Deep Learning

Abdelhak Mahmoudi
abdelhak.mahmoudi@um5.ac.ma

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2. Convolutional Neural Networks
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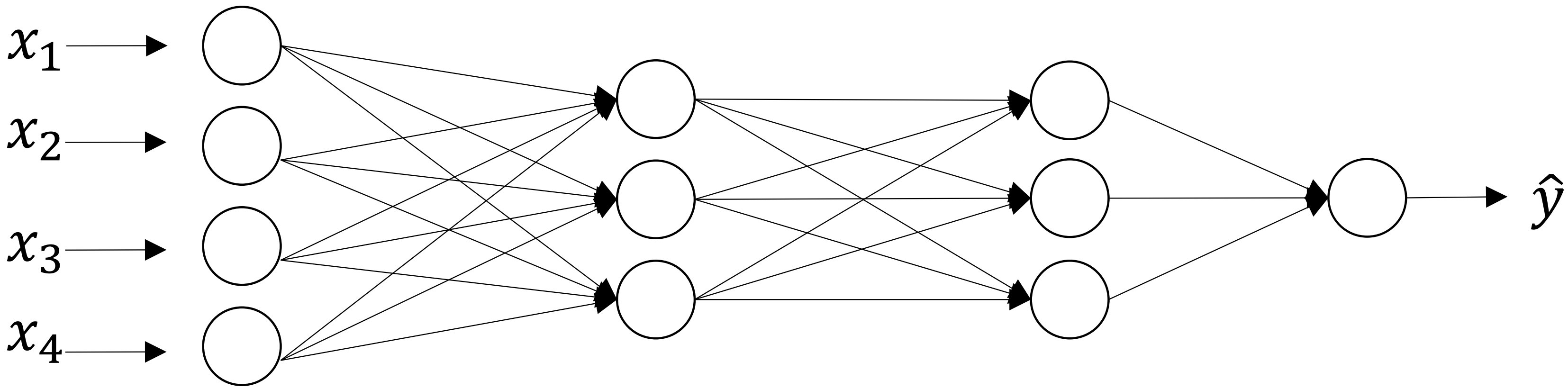
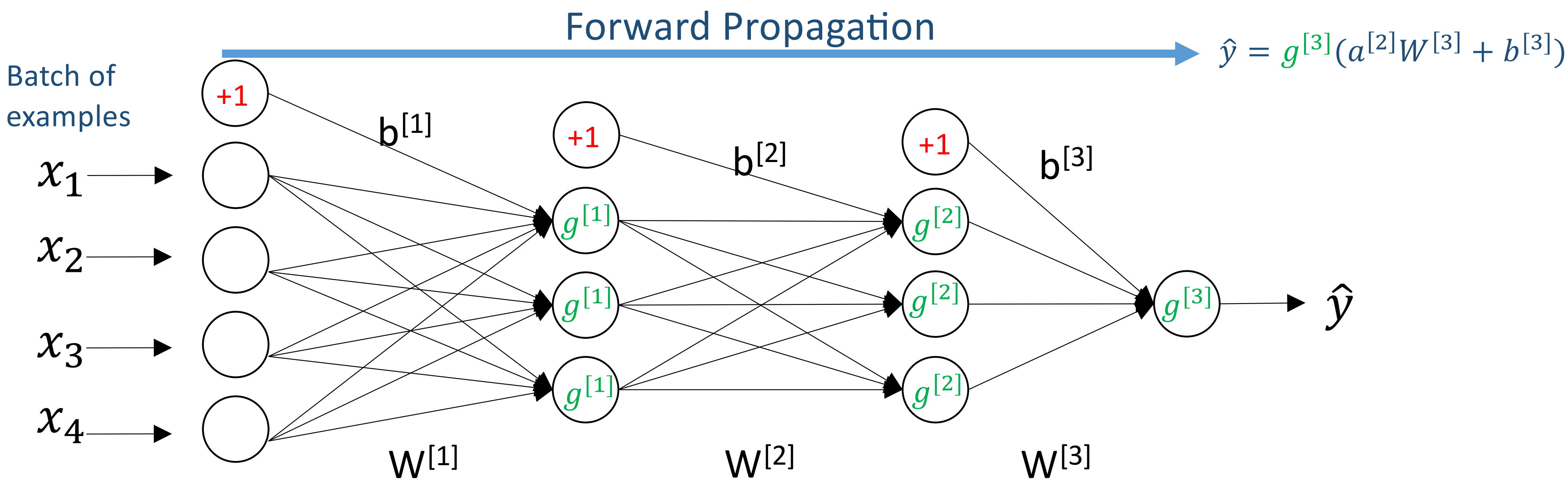
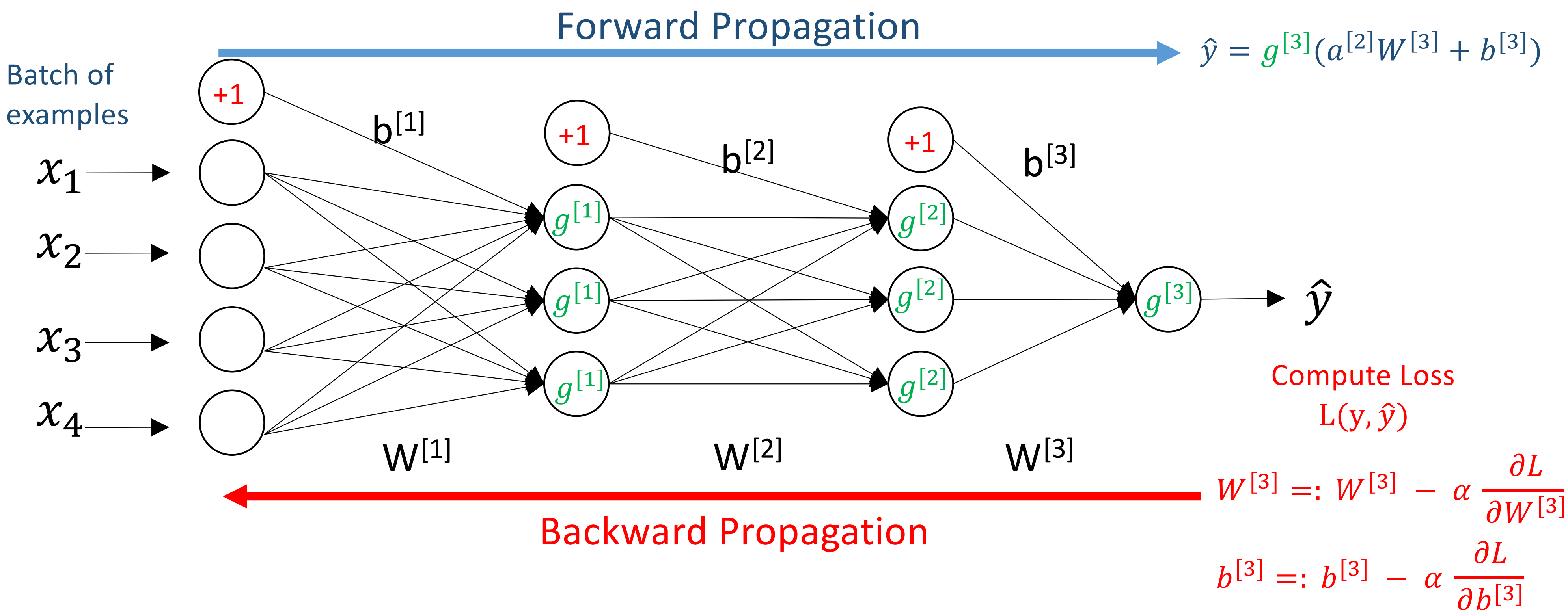
Artificial Neural Networks



