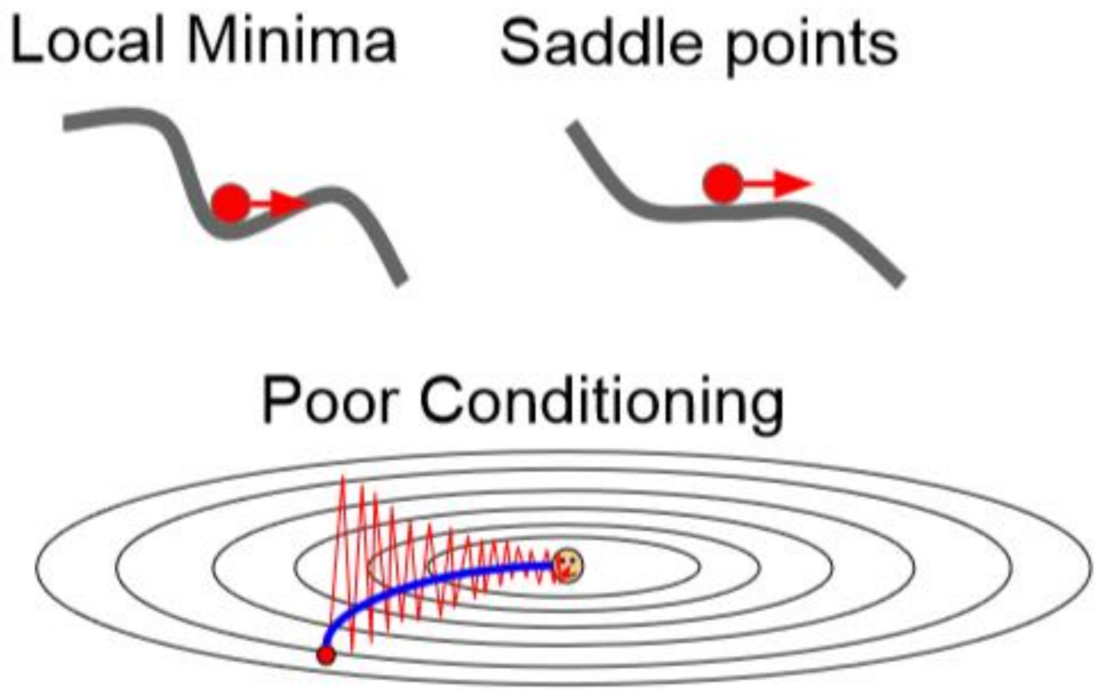
CS231n Lecture 7

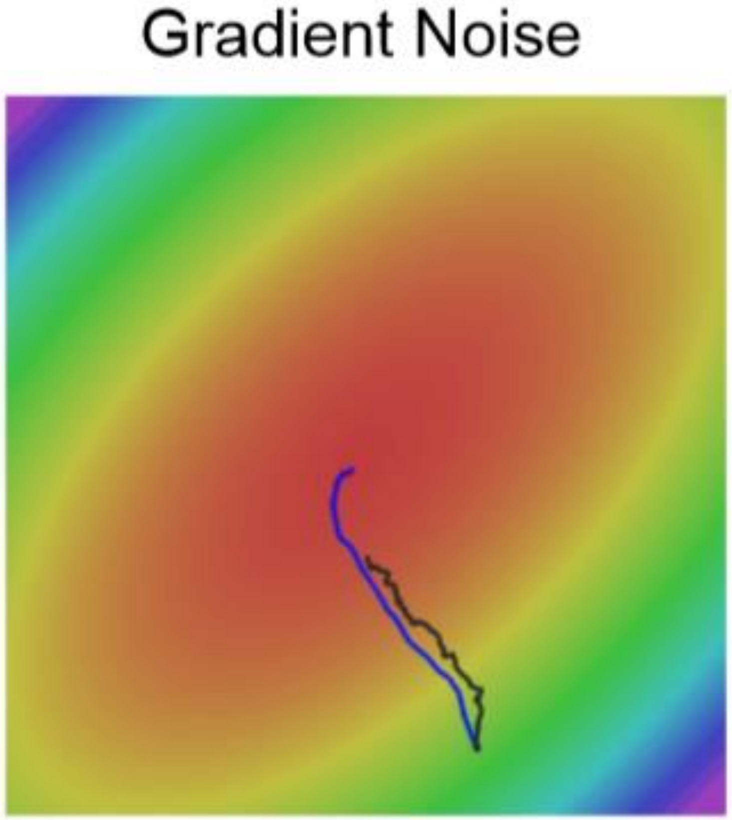
- BOAZ 10기 박성현
- BOAZ 11기 김태희
- BOAZ 11기 홍지민

