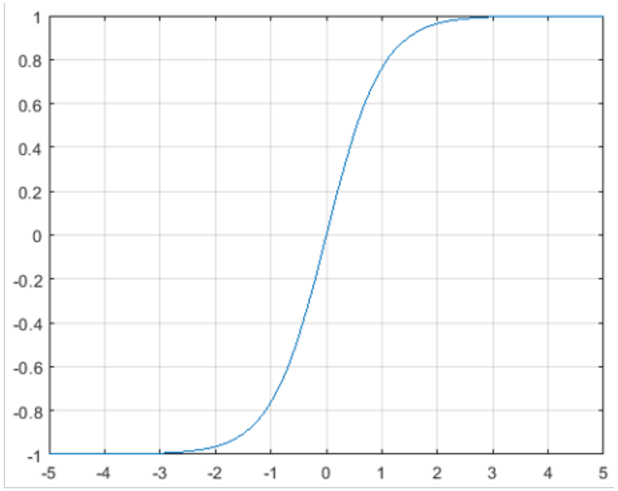
Important Techniques in Neural Network Training

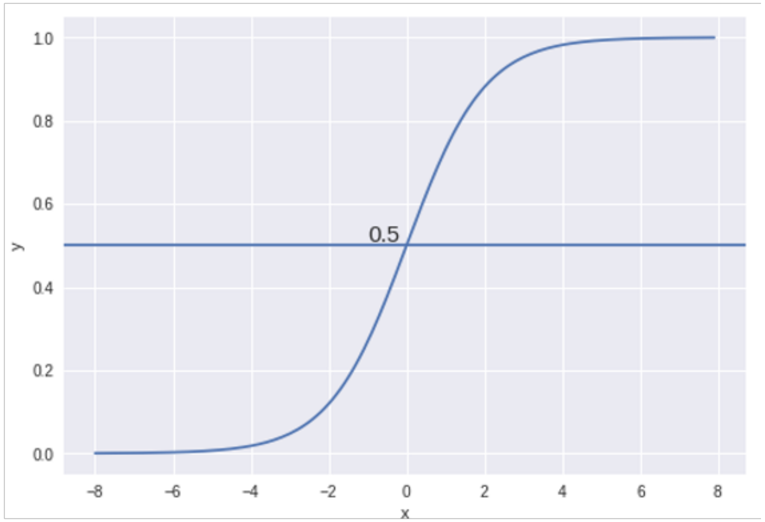
Gradient Explosion / Vanishing

- Deeper networks are harder to train:
  - Intuition: gradients are products over layers
  - Hard to control the learning rate

