Lecture 7.
Training Neural Networks II

Review

GPU란? 병렬계산↑ + TPU

Graphic Process Unit의 약자

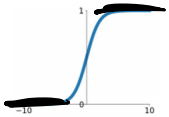
Activation Function

zero-centered.

Sigmoid

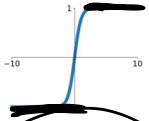
$$\sigma(x) = \frac{1}{1+e^{-x}}$$

0



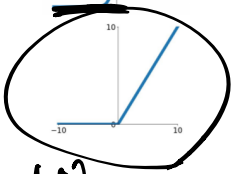
tanh

$$\tanh(x)$$



ReLU

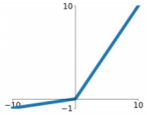
$$\max(0, x)$$



Dead ReLU.

Leaky ReLU

$$\max(0.1x, x)$$

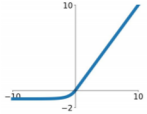


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

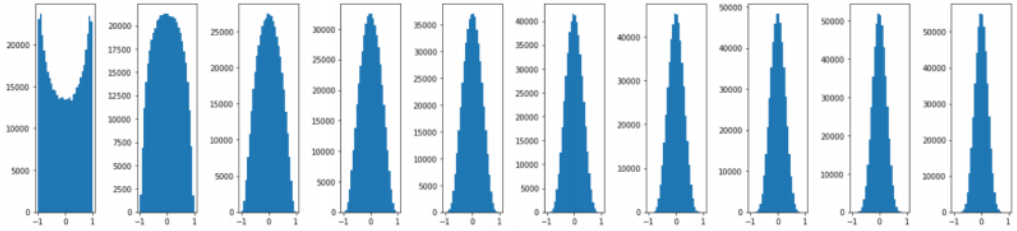


Review

Xavier initialize

$$np.random.randn(size = (D, H))/np.sqrt(D)$$

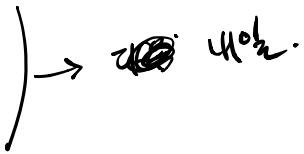
```
W = np. random.randn(fan_in, fan_out) / np.sqrt(fan_in)
```



Today's Contents

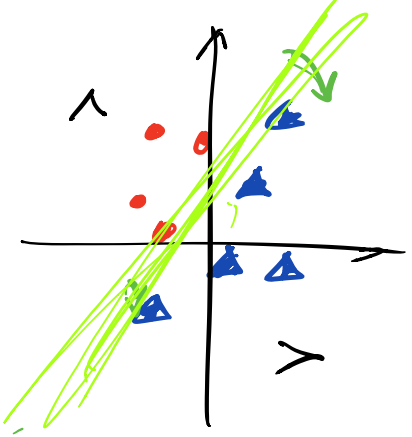
1. Basics for Training
   - Data Normalization
   - Batch Normalization
   - Hyperparameter Search

   + Image Augmentation
2. Change Optimization Process
   - Gradient based method
   - Regularization

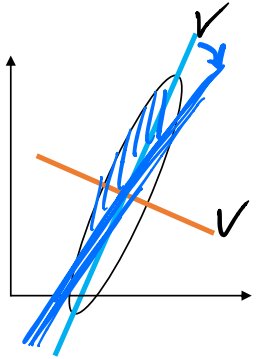


Data Normalization

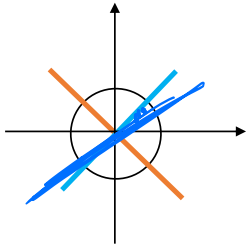
Why?

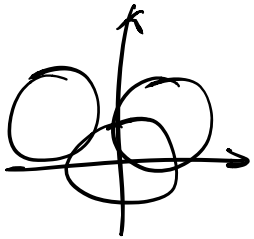


Before normalization



After normalization





CIFAR-10 (Before Normalization)

```
Train on 40000 samples, validate on 10000 samples
Epoch 1/10
40000/40000 [==============================] - 8s 190us/sample - loss: 2.6906 - acc: 0.3472 - val_loss: 1.5718 - val_acc: 0.4412
Epoch 2/10
40000/40000 [==============================] - 7s 183us/sample - loss: 1.4218 - acc: 0.4926 - val_loss: 1.3552 - val_acc: 0.5186
Epoch 3/10
40000/40000 [==============================] - 7s 182us/sample - loss: 1.2132 - acc: 0.5728 - val_loss: 1.3401 - val_acc: 0.5425
Epoch 4/10
40000/40000 [==============================] - 7s 182us/sample - loss: 1.0239 - acc: 0.6409 - val_loss: 1.2987 - val_acc: 0.5665
Epoch 5/10
40000/40000 [==============================] - 7s 183us/sample - loss: 0.8357 - acc: 0.7096 - val_loss: 1.4056 - val_acc: 0.5687
Epoch 6/10
40000/40000 [==============================] - 7s 184us/sample - loss: 0.6655 - acc: 0.7715 - val_loss: 1.6159 - val_acc: 0.5672
Epoch 7/10
40000/40000 [==============================] - 7s 183us/sample - loss: 0.5271 - acc: 0.8209 - val_loss: 1.7894 - val_acc: 0.5591
Epoch 8/10
40000/40000 [==============================] - 7s 182us/sample - loss: 0.4105 - acc: 0.8633 - val_loss: 2.2164 - val_acc: 0.5533
Epoch 9/10
40000/40000 [==============================] - 7s 185us/sample - loss: 0.3605 - acc: 0.8806 - val_loss: 2.4291 - val_acc: 0.5584
Epoch 10/10
40000/40000 [==============================] - 8s 188us/sample - loss: 0.3013 - acc: 0.9037 - val_loss: 2.5739 - val_acc: 0.5547
```

55%

CIFAR-10 (After Normalization)

GCN (std)

data /= 255

data -= np.mean(data)

