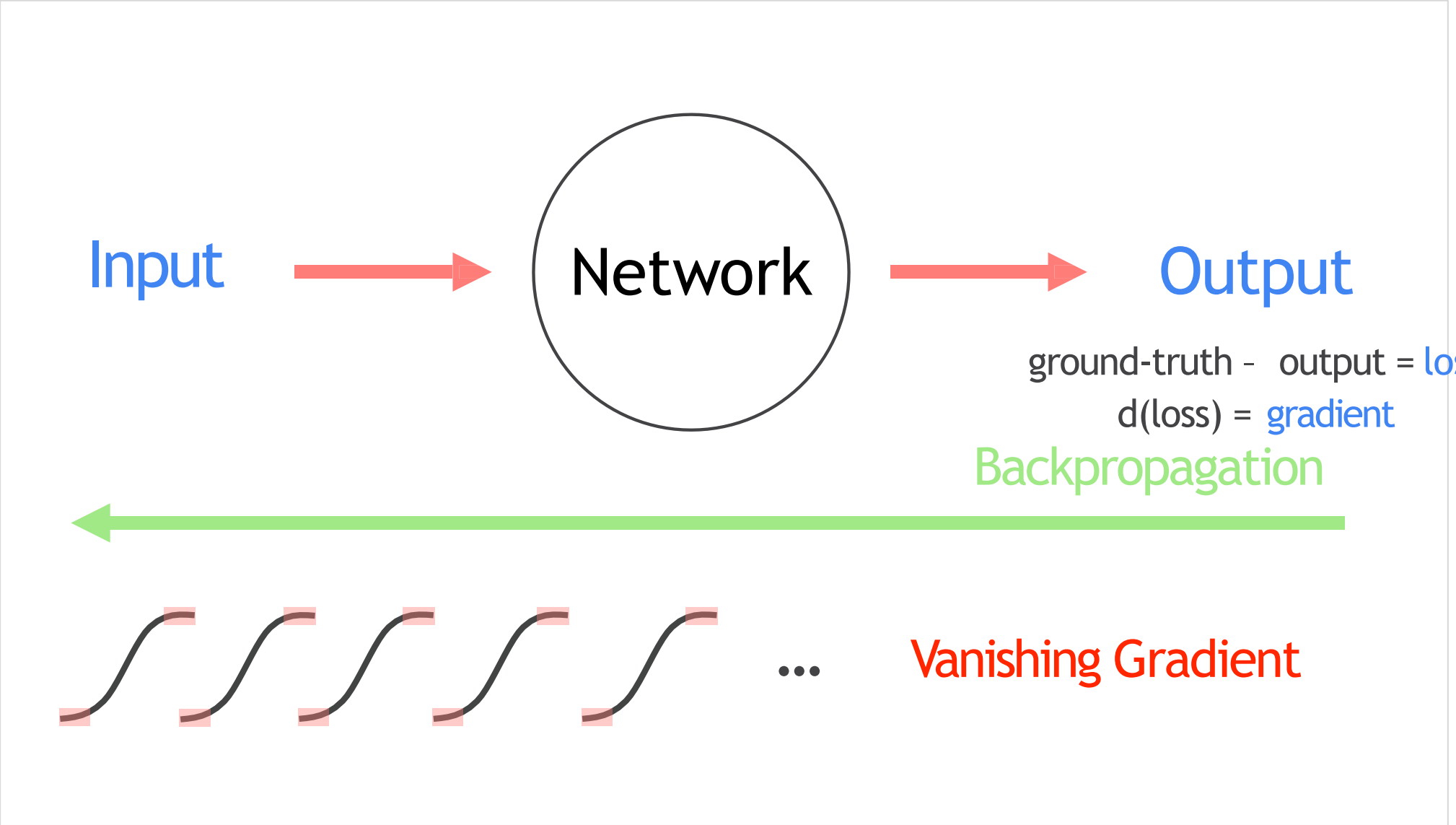

Go back in time
2000s

Geofferey Hinton’s summary of findings up to today

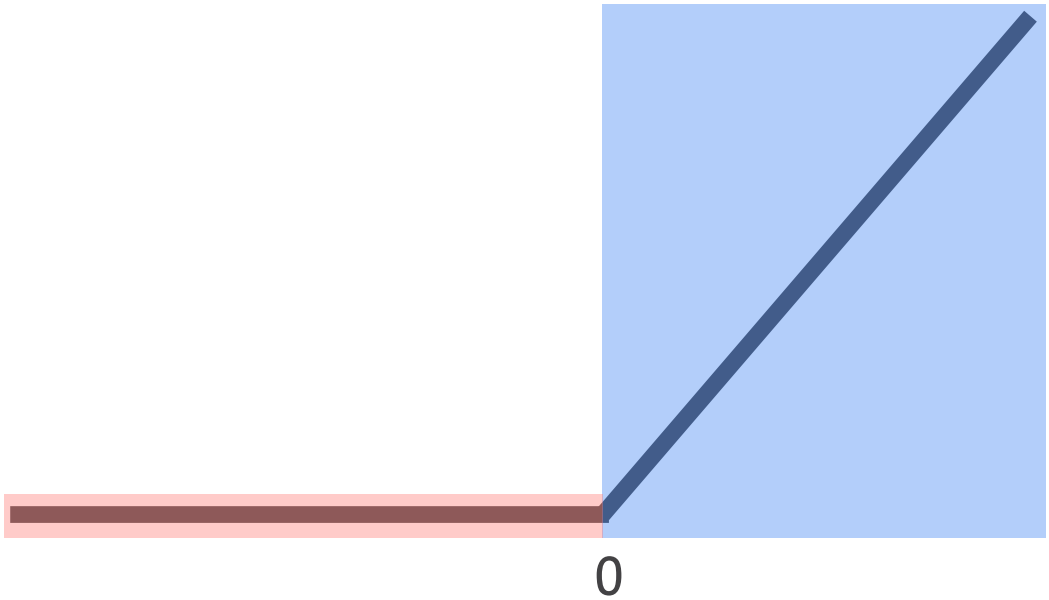
- Our labeled datasets were thousands of times too small
- Our computers were millions of times too slow
- We initialized the weights in a stupid way
- We used the wrong type of non-linearity

Problem of Sigmoid



Why Relu ?

