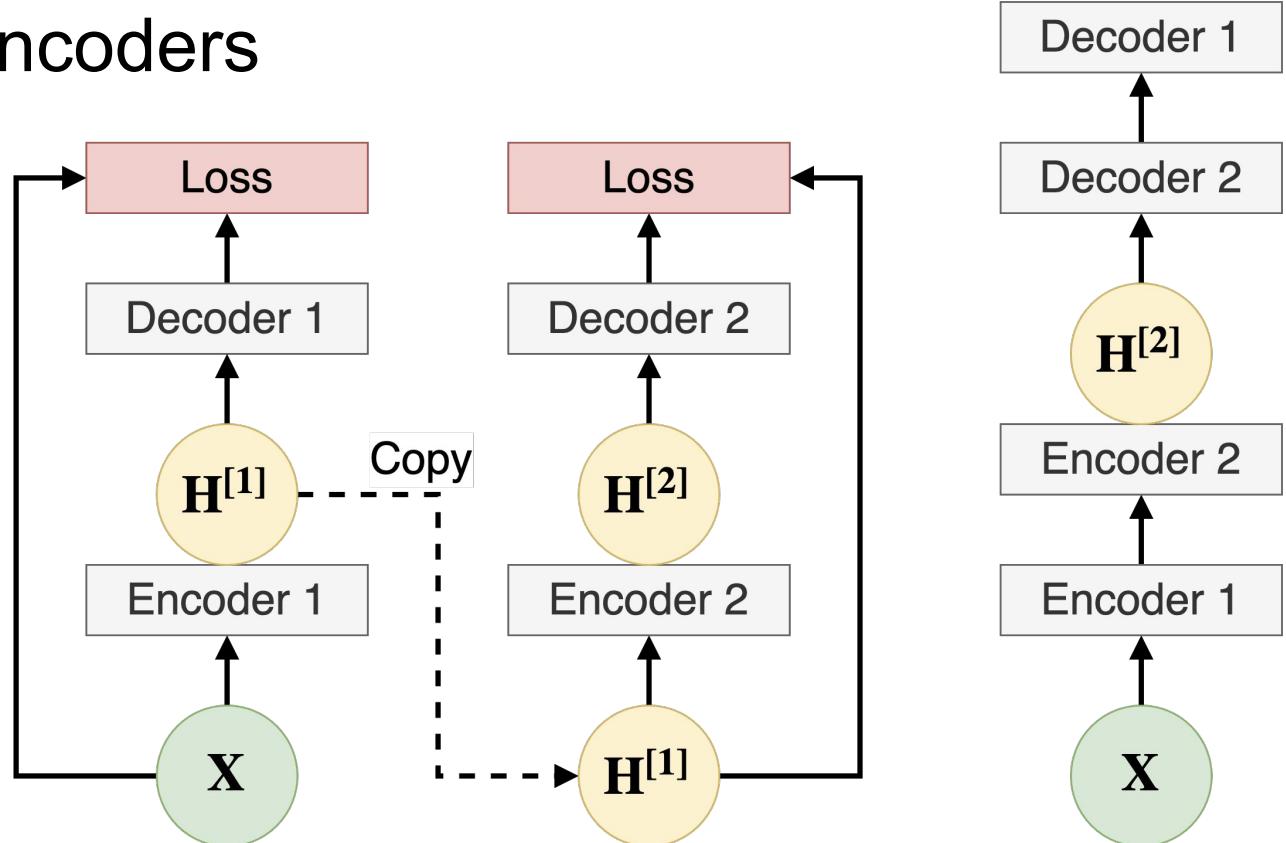


Stacked Autoencoders

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)

