Deep Learning

8. Regularization. Dropout. Batch normalization. CNN architectures.

Viacheslav Dudar

Taras Shevchenko National University of Kyiv

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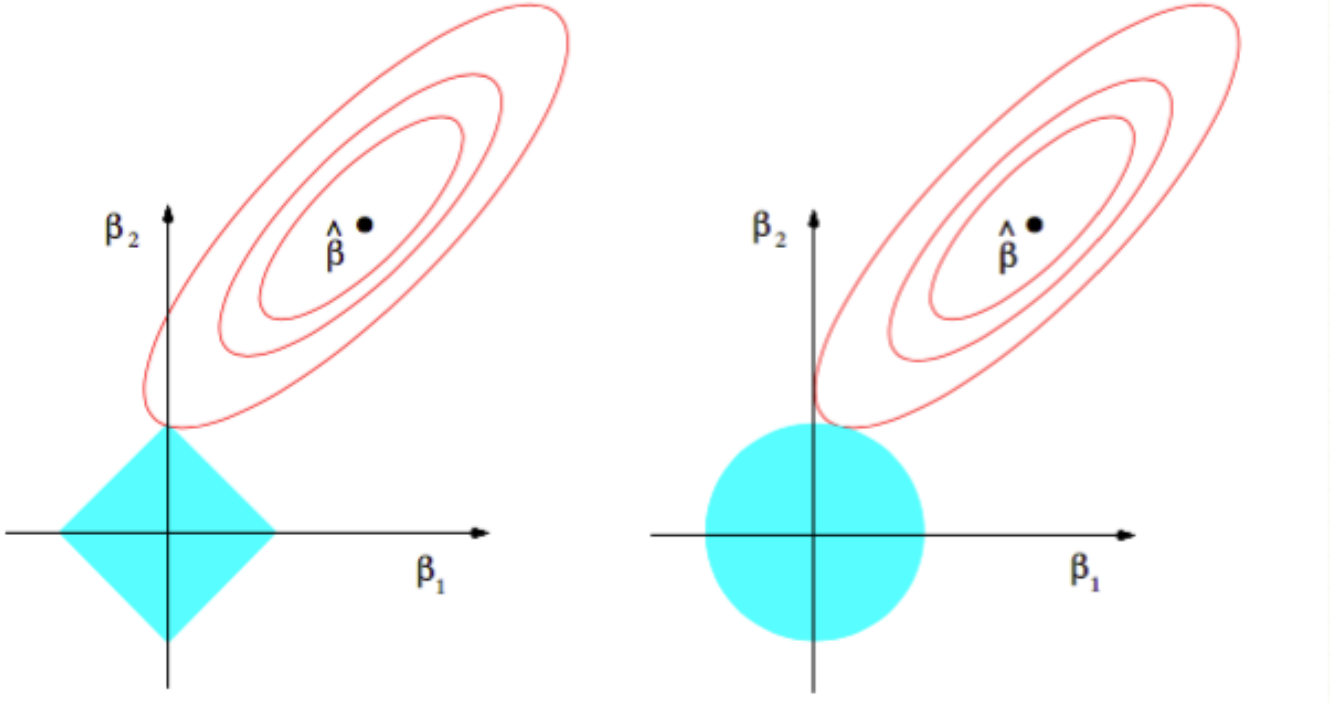
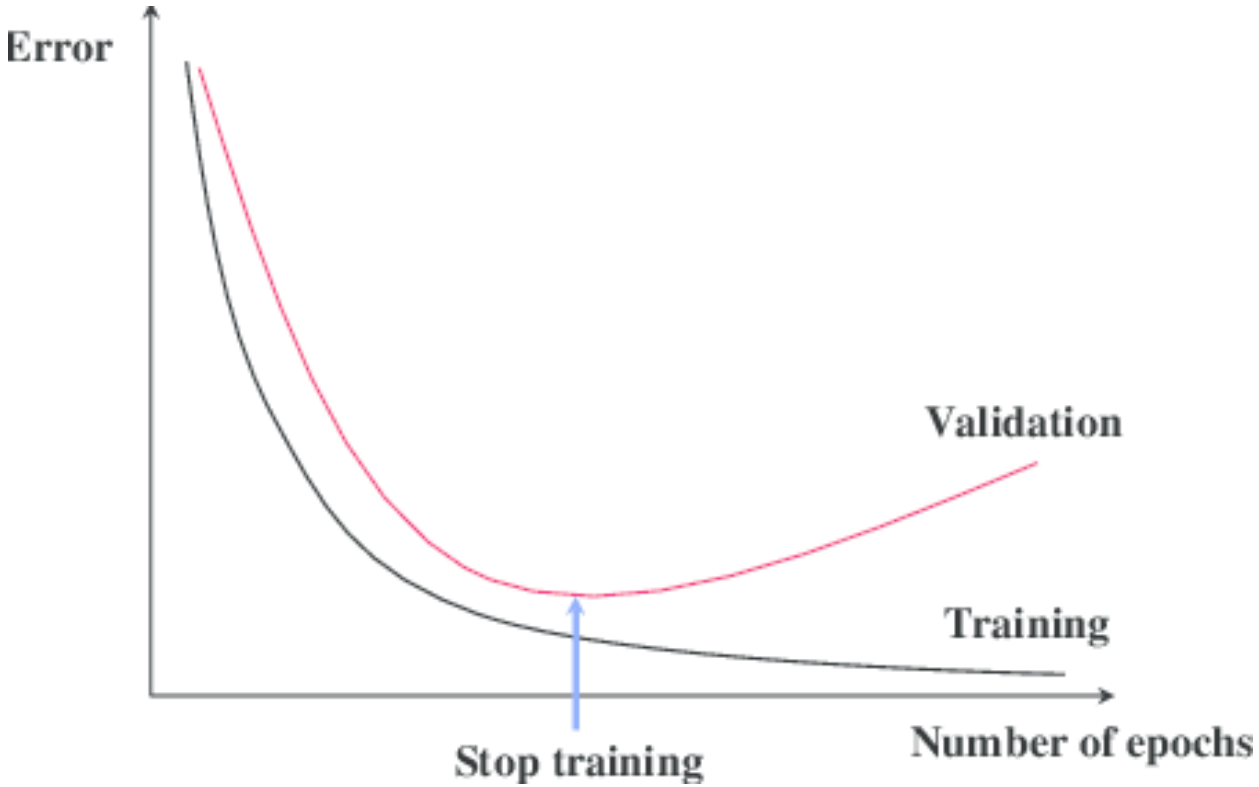
Classical regularization methods