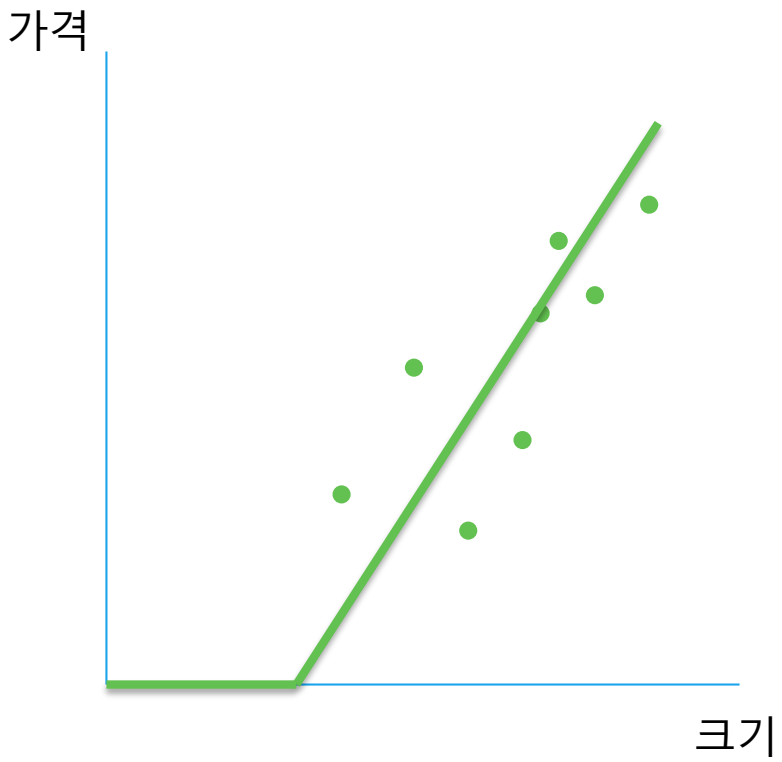
$$f(x) = \max(0, x)$$



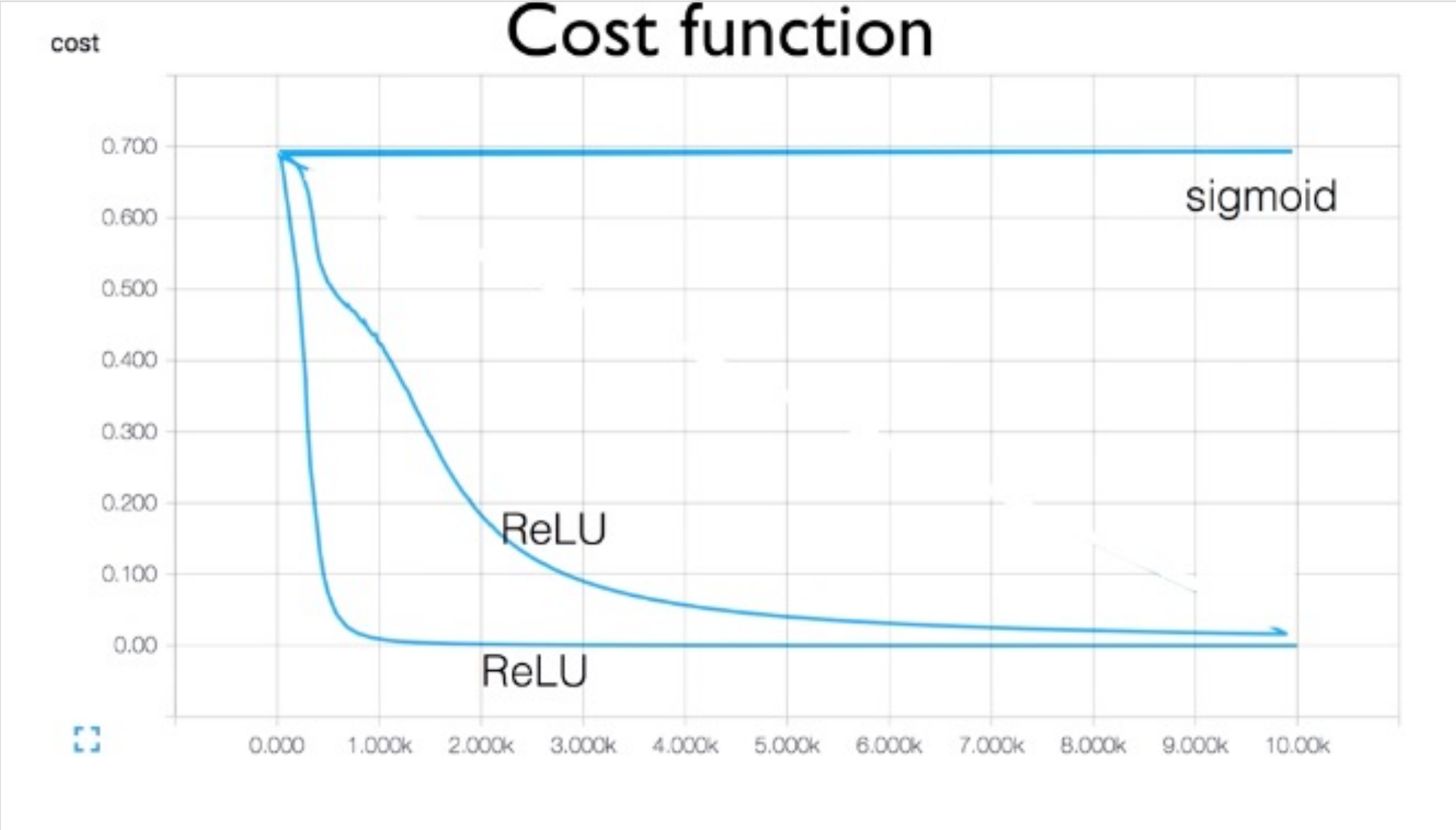
tf.keras.activations → sigmoid, tanh, relu, elu, selu

tf.keras.layers → leaky relu

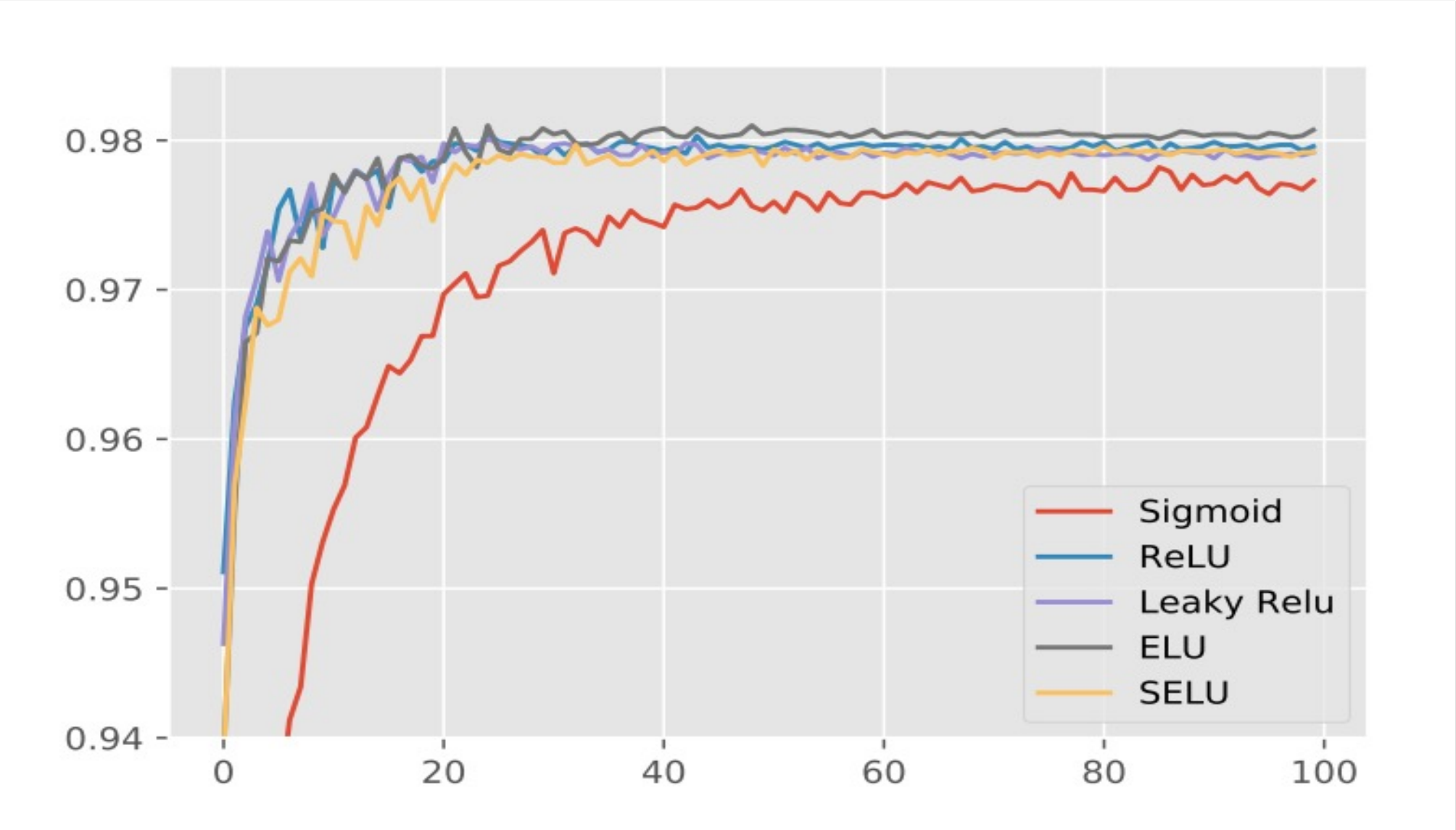
ReLU?