LCN

data /= np.stddev(data)

```
Train on 40000 samples, validate on 10000 samples
Epoch 1/10
40000/40000 [==============================] - 9s 231us/sample - loss: 1.2820 - acc: 0.5416 - val_loss: 1.0695 - val_acc: 0.6186
Epoch 2/10
40000/40000 [==============================] - 7s 180us/sample - loss: 0.8911 - acc: 0.6865 - val_loss: 0.8893 - val_acc: 0.6866
Epoch 3/10
40000/40000 [==============================] - 7s 180us/sample - loss: 0.6864 - acc: 0.7598 - val_loss: 0.8371 - val_acc: 0.7143
Epoch 4/10
40000/40000 [==============================] - 7s 180us/sample - loss: 0.4900 - acc: 0.8286 - val_loss: 0.8445 - val_acc: 0.7215
Epoch 5/10
40000/40000 [==============================] - 7s 180us/sample - loss: 0.2988 - acc: 0.8984 - val_loss: 0.9551 - val_acc: 0.7258
Epoch 6/10
40000/40000 [==============================] - 7s 179us/sample - loss: 0.1615 - acc: 0.9468 - val_loss: 1.1369 - val_acc: 0.7181
Epoch 7/10
40000/40000 [==============================] - 7s 178us/sample - loss: 0.0940 - acc: 0.9698 - val_loss: 1.3044 - val_acc: 0.7150
Epoch 8/10
40000/40000 [==============================] - 7s 179us/sample - loss: 0.0776 - acc: 0.9746 - val_loss: 1.3674 - val_acc: 0.7242
Epoch 9/10
40000/40000 [==============================] - 7s 179us/sample - loss: 0.0634 - acc: 0.9787 - val_loss: 1.5953 - val_acc: 0.7187
Epoch 10/10
40000/40000 [==============================] - 7s 178us/sample - loss: 0.0578 - acc: 0.9804 - val_loss: 1.5720 - val_acc: 0.7145
```

Data Normalization

Why?

Before

```
Epoch 10/10
40000/40000 [==============================] - 8s 188us/sample - loss: 0.3013 - acc: 0.9037 - val_loss: 2.5739 - val_acc: 0.5547
```

```
Epoch 10/10
40000/40000 [==============================] - 7s 178us/sample - loss: 0.0578 - acc: 0.9804 - val_loss: 1.5720 - val_acc: 0.7145
```

After normalization

Converges much faster!

Data Normalization

Scaling.