- l_1, l_2 regularizations



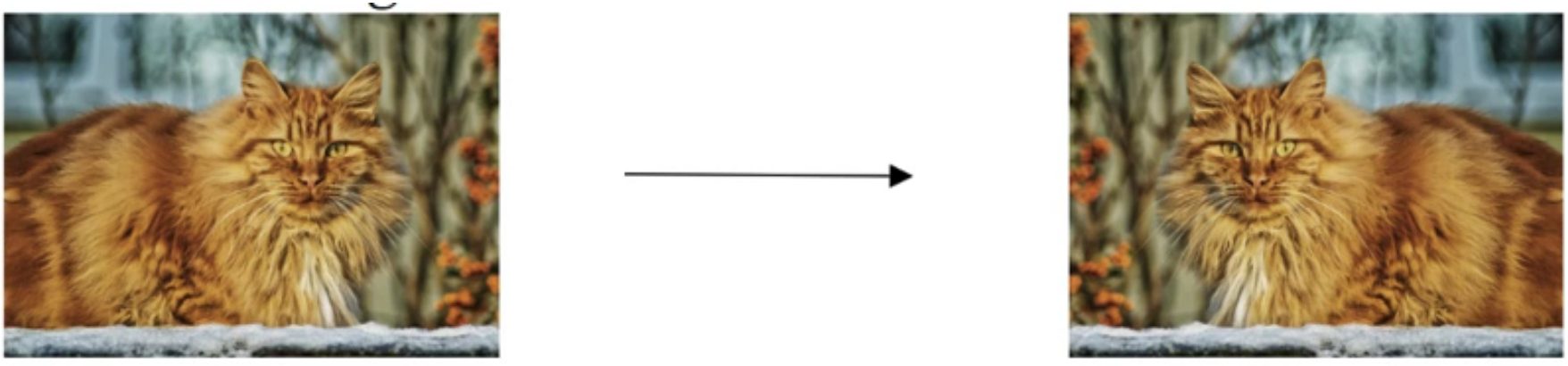
Drawback: no reasonable way to choose regularization coefficient
Partial solution: MacKay's quick and dirty method