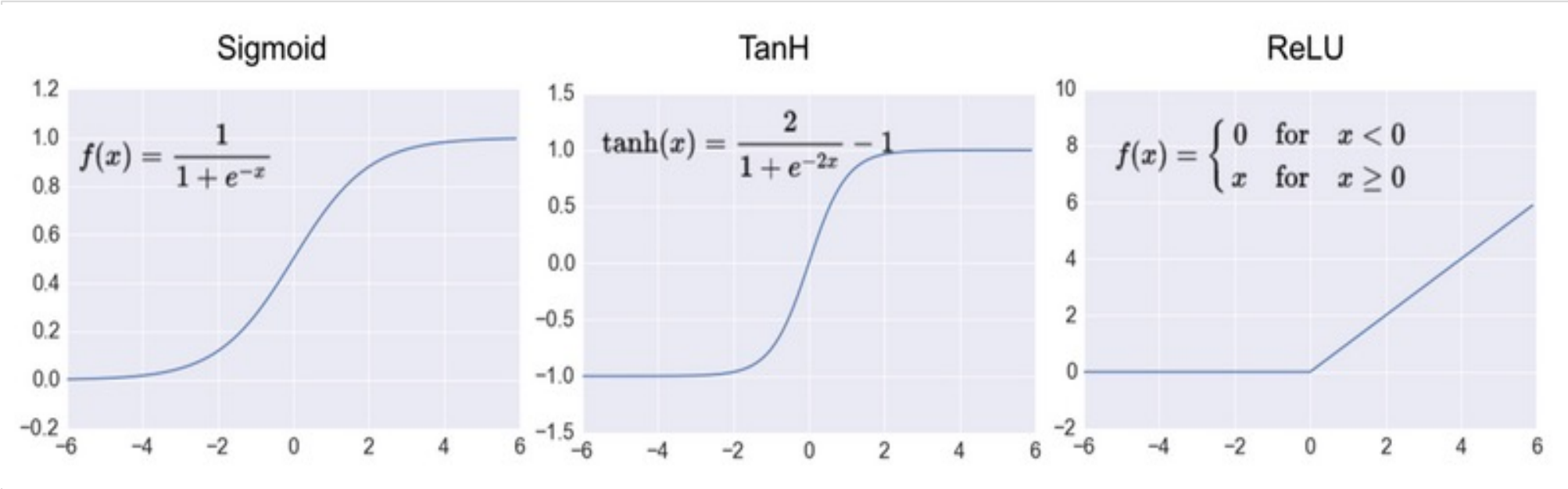
Sigmoid vs ReLU

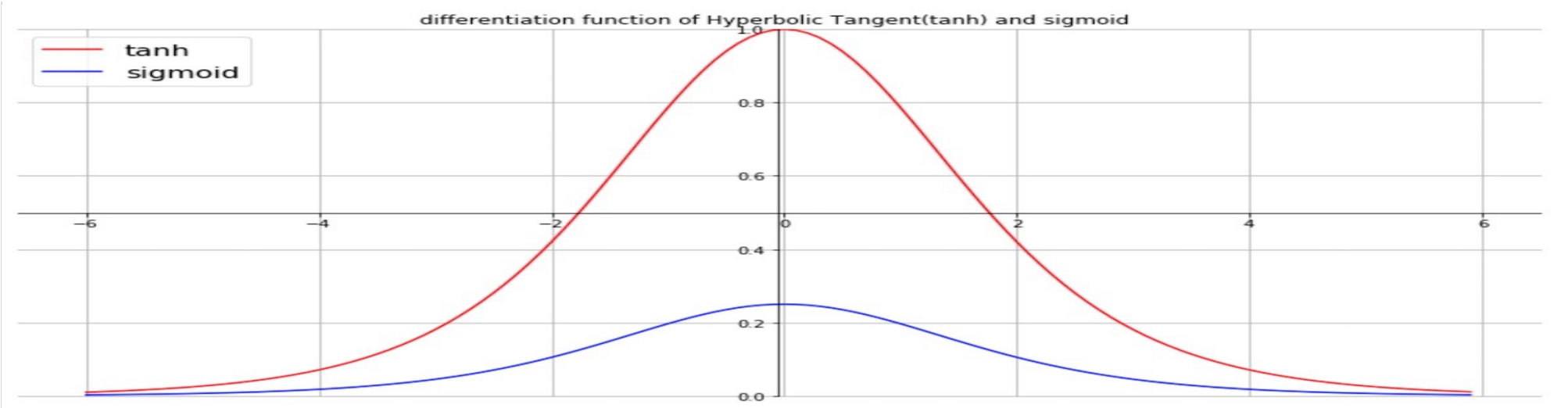


Cost function



Activation function





PRACTICE

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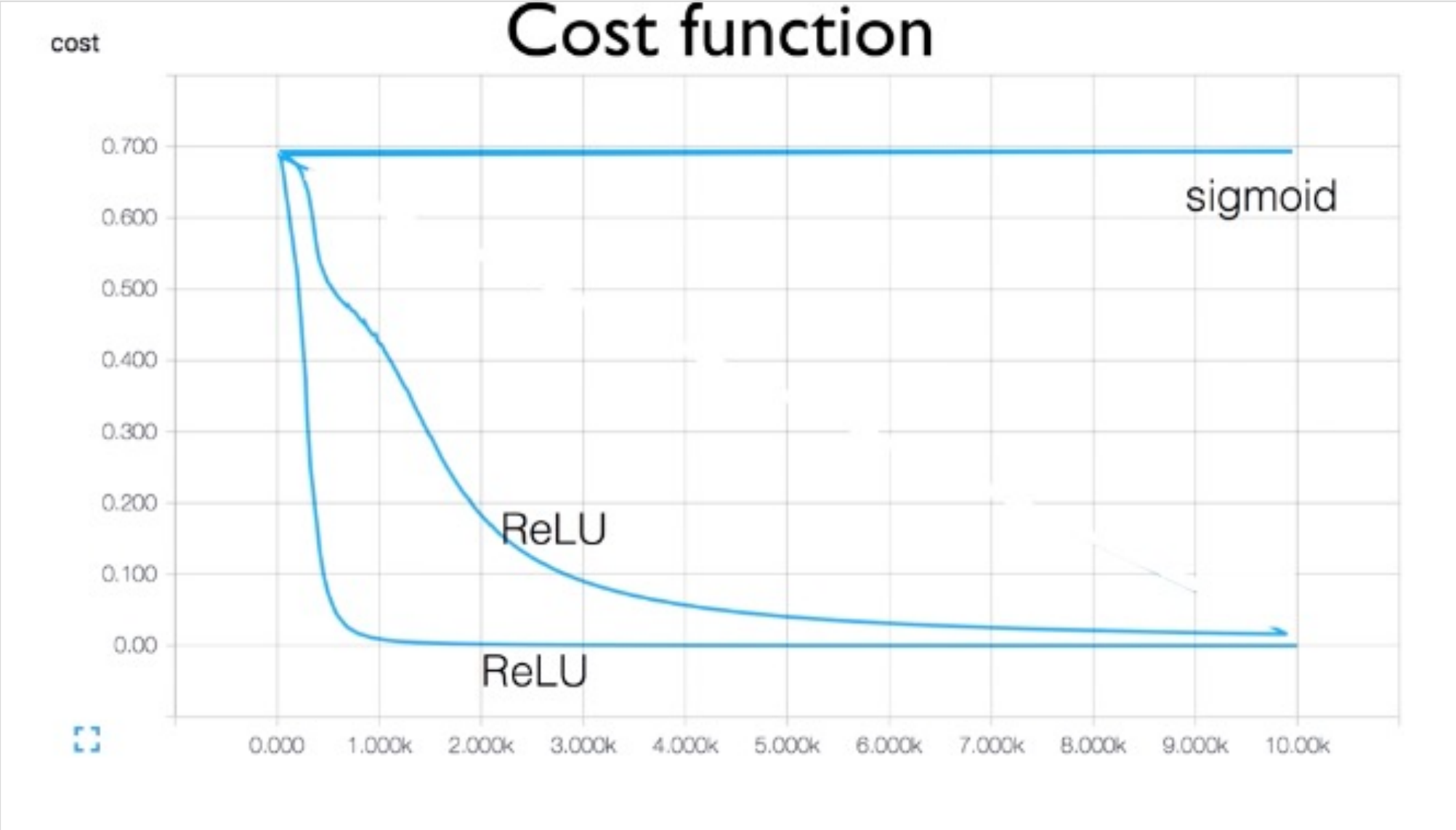
Same ReLU but different speed.. Why?



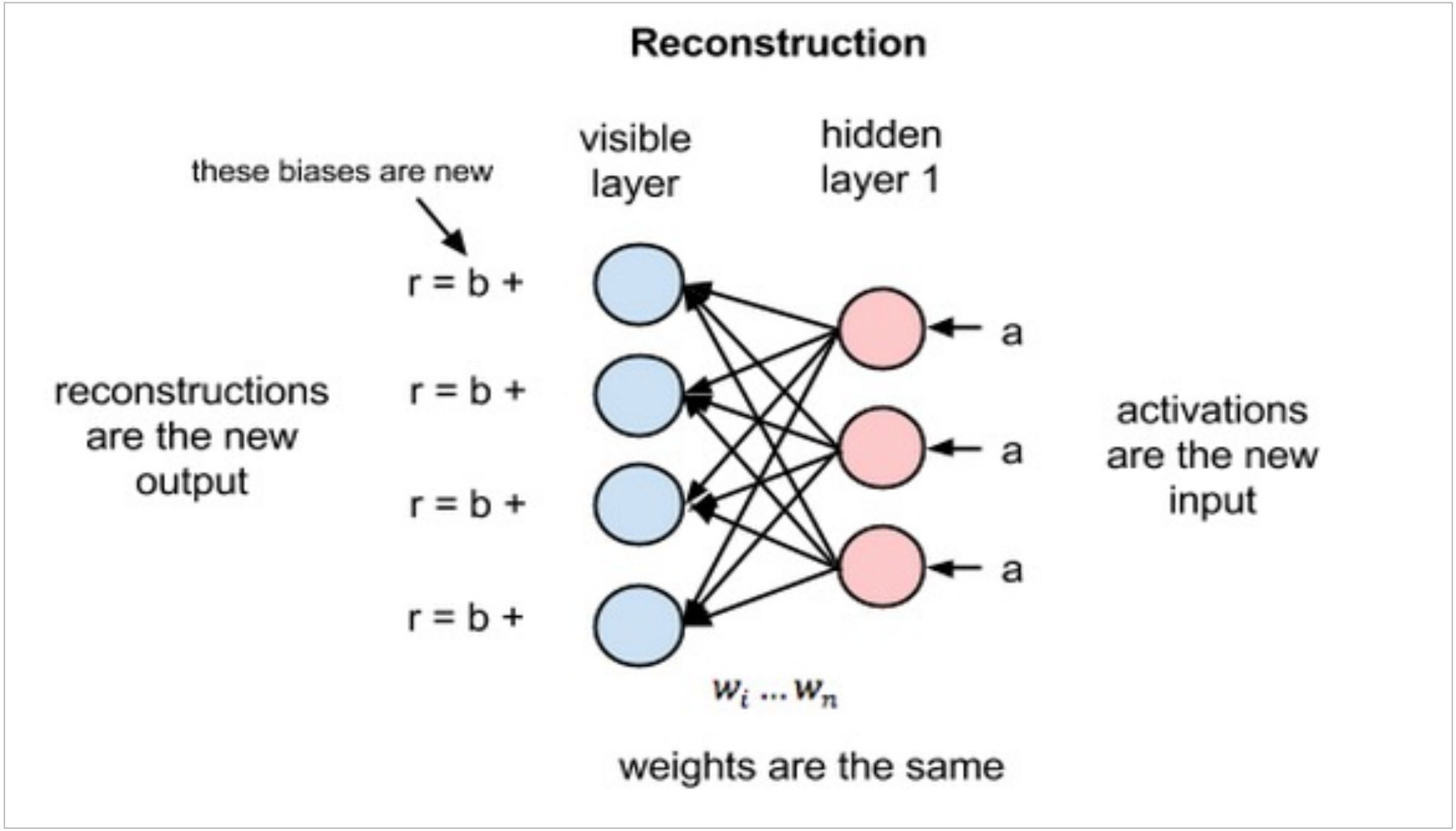
Breakthrough

- In 2006, Hinton, Simon Osindero, and Yee-Whye Teh published, "A fast learning algorithm for deep belief nets"
- Yoshua Bengio et al. in 2007 with "Greedy Layer-Wise Training of Deep Networks"