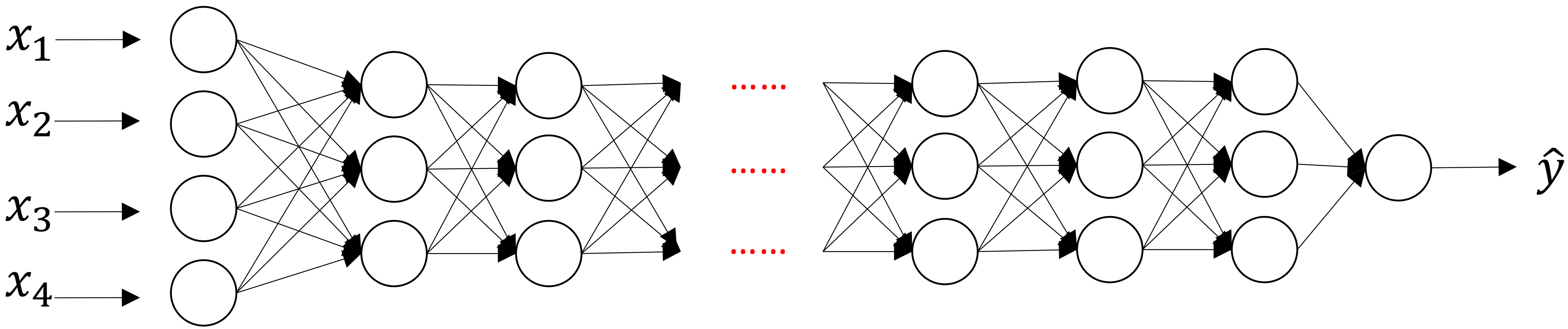
Artificial Neural Networks



Artificial Neural Networks

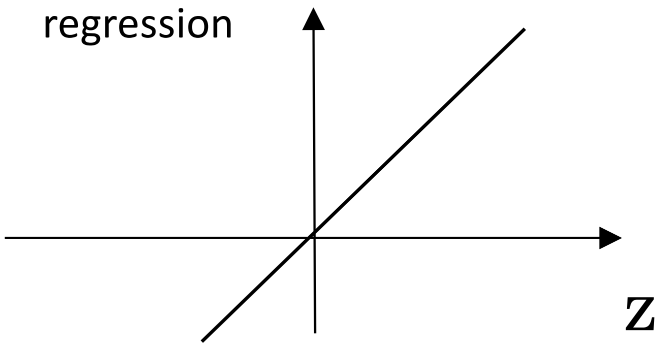


Deep Neural Networks

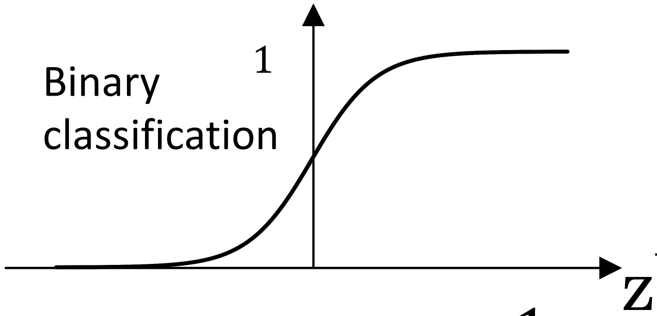


Activation Functions

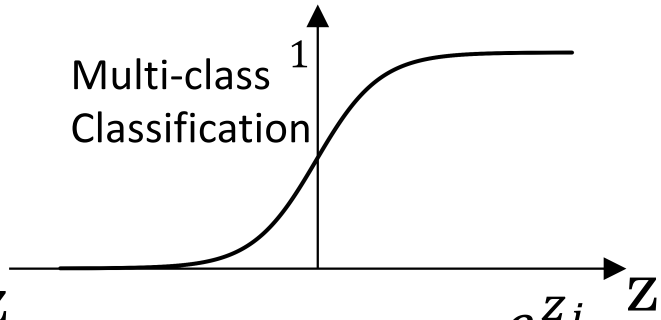
Output Layer



Linear $a = z$

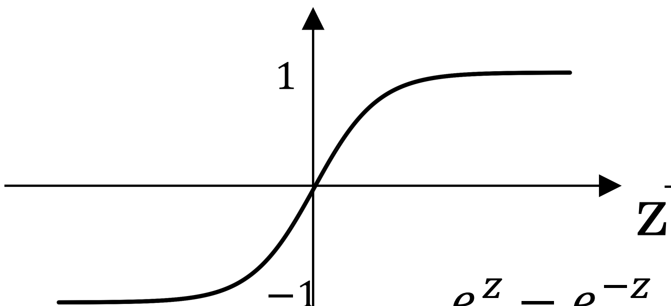


Sigmoid $a = \frac{1}{1 + e^{-z}}$

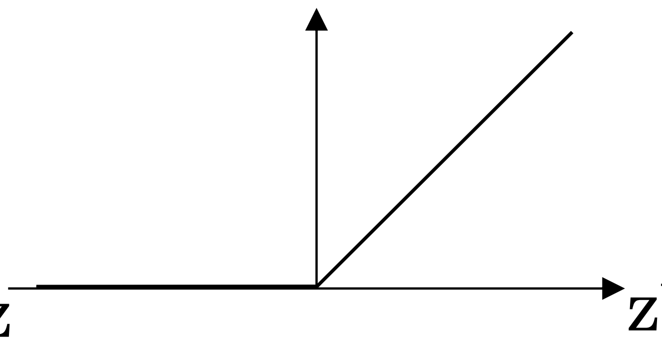


Softmax $a_j = \frac{e^{z_j}}{\sum_{j=1}^{K} e^{z_j}}$

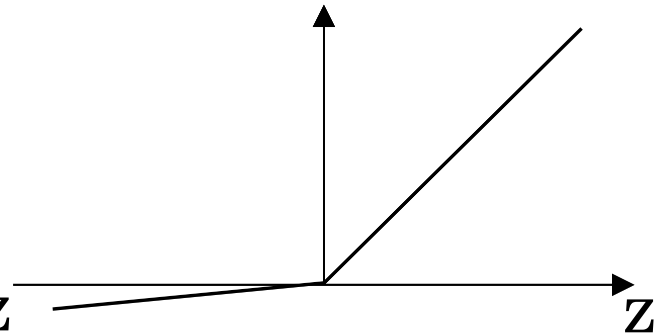
Hidden Layers



Tanh $a = \frac{e^z - e^{-z}}{e^z + e^{-z}}$

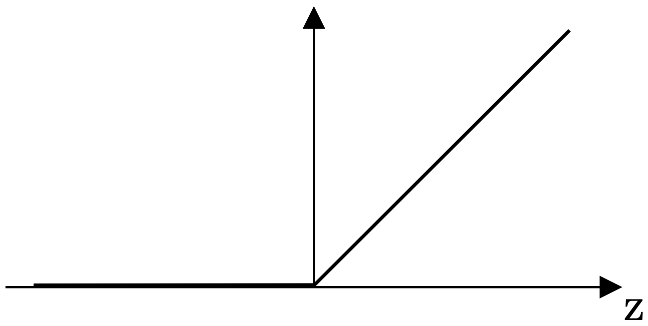


ReLU $a = \max(0, z)$



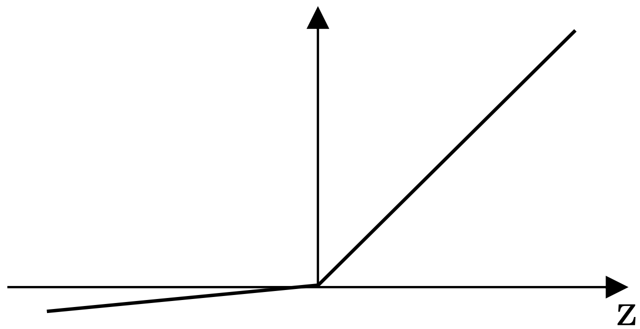