Early stopping



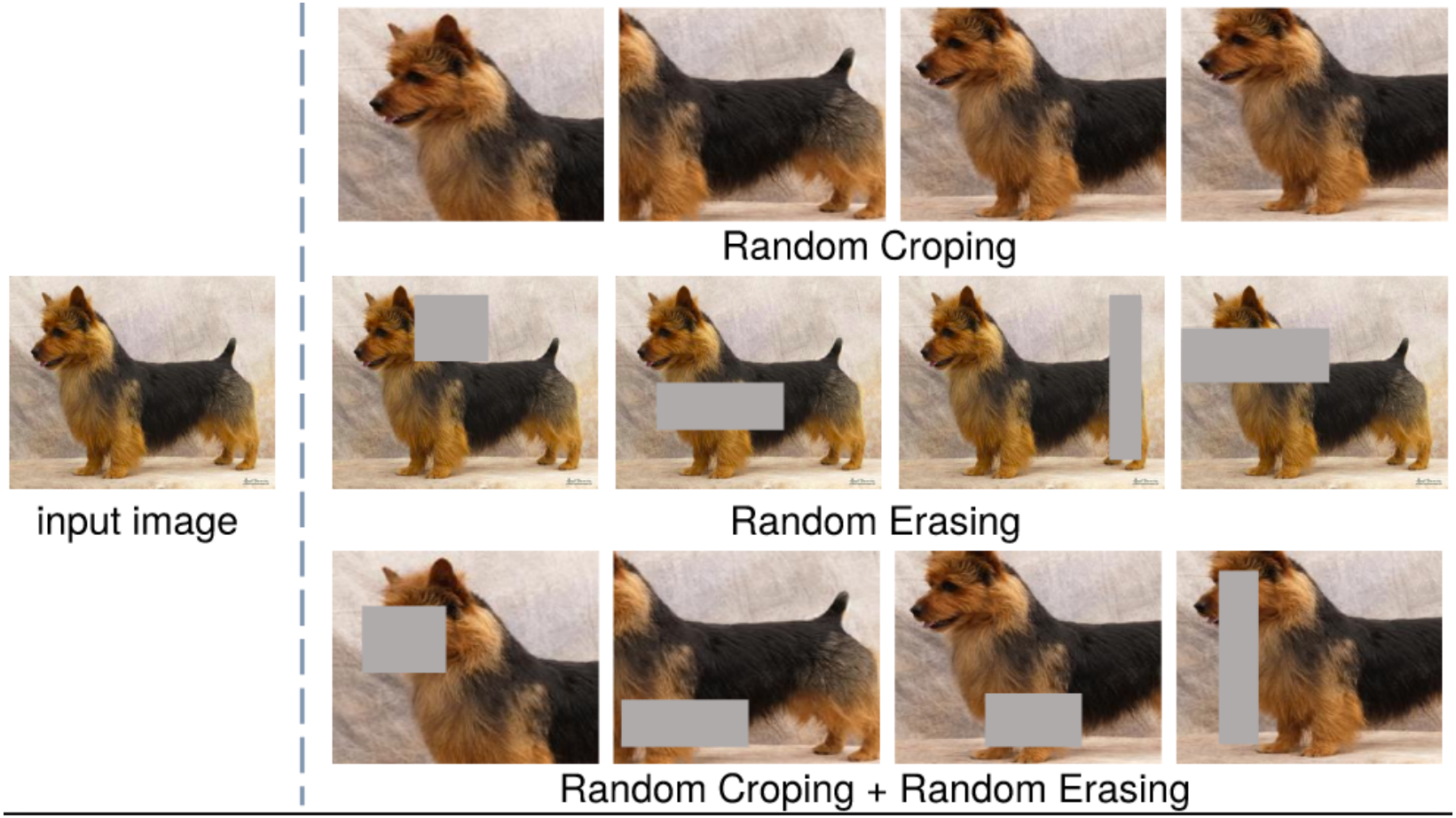
Data augmentation

Mirroring, or horizontal flipping



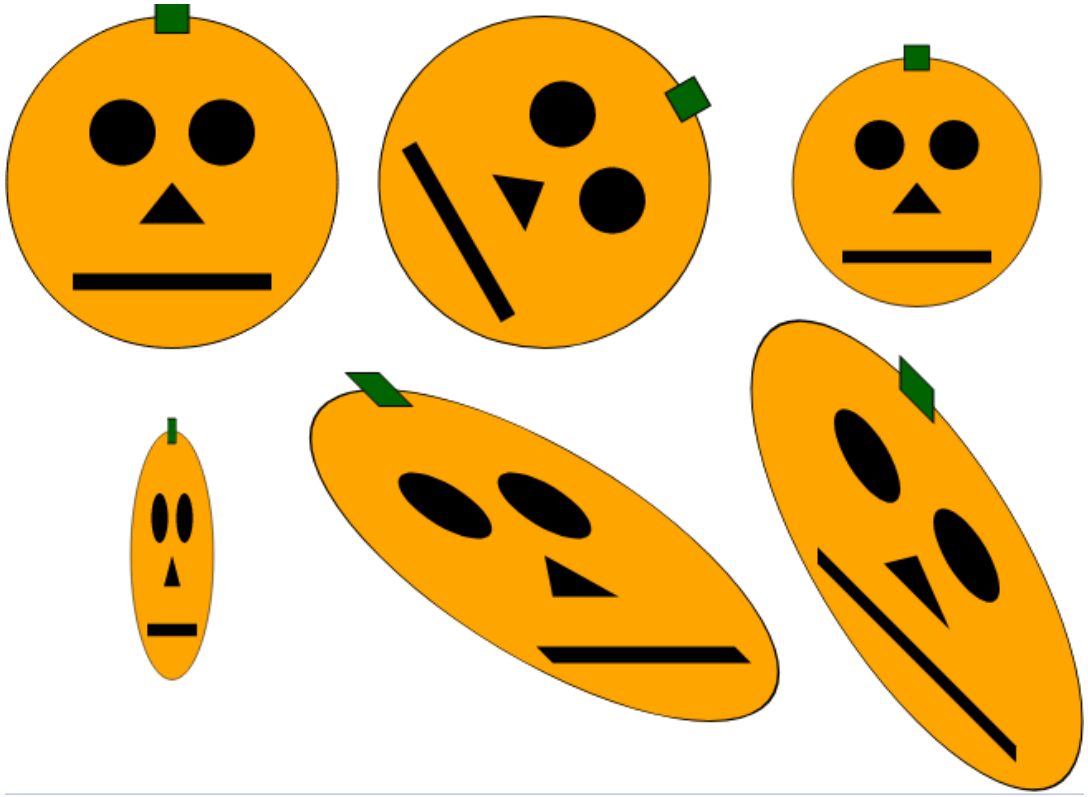
Data augmentation

Random cropping / erasing