Training Neural Network Overview

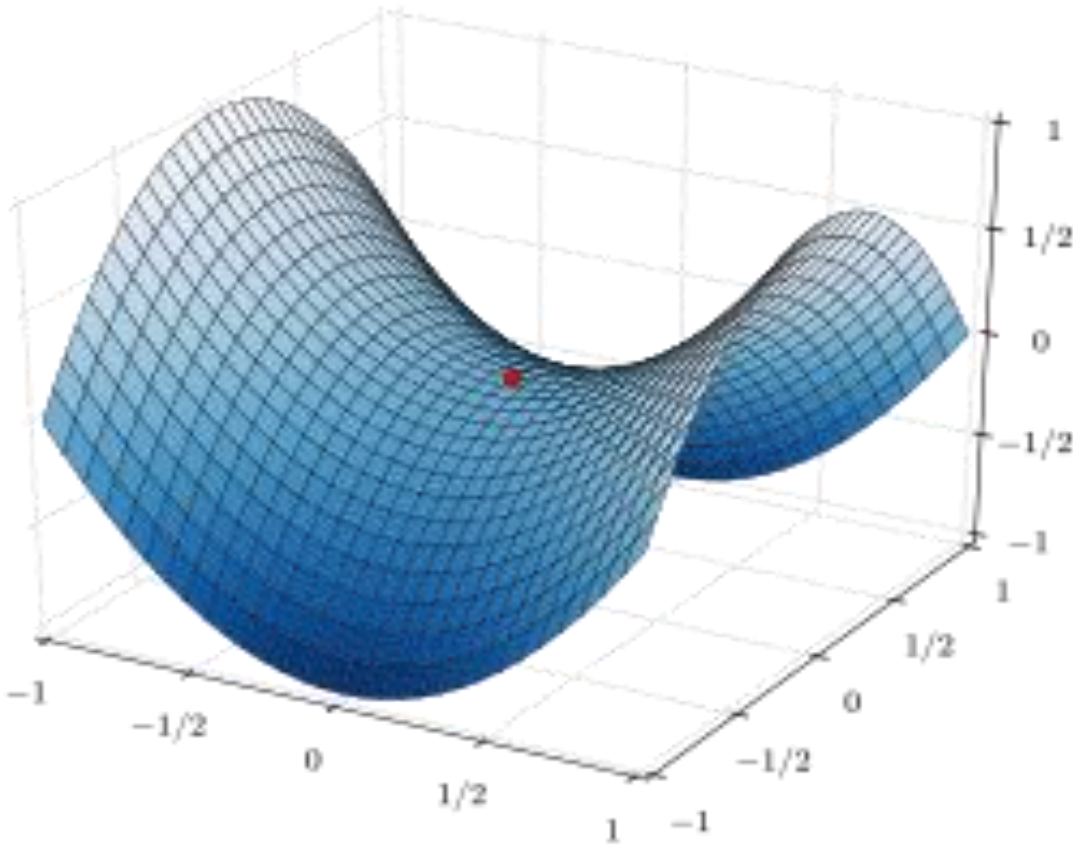
- Parameter update schemes
- Learning rate schedules
- Gradient checking
- Regularization (Dropout etc.)
- Evaluation (Ensembles etc.)
- Transfer learning / fine-tuning

02 Optimization (SGD Problem)





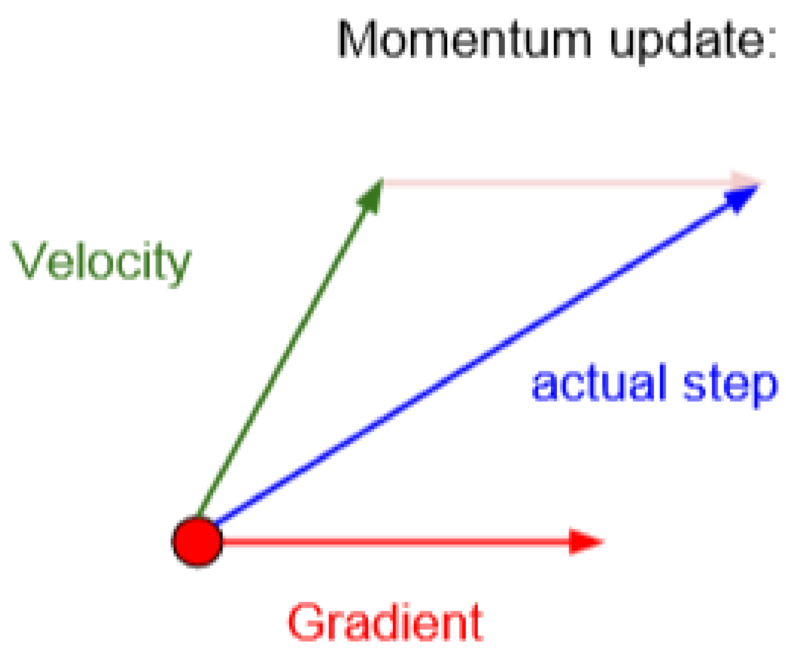
02 Optimization (SGD Problem)



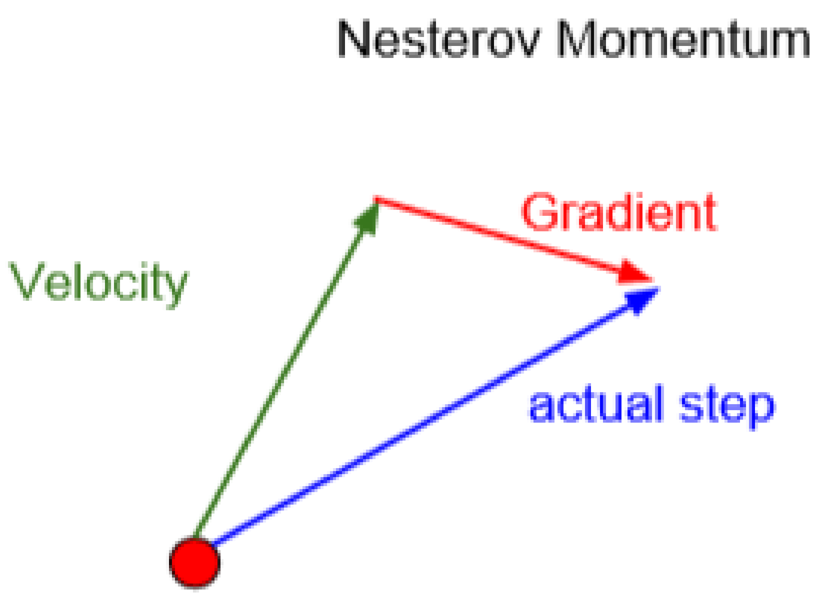
[Saddle Point]