Leaky ReLU $a = \max(0.01z, z)$

Activation Functions



ReLU $a = \max(0, z)$

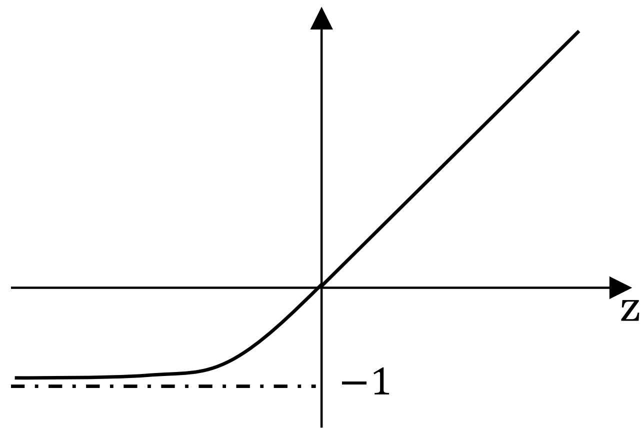
2010: Glorot and Bengio



Leaky ReLU $a = \max(\alpha z, z)$

$\alpha = 0.01$
$\alpha = 0.2$

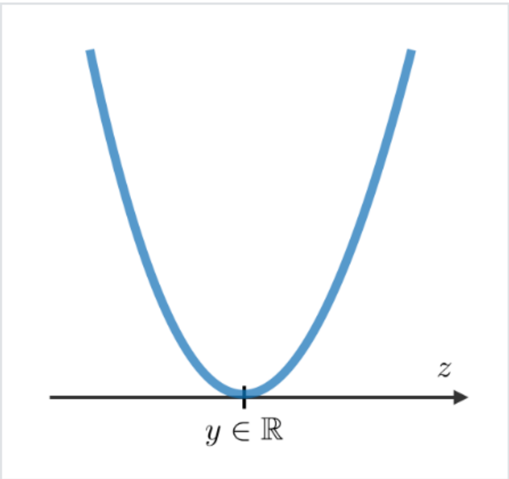
α can be learned: Parametric ReLU



Exponential ELU $a = \begin{cases} \alpha \exp(z - 1) & \text{if } z < 0 \\ z & \text{if } z \geq 0 \end{cases}$

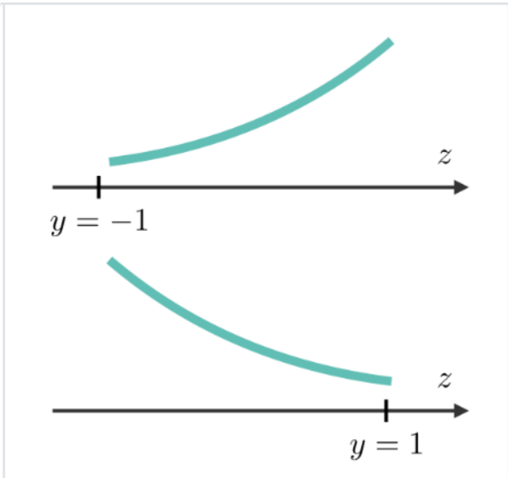
2015: Clevert et al.

Loss functions



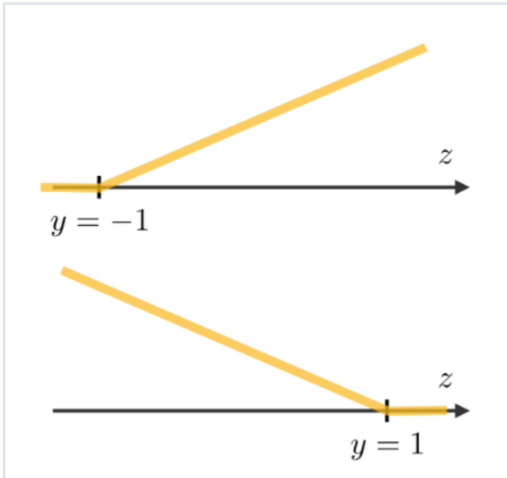
$L_i(\hat{y}, y) = (\hat{y} - y)^2$

Least squares loss



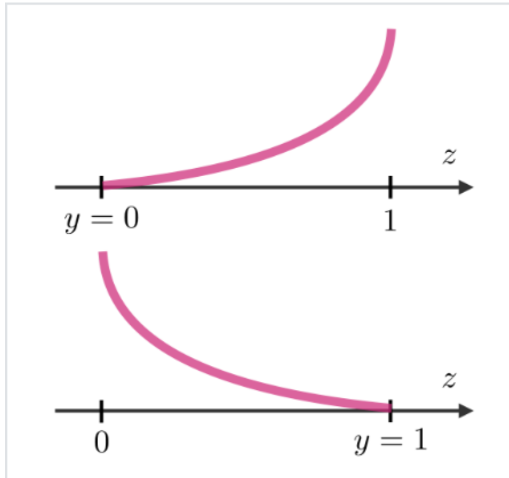
$L_i(\hat{y}, y) = \log(1 + \exp(-\hat{y}\, y))$