MNIST
EMNIST
→ 28×28×1

0~255
↓
0~1

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

0~255
↑ x_{min} ↑ x_{max}

데이터를 0에서 1사이의 값으로 변환!

```
data, test_data = data / 255.0, test_data / 255.0
```

$$x_{new} = \frac{x - 0}{255 - 0} = \frac{x}{255}$$

Data Normalization

Standardization

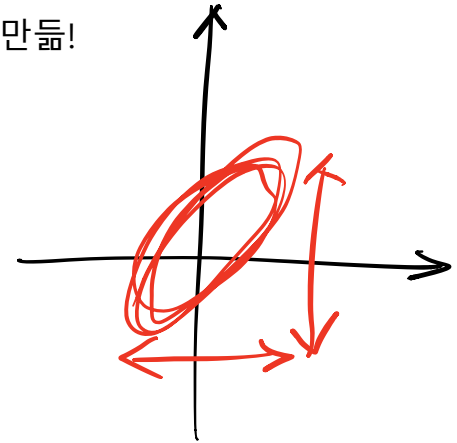
평균 / 표준편차

$$\frac{x - \bar{x}}{\sigma}$$

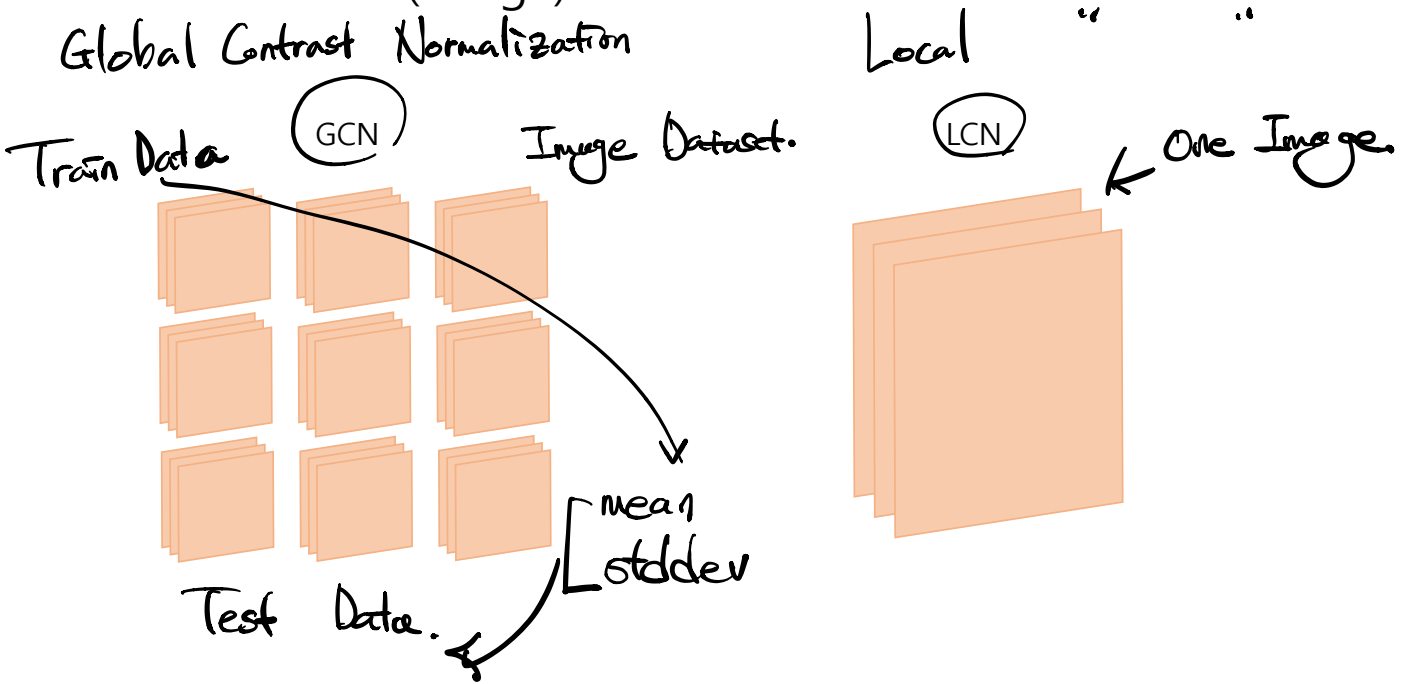
- 각 이미지에 → LCN
- 전체 → GCN

데이터를 평균이 0, 표준편차가 1인 분포로 만듦!

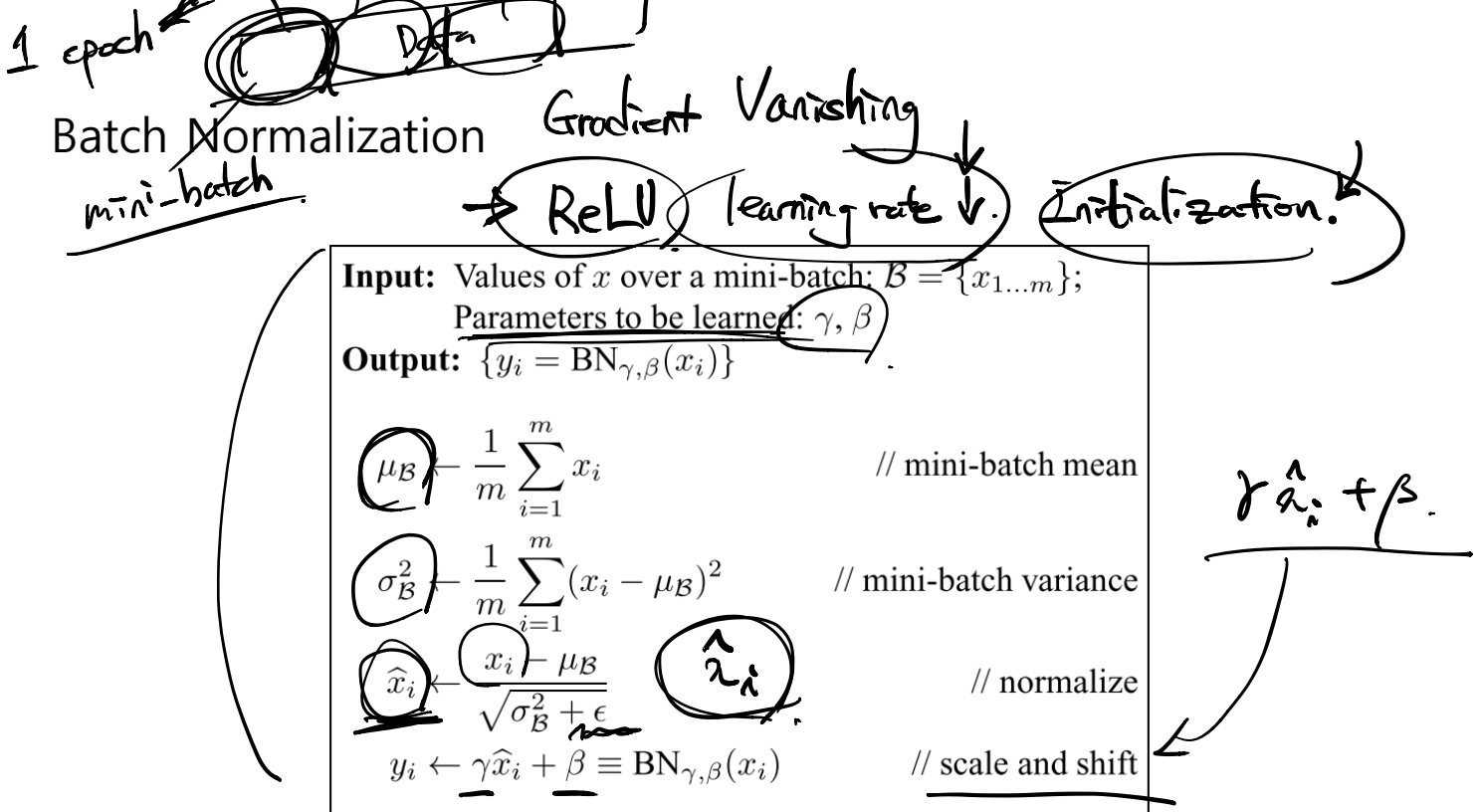
```
data -= np.mean(data)
data /= np.std(data)
```