Breakthrough in 2006 and 2007 by Hinton and Bengio

- Neural networks with many layers really could be trained well, if the weights are initialized in a clever way rather th an randomly.
- Deep machine learning methods are more efficient for difficult problems than shallow methods.
- Rebranding to ***Deep Nets***, ***Deep Learning***

Greedy Layer-Wise Training

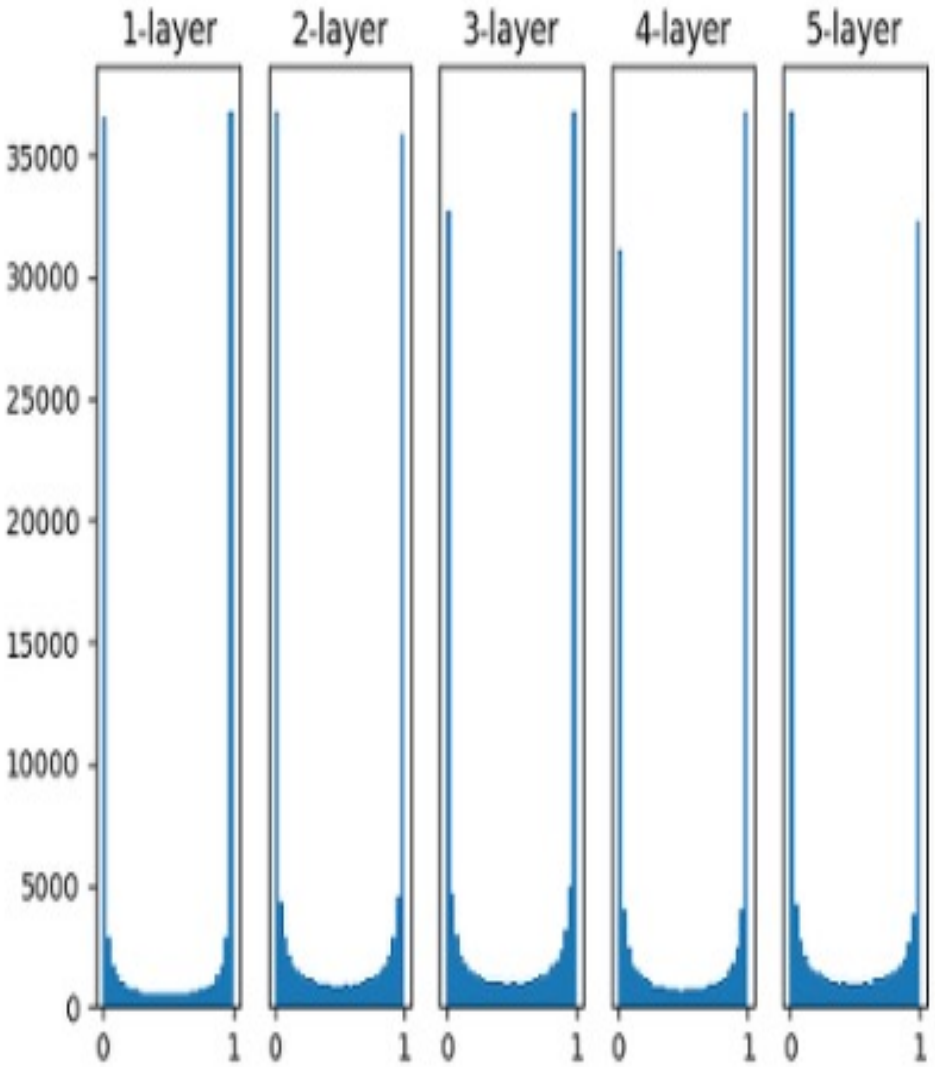


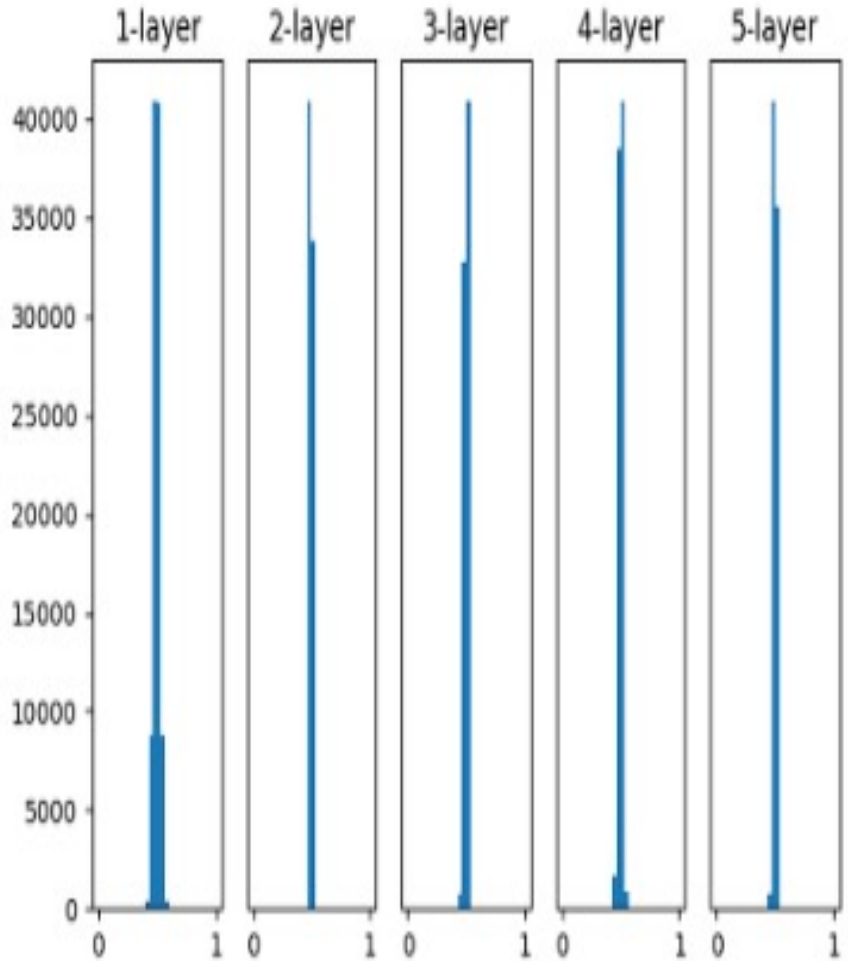
DBN 사용 vs 미사용 모델 성능 비교 논문 결과

Table 1. Algorithm accuracy (%)

Algorithm	Accuracy 1	Accuracy 2	Accuracy 3	Accuracy 4	Accuracy 5	Mean Accuracy
DBN	95.00	90.00	95.00	98.75	91.25	94.00
BP	50.00	25.00	50.00	50.00	25.00	40.00
P-DBN	98.75	92.50	98.75	91.25	92.50	94.75
P-BP	50.00	50.00	25.00	50.00	26.25	40.25