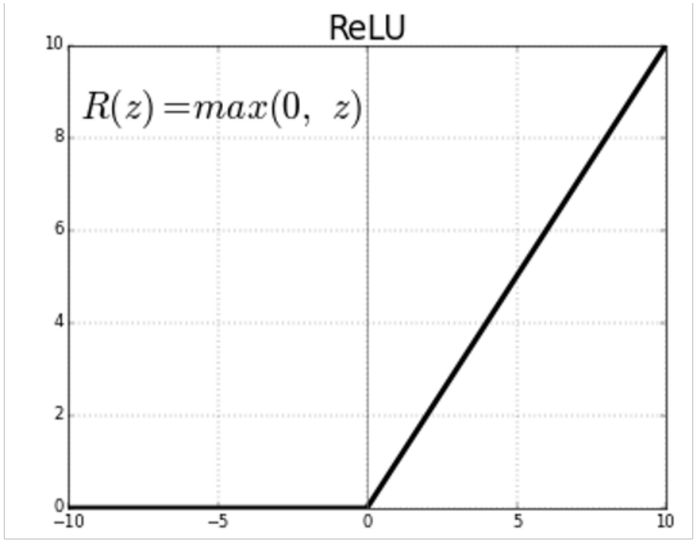
Activation Functions



tanh

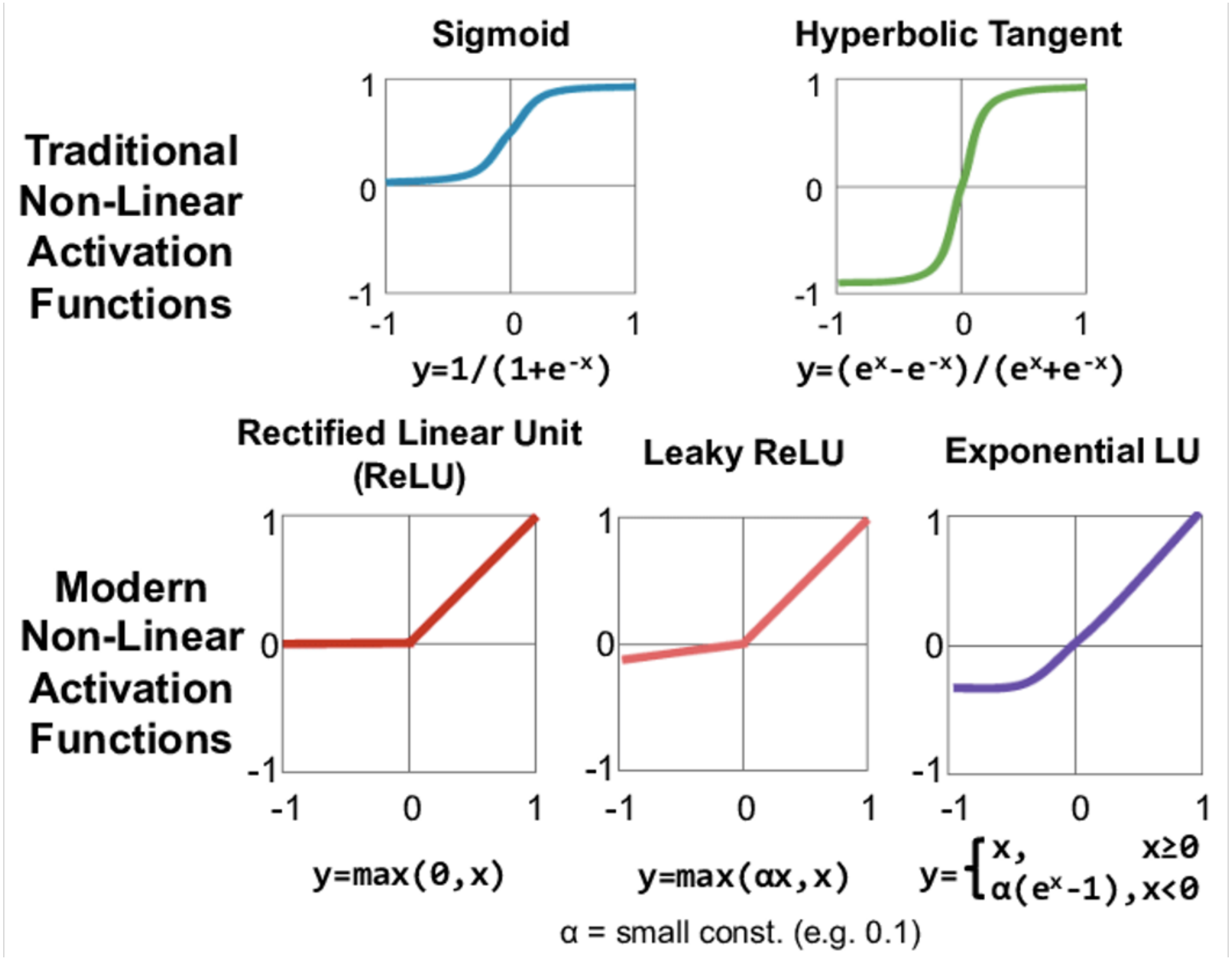


sigmoid



Rectified Linear United

Activation Function



Initialization

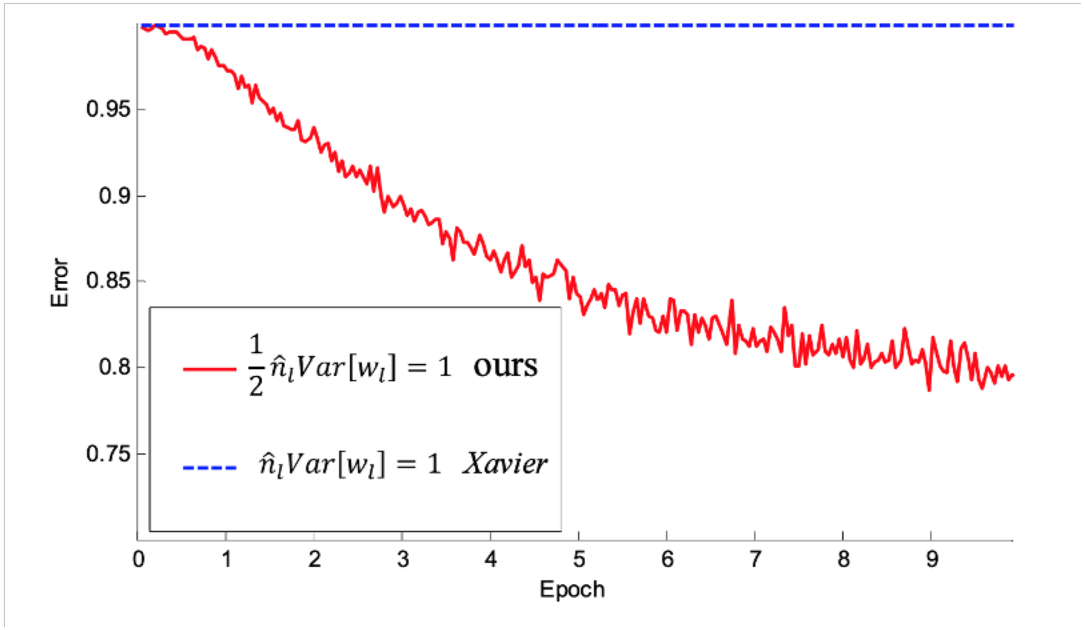
- Zero-initialization
- Large initialization
- Small initialization

- Design principles:
  - Zero activation mean

  - Activation variance remains same across layers

Kaiming Initialization (He et al. ’15)