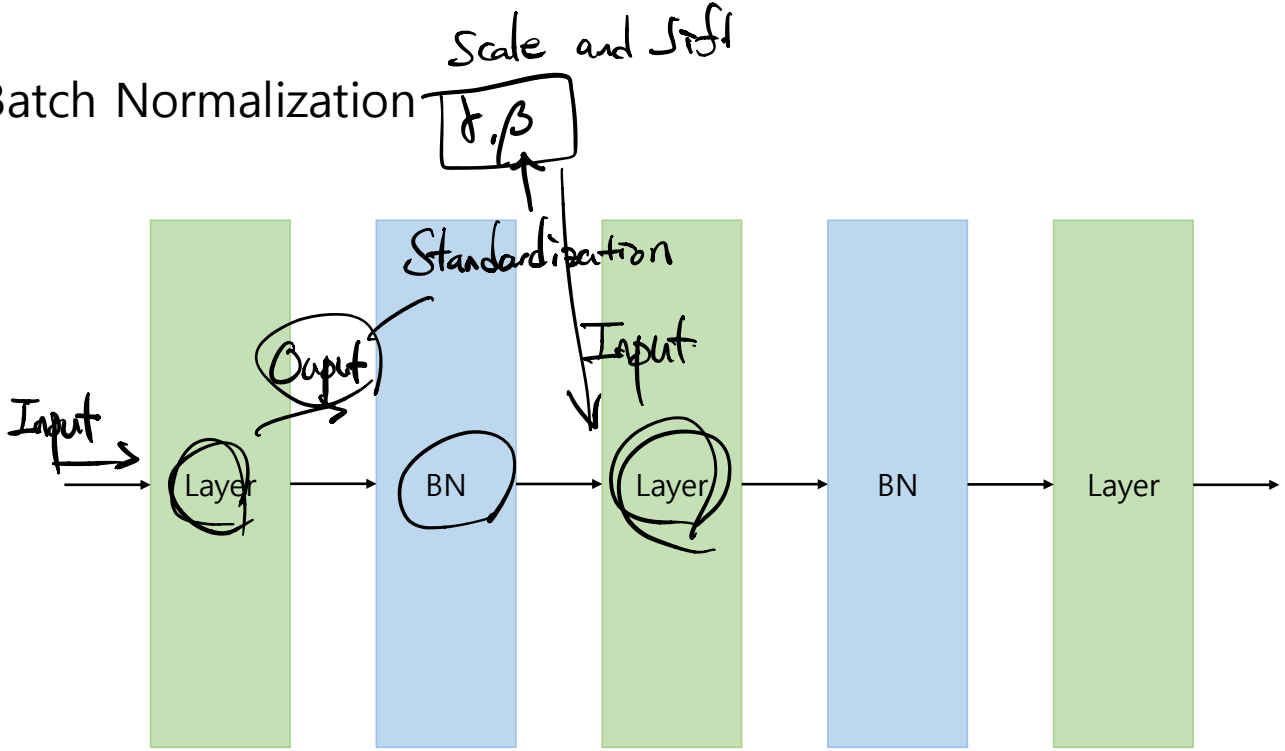
Data Normalization (Image)



Batch Normalization



Batch Normalization



Batch Normalization – CIFAR-10

4 param. [$\gamma, \beta \rightarrow$ Trainable / $\mu_B, \sigma_B \rightarrow$ Non-trainable]

Conv – Max – Conv – Max – FC – 10 Softmax

BN BN

Channel.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 64)	832
batch_normalization (BatchNo	(None, 32, 32, 64)	256
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 64)	16448
batch_normalization_1 (Batch	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 8, 8, 64)	0
flatten (Flatten)	(None, 4096)	0
dense (Dense)	(None, 1024)	4195328
dense_1 (Dense)	(None, 10)	10250

Total params: 4,223,370
Trainable params: 4,223,114
Non-trainable params: 256

trainable

128 128

1IP VS

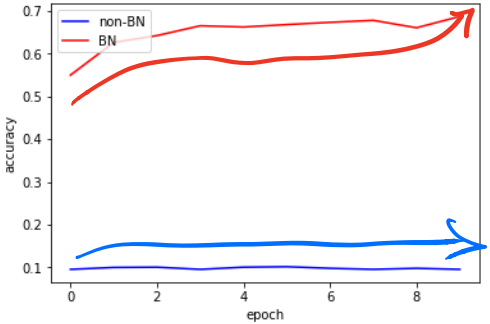
Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 32, 32, 64)	832
max_pooling2d_6 (MaxPooling2	(None, 16, 16, 64)	0
conv2d_7 (Conv2D)	(None, 16, 16, 64)	16448
max_pooling2d_7 (MaxPooling2	(None, 8, 8, 64)	0
flatten_3 (Flatten)	(None, 4096)	0
dense_6 (Dense)	(None, 1024)	4195328
dense_7 (Dense)	(None, 10)	10250

Total params: 4,222,858
Trainable params: 4,222,858
Non-trainable params: 0

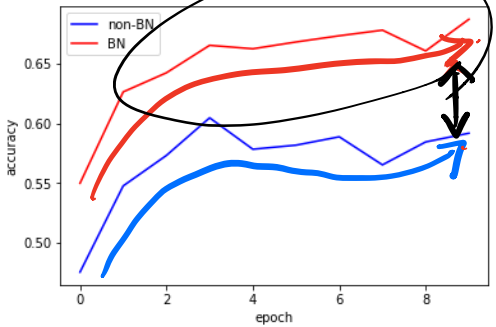
Batch Normalization

tf.keras.layers.BatchNormalization().

