Practical Tricks for CNNs

Neural Networks Design And Application

Practical tricks

- Batch normalization and local response normalization
- Data augmentation
- Dropout
- Regularization/weight decay
- Pre-train
- Stagewise training

Rescaling images

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# calculate mu and sig using the training set
d = x_train.shape[1]
mu = numpy.mean(x_train, axis=0).reshape(1, d)
sig = numpy.std(x_train, axis=0).reshape(1, d)

# transform the training features
x_train = (x_train - mu) / (sig + 1E-6)

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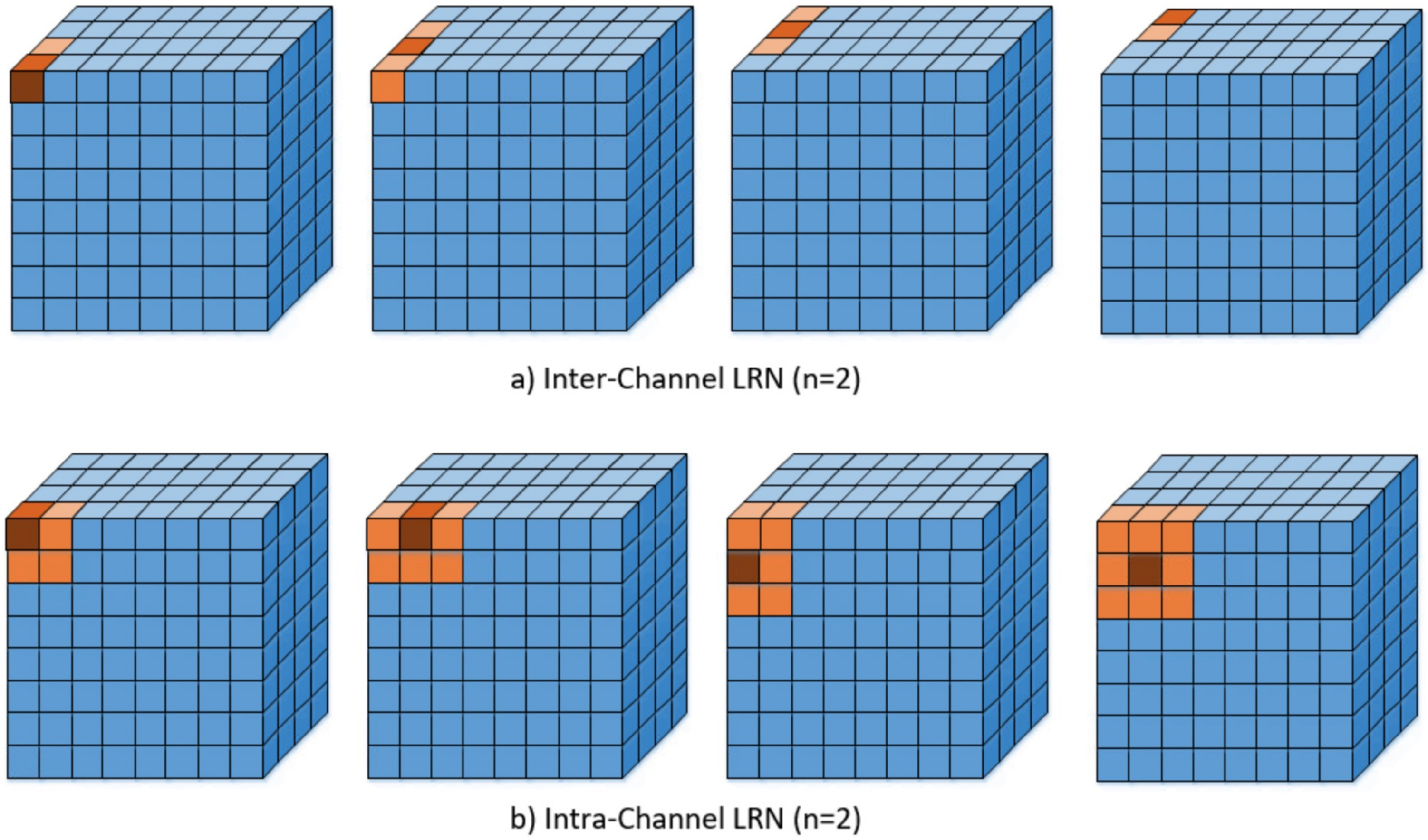
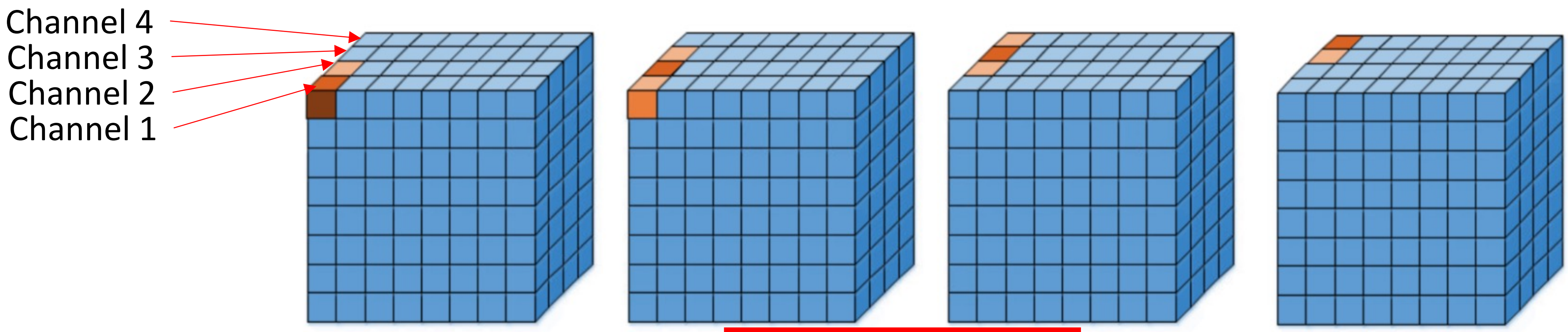
To bound the values of data

Local response normalization



https://towardsdatascience.com/difference-between-local-response-normalization-and-batch-normalization-272308c034ac

Local response normalization



a) Inter-Channel LRN (n=2)

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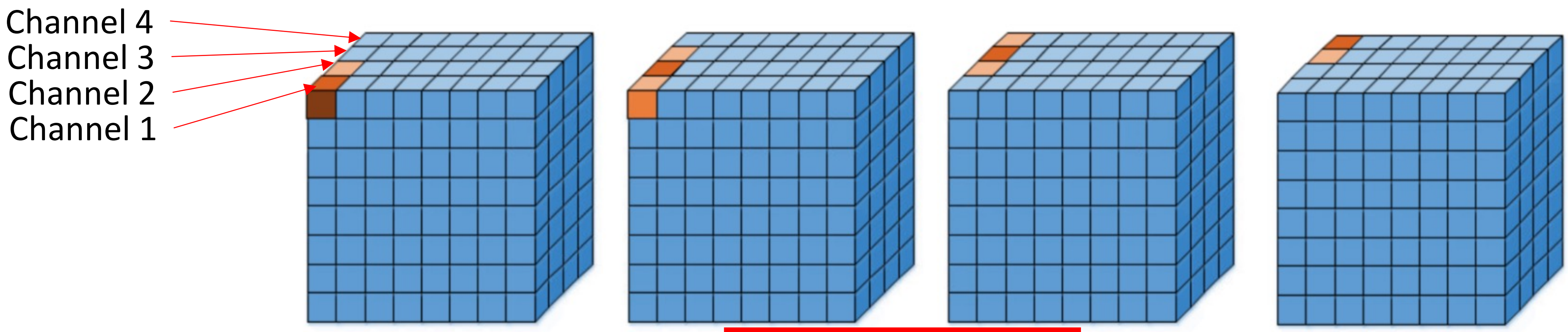

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$$b^i_{x,y} = a^i_{x,y} / \left(k + \alpha \sum_{j=\max(0, i-n/2)}^{\min(N-1, i+n/2)} (a^j_{x,y})^2 \right)^\beta$$

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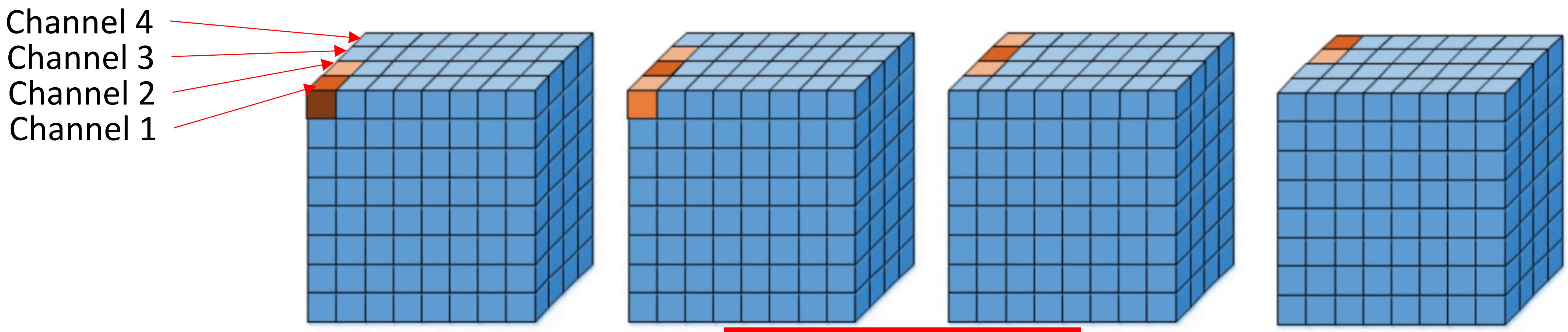

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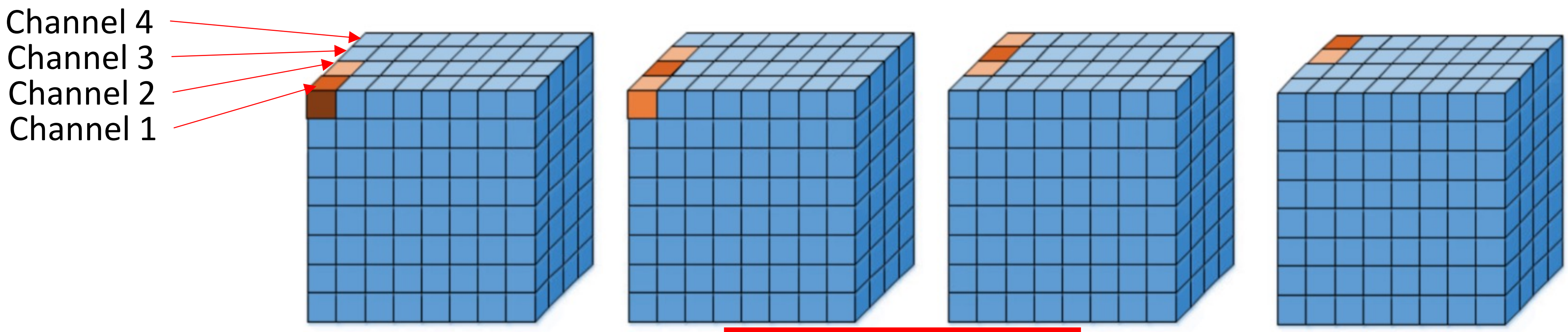

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Surrounding elements

Output value

Original value

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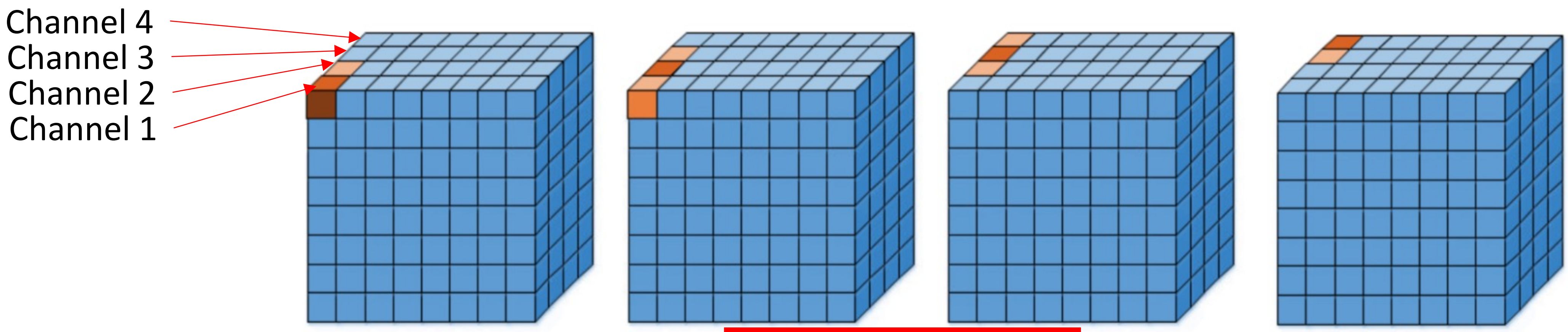
Local response normalization



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Squared values of surrounding elements

