

# ML/DL Study W02

- XOR – Neural Networks
- Forward/Back Propagation
- Sigmoid VS Relu
- Xavier VS He
- Drop out
- Batch Normalization

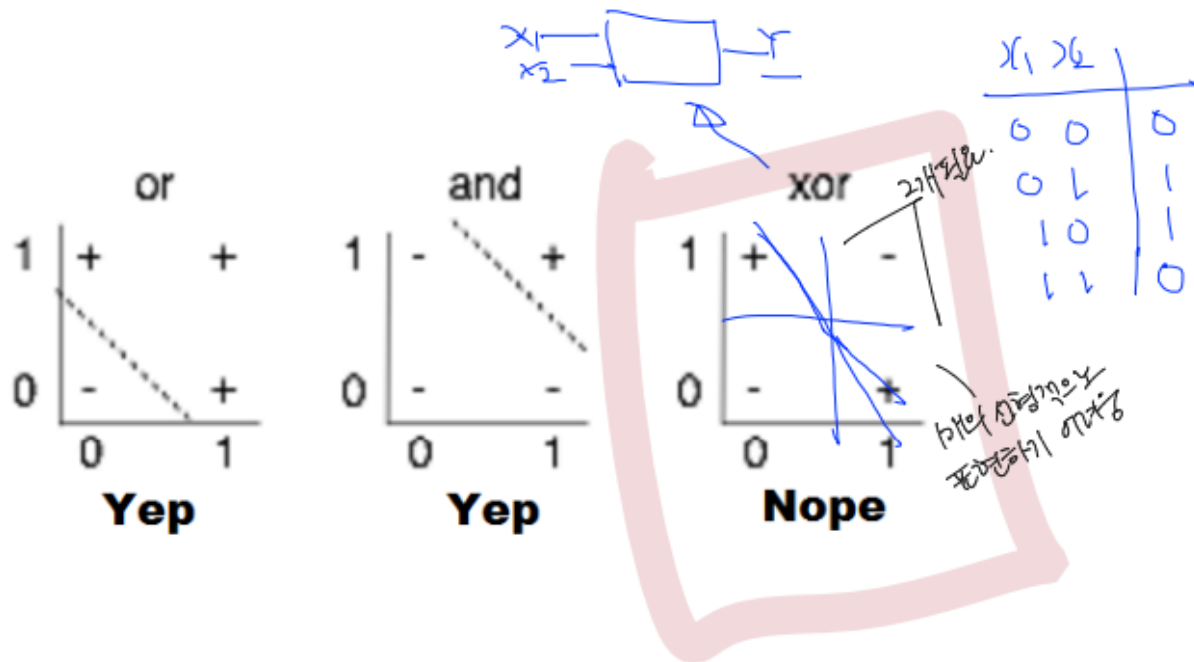
```
lookup.KeyValue  
f.constant(['em  
=tf.constant([0  
ce = tf.lookup.StaticV  
init,  
num_oov_buckets=5)
```

```
lookup.StaticVocabular  
initializer,  
num_oov_buckets,  
lookup_key_dtype=None  
name=None,  
experimental_is_open
```