Learning rate = 0.005



Learning rate = 0.001



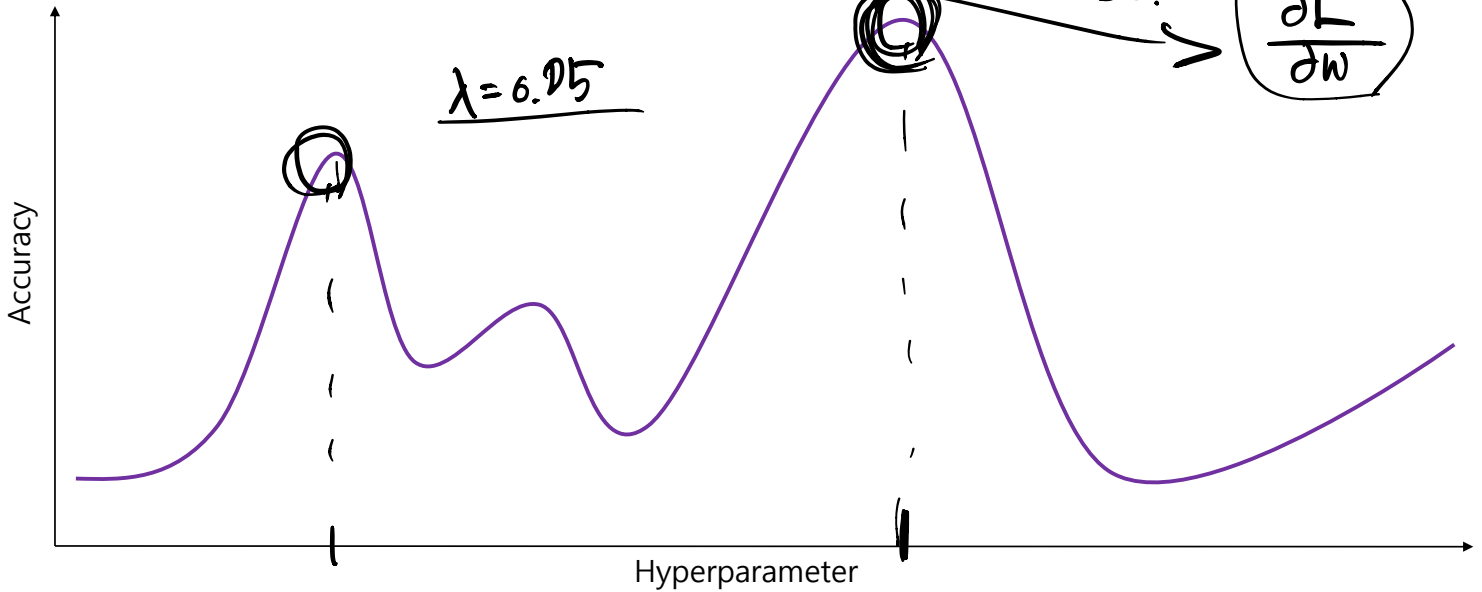
$$Loss = \frac{1}{N}\sum_{i=1} L_i + \lambda R(W)$$

$$weight \mathrel{-}= lr * gradient$$

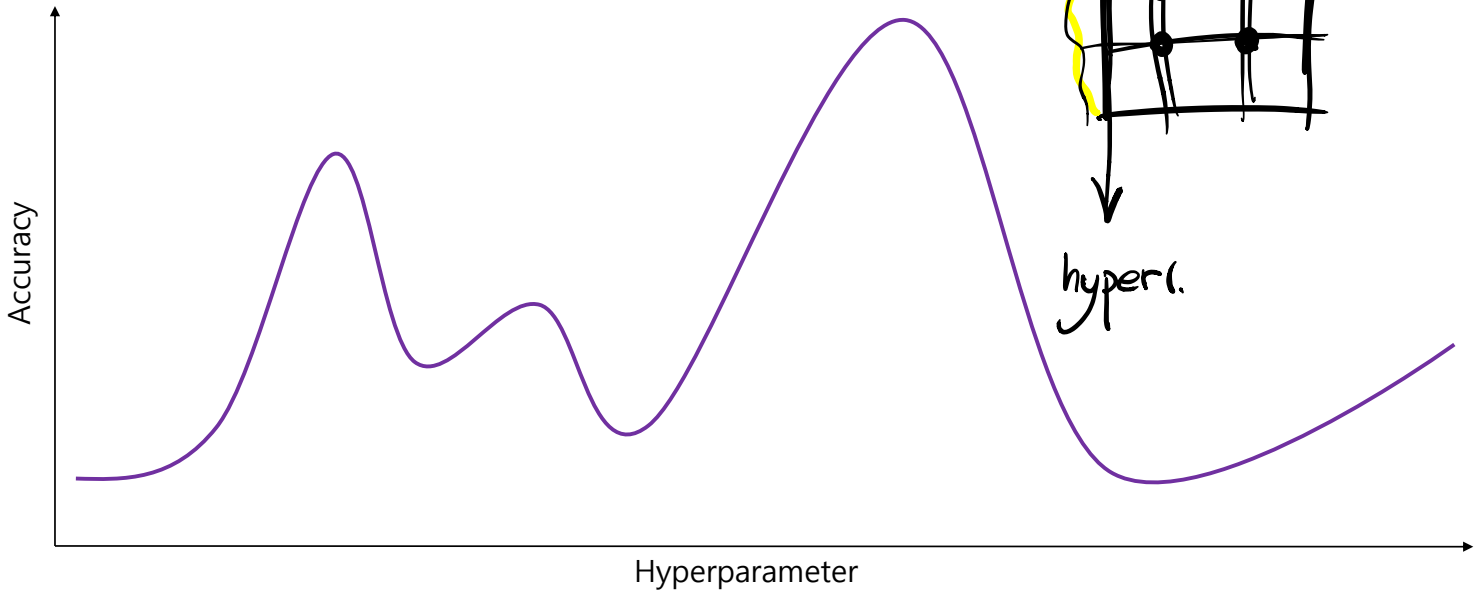
$$\frac{\partial L}{\partial W}$$

영향!