Surrounding elements

Output value

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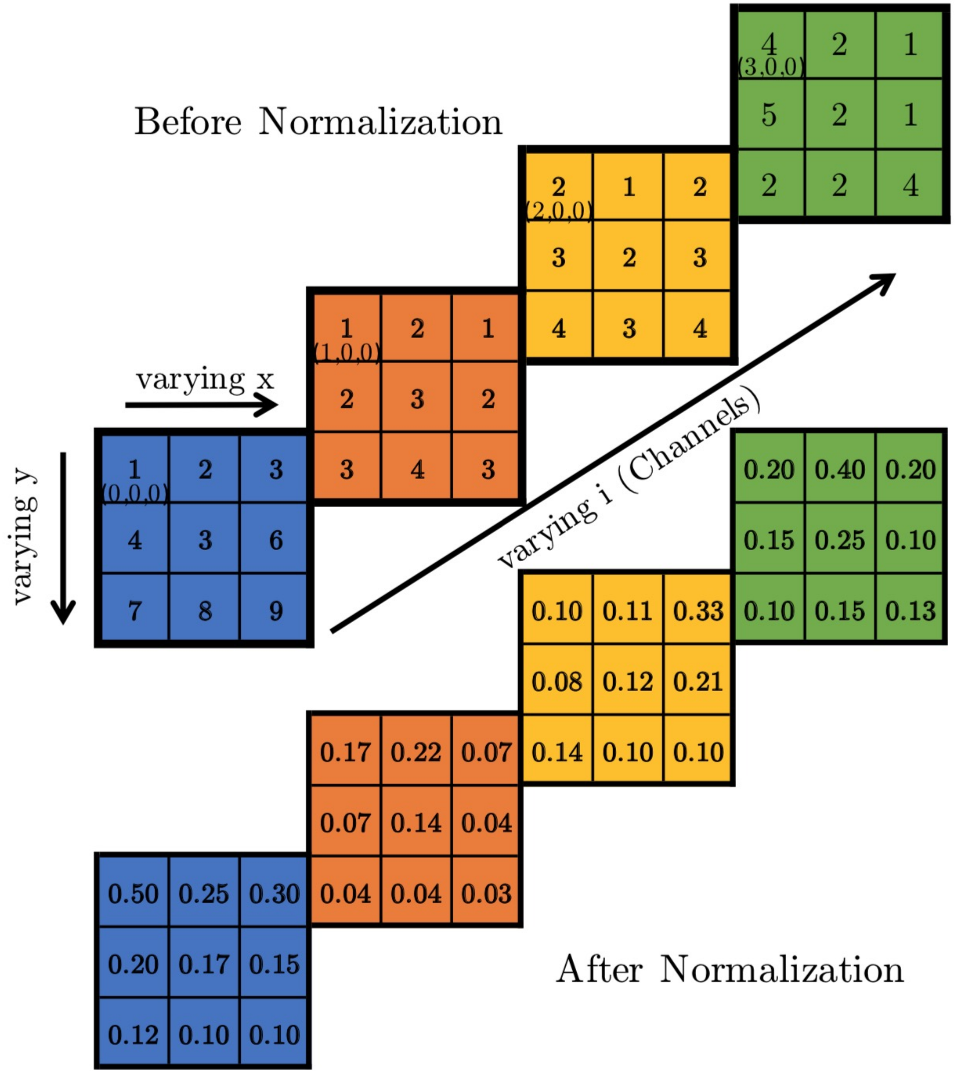
Local response normalization



N=2, K=0, $\alpha = 1, \beta = 1$

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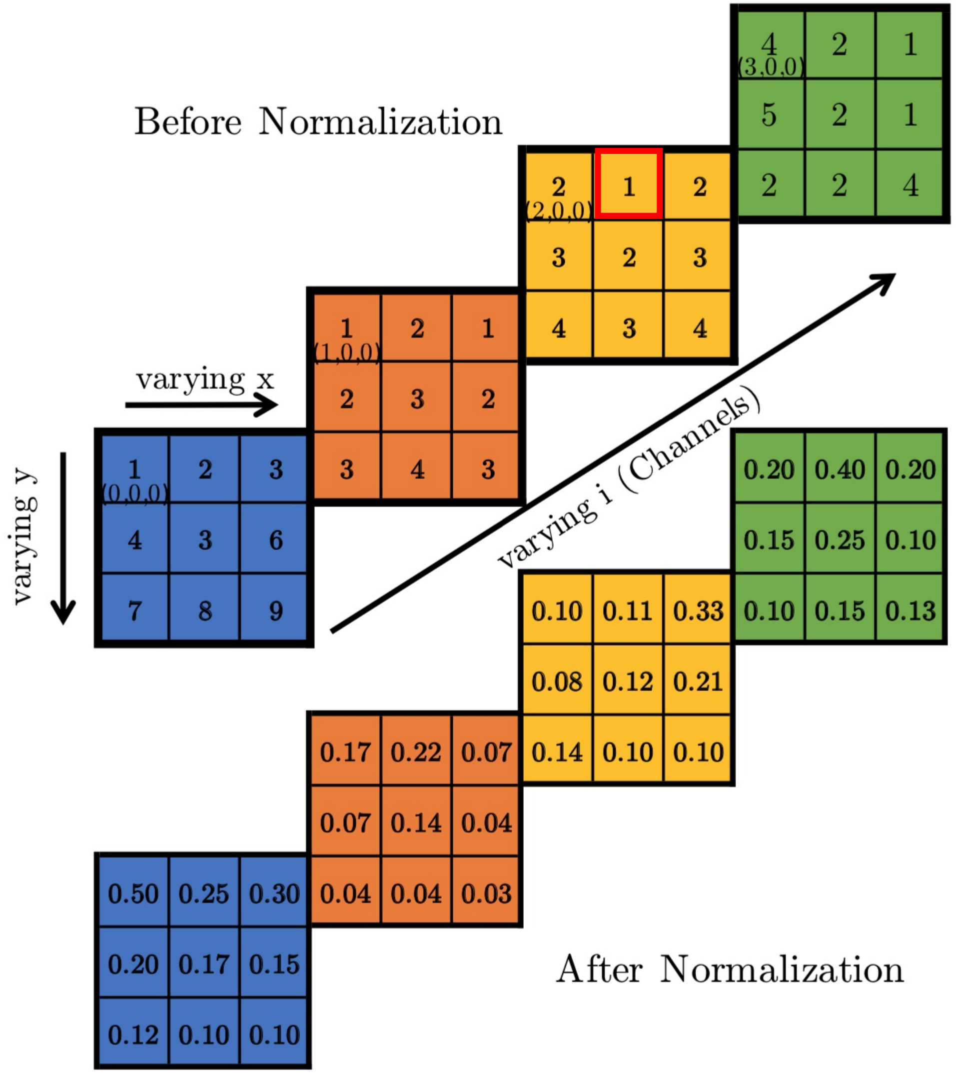

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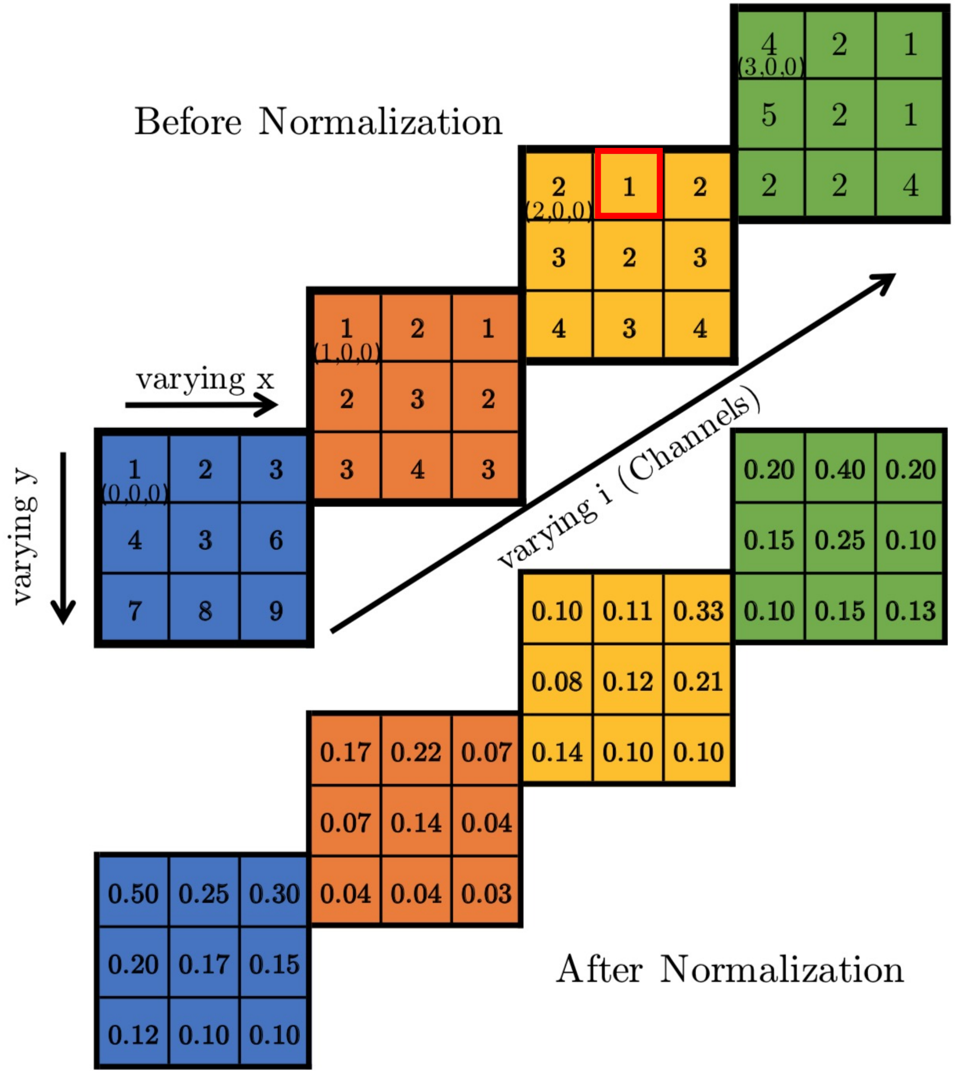

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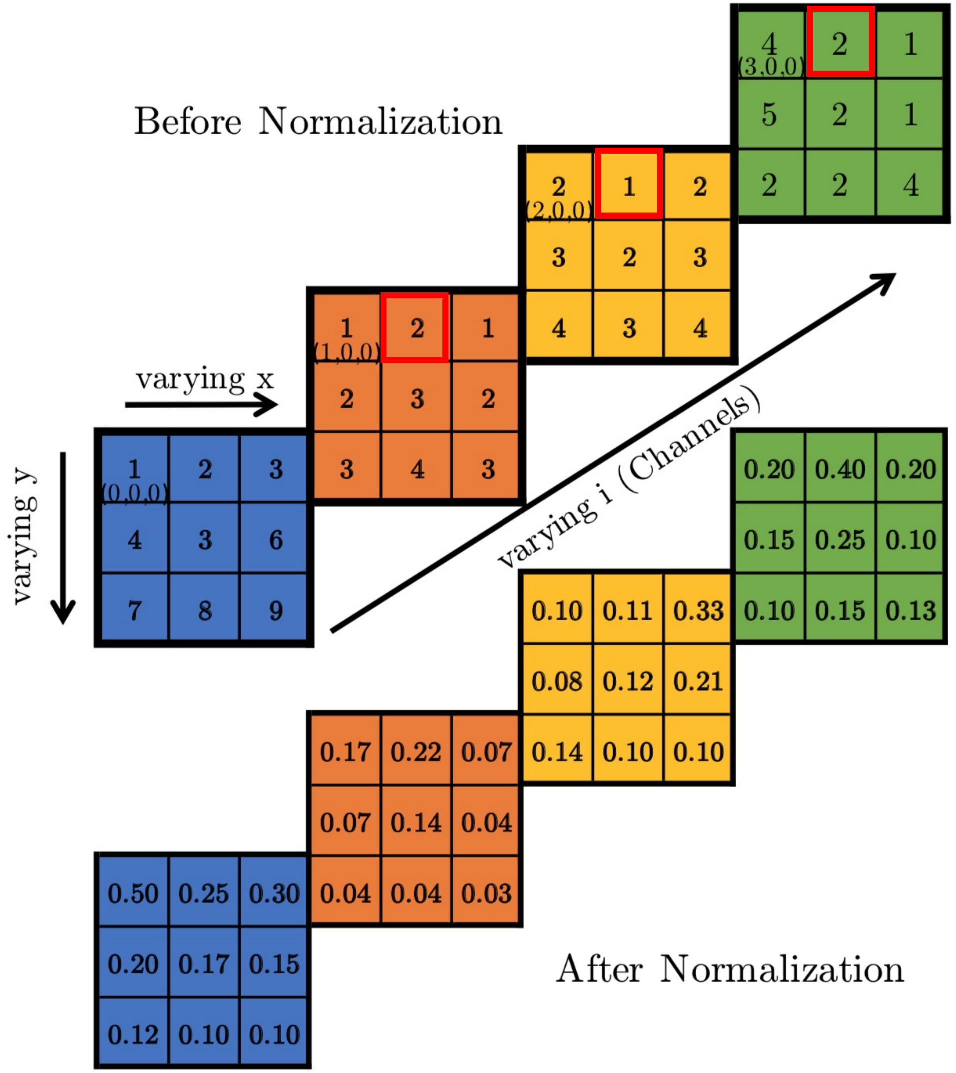