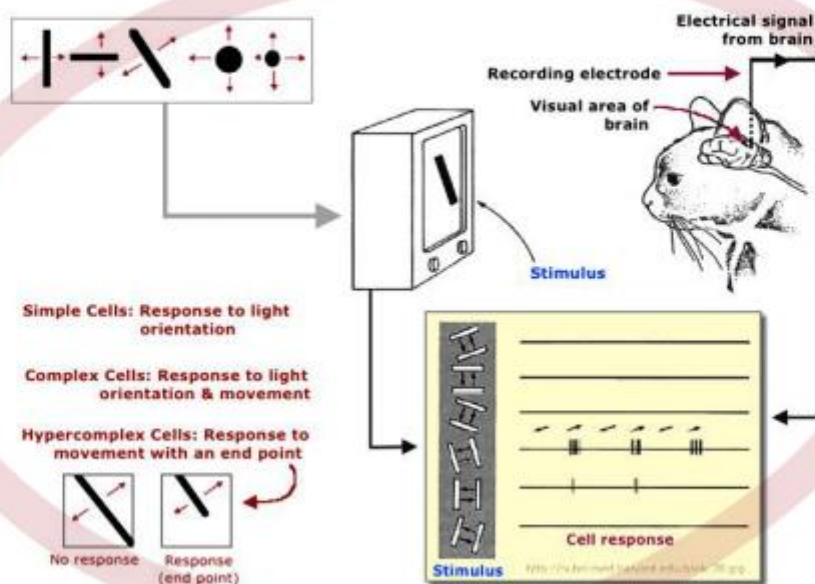
# XOR – NN

## XOR

## (Simple) XOR problem: linearly separable?



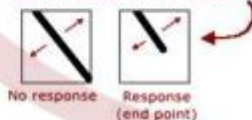
# Convolutional Neural Networks



Simple Cells: Response to light orientation

Complex Cells: Response to light orientation & movement

Hypercomplex Cells: Response to movement with an end point



22222 X

22222  
X  
X  
X  
X

42222 22222




$$\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 5 \\ 5 \end{bmatrix} - 8 = 5 + 5 - 8 = 2, \text{Sigmoid}(2) = 1$$

$$\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ -1 \end{bmatrix} + 3 = -1 + -1 + 3 = 1, \text{Sigmoid}(1) = 0$$

$$\begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} -1 \\ -1 \end{bmatrix} + 6 = -1 + 0 + 6 = 5, \text{Sigmoid}(5) = 1$$

$x_1$	$x_2$	$y_1$	$y_2$	$\bar{y}$	XOR
0	0	0	1	0	0 ✓
0	1	0	0	1	1 ✓
1	0	0	0	1	1 ✓
✓ 1	1	1	0	0	0 ✓

3rd layer learning



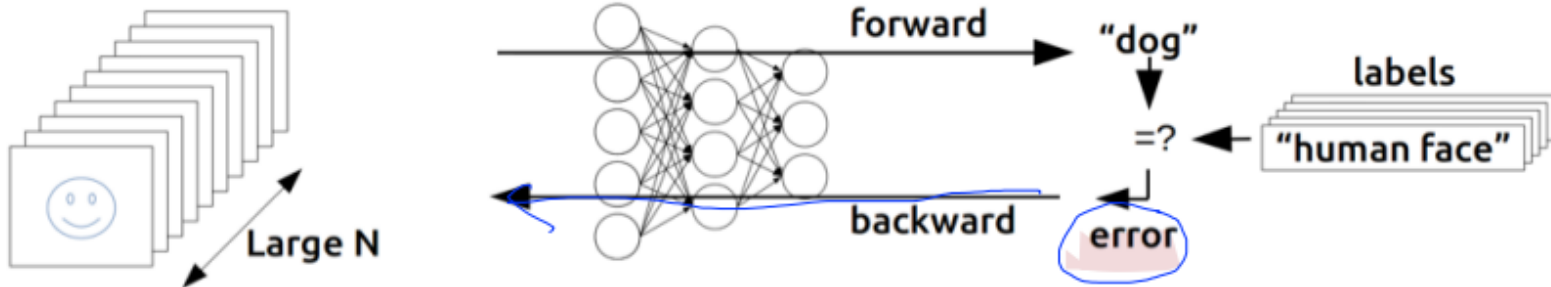
```
K = tf.sigmoid(tf.matmul(X, W1) + b1)
Hypothesis = tf.sigmoid(tf.matmul(K, W2) + b2)
```

# Forward/Back Propagation

# Backpropagation

(1974, 1982 by Paul Werbos, 1986 by Hinton)

Training

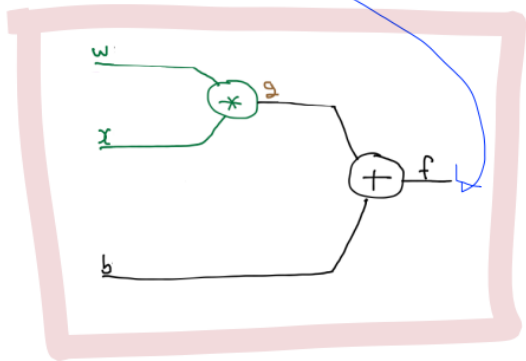




## Forward/Back Propagation

## Back propagation (chain rule)

$$f = wx + b, g = wx, f = g + b$$



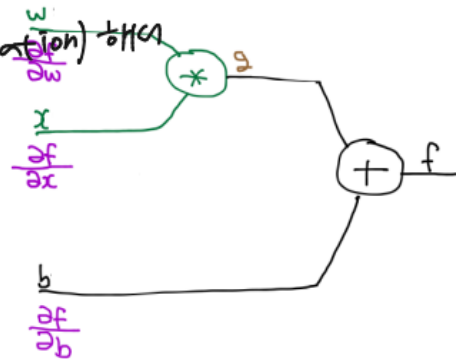
## Back propagation (chain rule)



역전파.

$$f = wx + b, g = wx, f = g + b$$

내 target과 실제 model이 계산한 output 사이  
cost를 구하고 이걸  
뒤로(back) 전파(propagation) 해서  
각 node가 갖는  
변수를 갱신해내는 AI.