Logistic loss



$L_i(\hat{y}, y) = (1 - \hat{y}\, y)_+$

Hinge loss

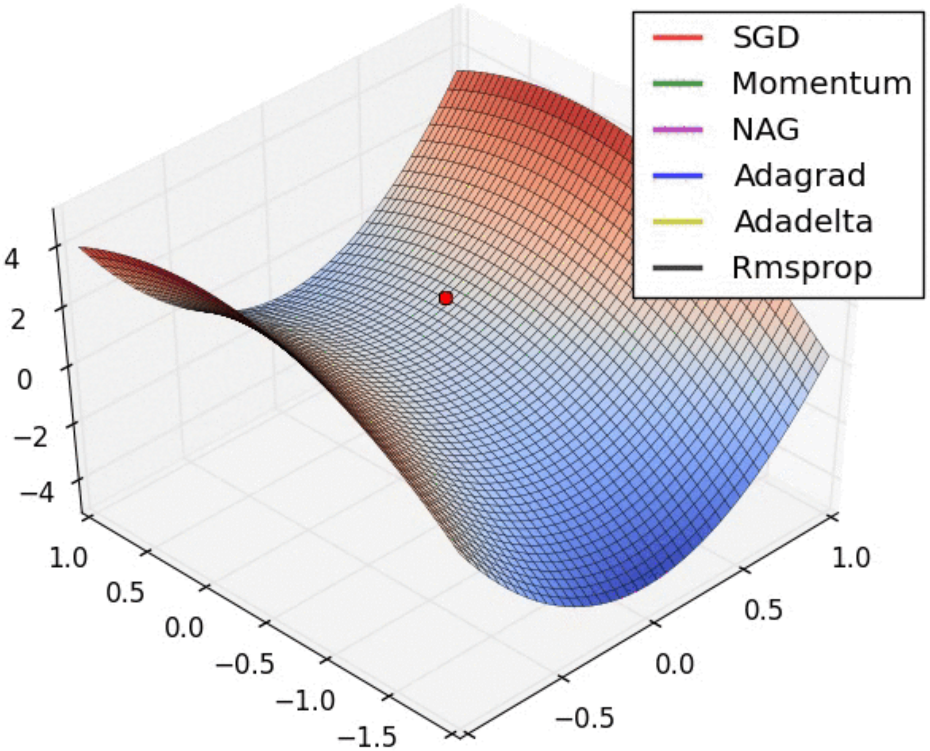


$L_i(\hat{y}, y) = -(y\log(\hat{y}) + (1 - y)\log(1 - \hat{y}))$

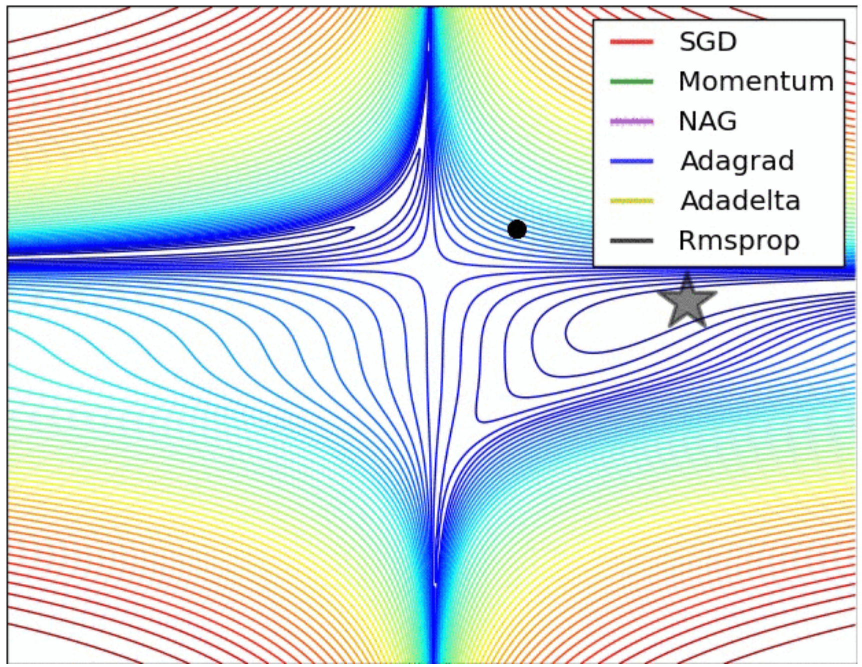
Cross Entropy loss

With K classes: $L_i(\hat{y}, y) = -\sum_{k=1}^{K} y_k \log(\hat{y}_k)$

Optimizers



SGD
Momentum
NAG
Adagrad
Adadelta
Rmsprop
4
2
0
−2
−4
1.0
0.5
0.0
−0.5
−1.0
−1.5
1.0
0.5
0.0
−0.5



SGD
Momentum
NAG
Adagrad
Adadelta
Rmsprop

Update_parameters

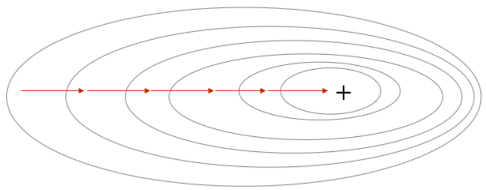
$$W := W - \alpha \, dW$$

Gradient Descent

Gradient Descent (All examples)

```
X = data_input
Y = labels
parameters = initialize_parameters(layers_dims)
for epoch in range(num_epochs):
    # Forward propagation
    a, caches = forward_propagation(X, parameters)
    # Compute cost.
    cost = compute_cost(a, Y)
    # Backward propagation.
    grads = backward_propagation(a, caches, parameters)
    # Update parameters.
    parameters = update_parameters(parameters, grads)
```

Converge smoothly but slowly



Update_parameters

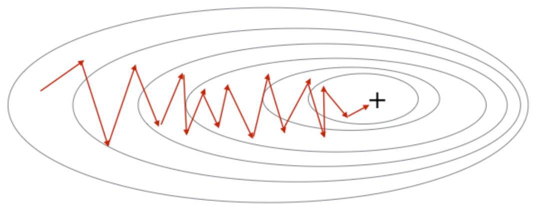
$$W := W - \alpha\, dW$$

Gradient Descent

Stochastic Gadient Descent (one single example each time)

```
X = data_input
Y = labels
parameters = initialize_parameters(layers_dims)
for epoch in range(num_epochs):
    for i in range(0, m):
        # Forward propagation
        a, caches = forward_propagation(X[:,i], parameters)
        # Compute cost
        cost = compute_cost(a, Y[:,i])
        # Backward propagation
        grads = backward_propagation(a, caches, parameters)
        # Update parameters.
        parameters = update_parameters(parameters, grads)
```

Converge quickly but oscillate



NB: Number of **epochs** is a hyperparameter that defines how many times we go through the **ENTIRE** training dataset.

Update_parameters

$W := W - \alpha \, dW$

Gradient Descent

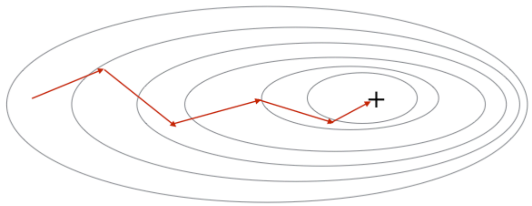
Mini-Batch Gadient Descent (a subset of examples each time)

```
X = data_input
Y = labels
parameters = initialize_parameters(layers_dims)
for epoch in range(num_epochs):
    mini_batches = random_mini_batches(X, Y, mini_batch_size)
    for mini_batch in mini_batches:
        # Forward propagation
        a, caches = forward_propagation(mini_batch[ 'X' ], parameters)
        # Compute cost
        cost = compute_cost(a, mini_batch[ 'Y' ])
        # Backward propagation
        grads = backward_propagation(a, caches, parameters)
        # Update parameters.
        parameters = update_parameters(parameters, grads)
```