- $W_{ij}^{(h)} \sim \mathcal{N}\left(0, \frac{2}{d_h}\right)$.
- $b^{(h)} = 0$
- Designed for ReLU activation
- 30-layer neural network



Kaiming Initialization (He et al. ’15)

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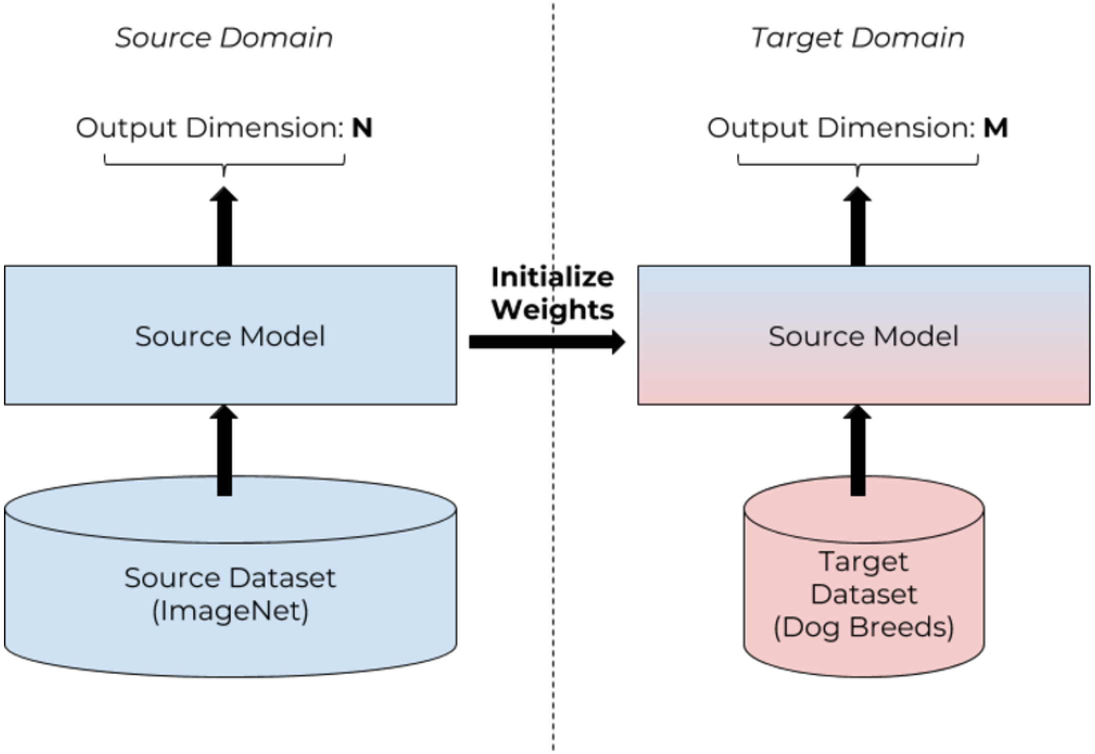
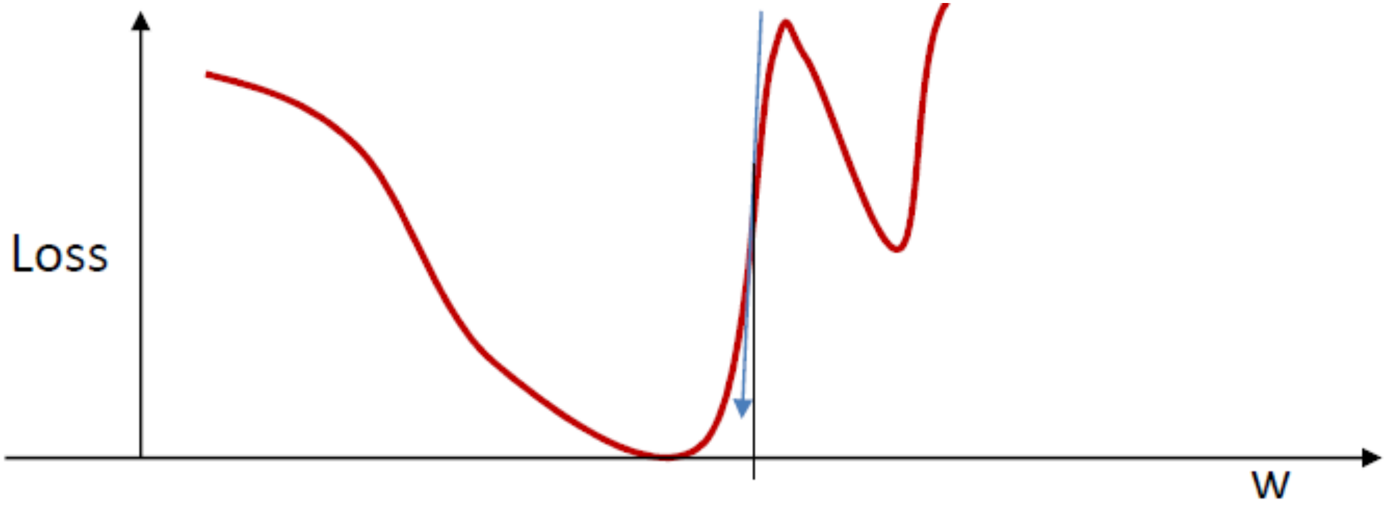
Initialization by Pre-training

- Use a pre-trained network as initialization
- And then fine-tuning



Gradient Clipping

- The loss can occasionally lead to a steep descent
- This result in immediate instability
- If gradient norm bigger than a threshold, set the gradient to the threshold.