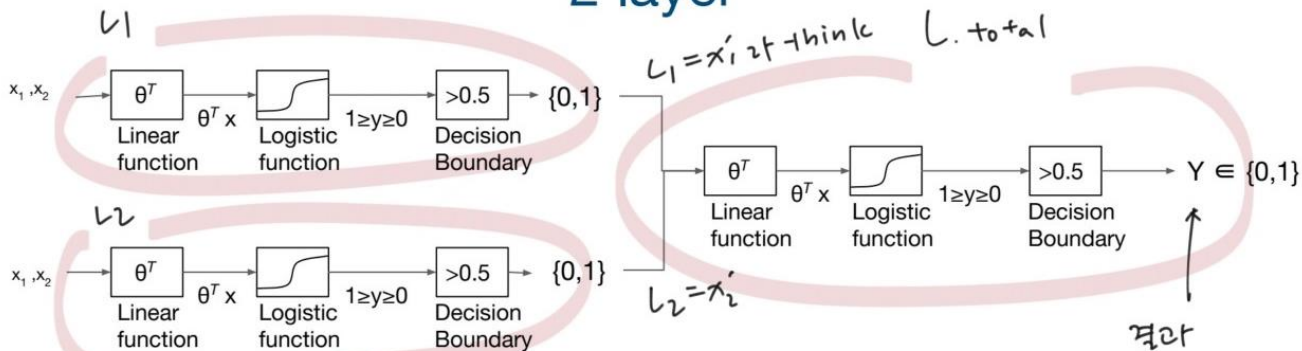


# Sigmoid VS Relu

# Sigmoid

## Neural Net

### 2 layer

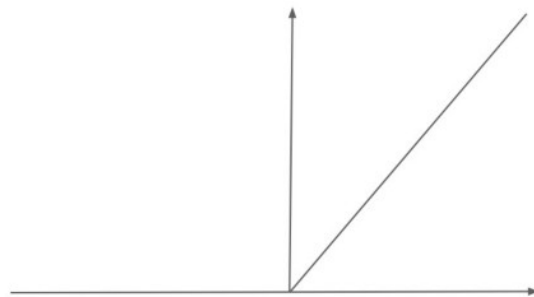
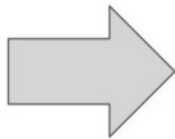
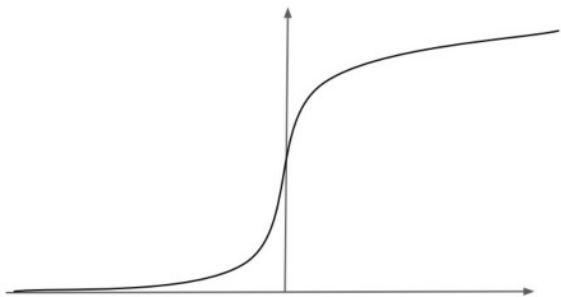


[Tensorflow Code]