Optimization (Momentum)

[SGD + Momentum]



[Nesterov Momentum]



Q. 2가지 방법의 차이점은?

02

Optimization (AdaGrad & RMSProp)

AdaGrad

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared += dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

RMSProp

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared = decay_rate * grad_squared + (1 - decay_rate) * dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

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02 Optimization (Adam)

```
first_moment = 0
second_moment = 0
for t in range(1, num_iterations):
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment  + (1 - beta1) * dx
  second_moment = beta2 * second_moment + (1 - beta2) * dx * dx
  first_unbias = first_moment / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)
  x -= learning_rate * first_unbias / (np.sqrt(second_unbias) + 1e-7))
```

Momentum

Bias correction

AdaGrad / RMSProp

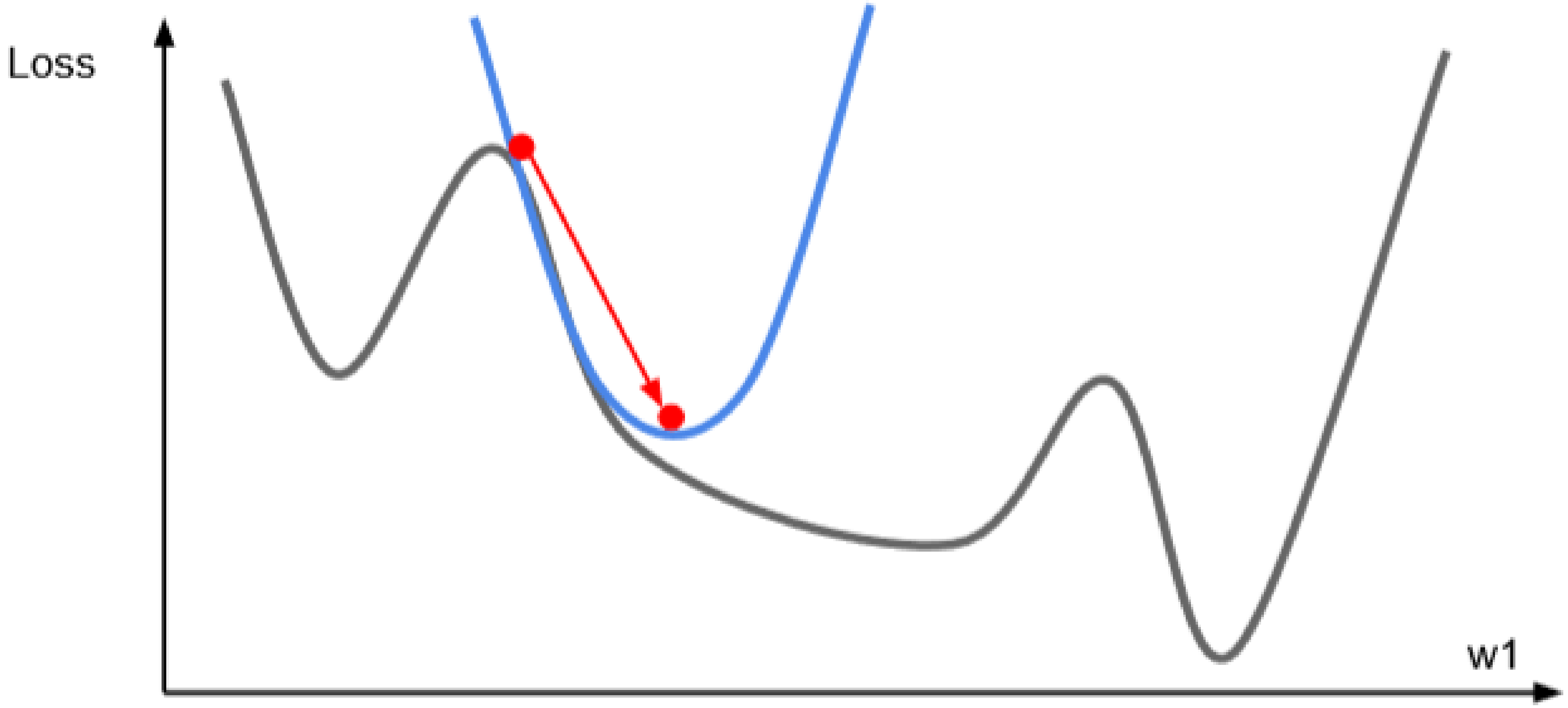
Bias correction for the fact that first and second moment estimates start at zero

Adam with beta1 = 0.9, beta2 = 0.999, and learning_rate = 1e-3 or 5e-4 is a great starting point for many models!