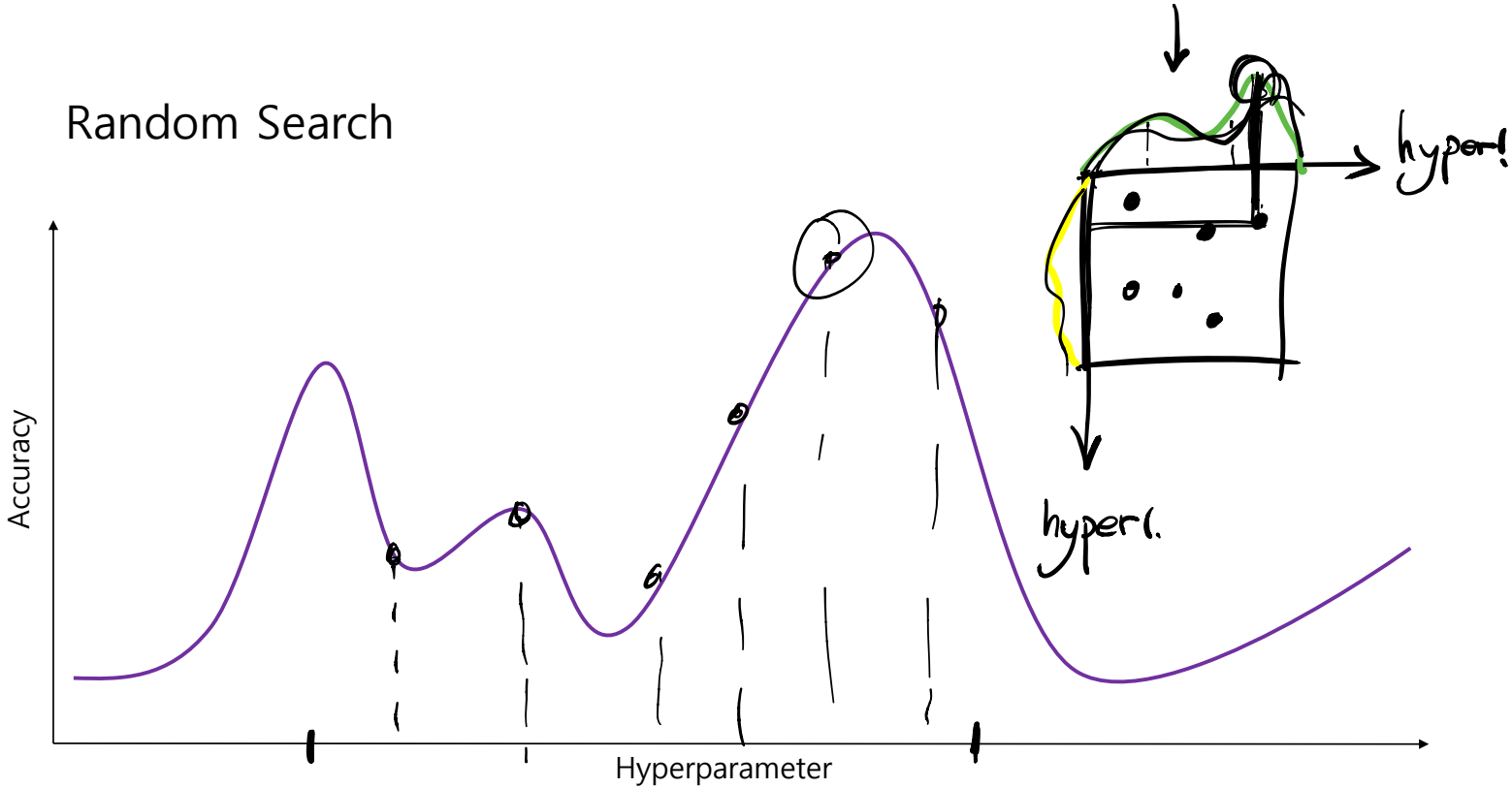
Hyperparameter Search



Grid Search



Random Search



* AutoML

요약: Machine Learning으로 Machine Learning 하기!

참고: http://research.sualab.com/introduction/practice/2019/02/19/bayesian-optimization-overview-1.html

+ Image Augmentation
- 1. 모델이 일반화 성능 ↑ overfitting 방지.
- 2. 데이터셋 크기 ↑.

robust

Crop, Scale, Flip, Translate, Rotate, add a nosie

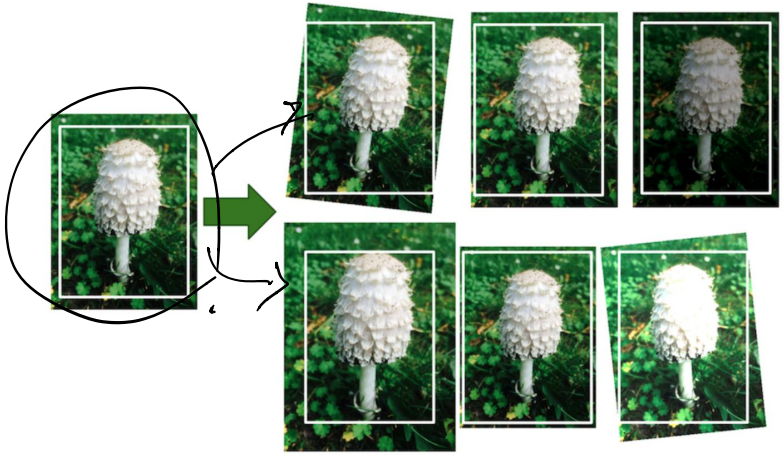
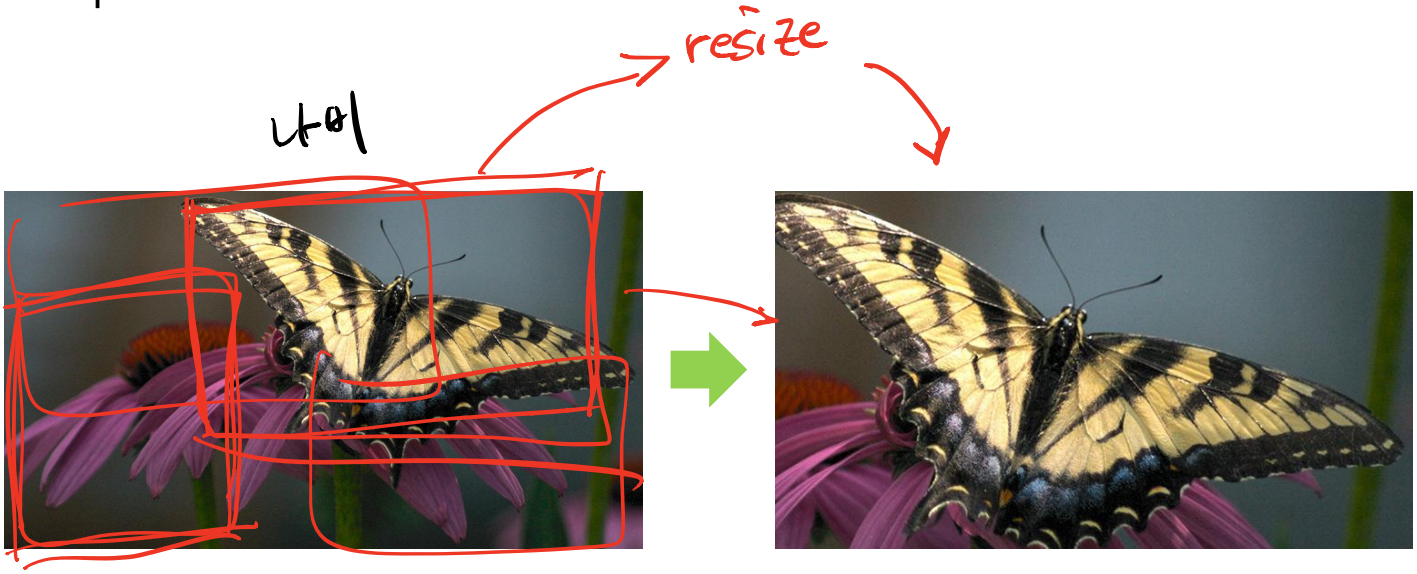