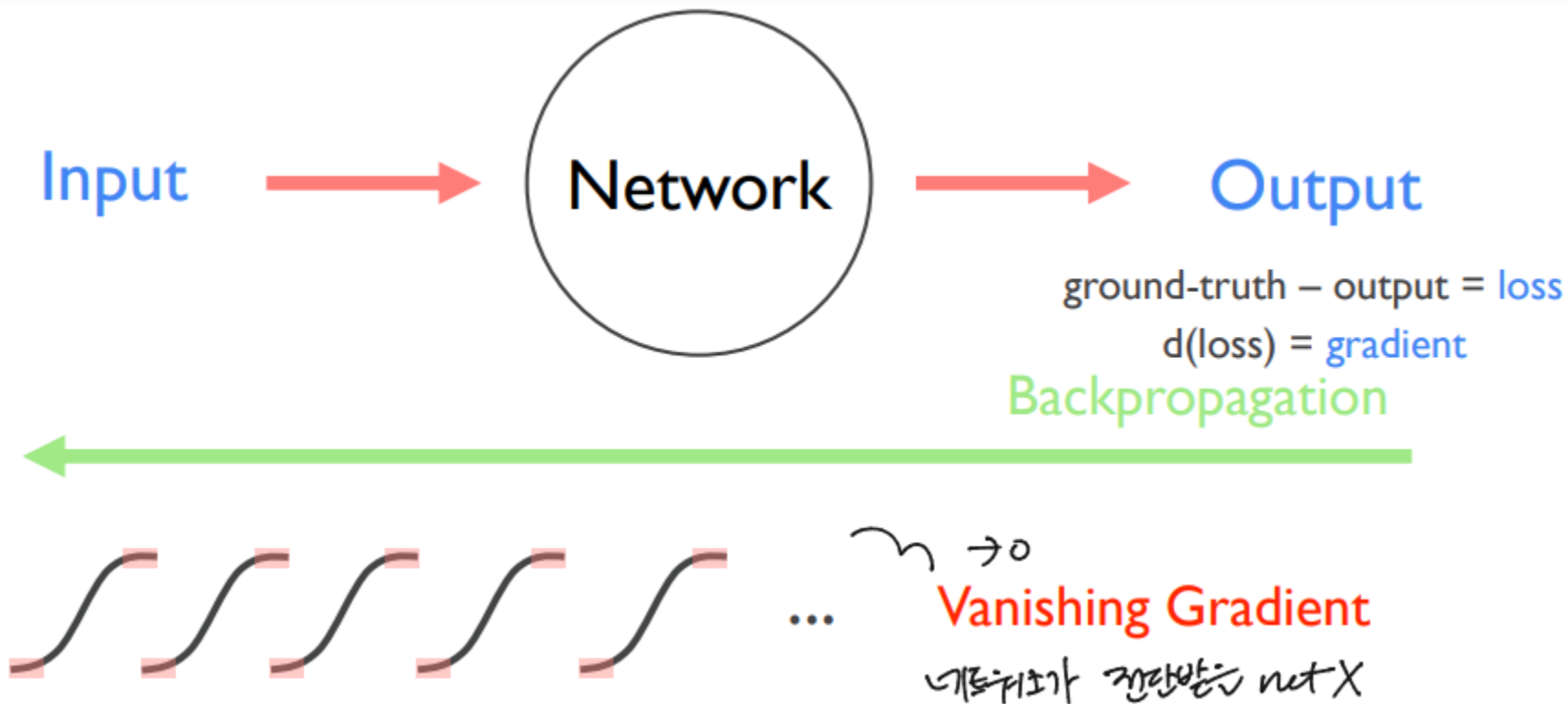
```
def neural_net(features):
    layer1 = tf.sigmoid(tf.matmul(features, W1) + b1) # W1=[2,1], b1=[1]
    layer2 = tf.sigmoid(tf.matmul(features, W2) + b2) # W2=[2,1], b2=[1]
    hypothesis = tf.sigmoid(tf.matmul(tf.concat([layer1, layer2], -1), W3) + b3) # W3=[2,1], b3=[1]
    return hypothesis
```