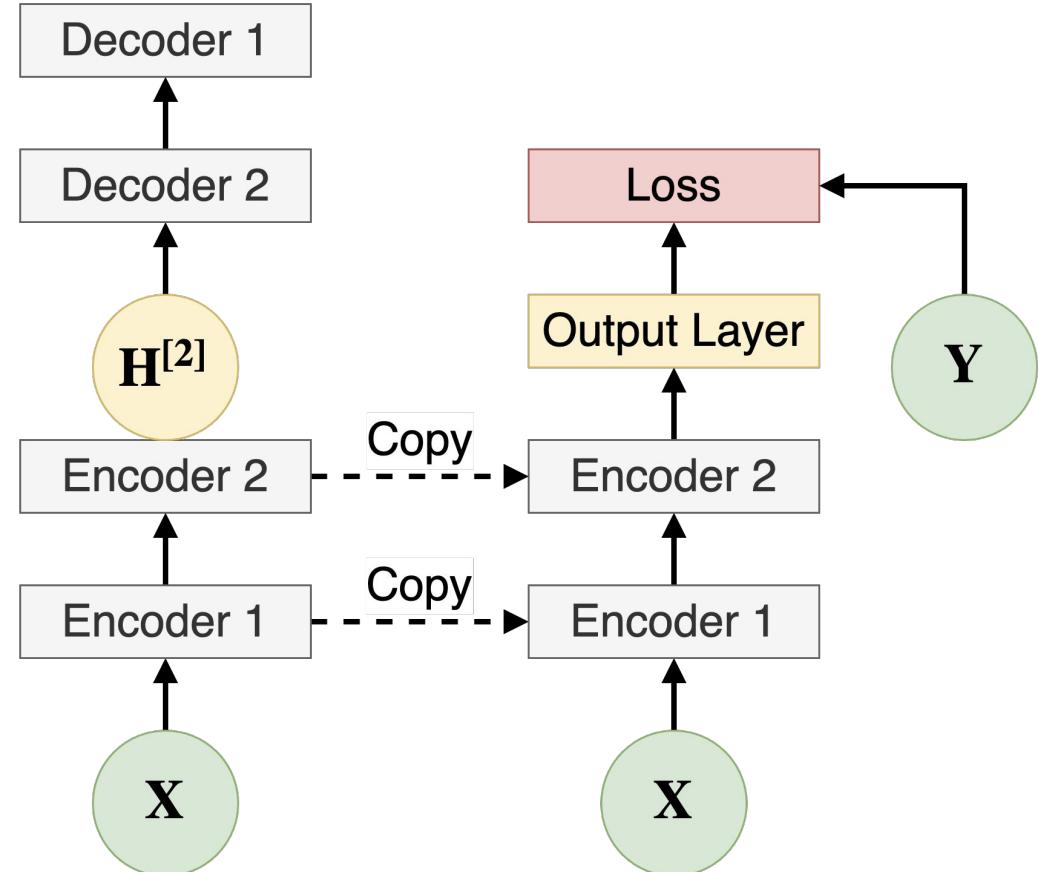
Deep Unsupervised Pre-training

Problem

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

Solution

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



Step 1: Store Records

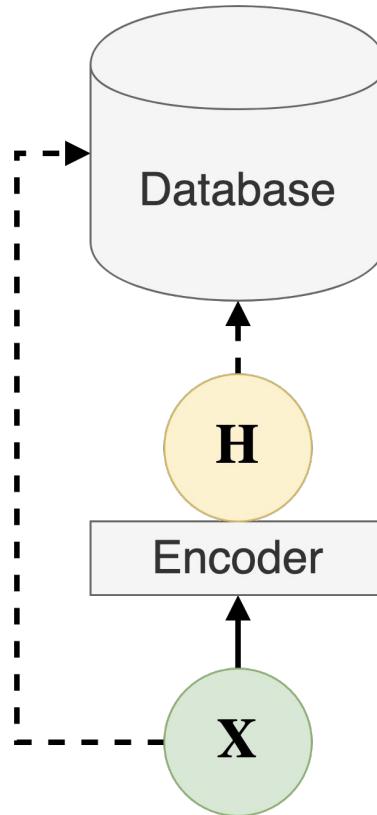
Use Case: Semantic Hashing

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)