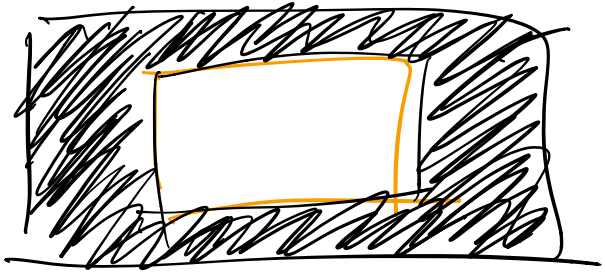
Image source: https://github.com/oryondark/-/blob/master/DeepLearning_master/Augmentation_Tutorial/Data%20Augmentation.md

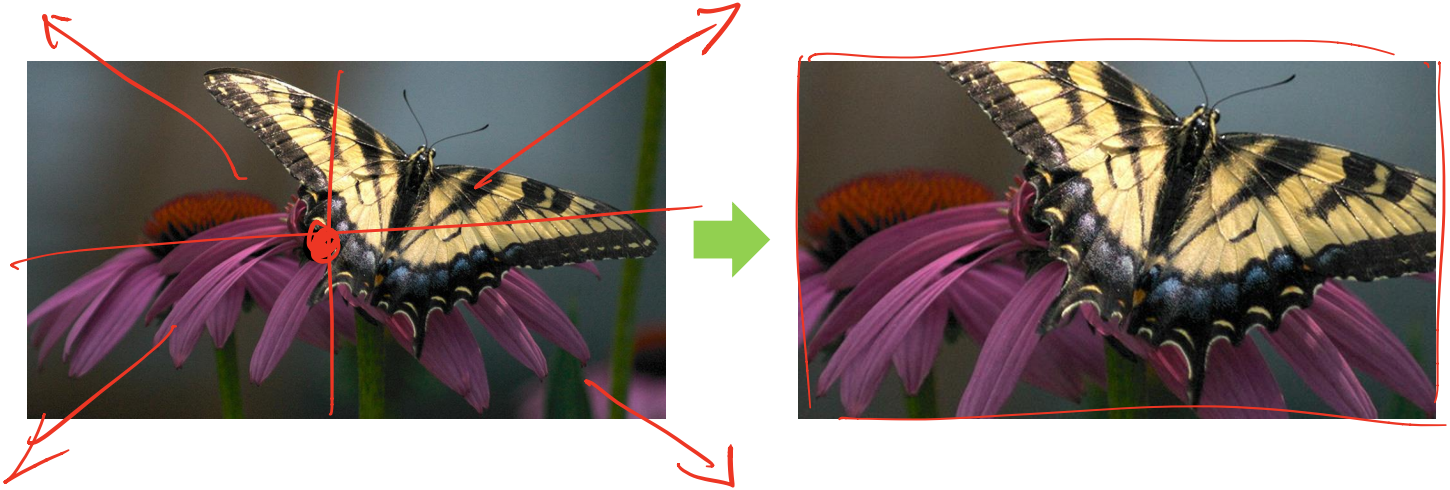
Crop



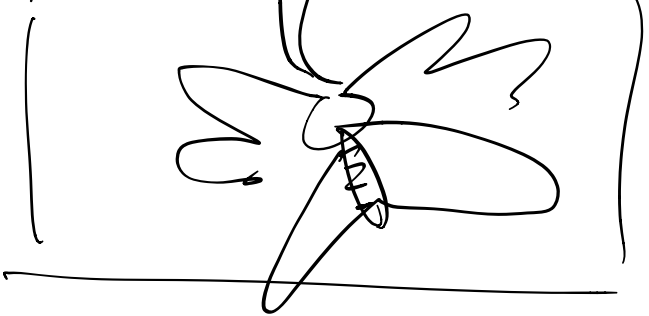
Scale

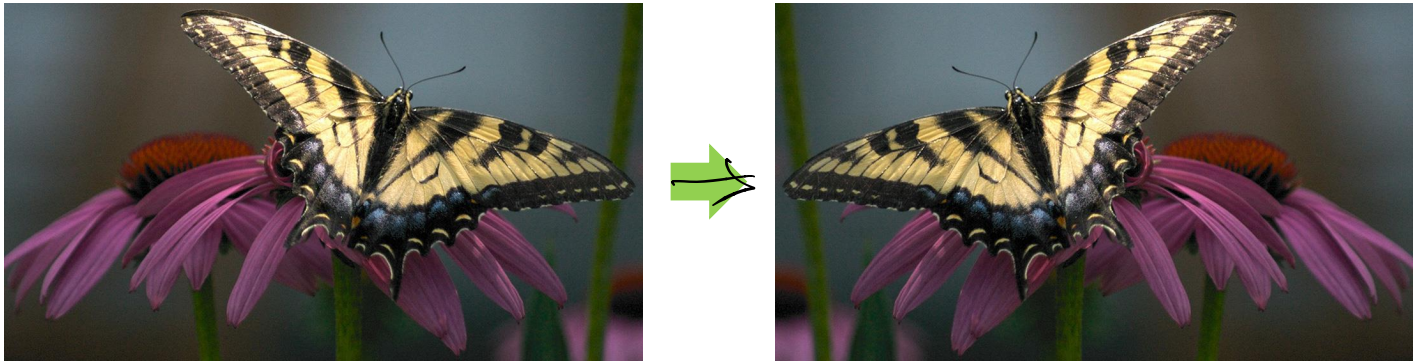
- Outward
- Inward



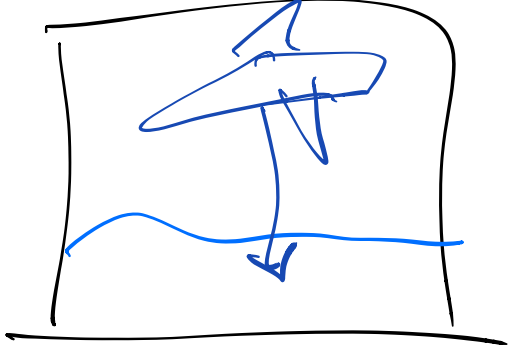


Flip

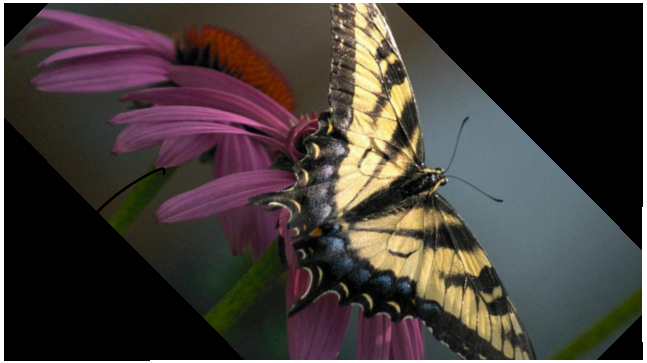




Translation



Rotate



Add a Noise

high frequency features.