## Sigmoid

**What's Next?**  
Sigmoid -> Relu



## Problem of Sigmoid



## Why Relu?

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

Sigmoid : 81.31 %  
Relu : 85.35 %

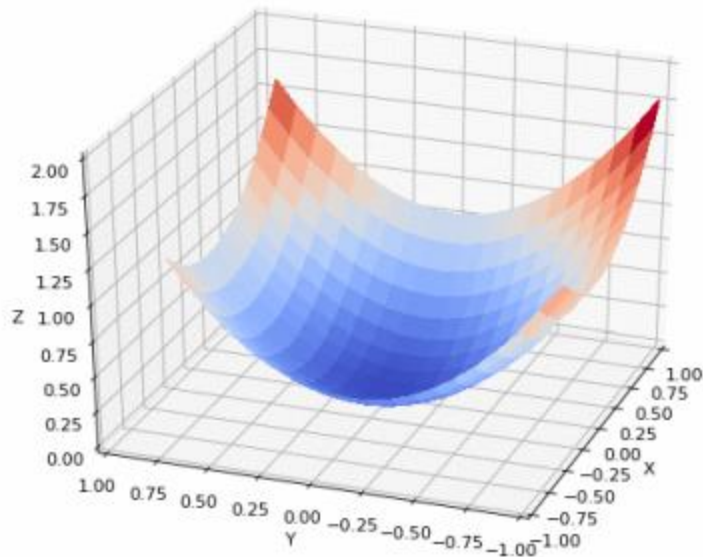
`tf.keras.activations`

functional or you can use

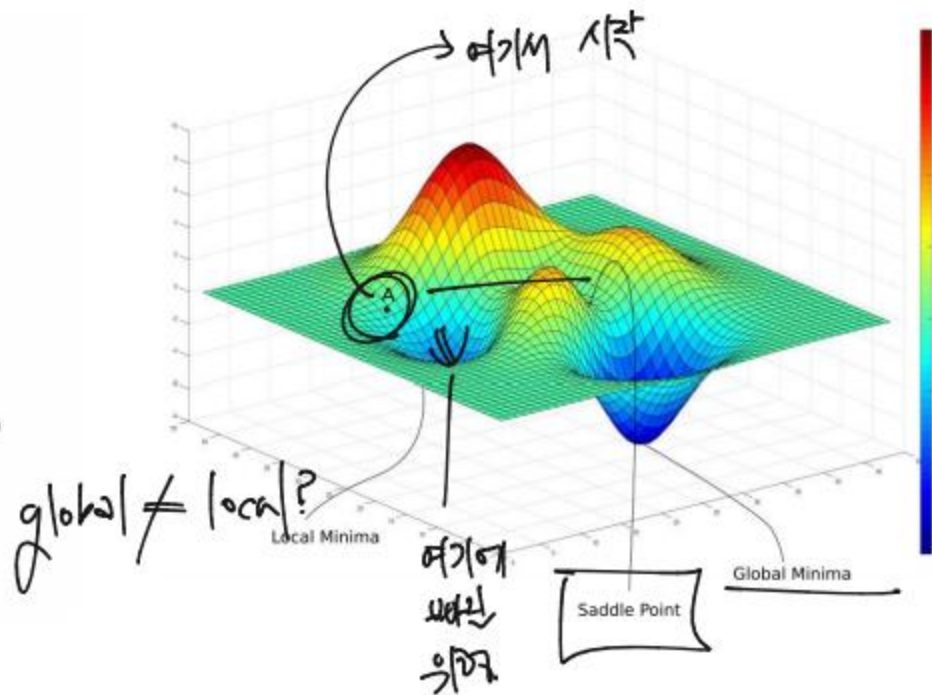
sigmoid, tanh  
relu, elu, selu

# Weight Initialization

## Xavier VS He



global min.





## Xavier VS He

# Create network

```
weight_init = tf.keras.initializers.RandomNormal()
```

```
weight_init = tf.keras.initializers.glorot_uniform()
```