Shuffling and Partitioning

e.g., 16, 32, 64, 128

Converge quickly with few oscillations

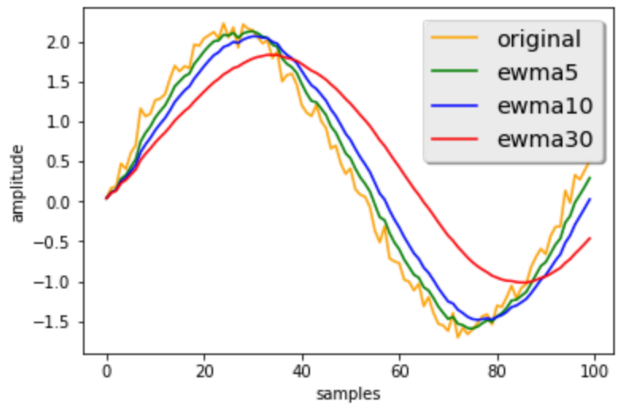


GD with Momentum

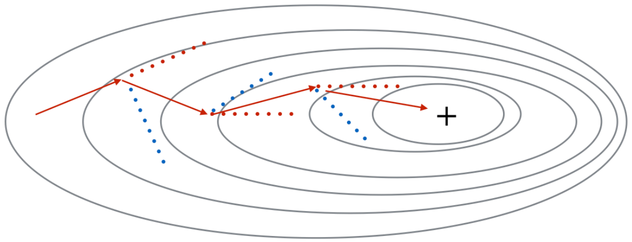
Update_parameters

$$v_{dW} := \beta v_{dW} + (1-\beta)dW$$
$$W := W - \alpha v_{dW}$$

- Generalization of mini-batch gradient descent ($\beta = 0$)
- Use EWMA (Exponentially Weighted Moving Averages) of dW and db.
- v_{dW} (velocity), dW (acceleration)
- Tuning hyperparameters α, β. Often ($\beta = 0.9$). Can be tuned using cross-validation.
- The larger the momentum β is, the smoother the update
- Nesterov Adaptive Gradient (NAG)
  - $v_{dW} := \beta v_{dW} + (1-\beta)d(W + \eta\, v_{dW})$
  - $W := W - \alpha v_{dW}$



Momentum



Reduce oscillations

Update_parameters

$$s_{dW} := \beta s_{dW} + (1-\beta)dW^2$$

$$W := W - \alpha \frac{dW}{\sqrt{s_{dW}} + \varepsilon}$$

GD with RMSprop

- RMSprop: Root Mean Square Propagation
- Uses Exponentially weighted averages of the second derivatives dW^2 (and db^2)
- ε avoid dividing by 0

GD with Adam

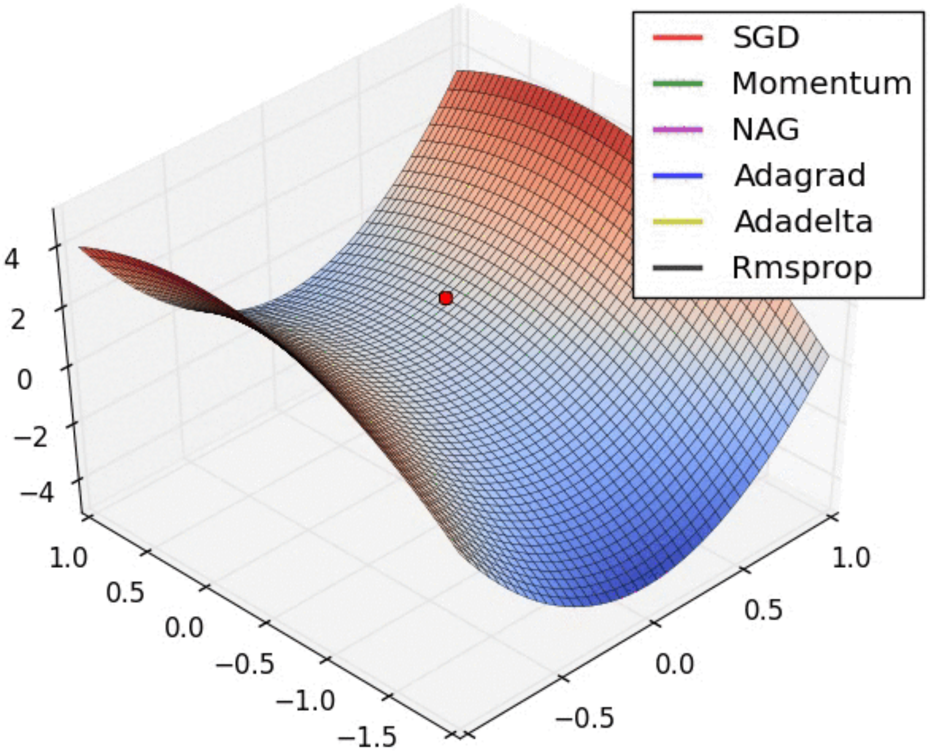
- Adam: Adaptive Moment Estimation
- Momentum + RMSprop
- Converges a lot faster and require low memory
- Usually works well even with little tuning of hyperparameters (except α)
- The most effective for DNNs !
- Variants
  - Nesterove Accelerated Gradient (NAG)
  - Adamax (infinity norm)
  - Nadam (Nesterov + RMSprop)

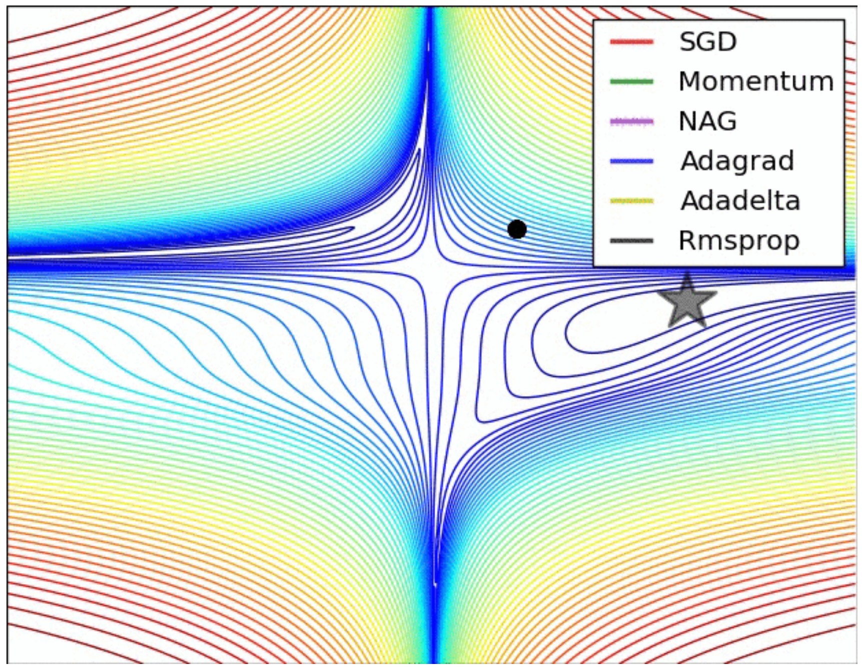
Update_parameters

$$v_{dW} := \beta_1 v_{dW} + (1-\beta_1)dW$$
$$v_{dW}^{corrected} = \frac{v_{dW}}{1-\beta_1^t}$$
$$s_{dW} := \beta_2 s_{dW} + (1-\beta_2)dW^2$$
$$s_{dW}^{corrected} = \frac{s_{dW}}{1-\beta_2^t}$$

$$W := W - \alpha \frac{v_{dW}^{corrected}}{\sqrt{s_{dW}^{corrected}} + \varepsilon}$$