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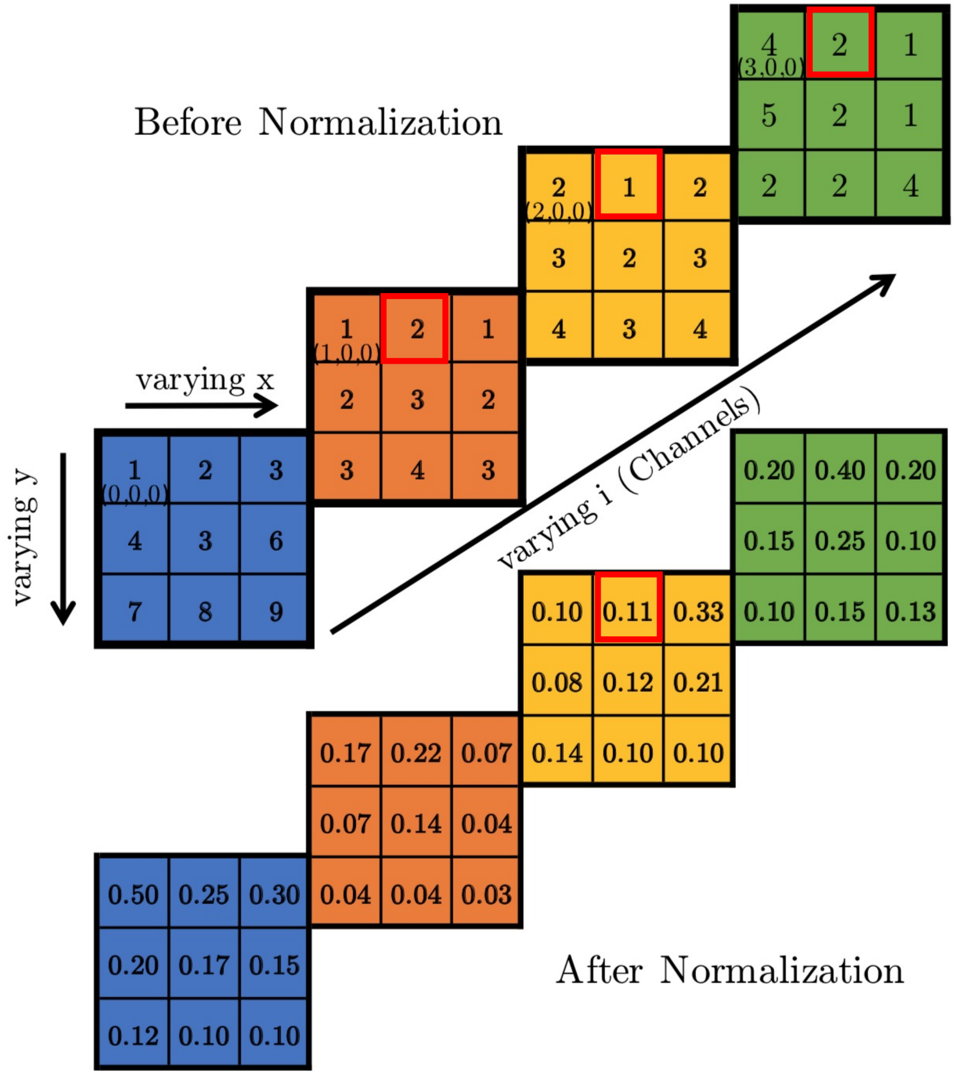
Local response normalization



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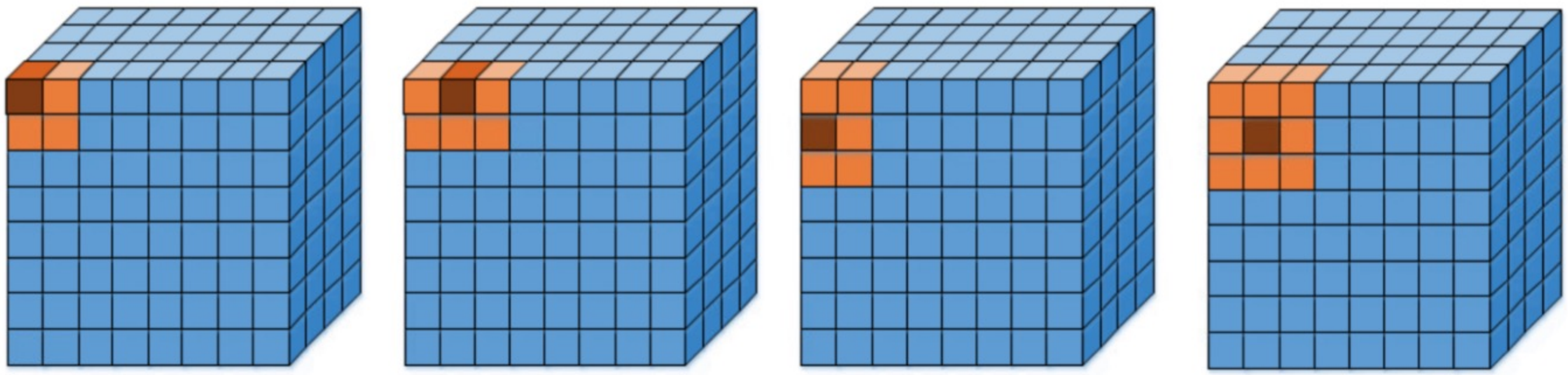
1/(0 + 4 + 1 + 4)=1/9

Local response normalization



b) Intra-Channel LRN (n=2)

$$b^k_{x,y} = a^k_{x,y} / \left(k + \alpha \sum_{i=max(0,x-n/2)}^{min(W,x+n/2)} \sum_{j=max(0,y-n/2)}^{min(H,y+n/2)} (a^k_{i,j})^2 \right)^{\beta}$$

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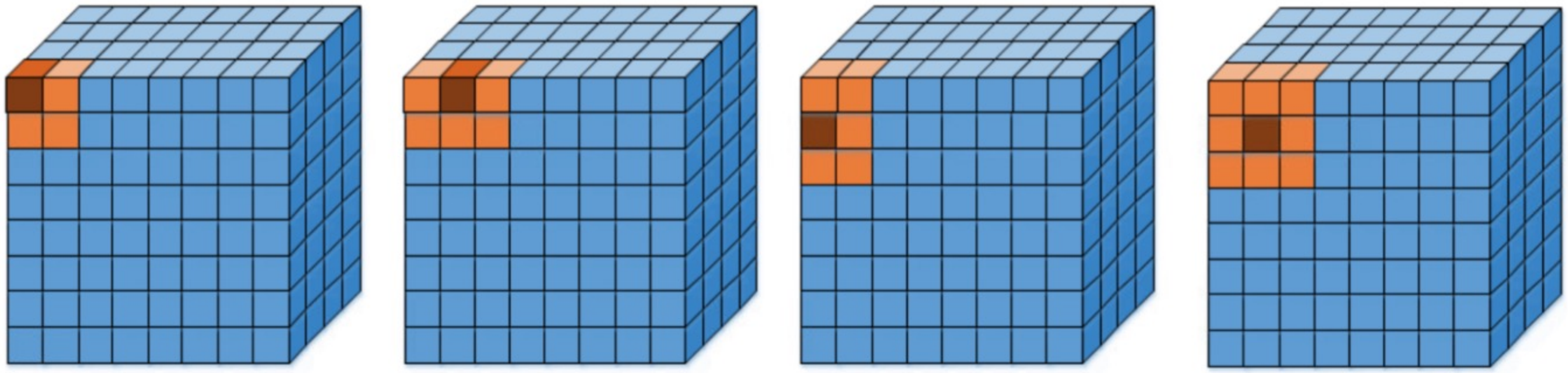

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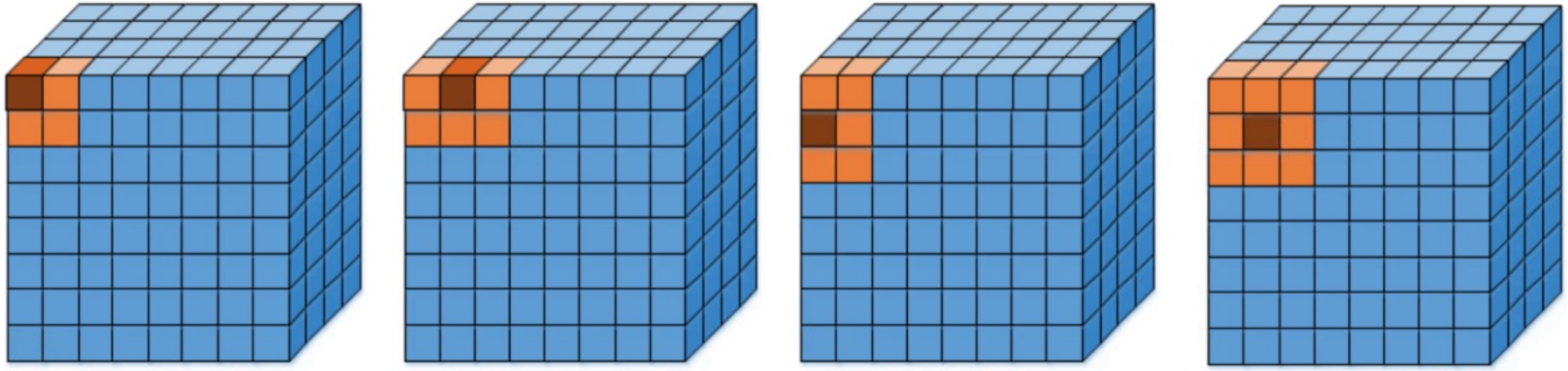

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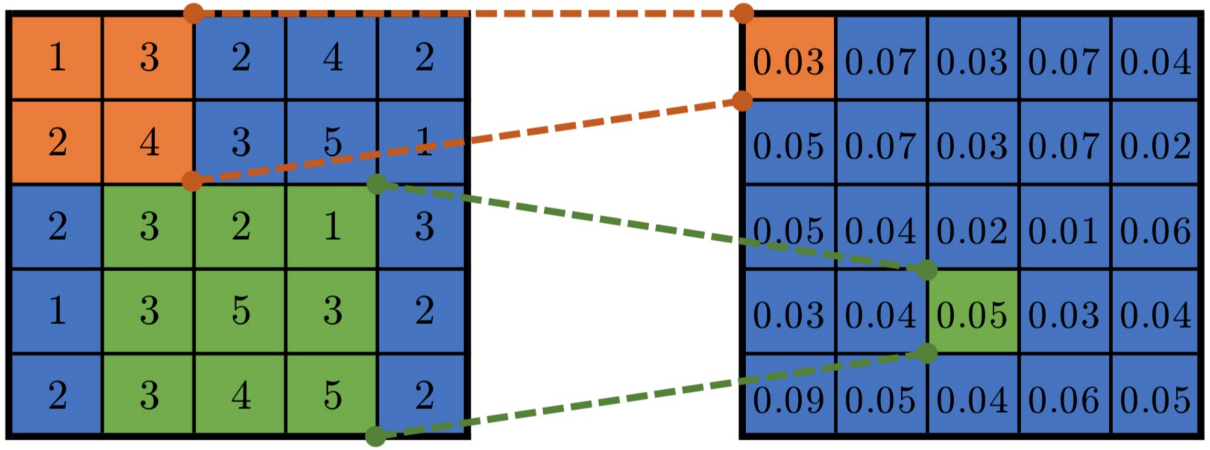

Before Normalization **After Normalization**

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Batch normalization [BN]

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \text{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

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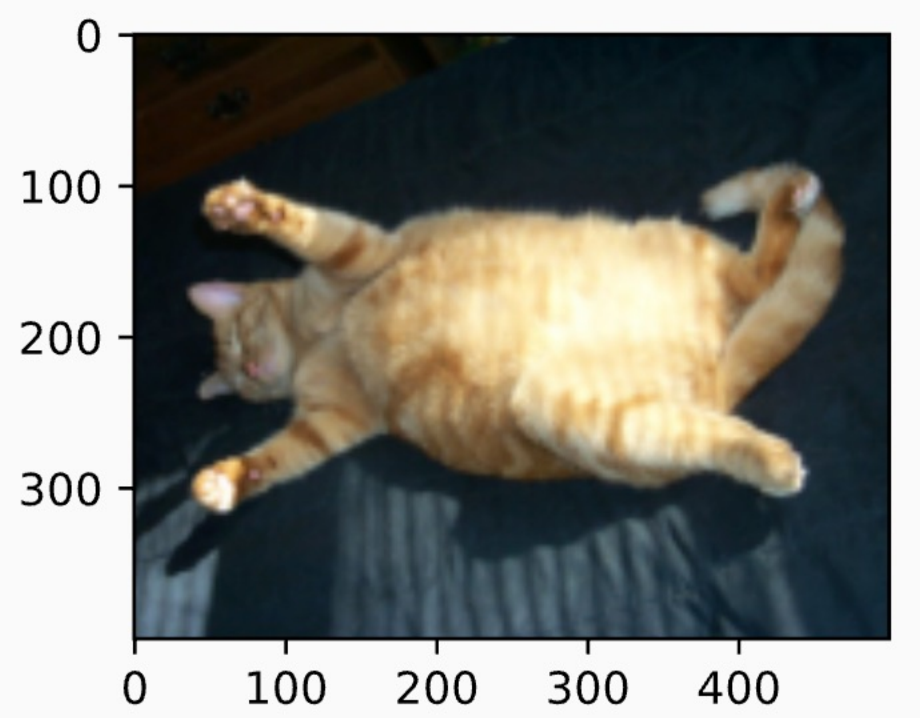
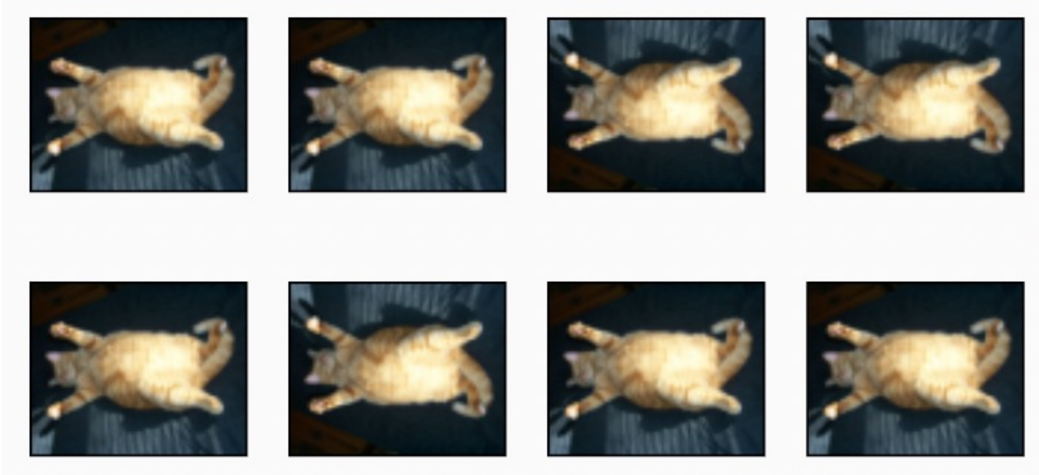
Rescaling for a batch