Data augmentation

Affine image transformations



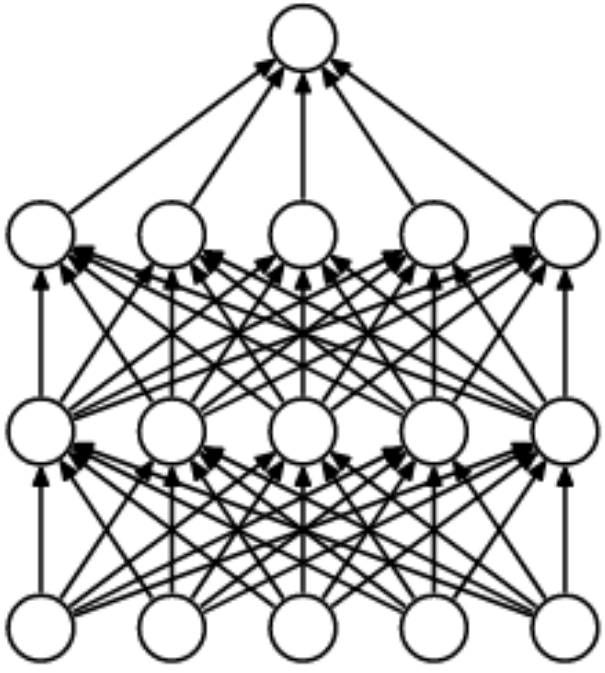
Are not always efficient because they change local statistical properties of pixels that could descrease generalization level.