Other Optimization Methods

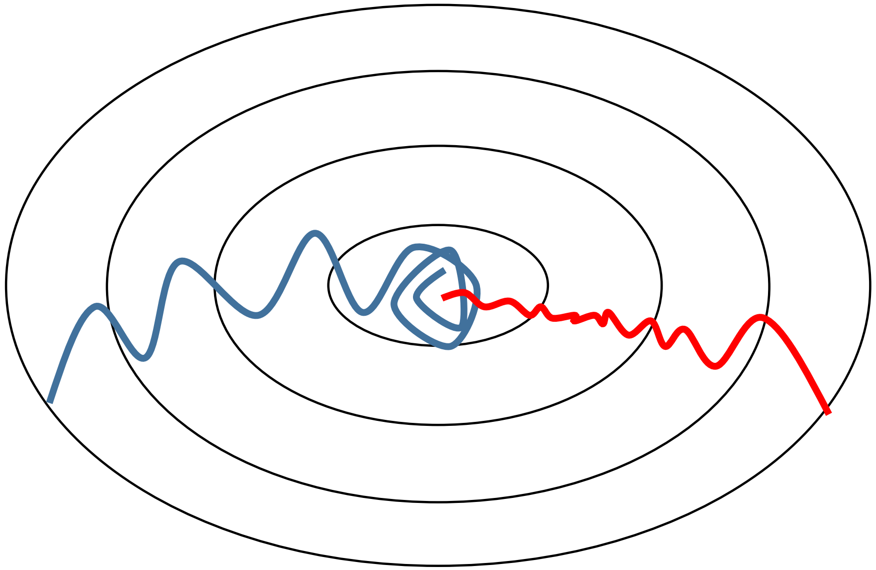




Learning Rate Decay

- Optimization with Constant learning rate may diverge

  → Reduce the learning rate every iteration
- Methods
  - Time based decay
  - Step decay
  - Exponential decay
  - Etc.



Learning Rate Decay

$\alpha = \alpha_0$

Fig 1 : Constant Learning Rate

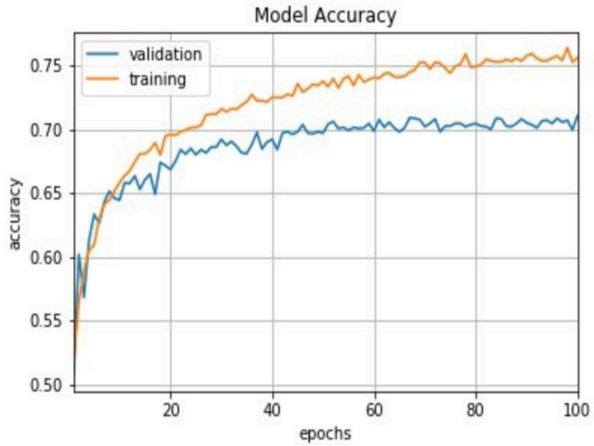


Fig 2 : Time-based Decay Schedule

$\alpha_t = \dfrac{1}{1 + kt} \alpha_0$

$\alpha_{t+s} = .5\ \alpha_t$

Reduce by half every step s

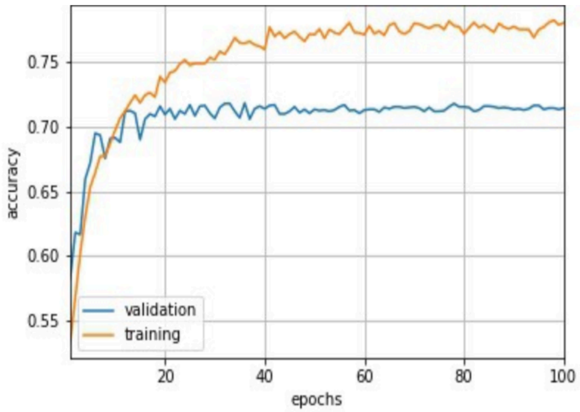


Fig 3a : Step Decay Schedule

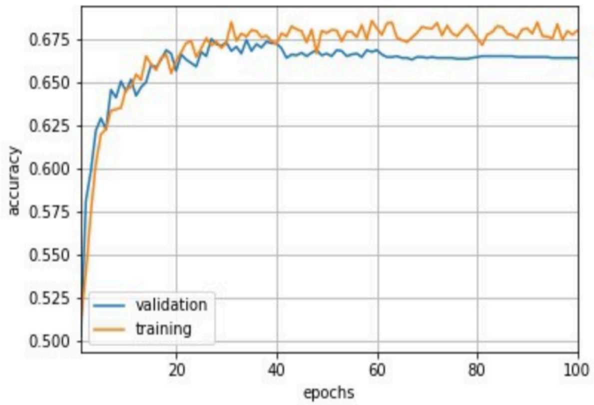
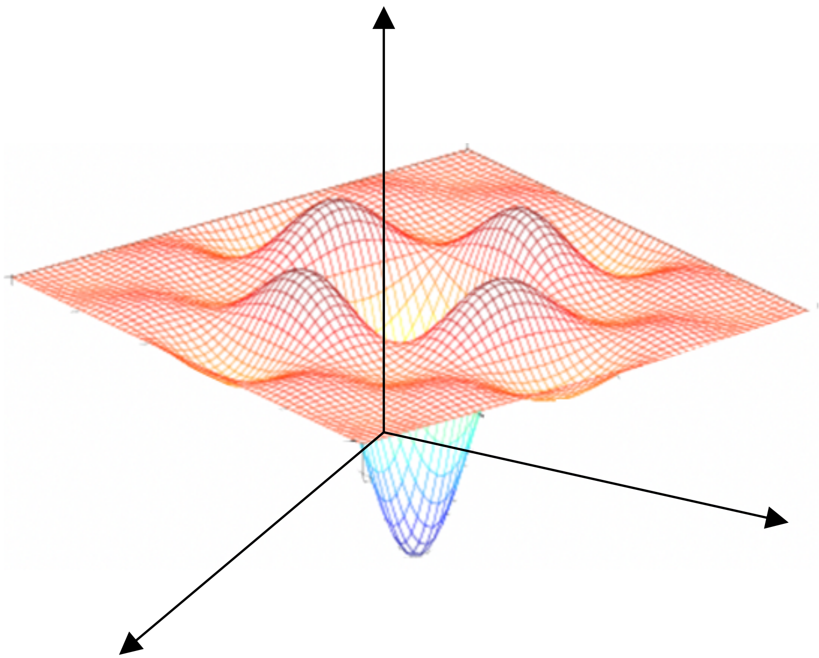
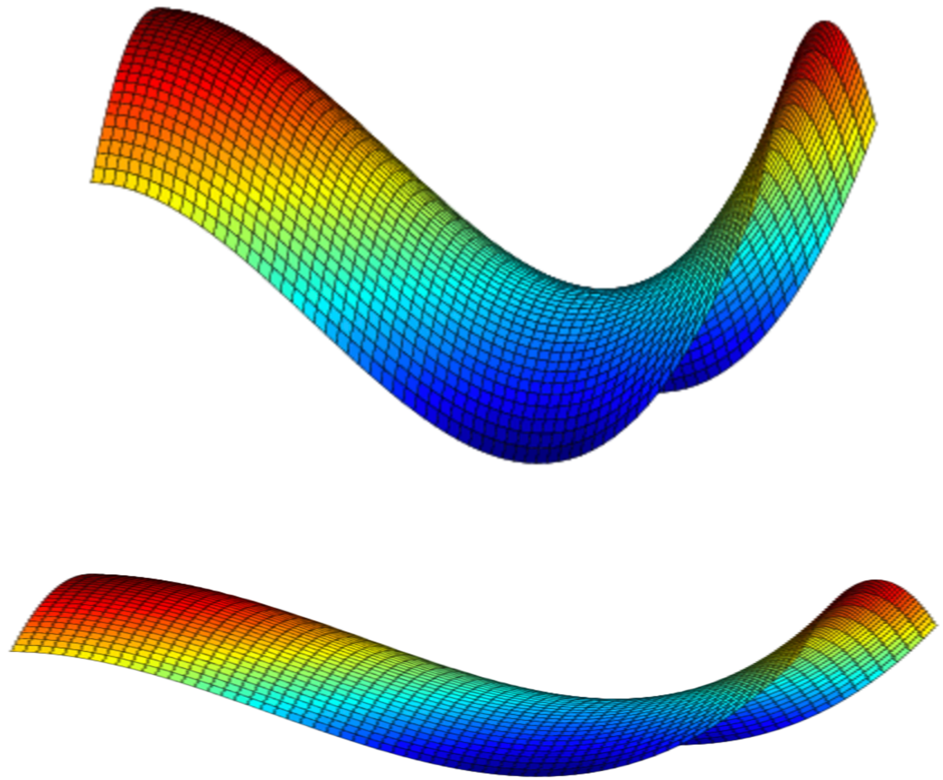