A linear model as output:
There are two learnable parameters

Data augmentation

- Increase the amount of data by:
  - Adding slightly modified copies of already existing data, or
  - Newly created synthetic data from existing data





Vertical flipping

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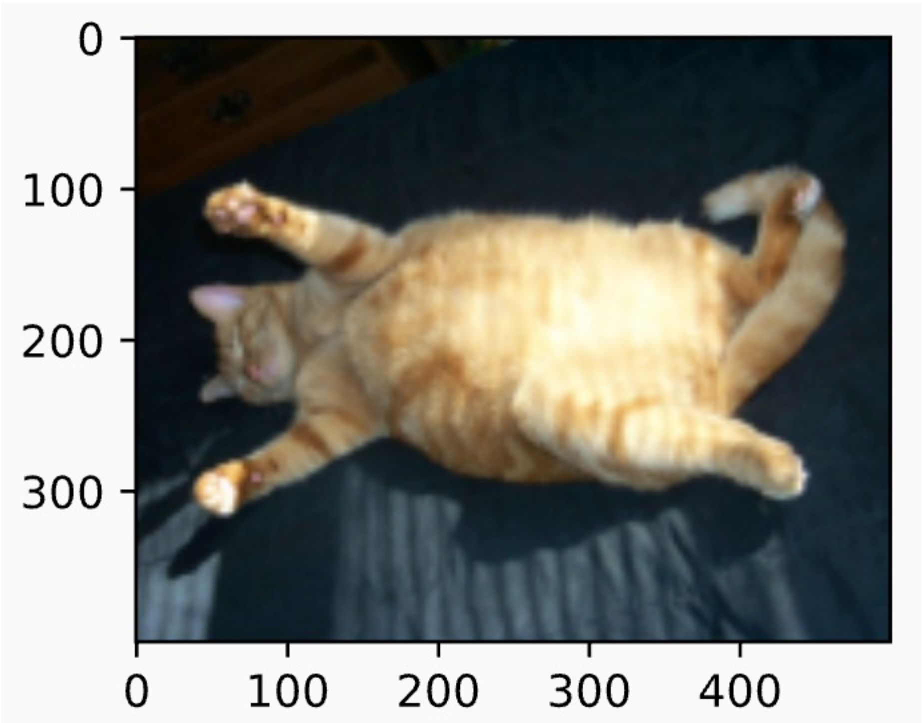

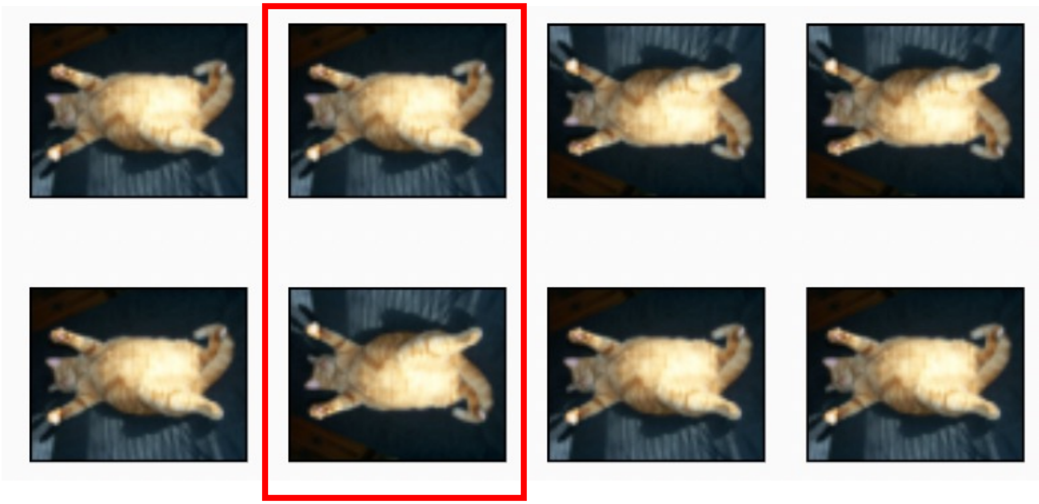

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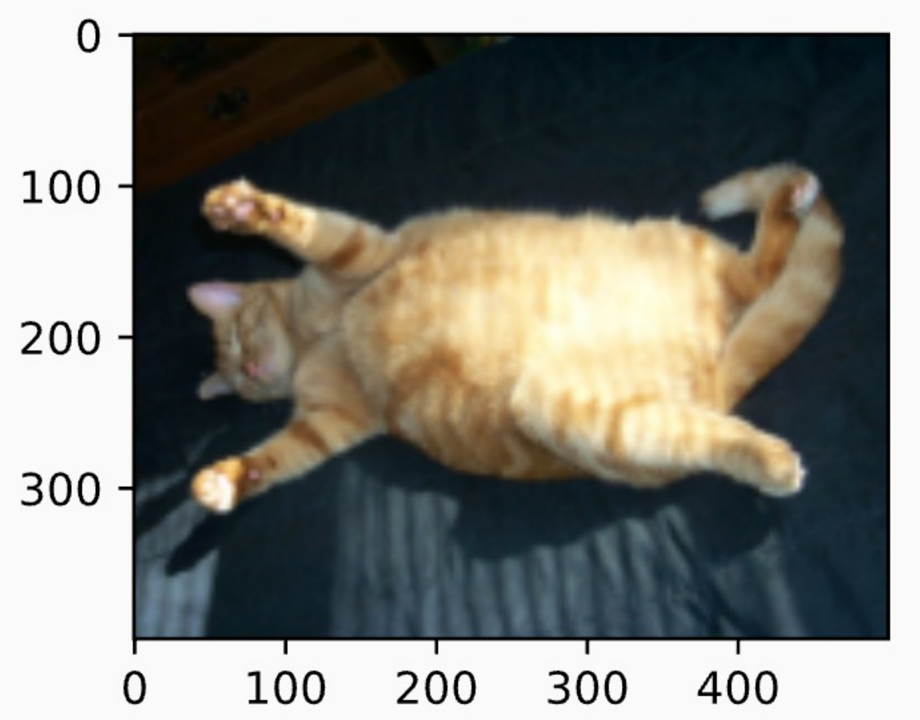

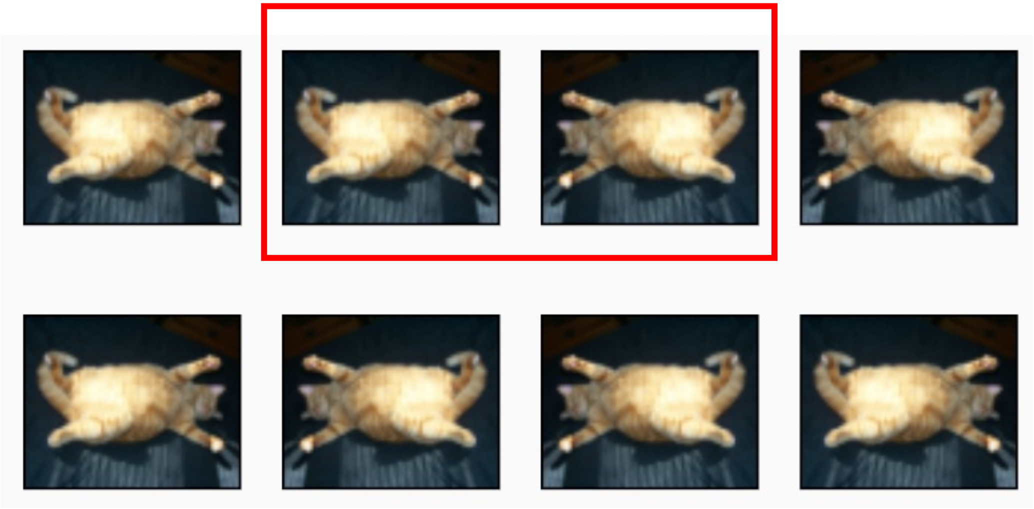

Horizontal flipping

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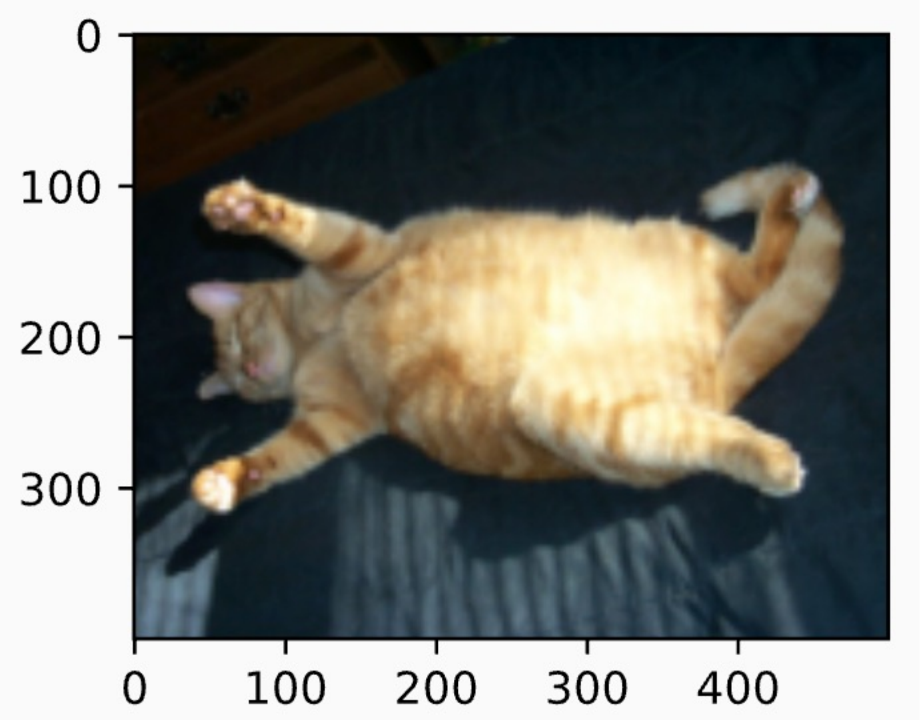

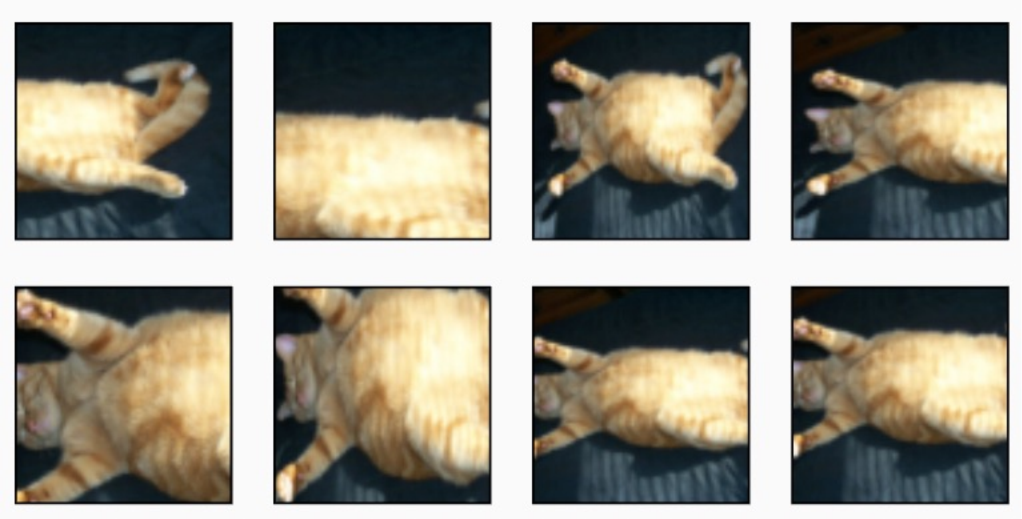

Resize and cropping

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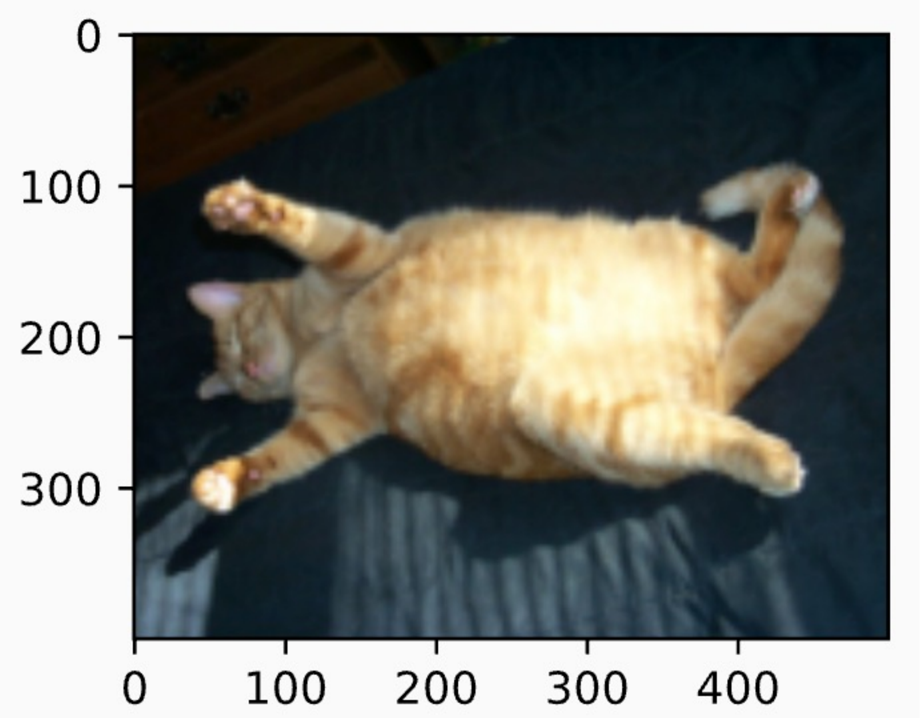