Data augmentation

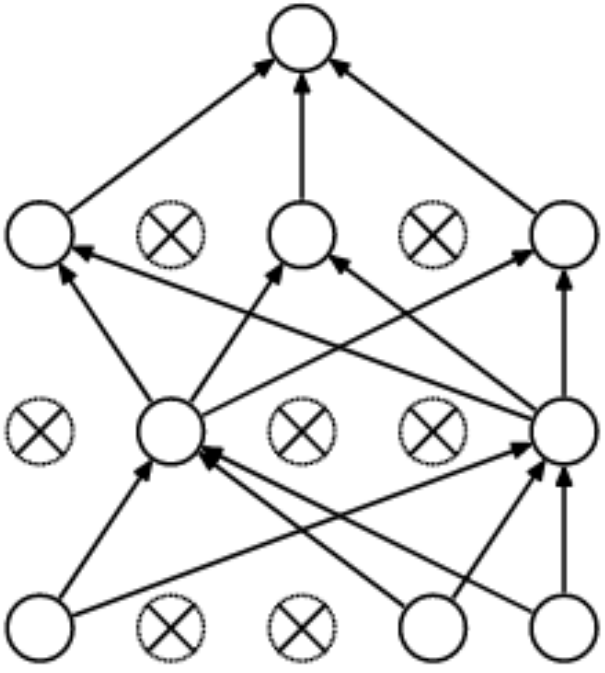
Most popular data augmentation settings:

- Random horizontal flip
- Random image crop with zero padding (image size does not change)
- Random image crop (with image size decrease) at train time; averaging of 5 images (4 corner and 1 center image) at test time

Dropout

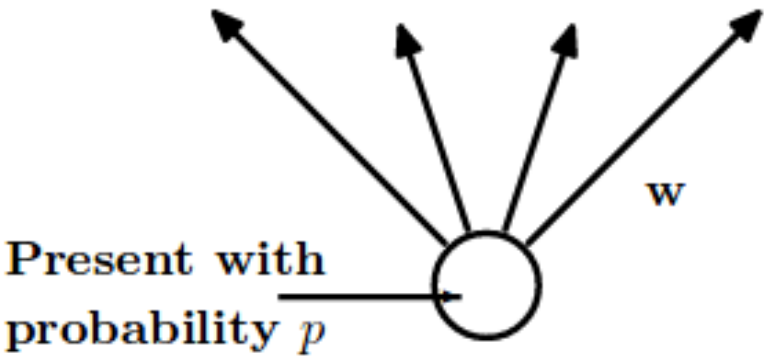


(a) Standard Neural Net

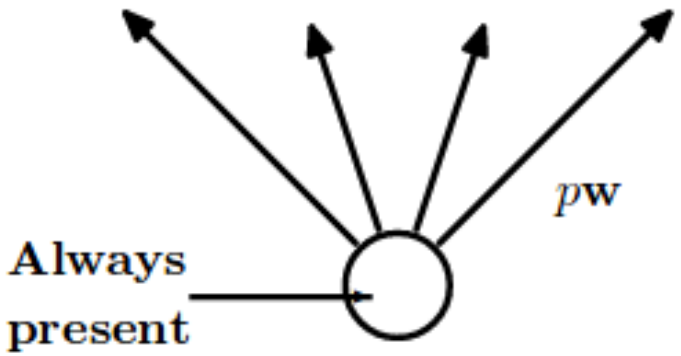


(b) After applying dropout.