Fig 4a : Exponential Decay Schedule

$\alpha_t = e^{-kt}\ \alpha_0$

Local Optima



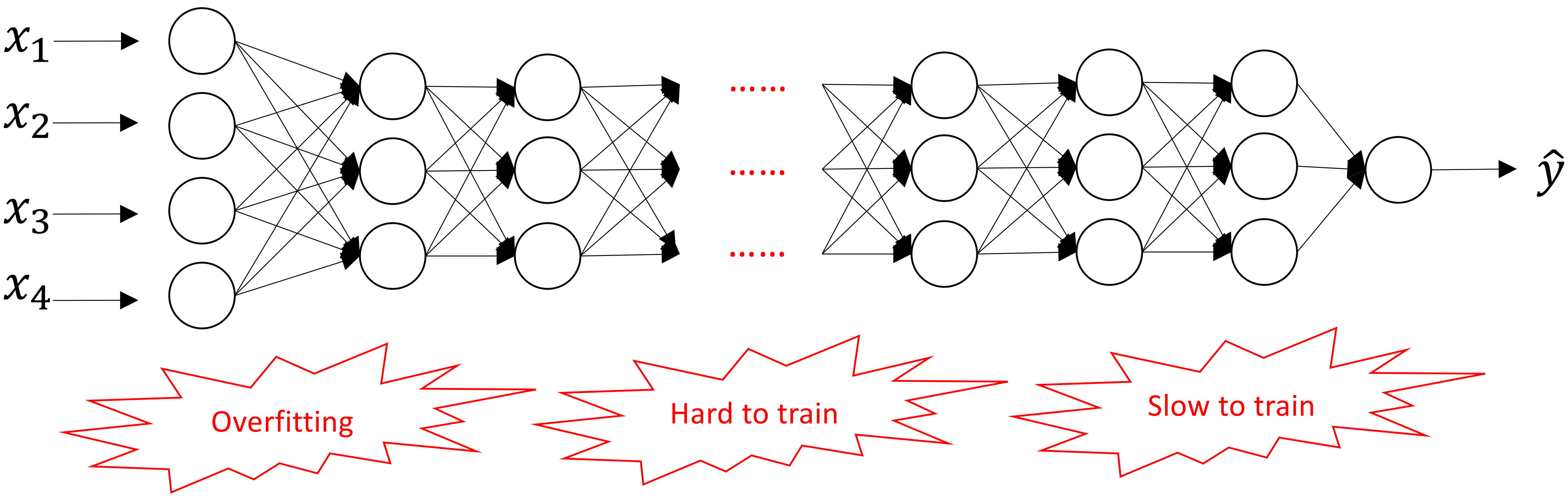


Plateaus can make learning slow

Hyper-parameter Tuning

- Hyperparameters
  - $\alpha, \lambda, \beta, \beta_1, \beta_2, \varepsilon, L, s_l$, minibatch size, epochs, etc.
- Using an appropriate scale to pick hyperparameters
- Random Search (Grid search is very costly)

Deep Neural Networks



A lot of parameters

Gradient vanishing
Gradient explosion

Deeper network
Covariate Shift

Reduce Overfitting

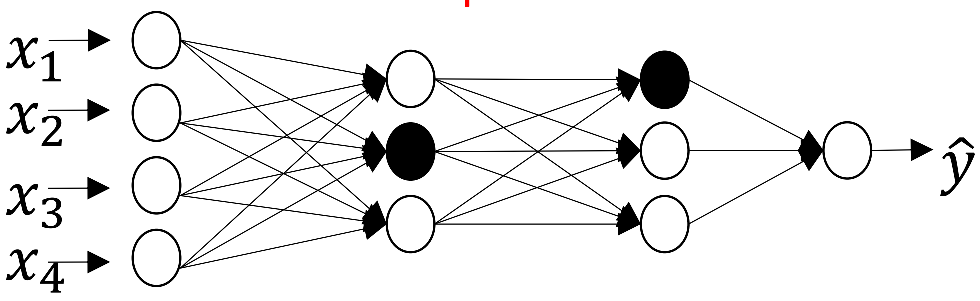
Regularization

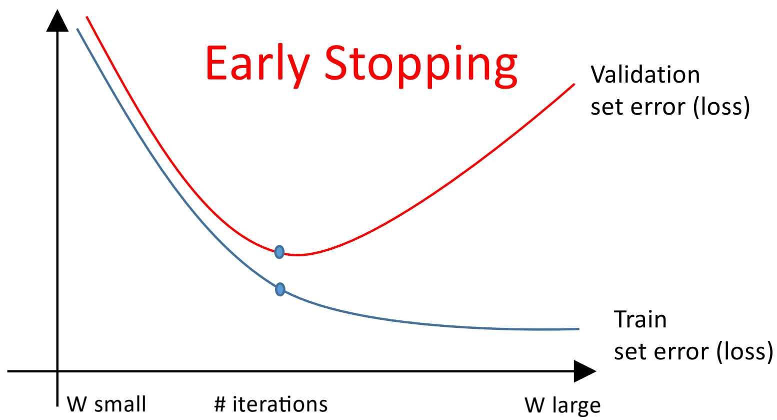
$$L(w) + \lambda\, w w^T$$

Data Augmentation

Big Data

Dropout





Vanishing/Exploding gradients

- $W^{[l]} =: W^{[l]} - \alpha \frac{\partial L}{\partial W^{[l]}}$
- $W^{[l]}$ <1 → $\frac{\partial L}{\partial W^{[l]}}$ <1→ Vanishing → slow down training
- $W^{[l]}$ >1 → $\frac{\partial L}{\partial W^{[l]}}$ >1→ Exploding → divergence