Optimization (Second-Order Optimization)

(1) Use gradient **and Hessian** to form **quadratic** approximation

(2) Step to the **minima** of the approximation



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Optimization (Second-Order Optimization)

second-order Taylor expansion:

$$J(\boldsymbol{\theta}) \approx J(\boldsymbol{\theta}_0) + (\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0) + \frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \boldsymbol{H}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)$$

Solving for the critical point we obtain the Newton parameter update:

$$\boldsymbol{\theta}^* = \boldsymbol{\theta}_0 - \boldsymbol{H}^{-1} \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0)$$

No hyperparameters!
No learning rate!

02 Optimization (Second-Order Optimization)

- Quasi-Newton methods (**BGFS** most popular):
  instead of inverting the Hessian (O(n^3)), approximate inverse Hessian with rank 1 updates over time (O(n^2) each).

- **L-BFGS** (Limited memory BFGS):
  Does not form/store the full inverse Hessian.

L-BFGS는 Style Transfer와 같이
Full Batch의 size가 작은 경우에 사용됨.

https://pytorch.org/docs/stable/optim.html

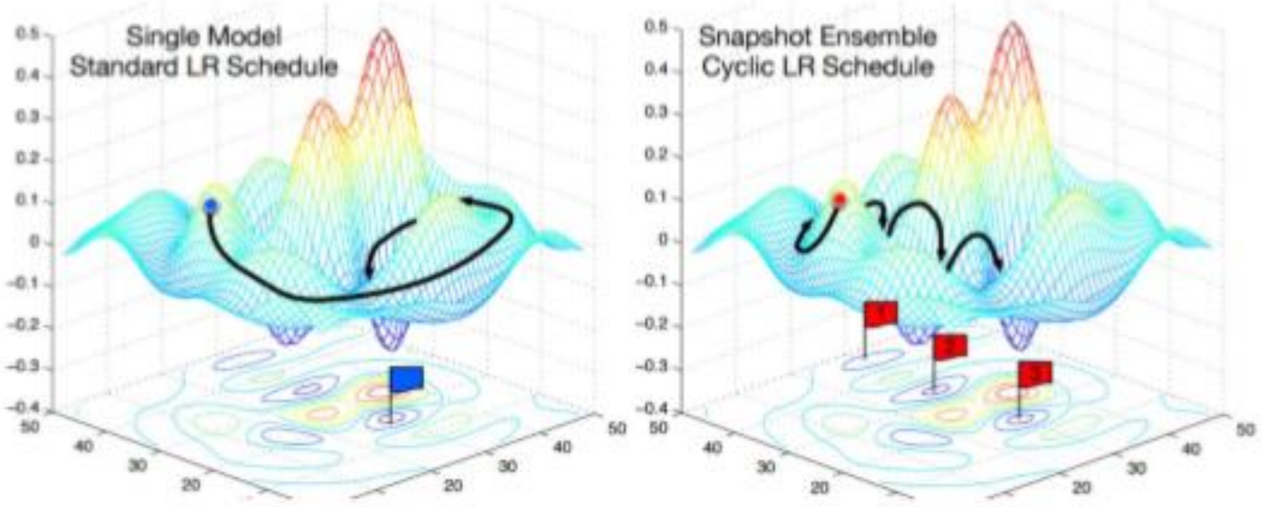
Model Ensembles

1. Train multiple independent models
2. At test time average their results

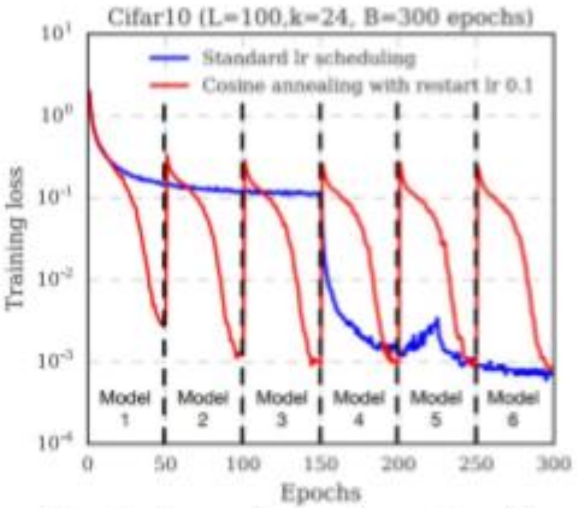
Enjoy 2% extra performance

Model Ensembles : Tips and Tricks

Instead of training independent models, use multiple snapshots of a single model during training!



Loshchilov and Hutter, "SGDR: Stochastic gradient descent with restarts", arXiv 2016
Huang et al, "Snapshot ensembles: train 1, get M for free", ICLR 2017
Figures copyright Yixuan Li and Geoff Pleiss, 2017. Reproduced with permission.



Cyclic learning rate schedules can make this work even better!

Regularization : Add term to loss

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i;W)_j - f(x_i;W)_{y_i} + 1) + \boxed{\lambda R(W)}$$

In common use:

L2 regularization $R(W) = \sum_k \sum_l W_{k,l}^2$ (Weight decay)