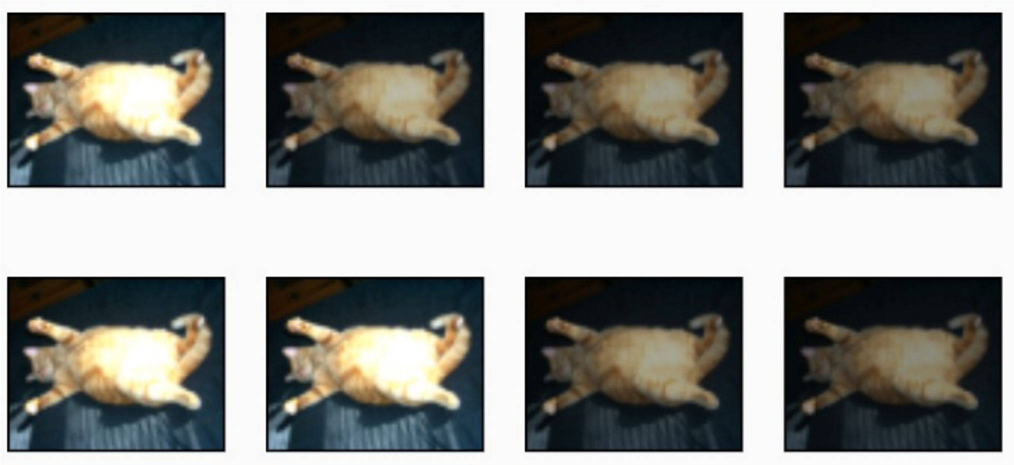

Changing brightness

Data augmentation

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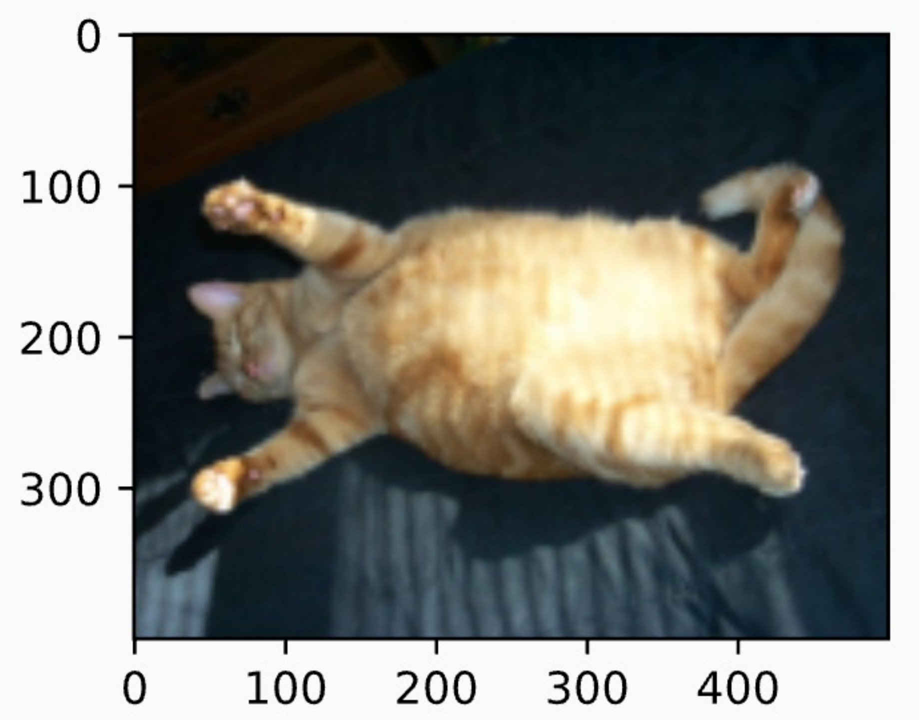

Color jitter:
brightness, contrast, saturation, hue

Why data augmentation

The two classes in our hypothetical dataset. The one in the left represents Brand A (Ford), and the one in the right represents Brand B (Chevrolet).

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A Ford car (Brand A), but facing right.

Our CNN may predict this car (facing right) to Chevrolet…

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Data augmentation:
Gives more variations for data

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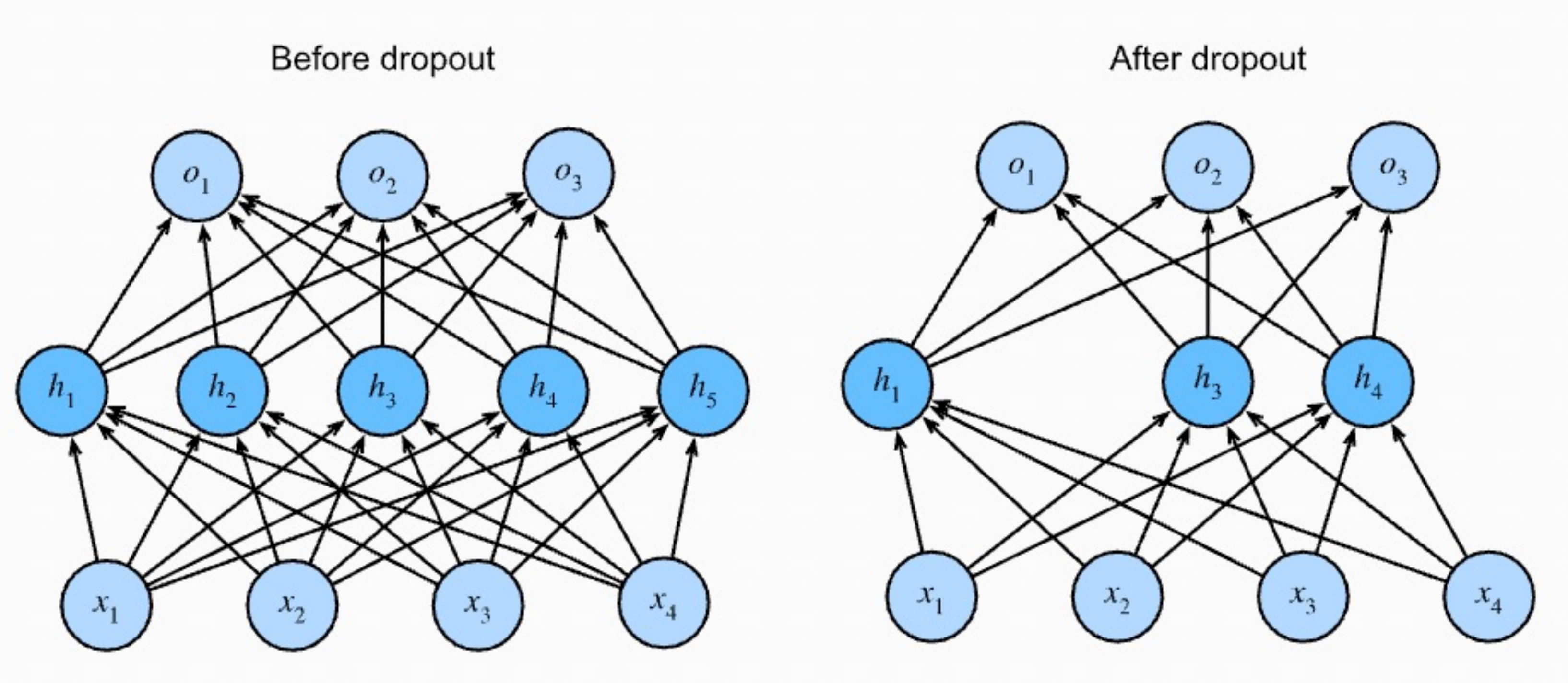
Data augmentation:
Gives more variations for data → better generalization

Dropout



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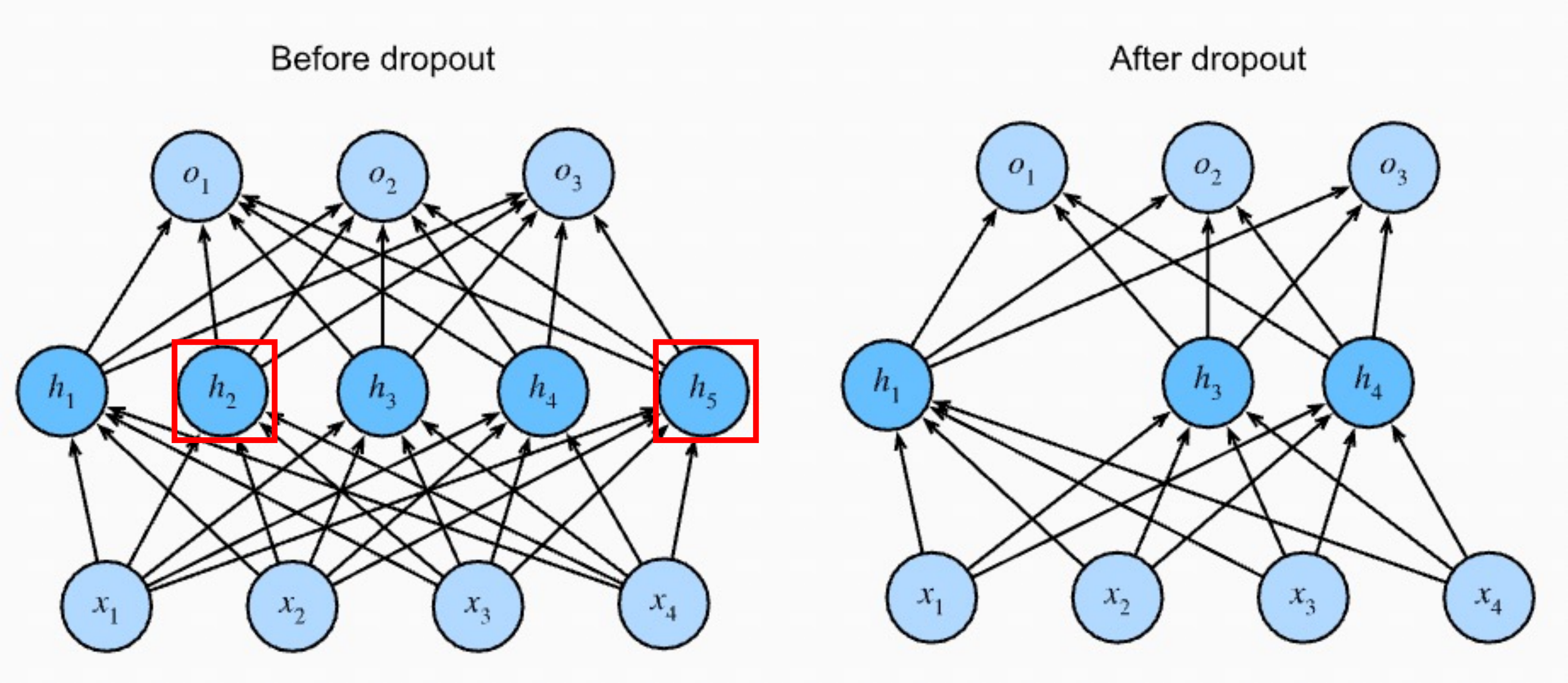