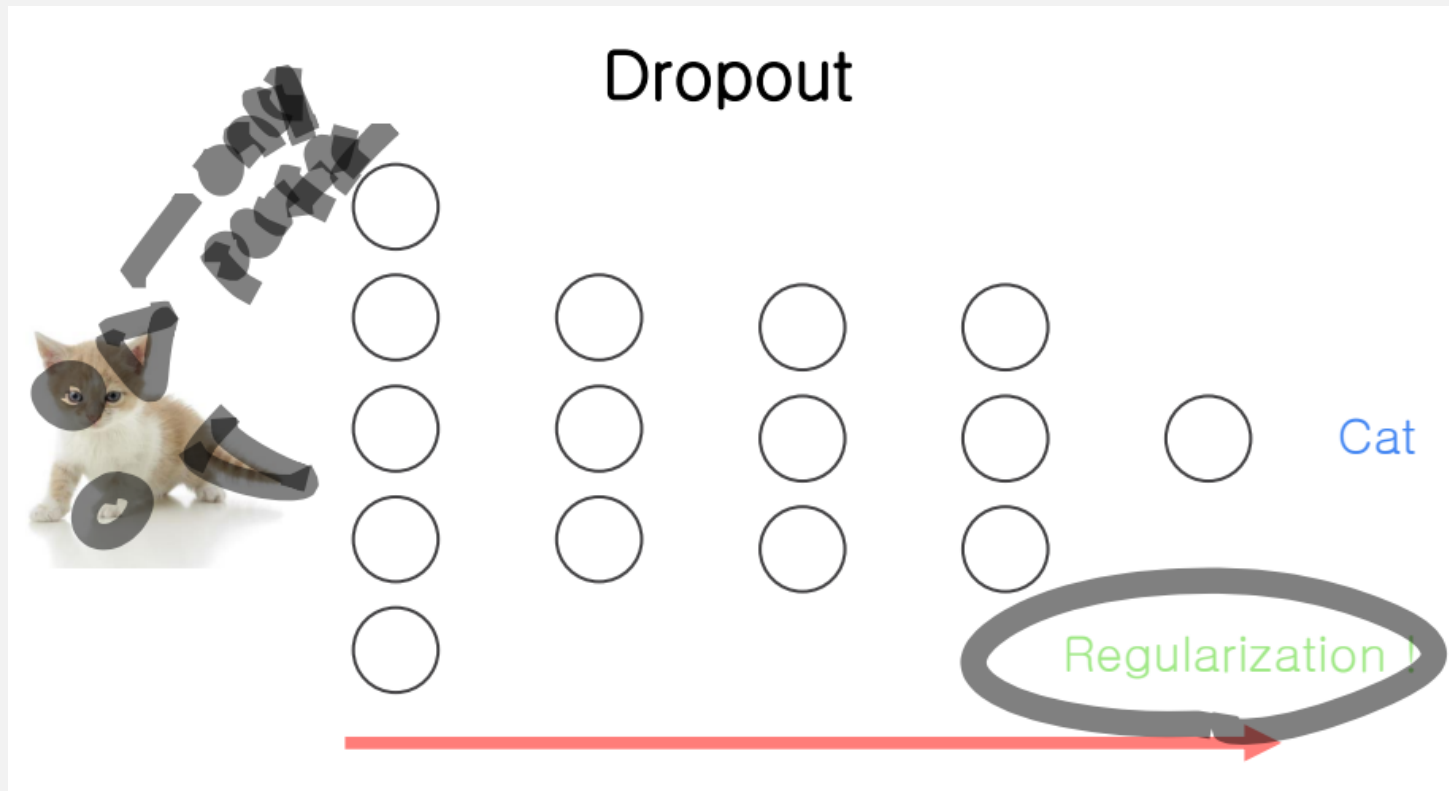
```
weight_init = tf.keras.initializers.he_uniform()
```

Random : 85.35 %

Xavier : 96.50 %

# Drop out

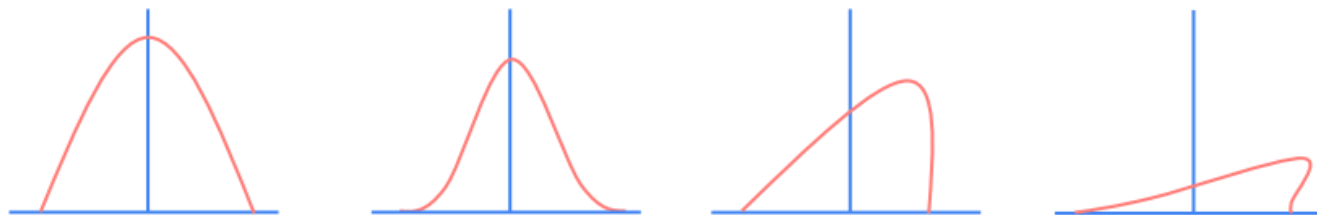
## Drop out



# Batch Normalization

## Batch Normalization

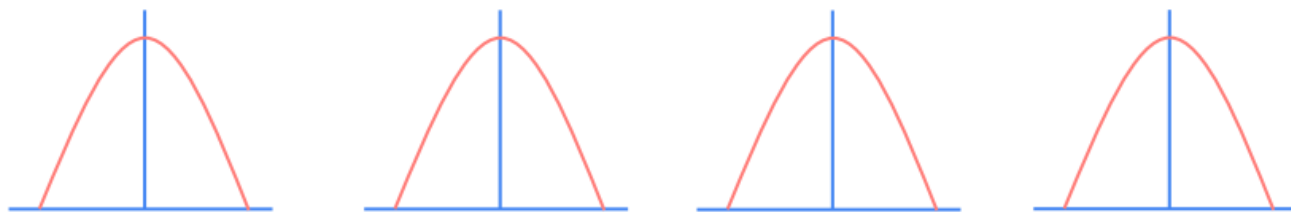
### Batch Normalization



Internal Covariate Shift

## Batch Normalization

## Batch Normalization



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

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