Use Case: Semantic Hashing

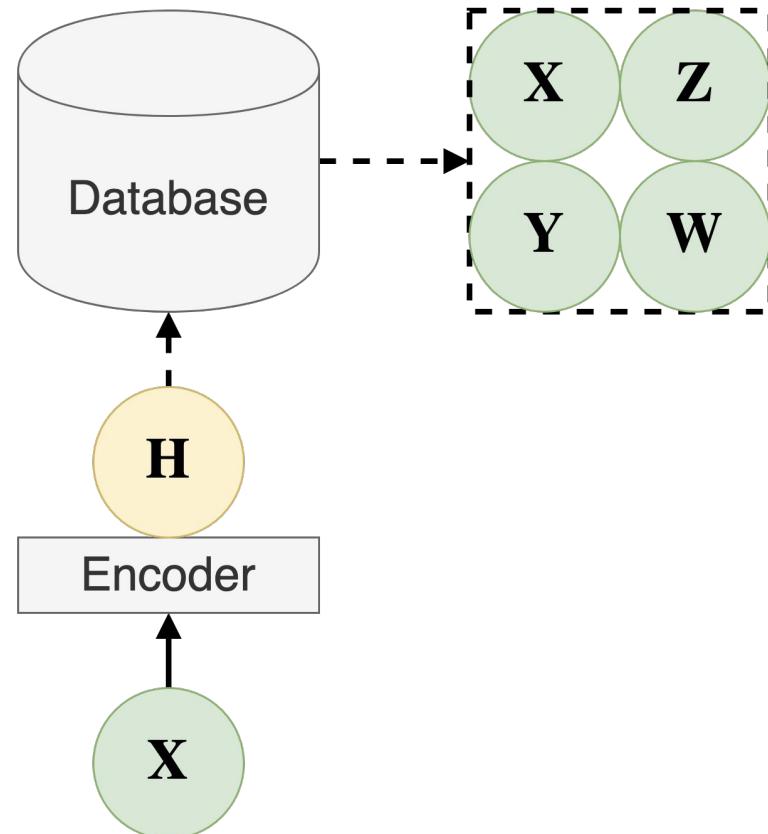
Problem

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

Solution

Use the latent representation as the key in a database.

Step 2: Retrieve Records



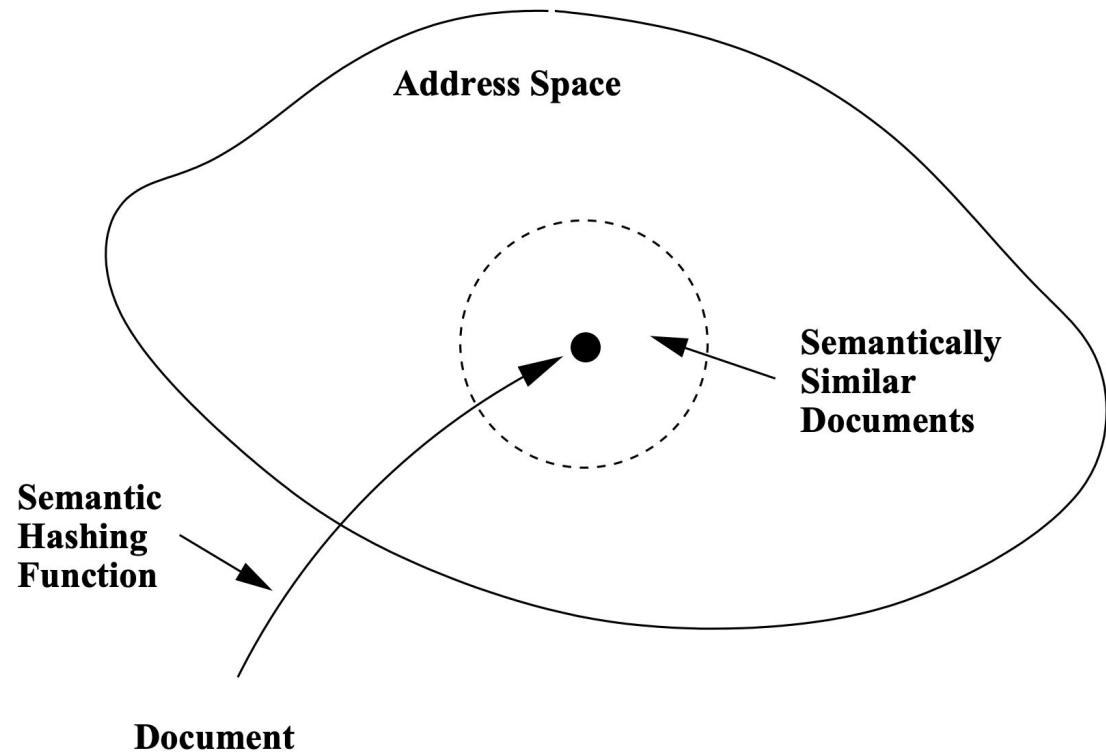
Use Case: Semantic Hashing

Problem

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

Solution

Use the latent representation as the key in a database.