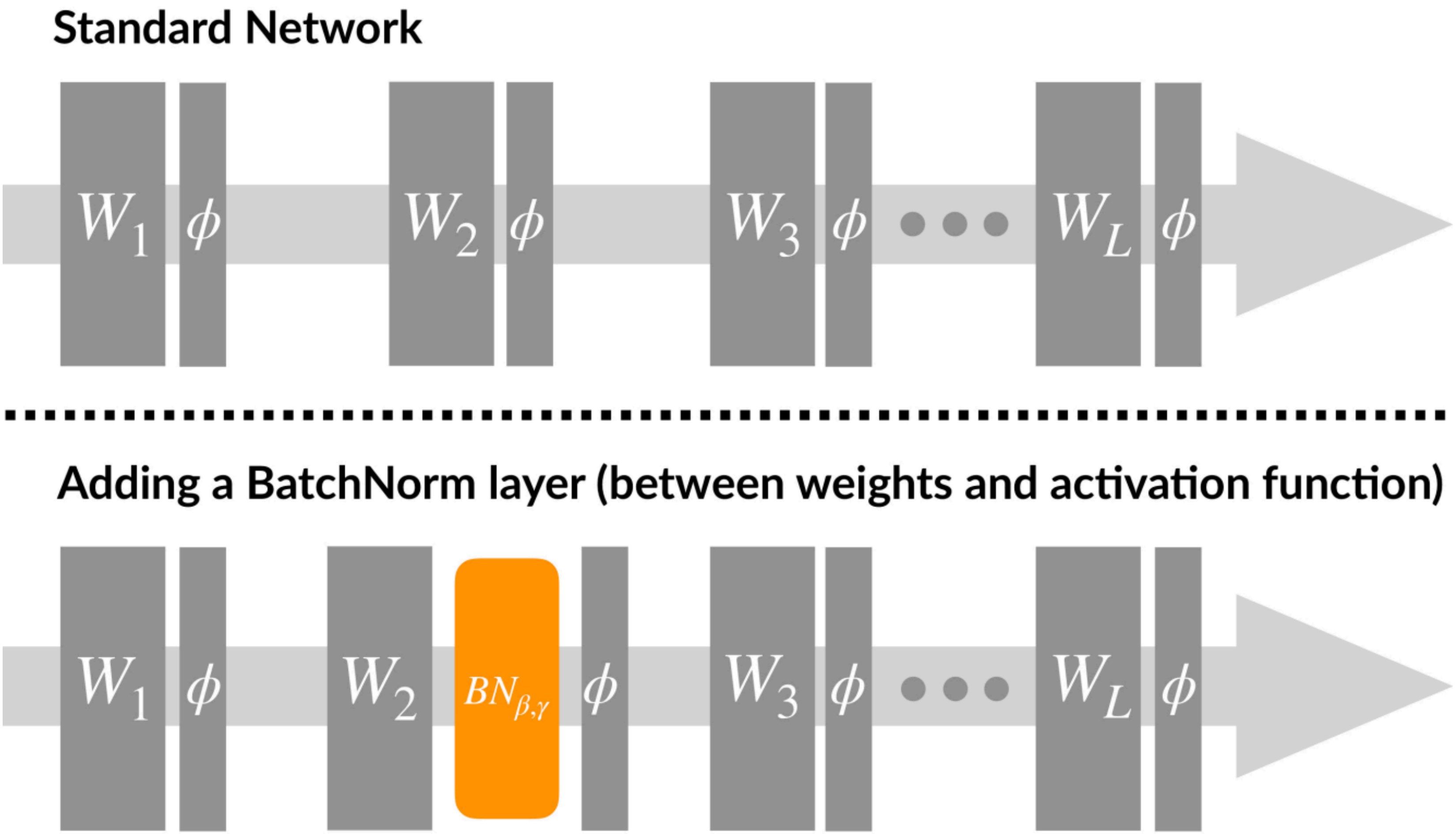


Batch Normalization (Ioffe & Szegedy, ’14)