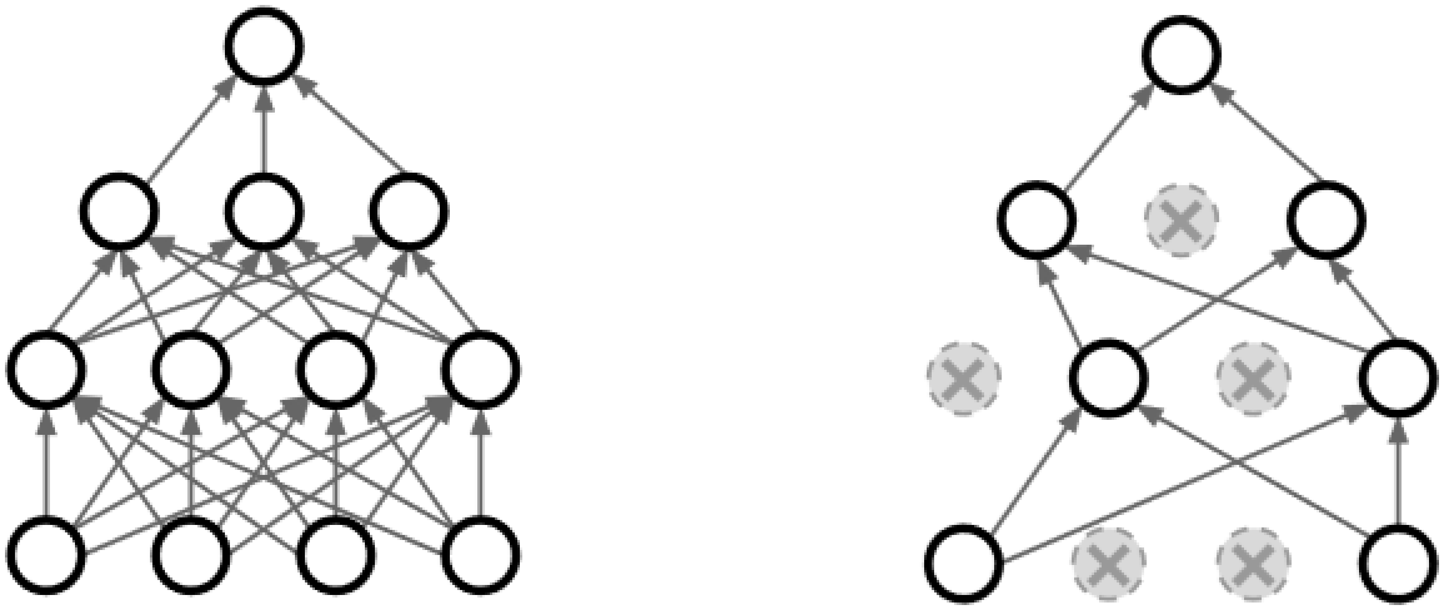
L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

04

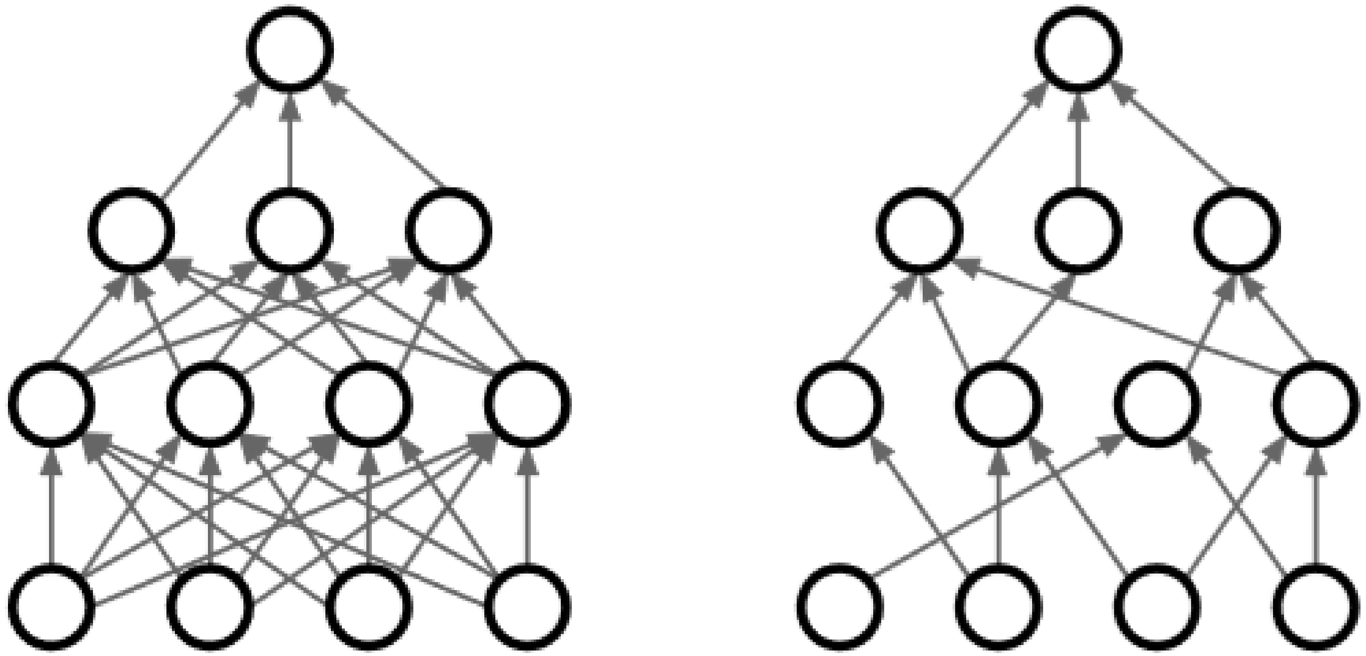
Regularization : Dropout

In each forward pass, randomly set some neurons to zero
Probability of dropping is a hyperparameter; 0.5 is common