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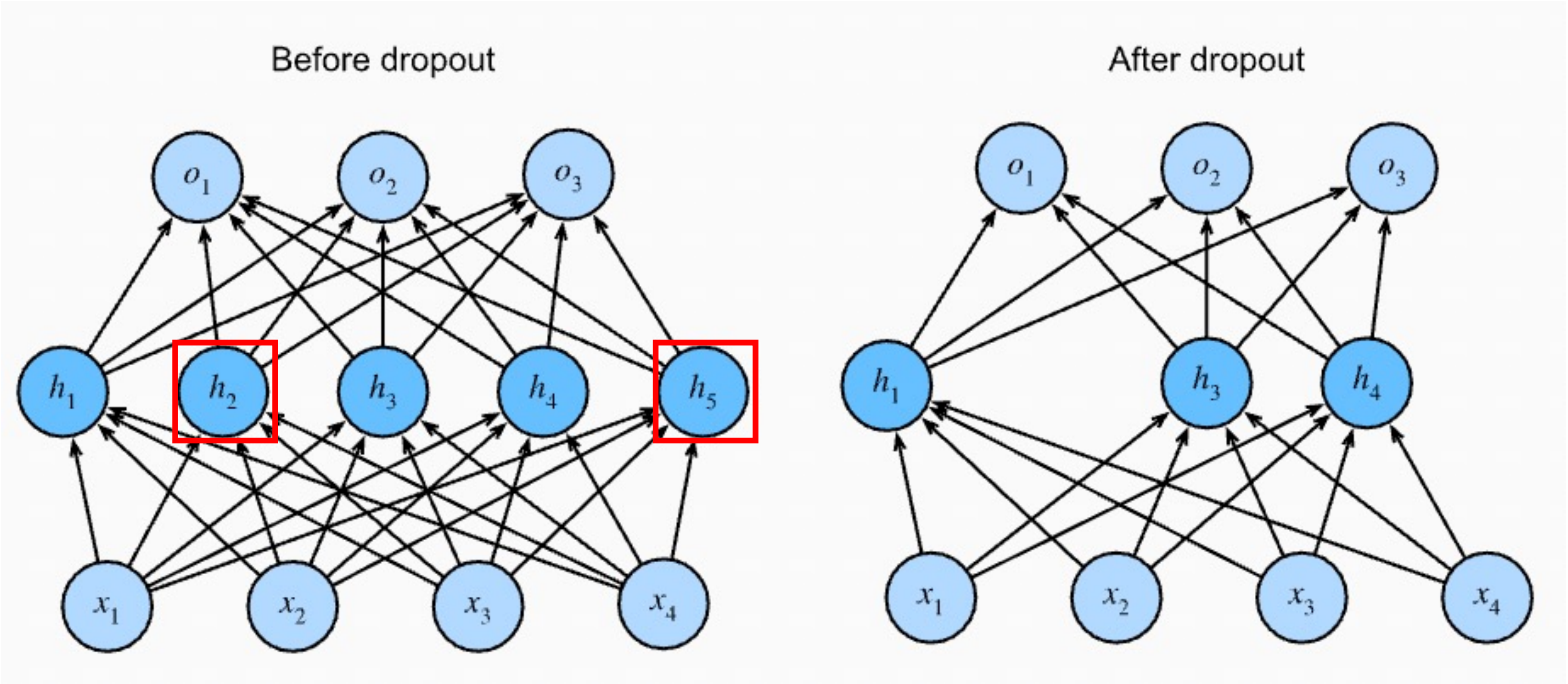
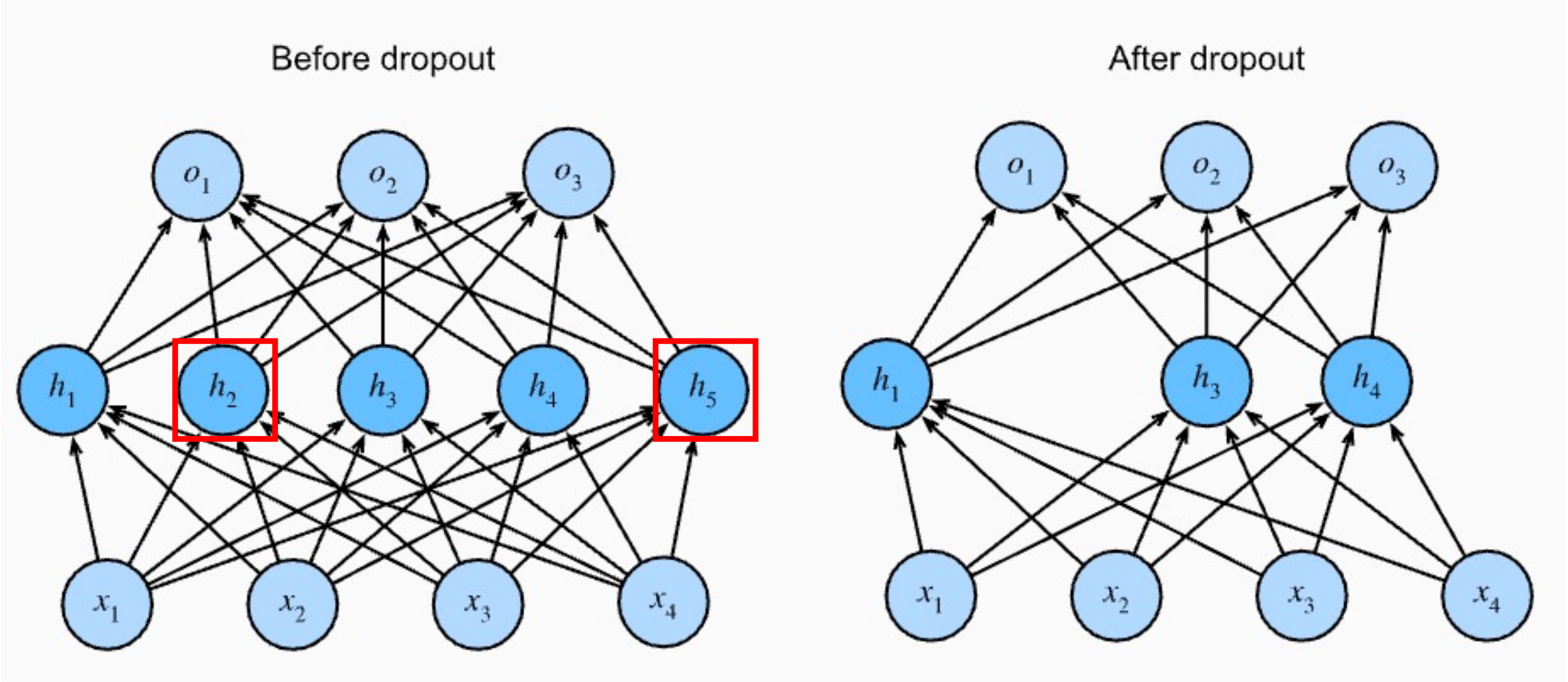


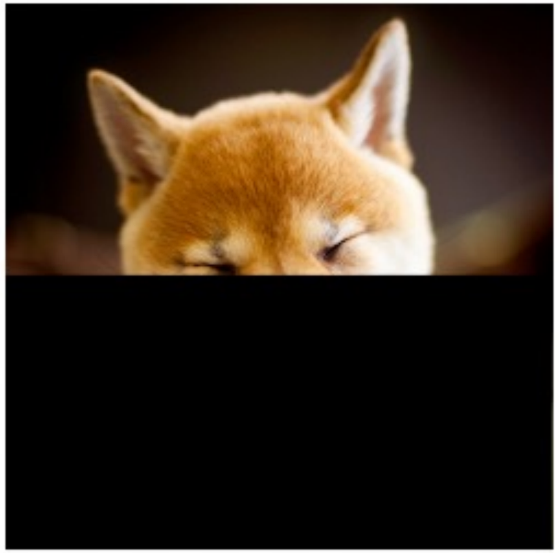
Dropout in training: select an arbitrary percentage of neurons (weights) and mask them

Dropout



Dropout in training: select an arbitrary percentage of neurons (weights) and mask them
Dropout in testing: use all parameters, no dropout

Dropout

Dropout

Why dropout?

Dropout

Why dropout? → alleviate overfitting

Regularization/weight decay

$$\tilde{J}(\boldsymbol{\theta}; \boldsymbol{X}, \boldsymbol{y}) = J(\boldsymbol{\theta}; \boldsymbol{X}, \boldsymbol{y}) + \alpha\Omega(\boldsymbol{\theta}),$$

$$\Omega(\boldsymbol{\theta}) = \frac{1}{2}\|\boldsymbol{w}\|_2^2$$

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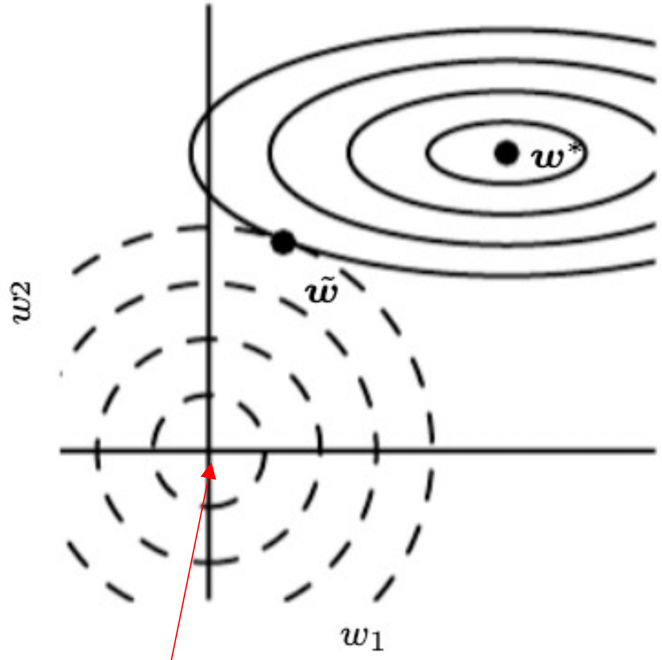

Origin

Regularization/weight decay

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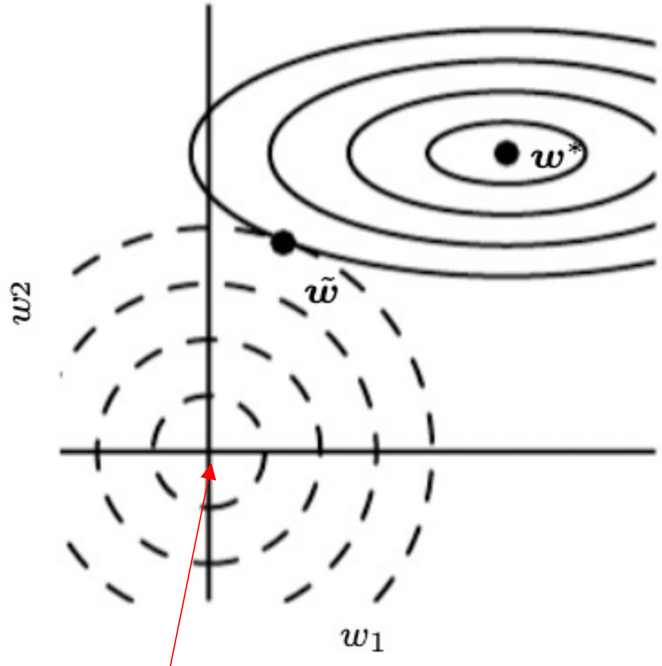
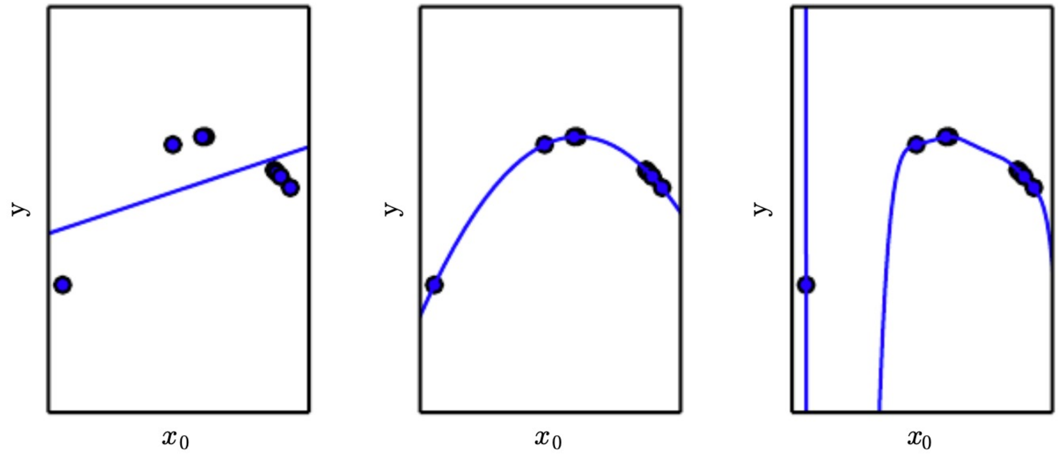


Origin



Linear model

Quadratic model

Polynomial model (9 degree)

Regularization/weight decay

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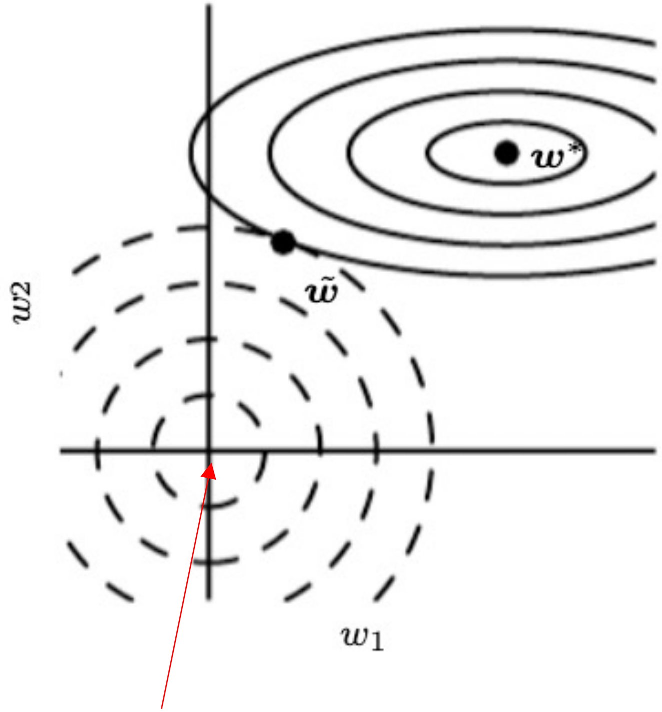