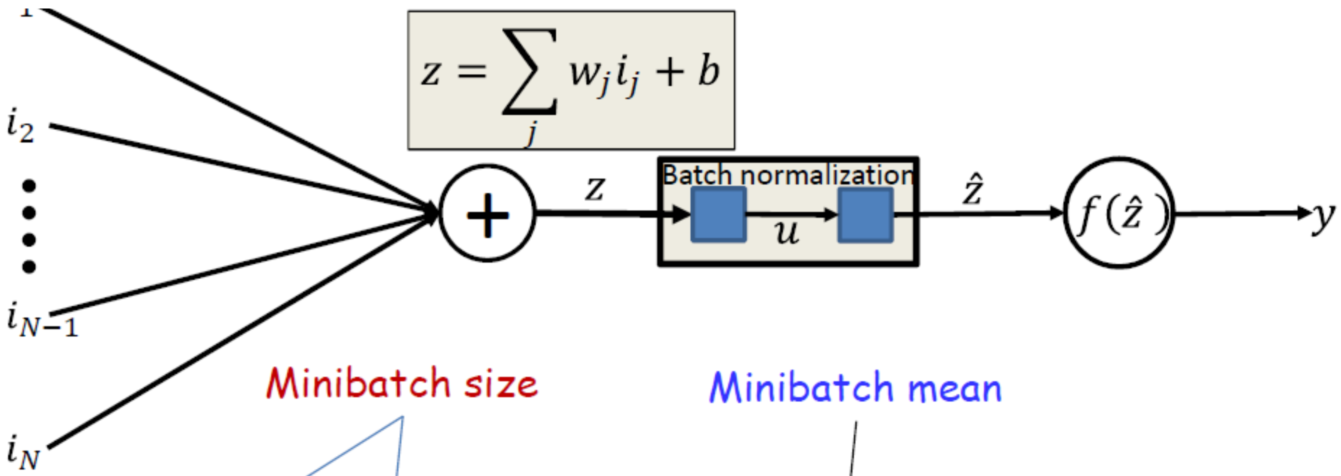
- Normalizing/whitening (mean = 0, variance = 1) the inputs is generally useful in machine learning.
  - Could normalization be useful at the level of hidden layers?
  - **Internal covariate shift**: the calculations of the neural networks change the distribution in hidden layers even if the inputs are normalized

- **Batch normalization** is an attempt to do that：
  - Each unit’s **pre-activation** is normalized (mean subtraction, std division)
  - During training, mean and std is computed for each minibatch (can be backproped!

Batch Normalization (Ioffe & Szegedy, ’14)



Batch Normalization (Ioffe & Szegedy, ’14)



$$z = \sum_j w_j i_j + b$$

Minibatch size

Minibatch mean

Minibatch standard deviation

$$\mu_B = \frac{1}{B}\sum_{i=1}^{B} z_i$$

$$\sigma_B^2 = \frac{1}{B}\sum_{i=1}^{B} (z_i - \mu_B)^2$$

$$u_i = \frac{z_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$\hat{z}_i = \gamma u_i + \beta$$

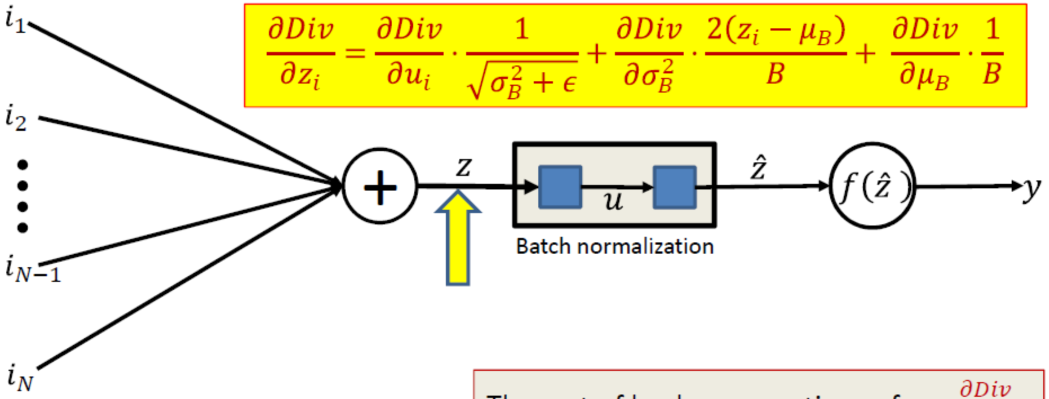
Batch Normalization (Ioffe & Szegedy, ’14)

- BatchNorm at training time
  - Standard backprop performed for each single training data
  - Now backprop is performed over entire batch.

$$\frac{\partial Div}{\partial \sigma_B^2} = \frac{-1}{2}(\sigma_B^2+\epsilon)^{-3/2}\sum_{i=1}^{B}\frac{\partial Div}{\partial u_i}$$