- Solution
  - Batch normalization
  - Random Weights Initialization

Addressing Vanishing/exploding Gradient

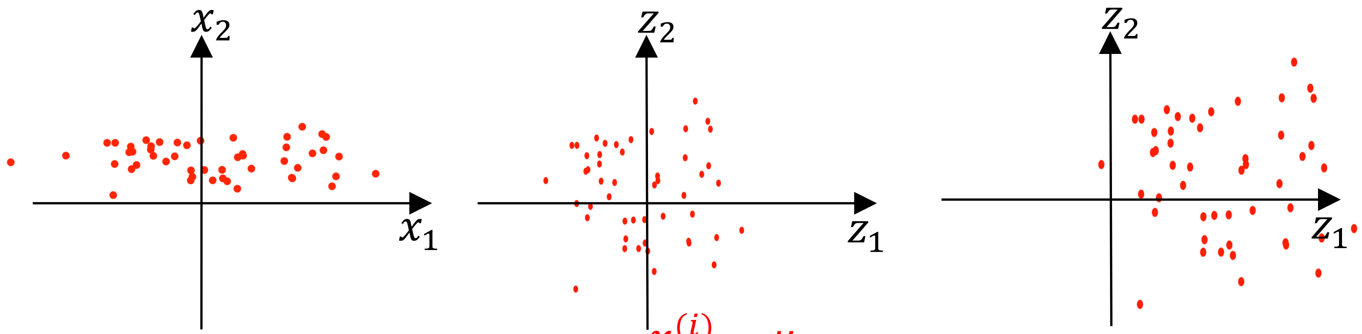
Random weights Initialization

Relu: $W^{[l]}$ = randn$(l-1, l)$ * $\sqrt{\frac{2}{n^{[l-1]}}}$ (He Initialization)

Tanh: $W^{[l]}$ = randn$(l-1, l)$ * $\sqrt{\frac{2}{n^{[l-1]}+n^{[l]}}}$ (Xavier Glorot Initialization)

Addressing Vanishing/exploding Gradient and Speedup Training

Batch Normalization



μ_B, σ_B

Mean and variance of the Batch

$$\tilde{x}^{(i)} = \frac{x^{(i)} - \mu_B}{\sqrt{\sigma_B{}^2 + \epsilon}}$$

smoothing parameter

$$z^{(i)} = \gamma\tilde{x}^{(i)} + \beta$$

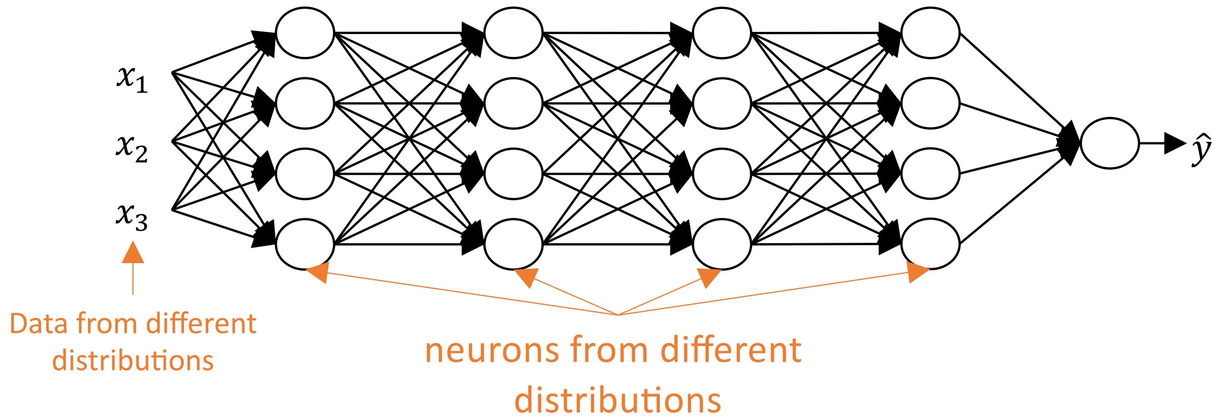
scaling parameter

shifting parameter

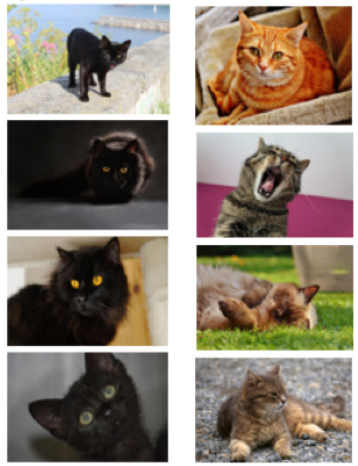
- Other methods
  - Synthetic gradients
  - Gradient Clipping

Problem of Covariate Shift

- **Definition**
  - different distributions in the data or from layer to layer !
  - The input data and the neurons of the hidden layers could be considered as coming from different distributions!
- **Solution**: Batch Normalization to normalize the hidden layers!



Cats from different distributions



Batch Normalization

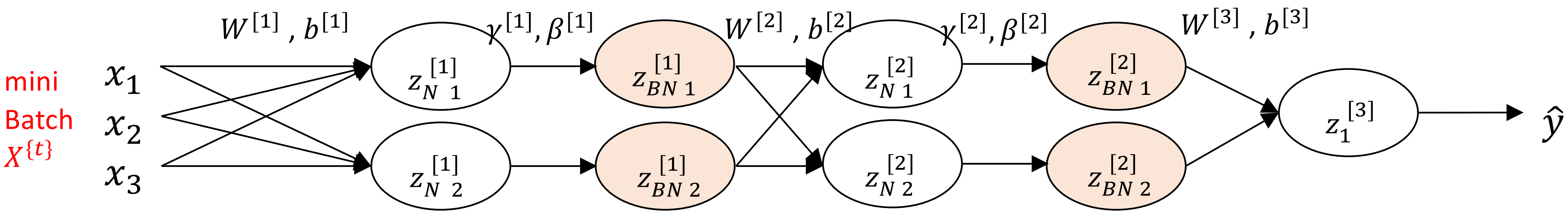
1. Pick a mini batch $X^{\{b\}}$ $(b \in 1..B)$ from X, compute $\mu^{\{b\}}$ and $\sigma^{\{b\}}$ and perform normalization: $x_N^{(i)} = \frac{(x^{(i)} - \mu^{\{b\}})}{\sqrt{\sigma^{\{b\}2} + \varepsilon}}$

Avoid dividing by zero

2. Normalize the activations $A^{[l]}$ (or logits $Z^{[l]}$) in each layer l : $z_N^{(i)[l]} = \frac{(z^{(i)[l]} - \mu^{\{b\}[l]})}{\sqrt{\sigma^{\{b\}[l]2} + \varepsilon}}$

3. Rescale: $z_{BN}^{(i)[l]} = \gamma^{[l]} z_N^{(i)[l]} + \beta^{[l]}$, with $\gamma^{[l]}$ and $\beta^{[l]}$ are learnable parameters like $W^{[l]}$ and $b^{[l]}$

- Note that if $\gamma^{[l]} = \sqrt{\sigma^{\{b\}[l]2} + \varepsilon}$ and $\beta^{[l]} = \mu^{\{b\}[l]}$, then $z_{BN}^{(i)[l]} = z_N^{(i)[l]}$ (no batch norm effect)
- At test time: $\mu^{\{test\}[l]}$ and $\sigma^{\{test\}[l]}$ are estimated using EWMA of all $\mu^{\{b\}[l]}$ and $\sigma^{\{b\}[l]}$ respectively.



Tune Hyper-parameters

- $\alpha, L, s_l,$ mini-batch size, epochs, etc.
- $\beta, \beta_1, \beta_2, \varepsilon,$ etc. (optimization hyper-parameters)
- Etc.

Deep learning Tools

- Python / Julia
- Anaconda
- VSCode
- Jupyter Notebook
- Github
- Etc,

- TensorFlow,
- Keras
- PyTorch
- Caffe/Caffe2,
- CNTK,
- DL4J,
- Lasagne,
- MxNet,
- Etc,

- Apache Spark Mllib
- Amazon ML (AML)
- Google Cloud ML Engine
- Google ML Kit for Mobile
- Apple’s Core ML
- Etc,