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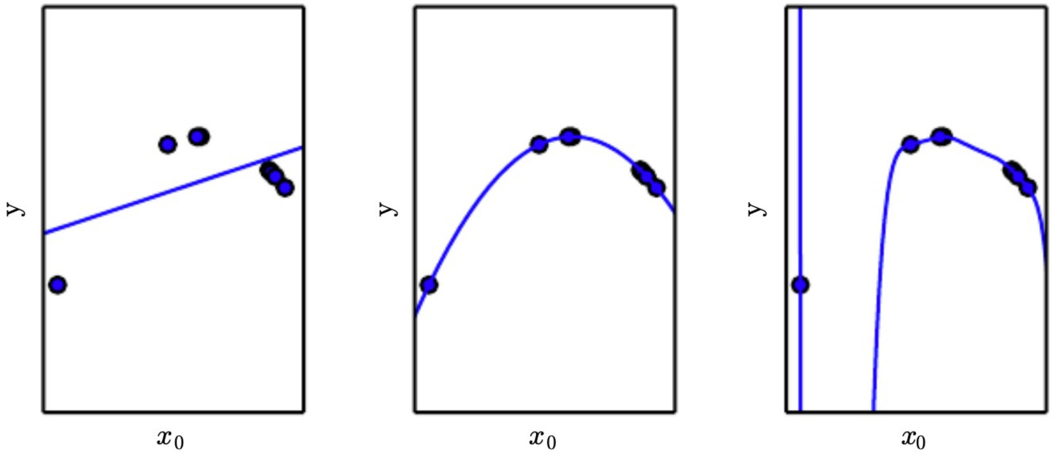


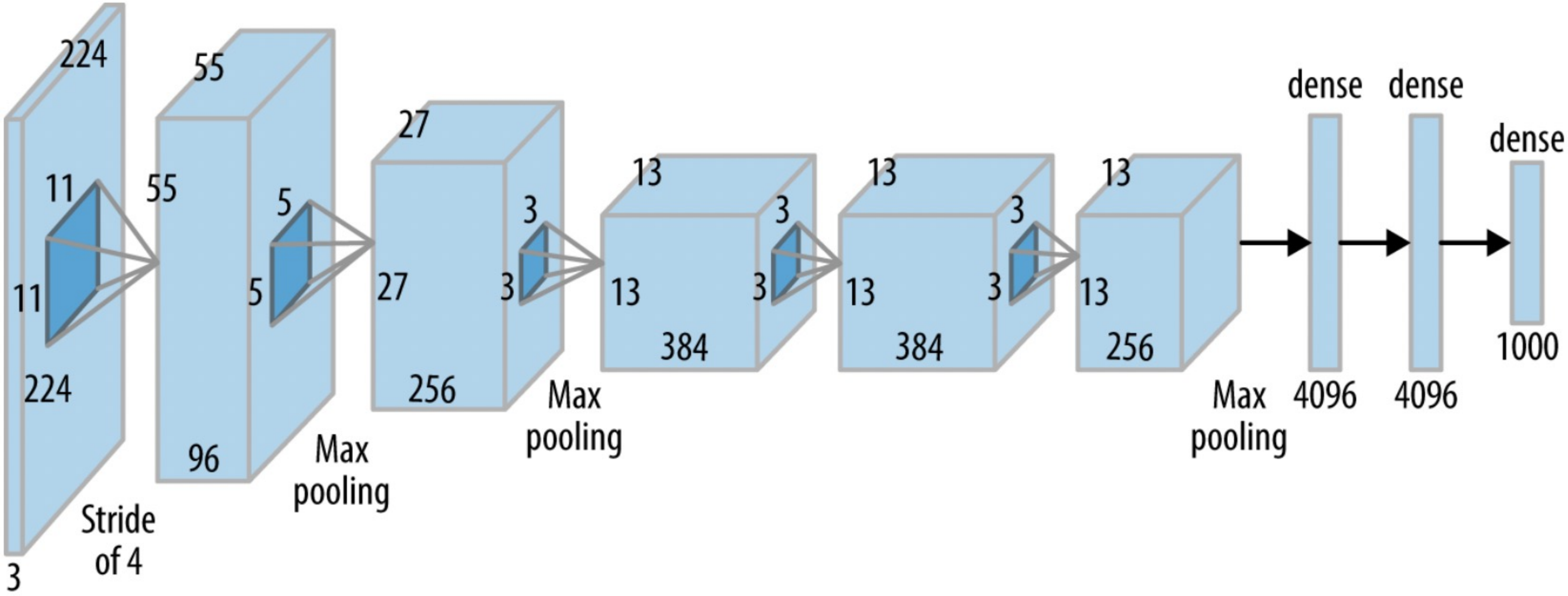
Linear model

Quadratic model

Polynomial model (9 degree)

Improve generalization performance

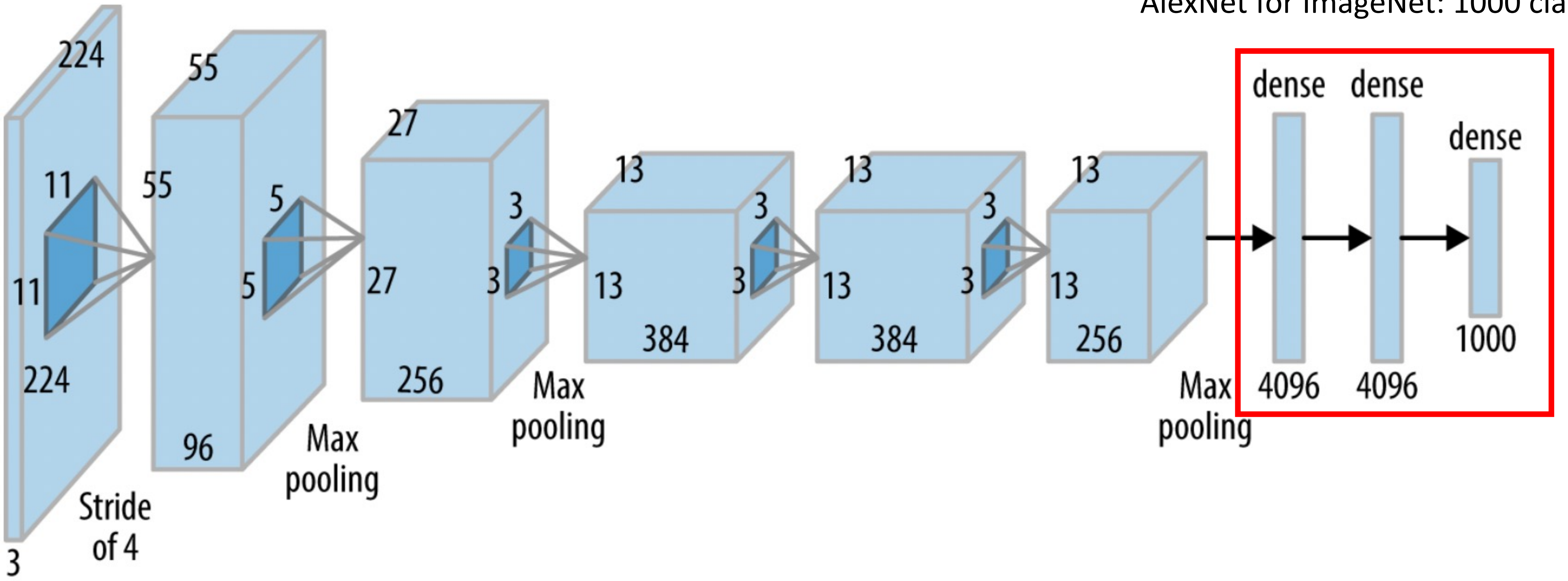
Pre-train



Suppose we have a learned model → weight parameters are determined and fixed

Pre-train

AlexNet for ImageNet: 1000 classes



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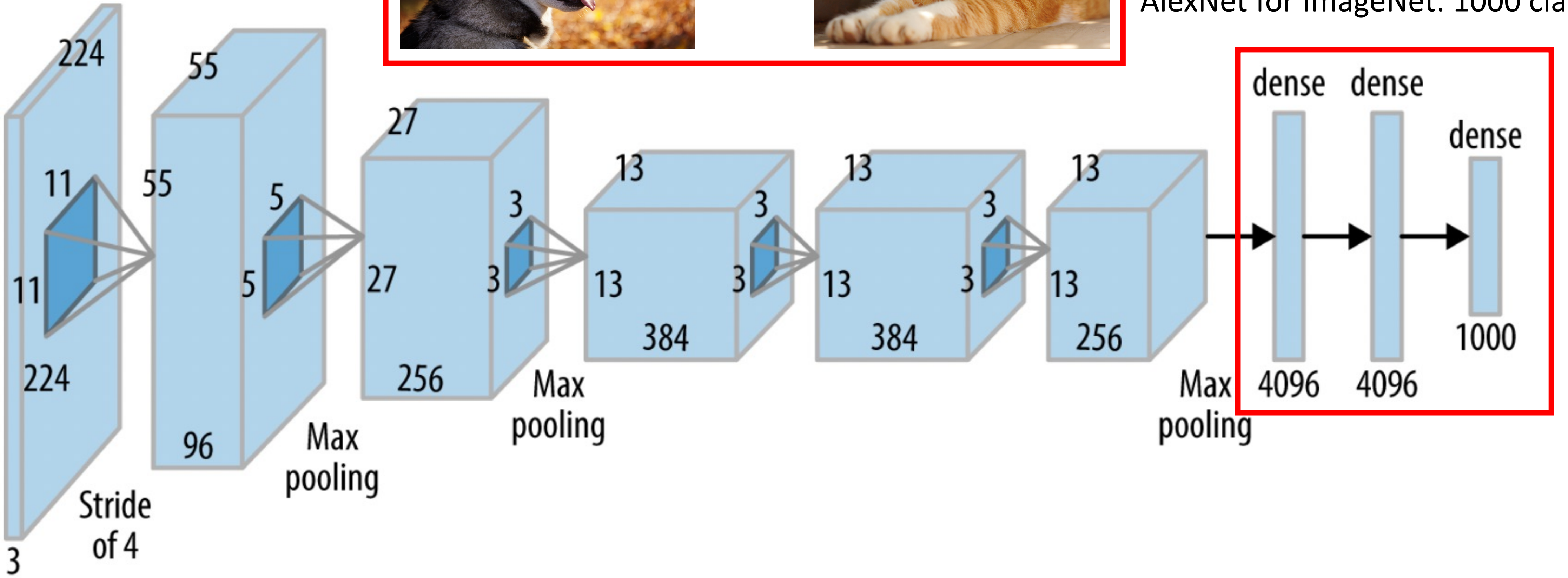
Pre-train

Now: Two classes

vs

AlexNet for ImageNet: 1000 classes



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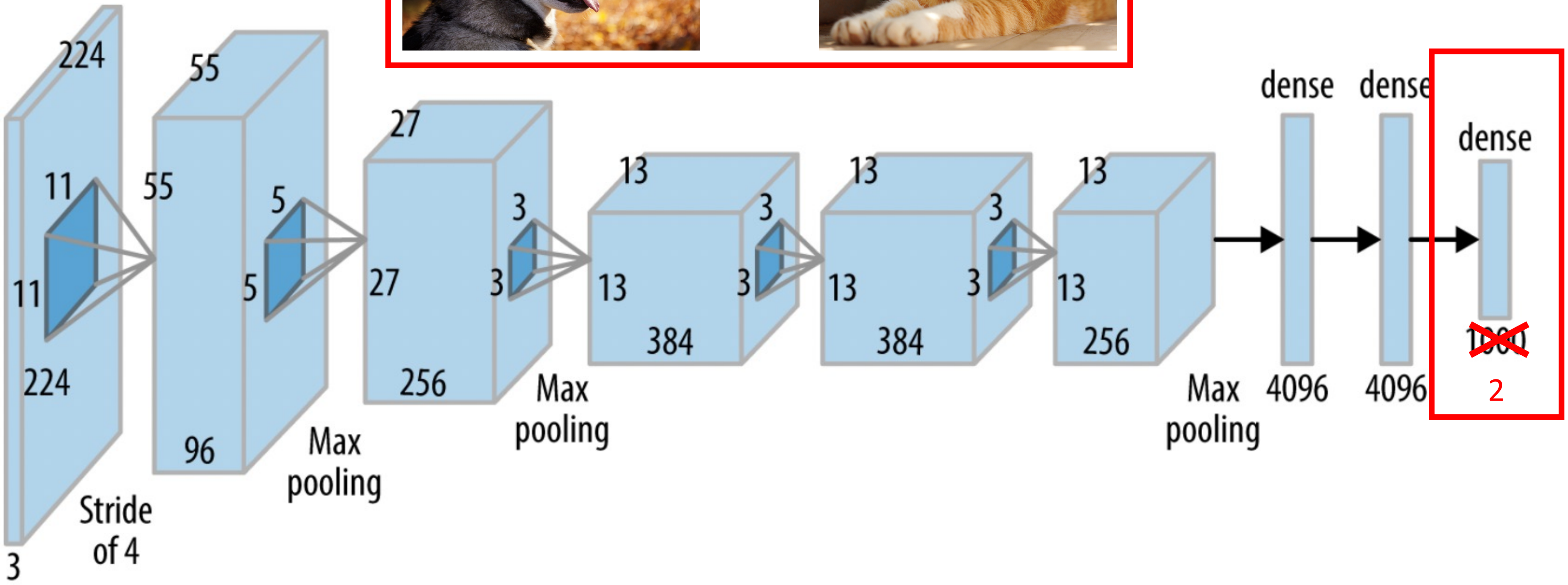
vs