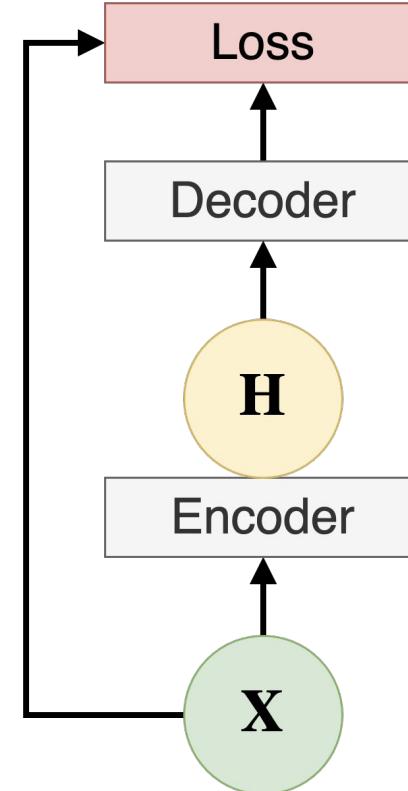
Use Case: Anomaly Detection

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.



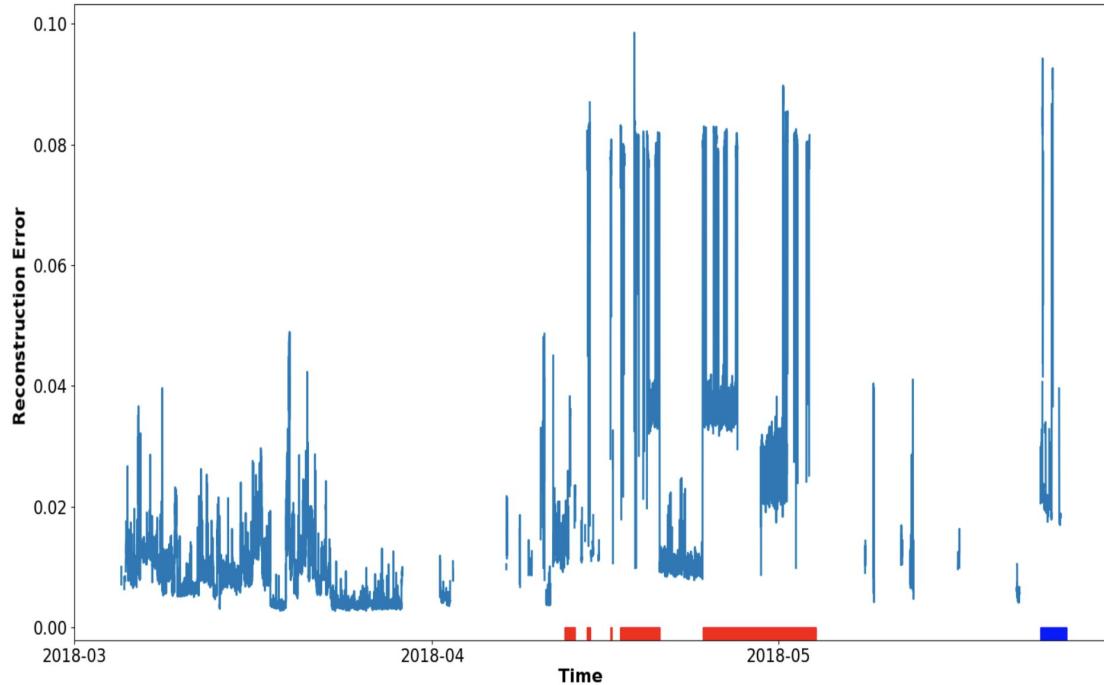
Use Case: Anomaly Detection

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.



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