Gradient vanishing vs Gaussian mixture weight initialization

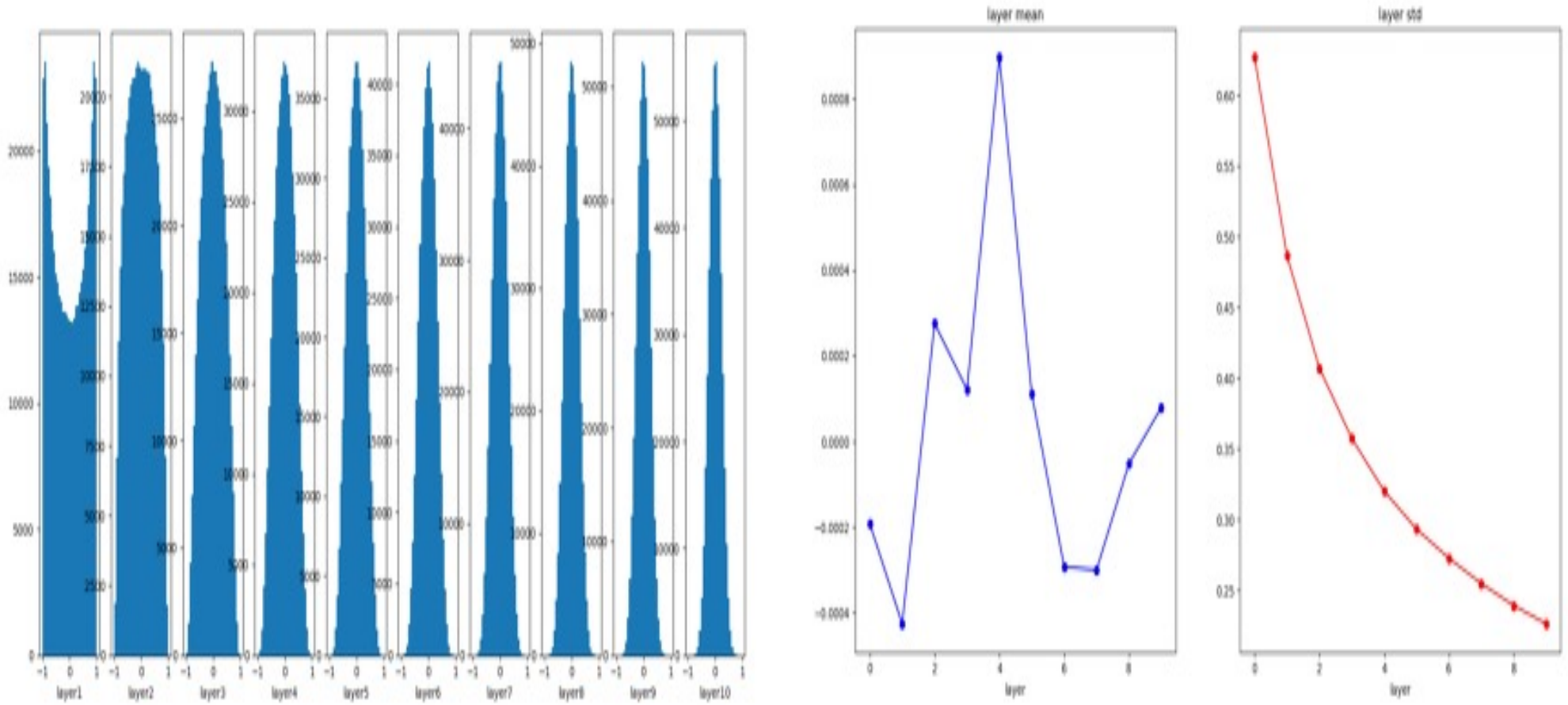




출처: Standford university

Xavier Initialization

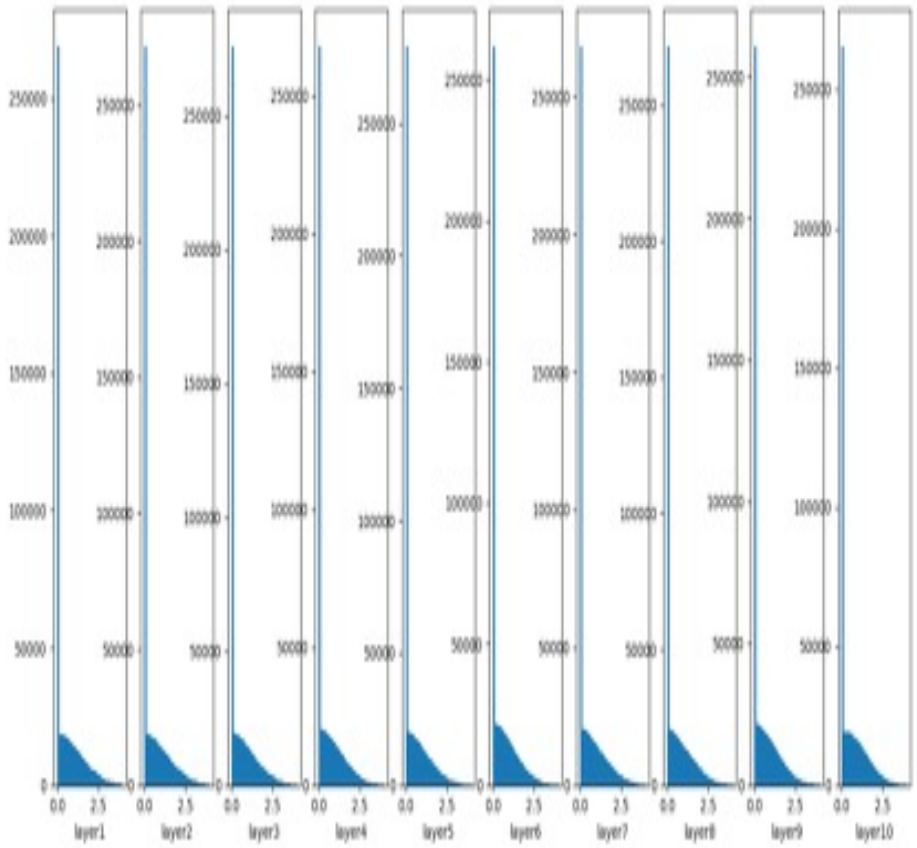
w = np.random.randn(n_input, n_output) / sqrt(n_input)

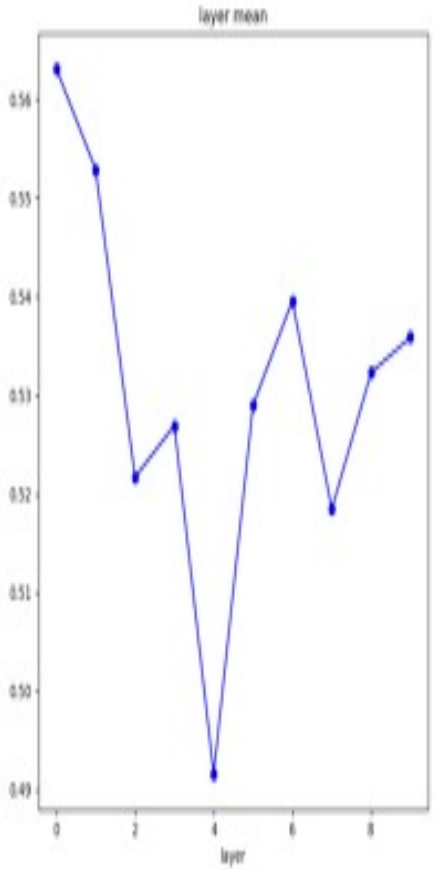


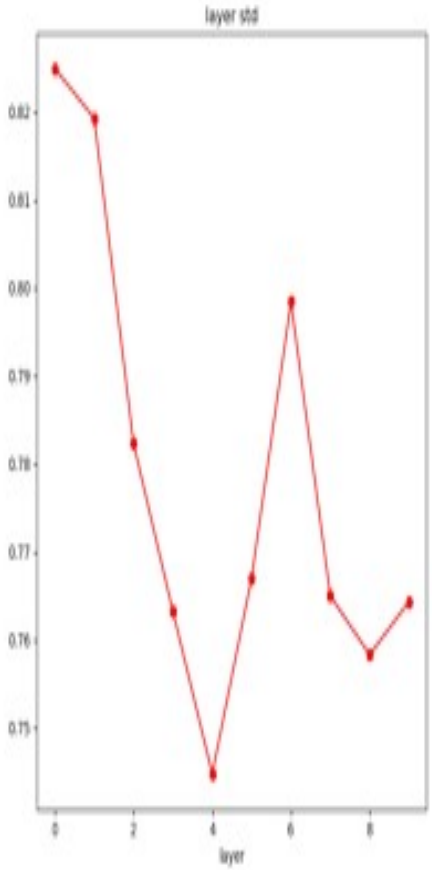
출처: Standford university

He Initialization

w = np.random.randn(n_input, n_output) / sqrt(n_input/2)