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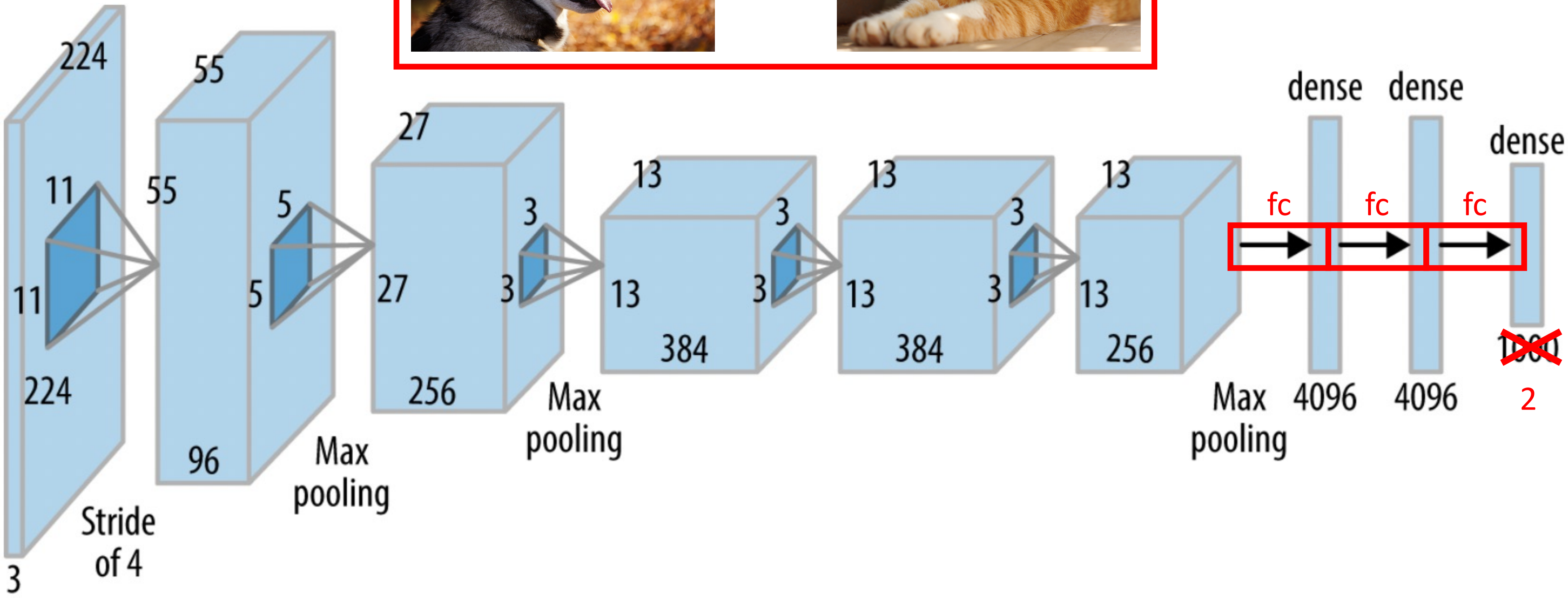
Now: Two classes



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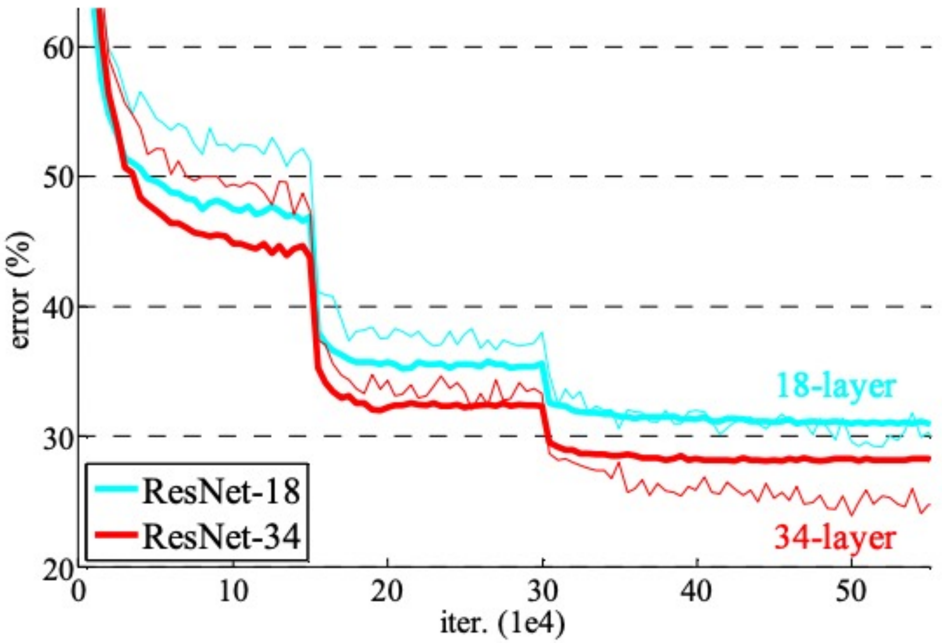
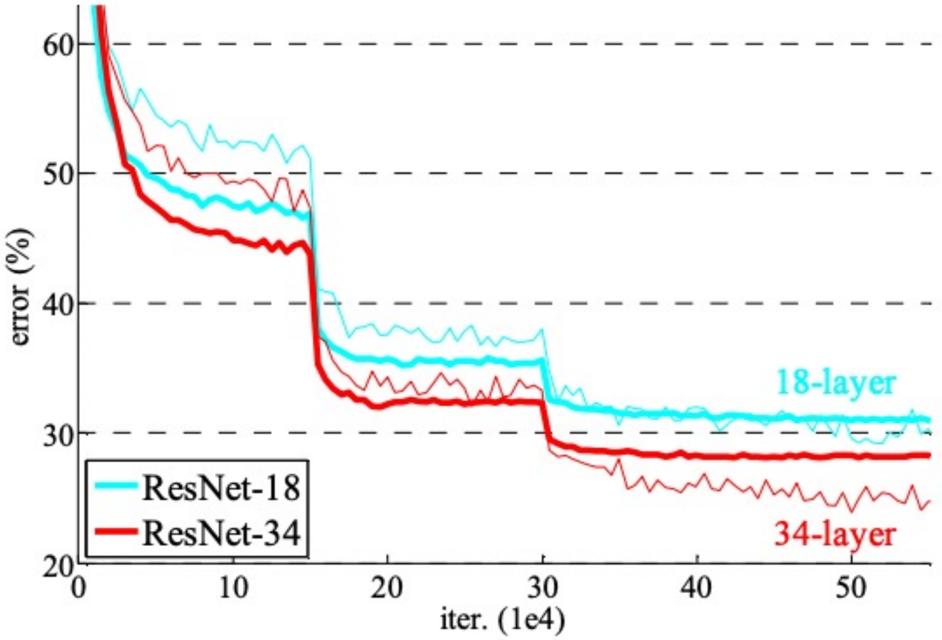
Stagewise/restart training



Stagewise/restart training



One-loop SGD

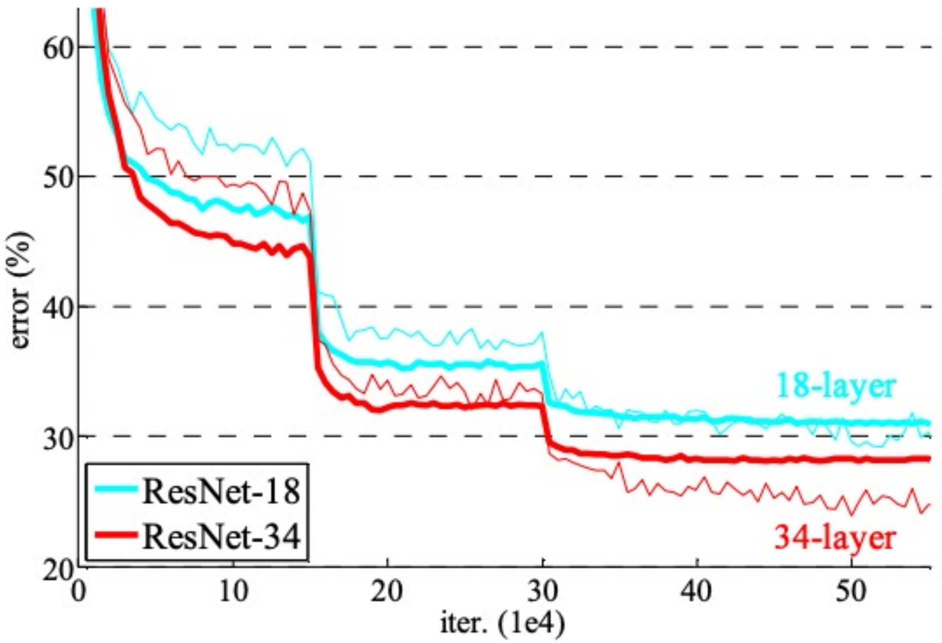
For t=1→T

  Compute stochastic gradients G_t for w_t

  Update $w_{t+1} = w_t - \eta G_t$

Endfor

Stagewise/restart training



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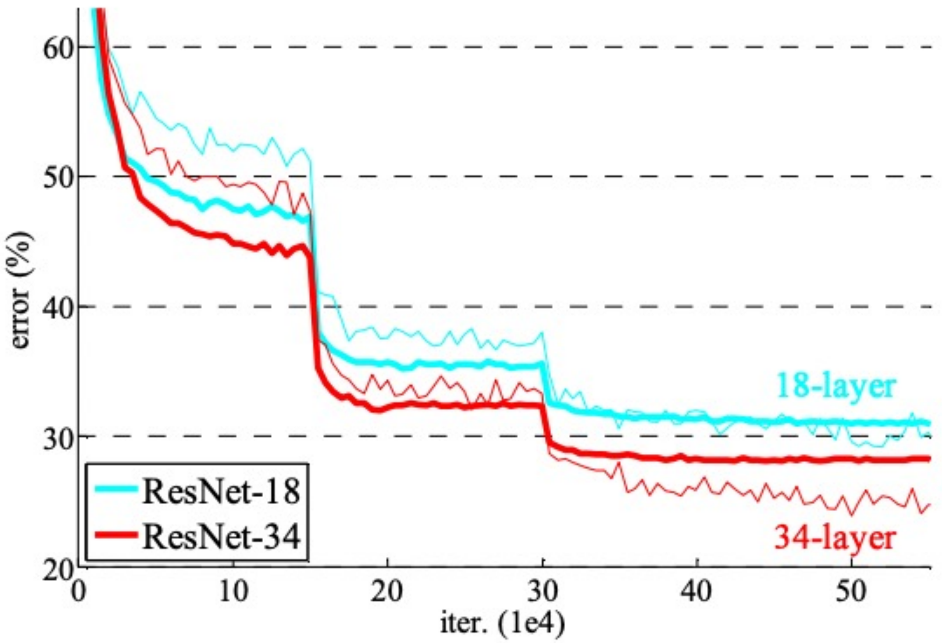

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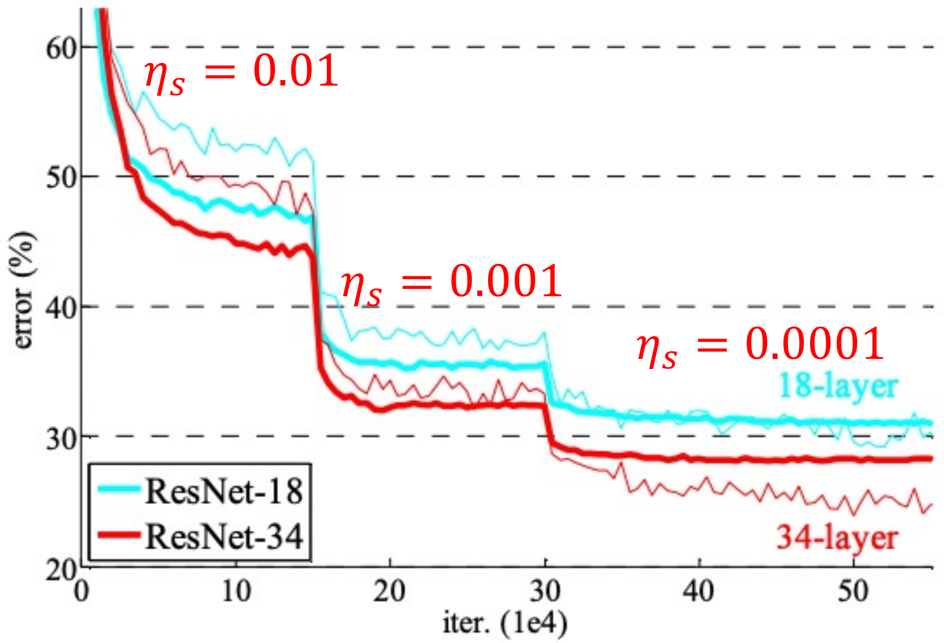

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Endfor

Endfor

Many other tricks for CNNs

- Large mini-batch in stochastic gradient descent
- Learning rate warmup [warmup]
- Mixup augmentation [mixup]
- Others, e.g., [BagOfTricks]

References

- [BN] Ioffe, Sergey, and Christian Szegedy. “Batch normalization: Accelerating deep network training by reducing internal covariate shift.” *arXiv preprint arXiv:1502.03167* (2015).
- [warmup] Goyal, Priya, Piotr Dollár, Ross Girshick, Pieter Noordhuis, Lukasz Wesolowski, Aapo Kyrola, Andrew Tulloch, Yangqing Jia, and Kaiming He. "Accurate, large minibatch sgd: Training imagenet in 1 hour." *arXiv preprint arXiv:1706.02677* (2017).
- [mixup] Zhang, Hongyi, Moustapha Cisse, Yann N. Dauphin, and David Lopez-Paz. "mixup: Beyond empirical risk minimization." *arXiv preprint arXiv:1710.09412* (2017).
- [BagOfTricks] He, Tong, Zhi Zhang, Hang Zhang, Zhongyue Zhang, Junyuan Xie, and Mu Li. "Bag of tricks for image classification with convolutional neural networks." In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 558-567. 2019.