Regularization : Dropconnect

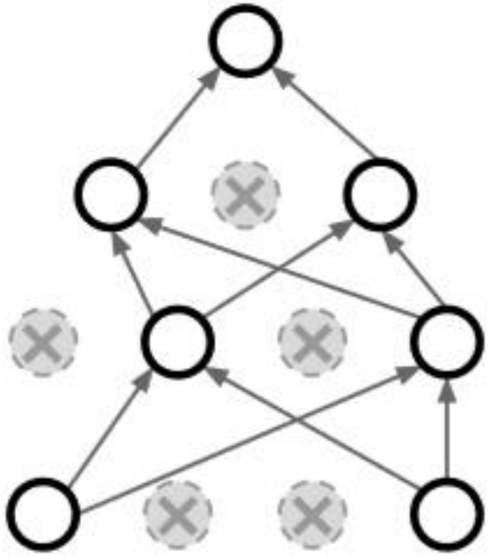
Q. Dropout과 Dropconnect의 차이점은?



04 Regularization : Dropout

```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)
```

Example forward pass with a 3-layer network using dropout



Regularization : Dropout

Q. Predict를 할 때, p를 곱해주는 이유는?

```
def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

At test time all neurons are active always

=> We must scale the activations so that for each neuron:

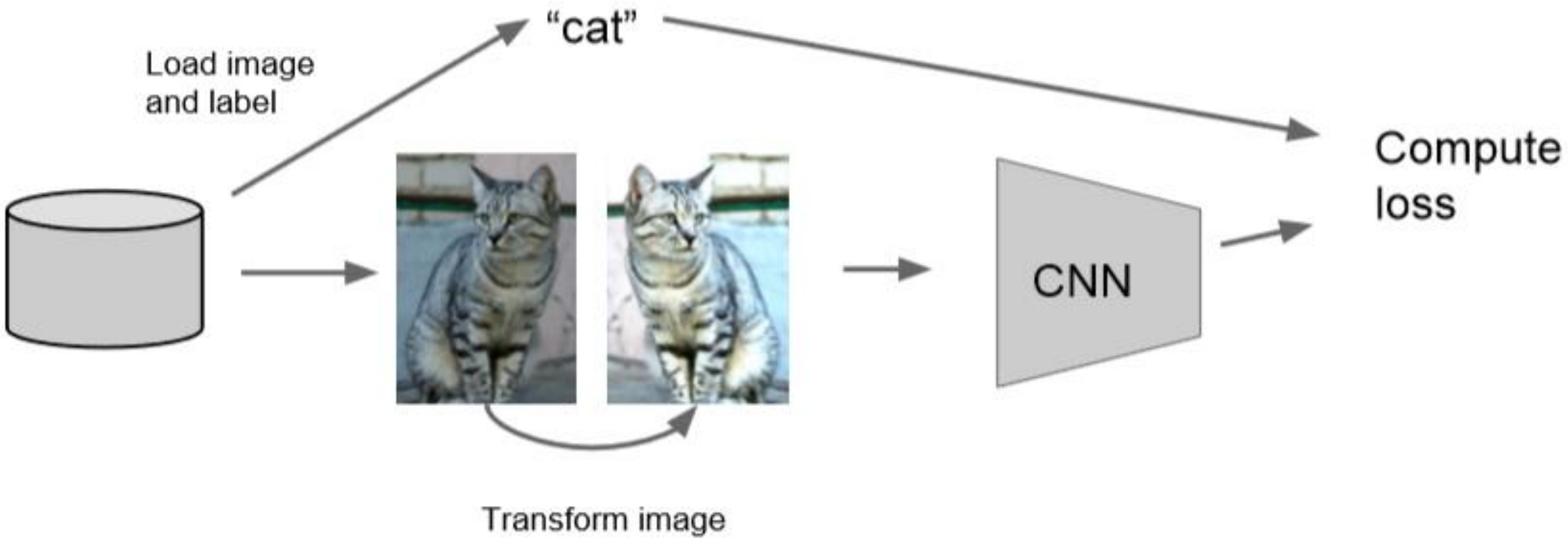
<u>output at test time</u> = <u>expected output at training time</u>

Regularization : Inverted dropout