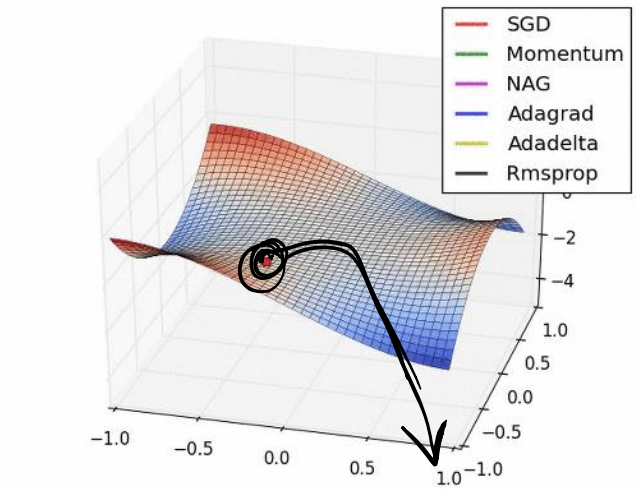
whatting.

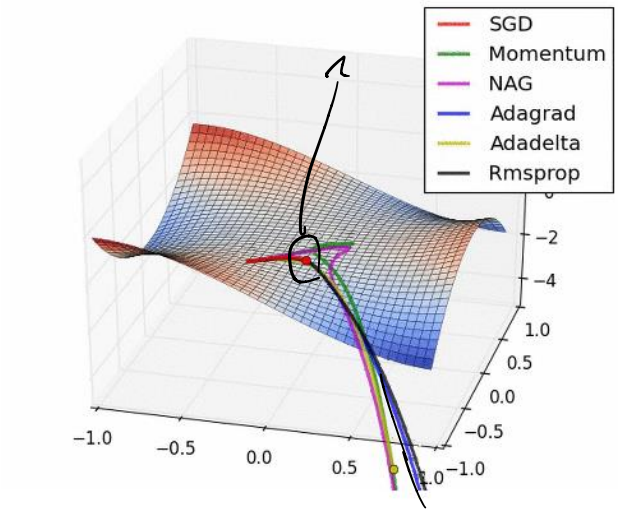
Image Augmentation

Make 2 ~ 3 more images

1. Small dataset ➔ Large dataset
2. Prevent overfitting
3. BUT, take a right way!!

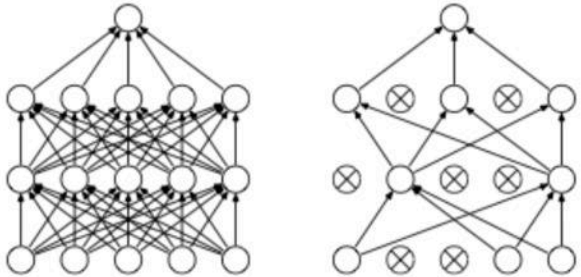
Preview on Next Class





Preview on Next Class

Dropout: A Simple Way to Prevent Neural Networks from Overfitting [Srivastava et al. 2014]



(a) Standard Neural Net (b) After applying dropout.