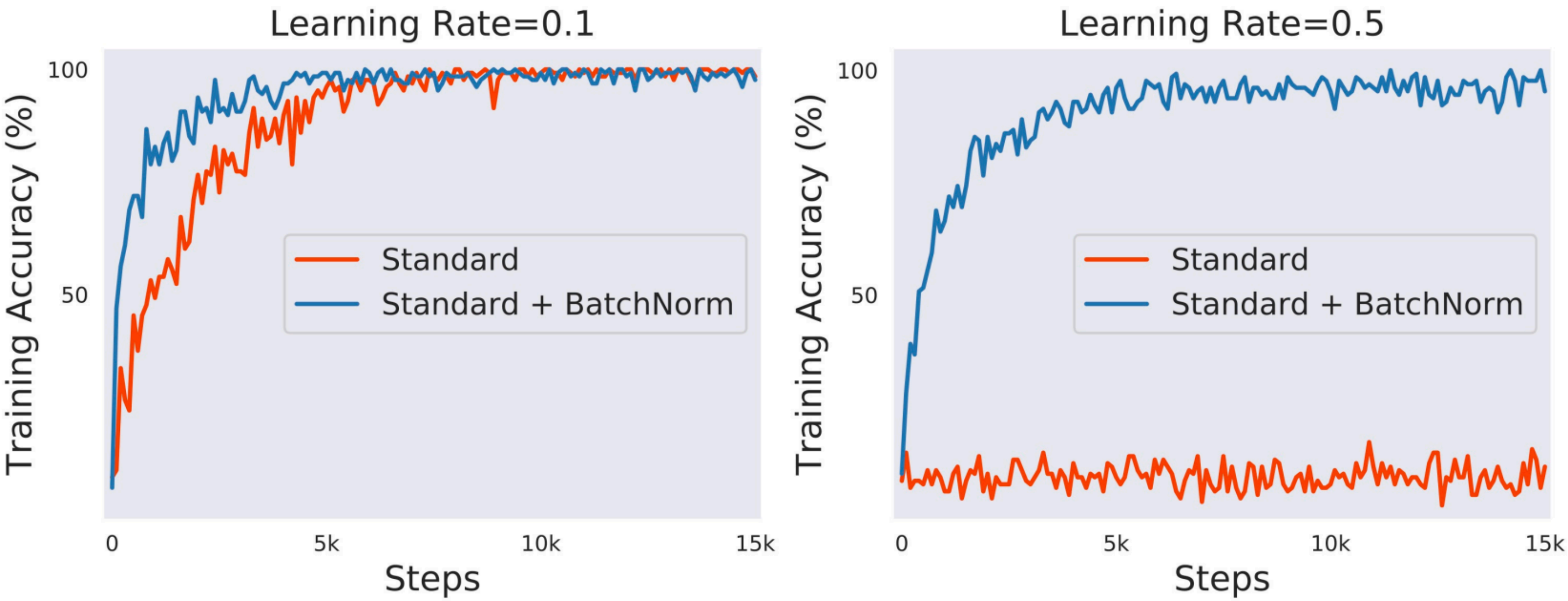
$$\frac{\partial Div}{\partial \mu_B} = \frac{-1}{\sqrt{\sigma_B^2+\epsilon}}\sum_{i=1}^{B}\frac{\partial Div}{\partial u_i}$$

$$\frac{\partial Div}{\partial z_i} = \frac{\partial Div}{\partial u_i}\cdot\frac{1}{\sqrt{\sigma_B^2+\epsilon}} + \frac{\partial Div}{\partial \sigma_B^2}\cdot\frac{2(z_i-\mu_B)}{B} + \frac{\partial Div}{\partial \mu_B}\cdot\frac{1}{B}$$



The rest of backprop continues from $\frac{\partial Div}{\partial z_i}$

Batch Normalization (Ioffe & Szegedy, ’14)



What is BatchNorm actually doing?

- May not due to covariate shift (Santurkar et al. ‘18):
  - Inject non-zero mean, non-standard covariance Gaussian noise after BN layer: removes the whitening effect
  - Still performs well.

- Only training β, γ with random convolution kernels gives non-trivial performance (Frankle et al. ’20)

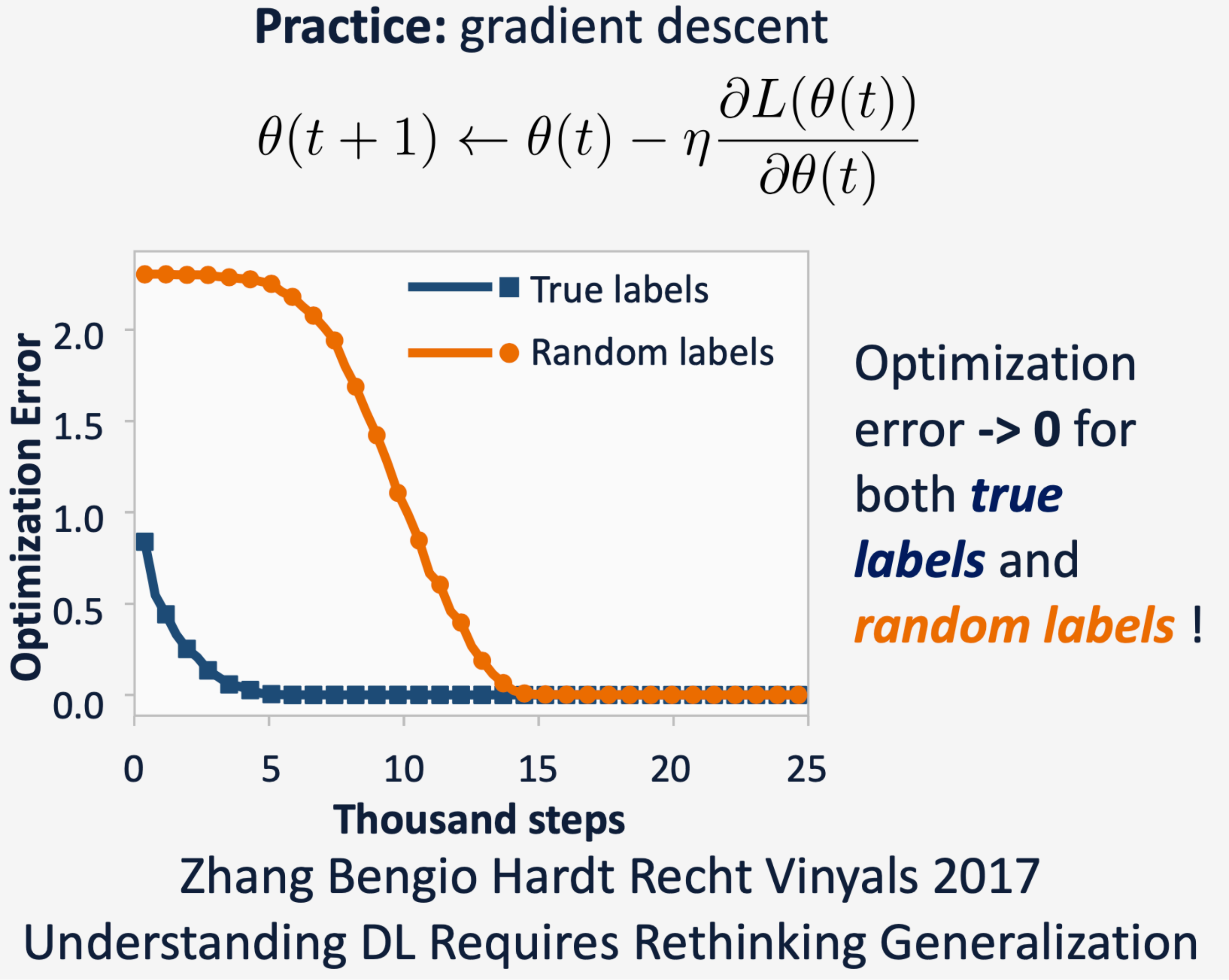
- BN can use exponentially increasing learning rate! (Li & Arora ’19)