```
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = (np.random.rand(*H1.shape) < p) / p # first dropout mask. Notice /p!
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = (np.random.rand(*H2.shape) < p) / p # second dropout mask. Notice /p!
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) # no scaling necessary
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  out = np.dot(W3, H2) + b3
```

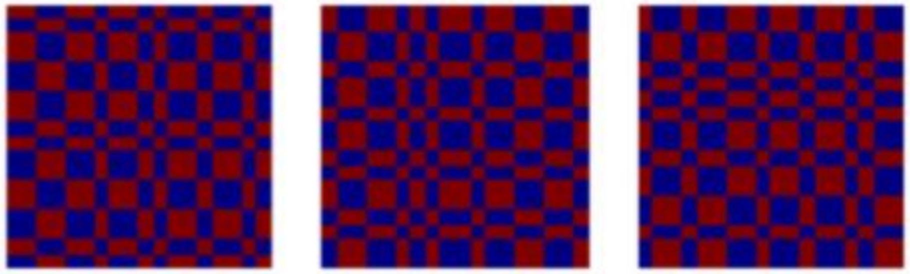
test time is unchanged!

Regularization : Data Augmentation

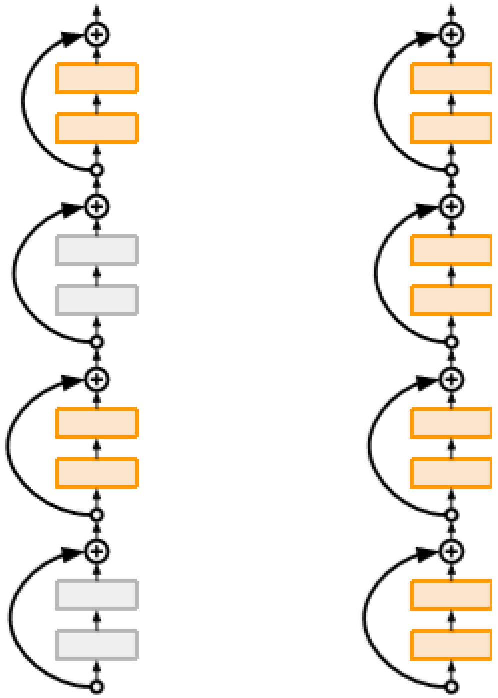


- Horizontal Flips
- Random crops and scales
- Color Jitter
- Random mix / combinations of rotation, translation etc..

Regularization : 이외의 방법

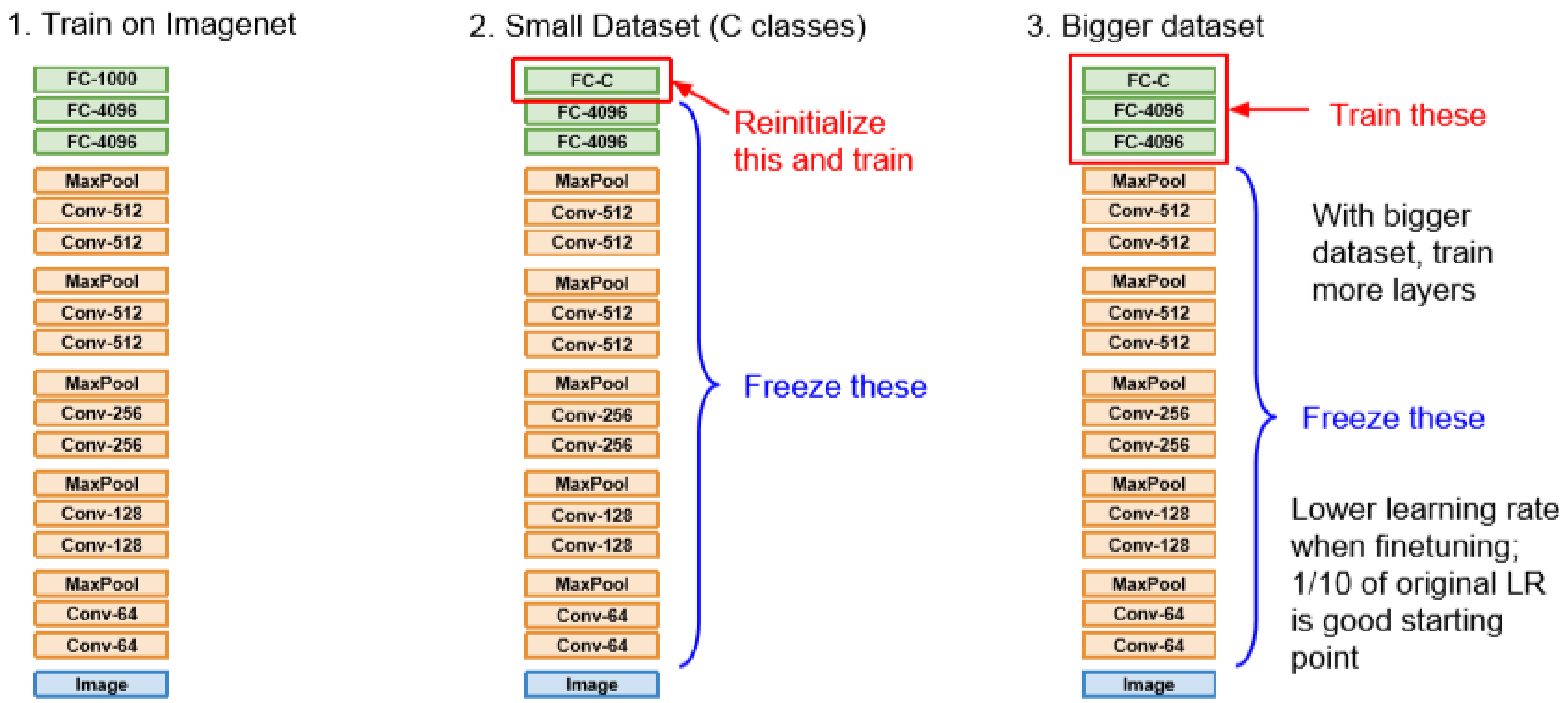


[Fractional Max Pooling]



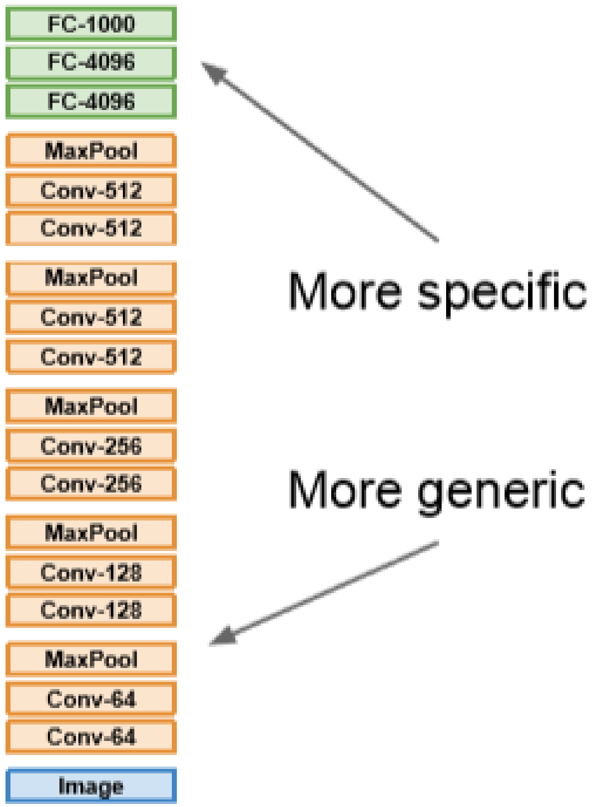
[Stochastic Depth]

05 Transfer Learning



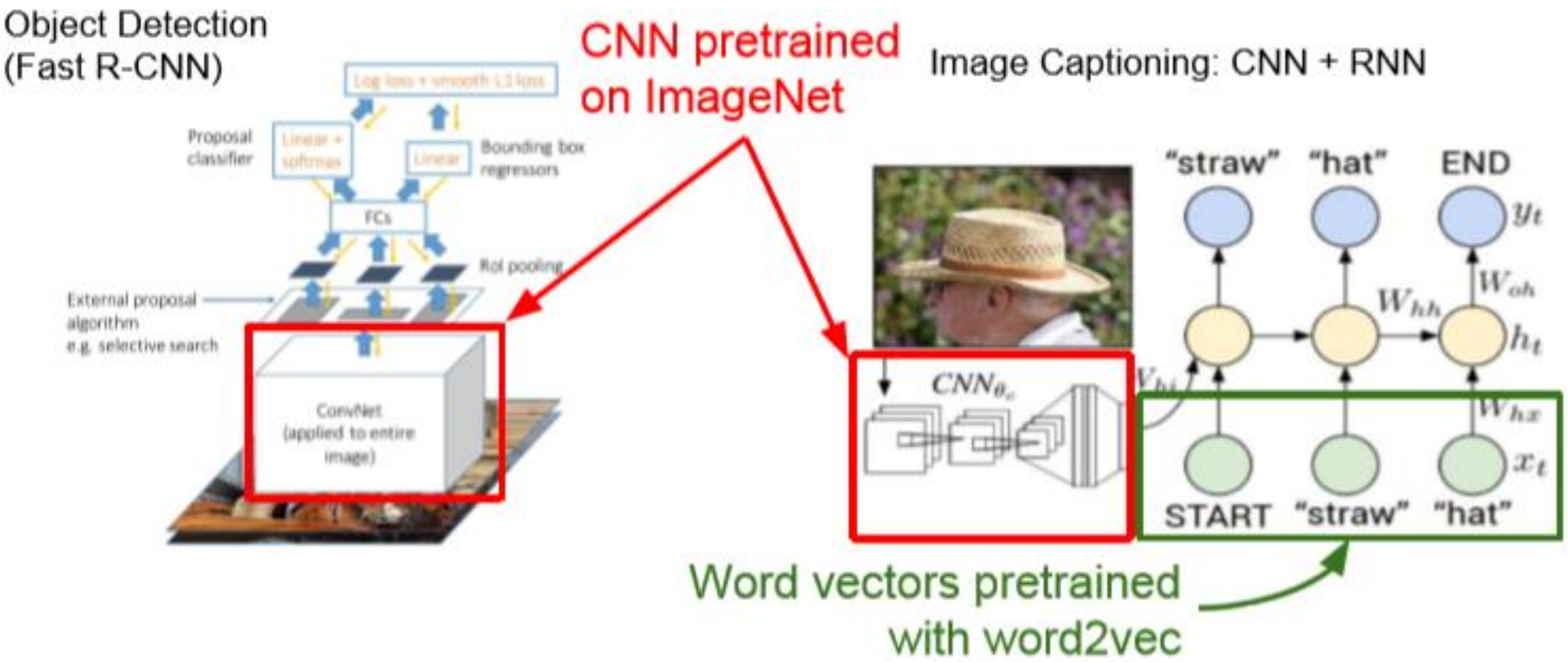
보통 VGG16, ResNet을 이용하여, Transfer Learning

05 Transfer Learning



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)



05

Transfer Learning (Pytorch Model zoo)

Network	Top-1 error	Top-5 error
AlexNet	43.45	20.91
VGG-11	30.98	11.37
VGG-13	30.07	10.75
VGG-16	28.41	9.62
VGG-19	27.62	9.12
VGG-11 with batch normalization	29.62	10.19
VGG-13 with batch normalization	28.45	9.63
VGG-16 with batch normalization	26.63	8.50
VGG-19 with batch normalization	25.76	8.15
ResNet-18	30.24	10.92
ResNet-34	26.70	8.58
ResNet-50	23.85	7.13
ResNet-101	22.63	6.44

https://pytorch.org/docs/stable/torchvision/models.html

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참고 자료

CS231n : http://cs231n.stanford.edu/syllabus.html

Pytorch Optimization : https://pytorch.org/docs/stable/optim.html

PyTorch Model Zoo : https://pytorch.org/docs/stable/torchvision/models.html