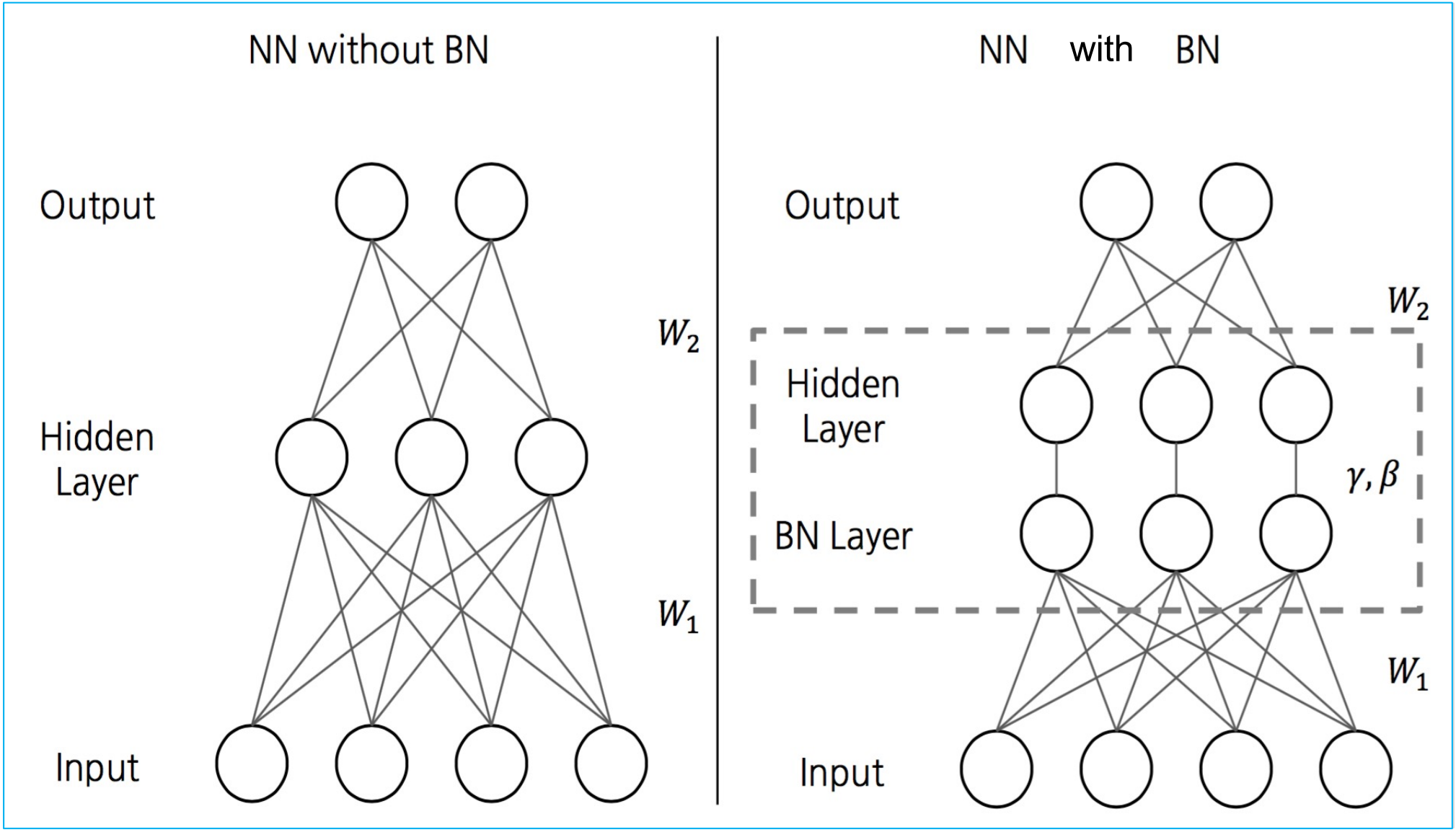




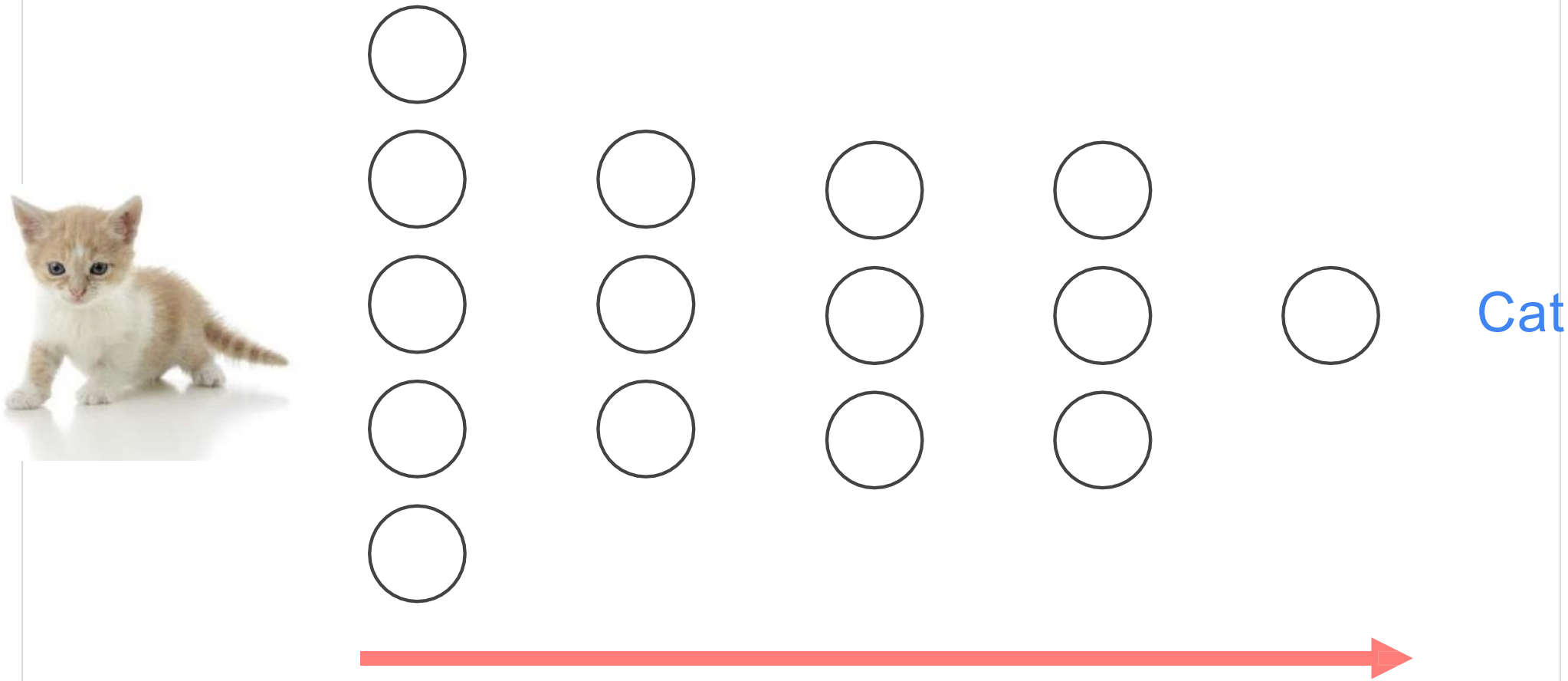


출처: Standford university

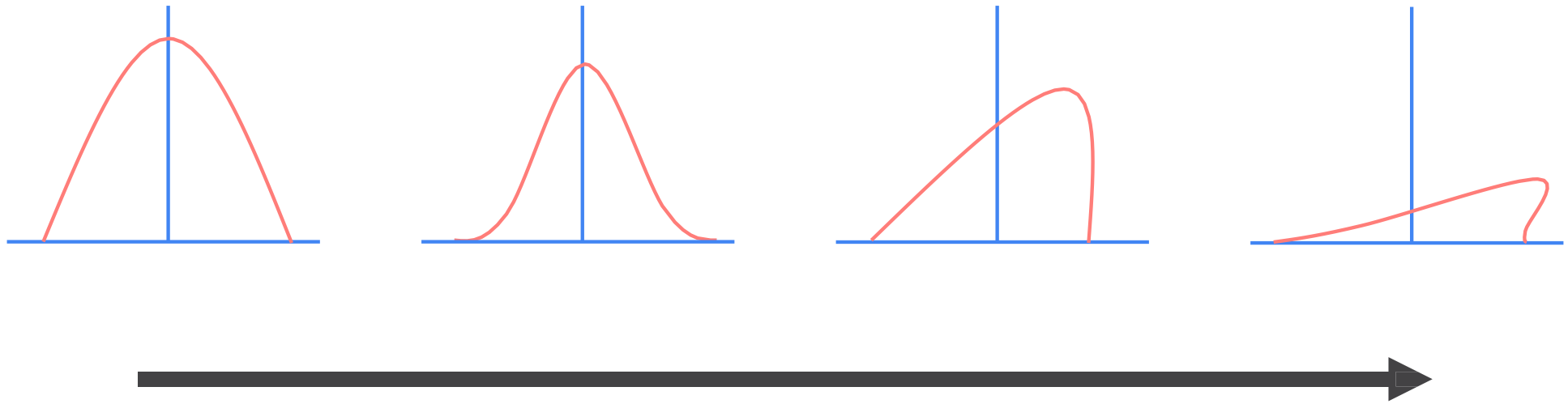
Batch Normalization



Batch Normalization

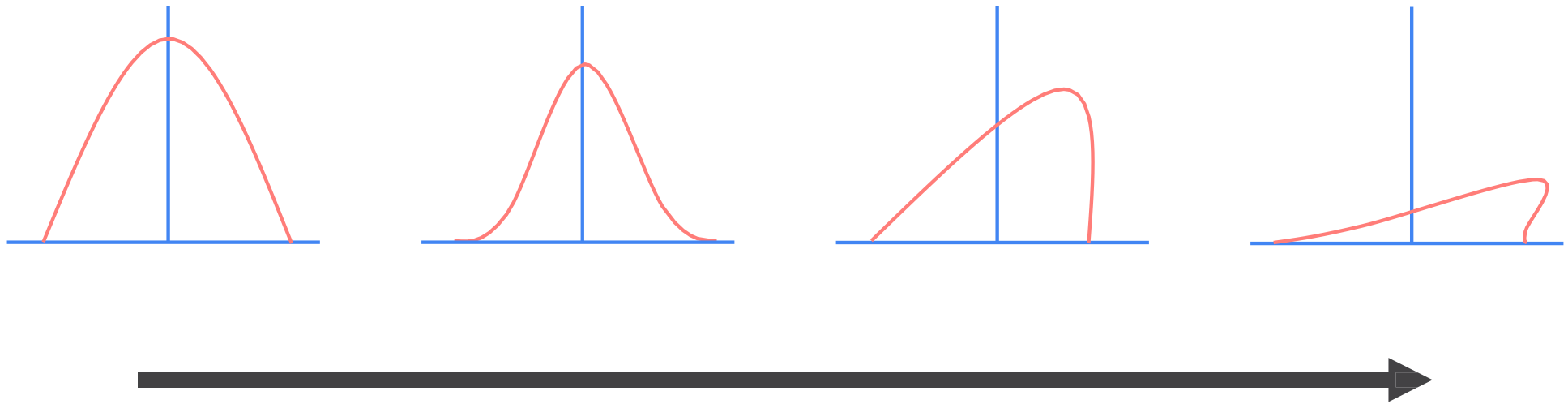


Batch Normalization



Internal Covariate Shift

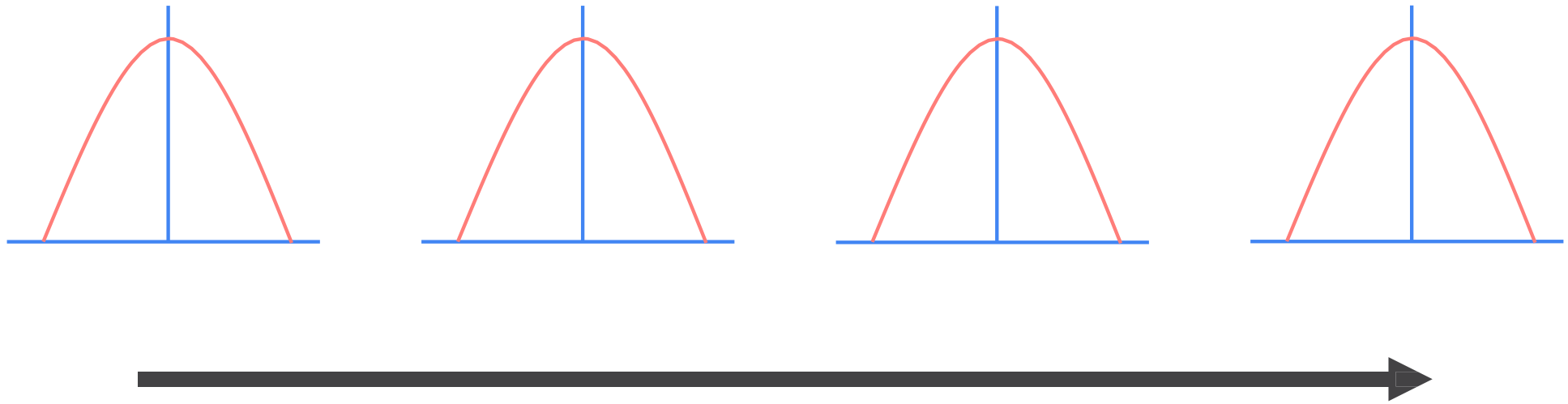
Batch Normalization



$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$y = \gamma \hat{x} + \beta$$