More normalizations

- Layer normalization (Ba, Kiros, Hinton, ’16)
    - Batch-independent
    - Suitable for RNN, MLP
- Weight normalization (Salimans, Kingma, ’16)
    - Suitable for meta-learning (higher order gradients are needed)
- ….

Non-convex Optimization Landscape

Gradient descent finds global minima



Practice: gradient descent

$$\theta(t+1) \leftarrow \theta(t) - \eta \frac{\partial L(\theta(t))}{\partial \theta(t)}$$

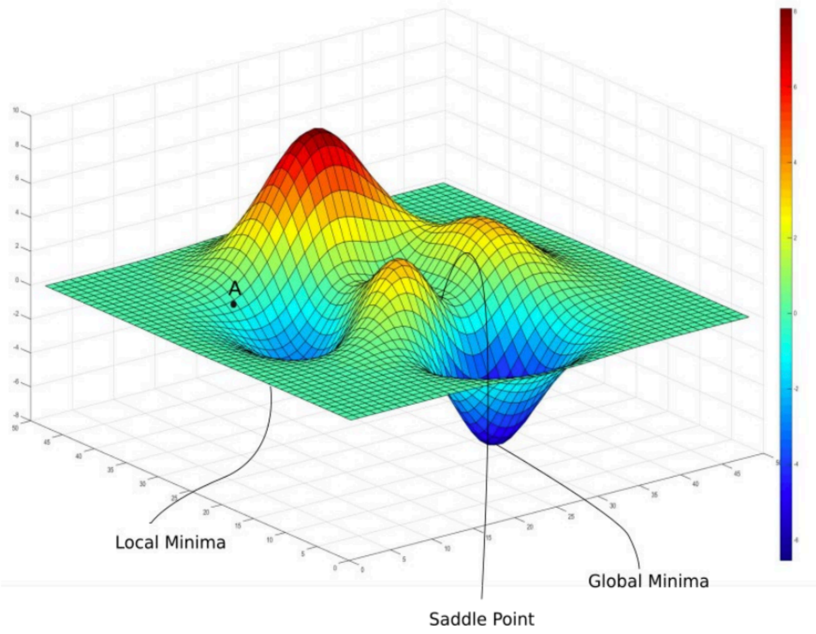
Optimization error **-> 0** for both ***true labels*** and ***random labels*** !