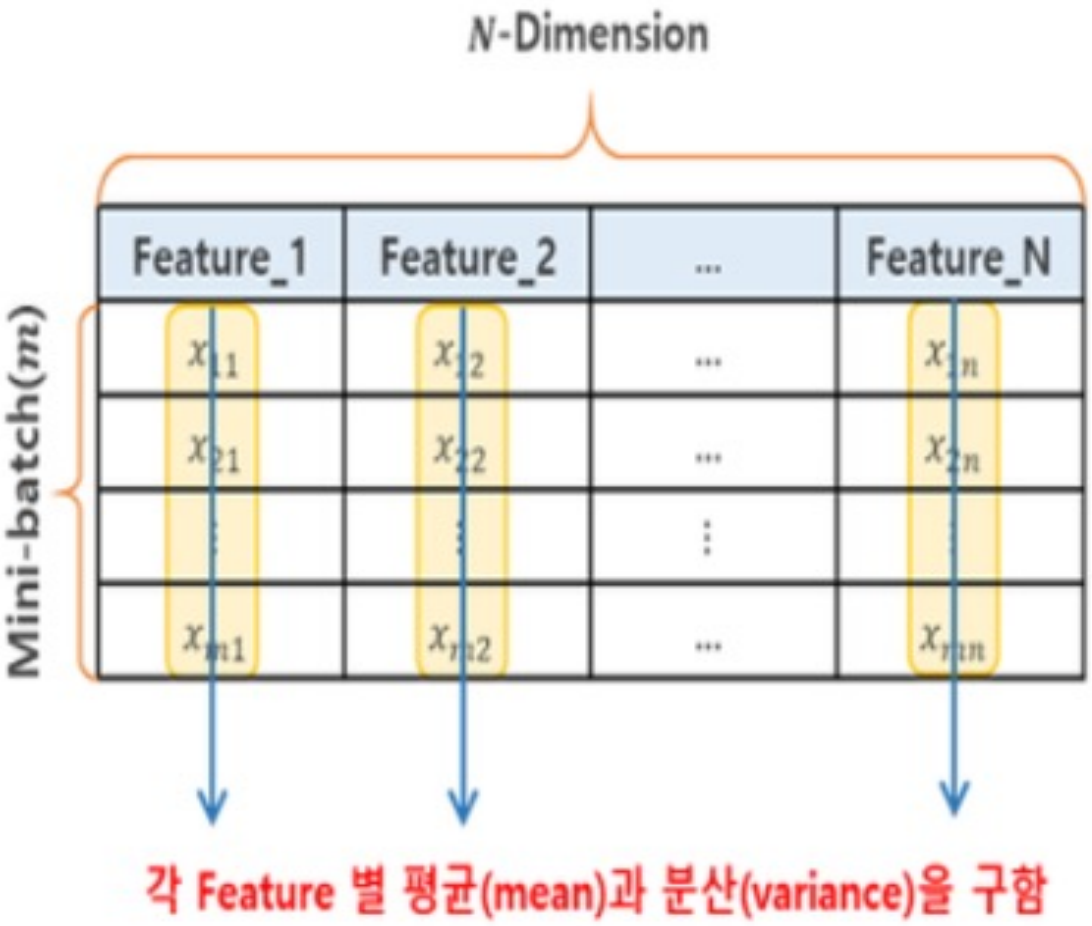
Batch Normalization



$$\bar{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \in}}$$

$$y = \gamma \hat{x} + \beta$$

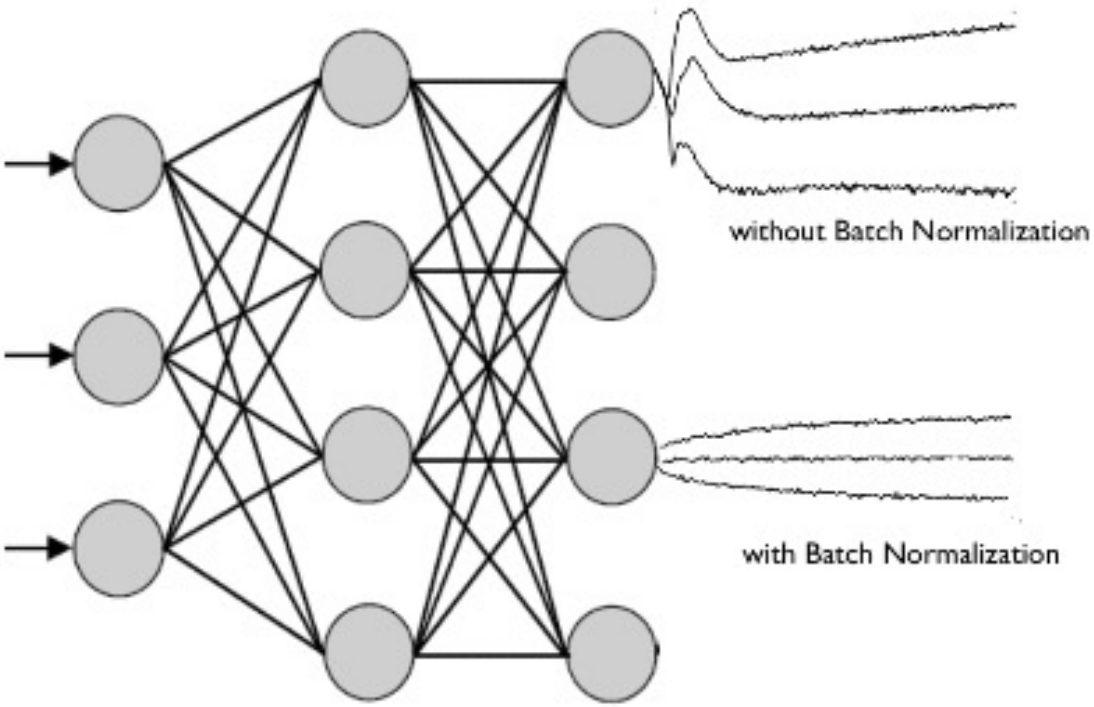
Batch Normalization



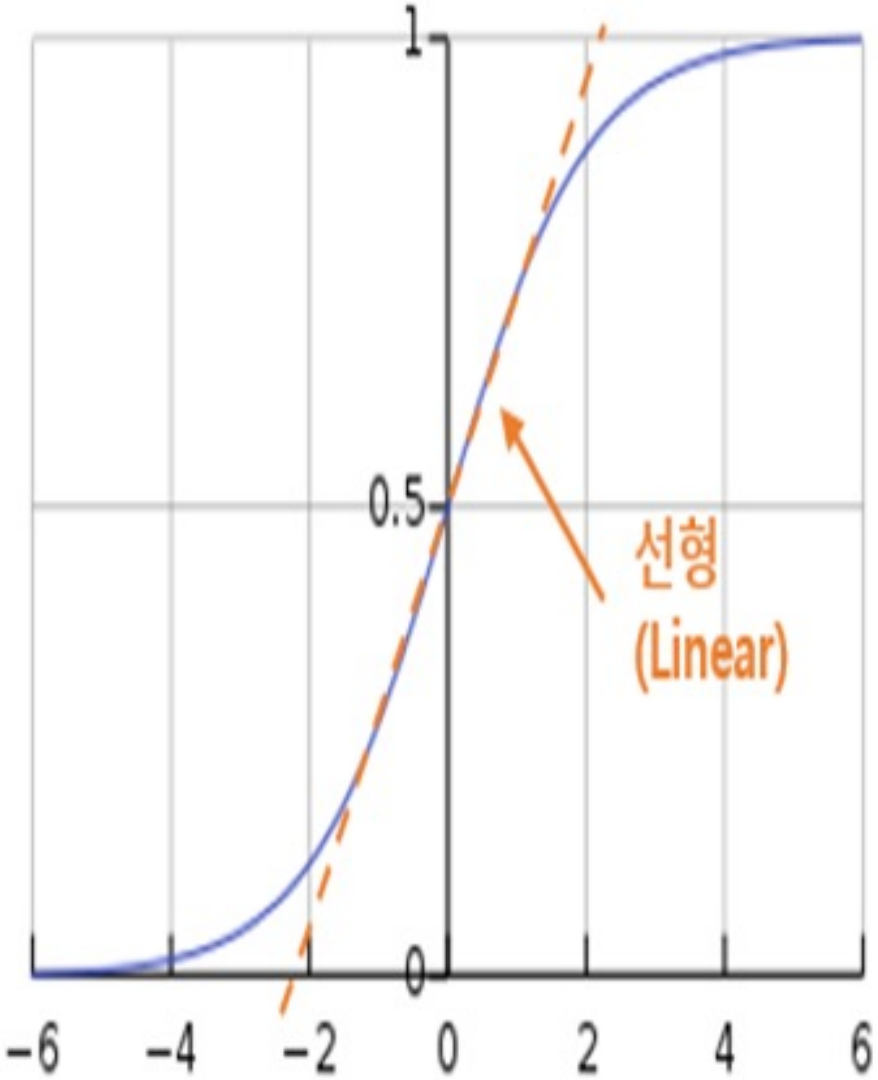
Normalize

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}}$$

Batch Normalization



Batch Normalization



Advantages of Batch Normalization

1. BN enables higher learnig rate.
2. BN regularizes the model
3. 초기값에 크게 의존하지 않습니다.

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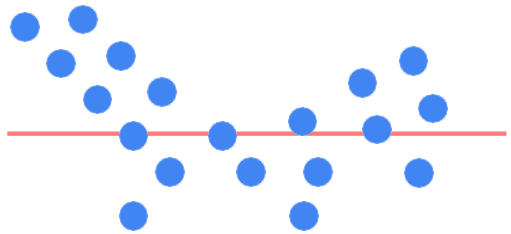
- Our labeled datasets were thousands of times too small → 레이블링 데이터셋 구축
- Our computers were millions of times too slow → 병렬처리
- ~~We initialized the weights in a stupid way~~
- ~~We used the wrong type of non-linearity~~

딥러닝에서도 과적합?

Dropout

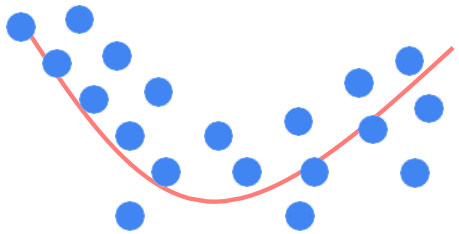
Dropout



Under-fitting

Train ↓

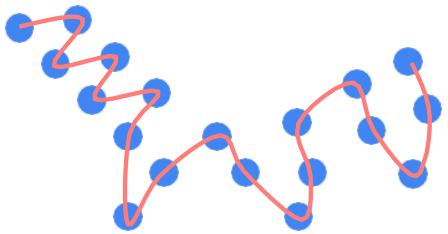
Test ↓



Good

Train =

Test ↑

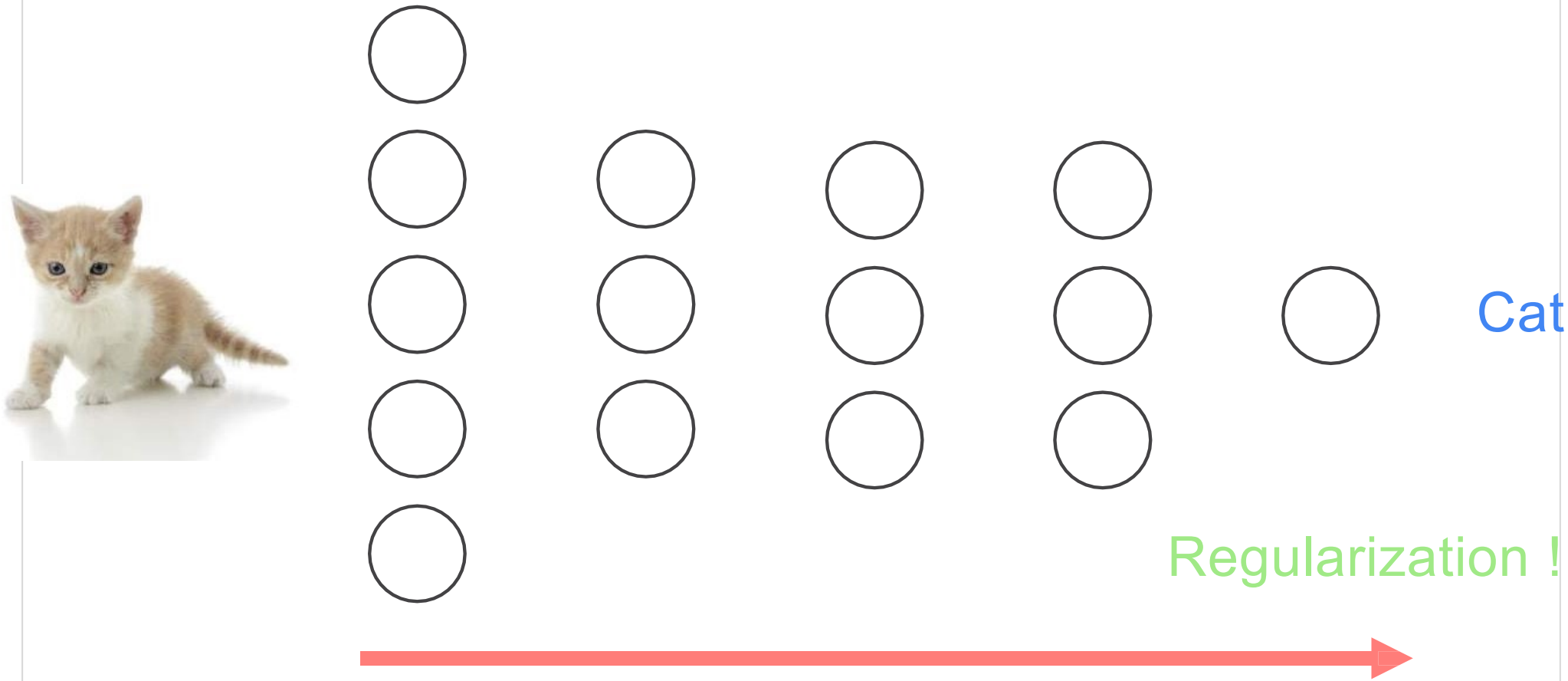


Over-fitting

Train ↑

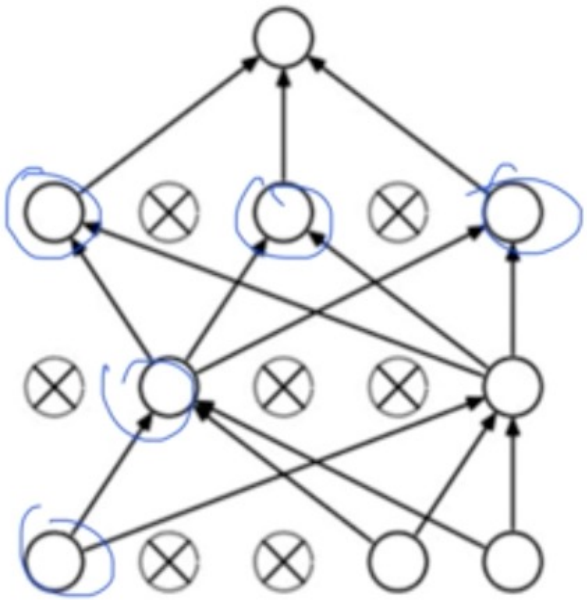
Test ↓

Dropout



Dropout

Waaaait a second…
How could this possibly be a good idea?



Forces the network to have a redundant representation.