Zhang Bengio Hardt Recht Vinyals 2017

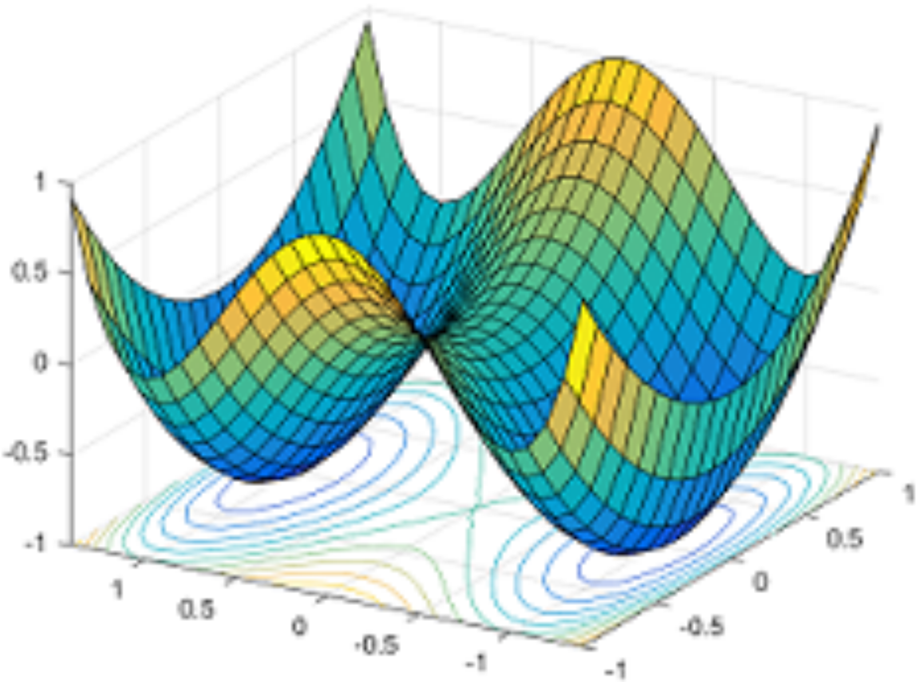
Understanding DL Requires Rethinking Generalization

Types of stationary points

- Stationary points: $x : \nabla f(x) = 0$
- Global minimum: $x : f(x) \leq f(x') \forall x' \in \mathbb{R}^d$
- Local minimum: $x : f(x) \leq f(x') \forall x' : \|x - x'\| \leq \epsilon$
- Local maximum: $x : f(x) \geq f(x') \forall x' : \|x - x'\| \leq \epsilon$
- Saddle points: stationary points that are not a local min/max

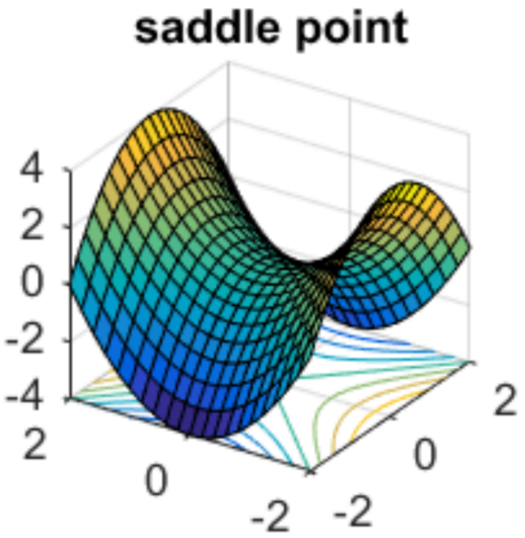


Landscape Analysis



- All local minima are global!
- Gradient descent can escape saddle points.

Strict Saddle Points (Ge et al. ’15, Sun et al. ’15)



- Strict saddle point: a saddle point and $\lambda_{\min}(\nabla^2 f(x)) < 0$

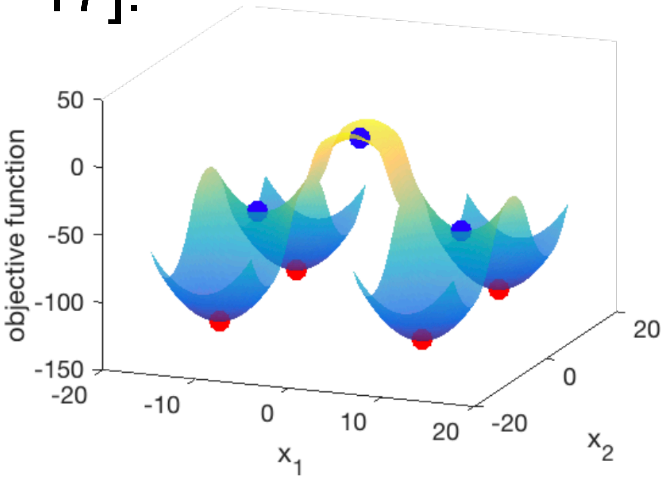
Escaping Strict Saddle Points

- Noise-injected gradient descent can escape strict saddle points in polynomial time [Ge et al., ’15, Jin et al., ’17].

- Randomly initialized gradient descent can escape all strict saddle points asymptotically [Lee et al., ’15].
  - Stable manifold theorem.

- Randomly initialized gradient descent can take exponential time to escape strict saddle points [Du et al., ’17].

If 1) all local minima are global, and 2) are saddle points are strict, then noise-injected (stochastic) gradient descent finds a global minimum in polynomial time



What problems satisfy these two conditions

- Matrix factorization
- Matrix sensing
- Matrix completion
- Tensor factorization
- Two-layer neural network with quadratic activation

What about neural networks?

- Linear networks (neural networks with linear activations functions): all local minima are global, but there exists saddle points that are not strict [Kawaguchi ’16].

- Non-linear neural networks with:
  - Virtually any non-linearity,
  - Even with Gaussian inputs,
  - Labels are generated by a neural network of the same architecture,

There are many bad local minima [Safran-Shamir ’18, Yun-Sra-Jadbaie ’19].