Dropout: train-test time



(a) At training time



(b) At test time

Dropout notes

- Corresponds to averaging of exponential number of smaller models
- Does not have model averaging interpretability if applied to earlier layers, but still improves generalization
- Prevents coadaptation of features
- Popular drop rates are 0.2 - 0.5

Batch normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

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

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

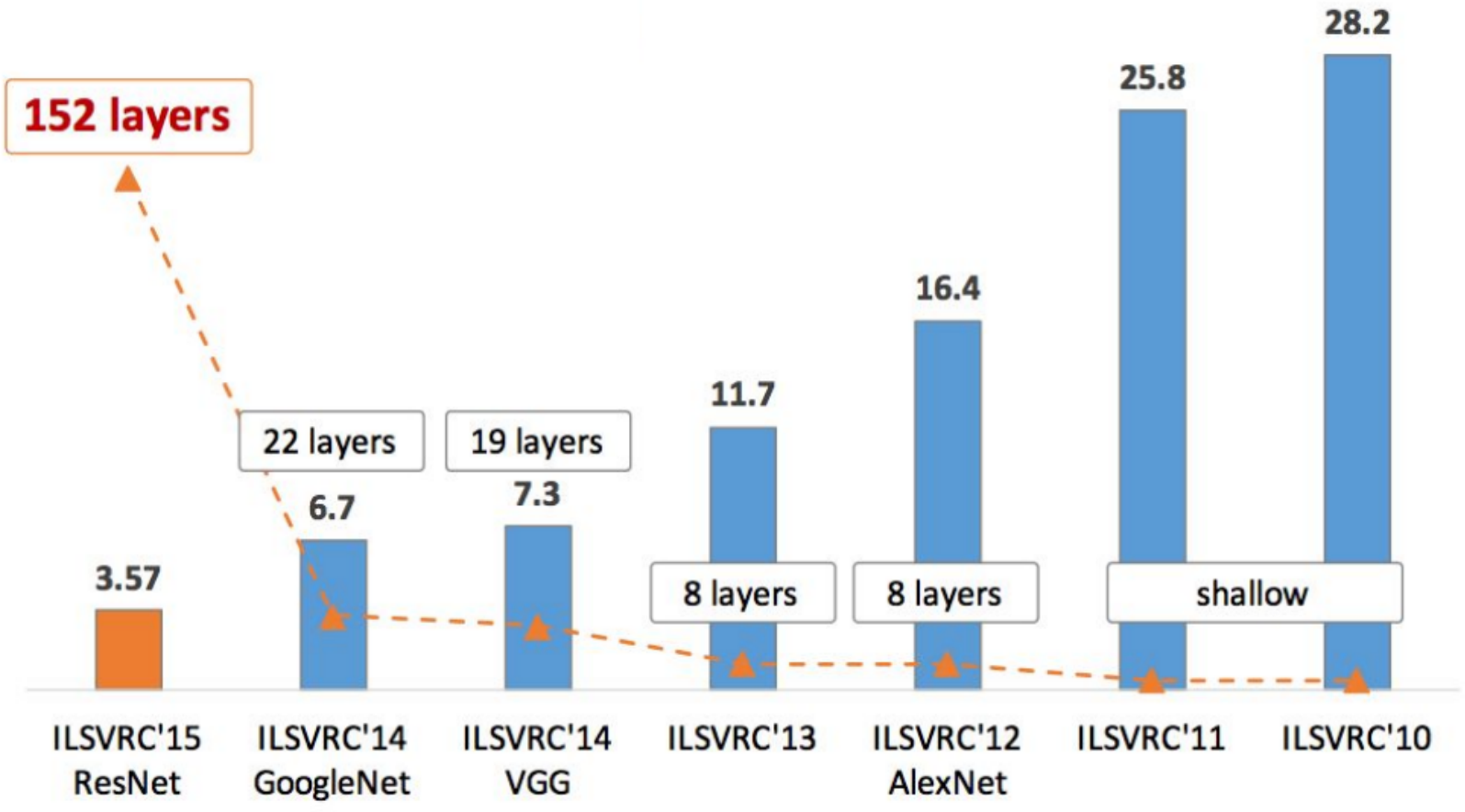
$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

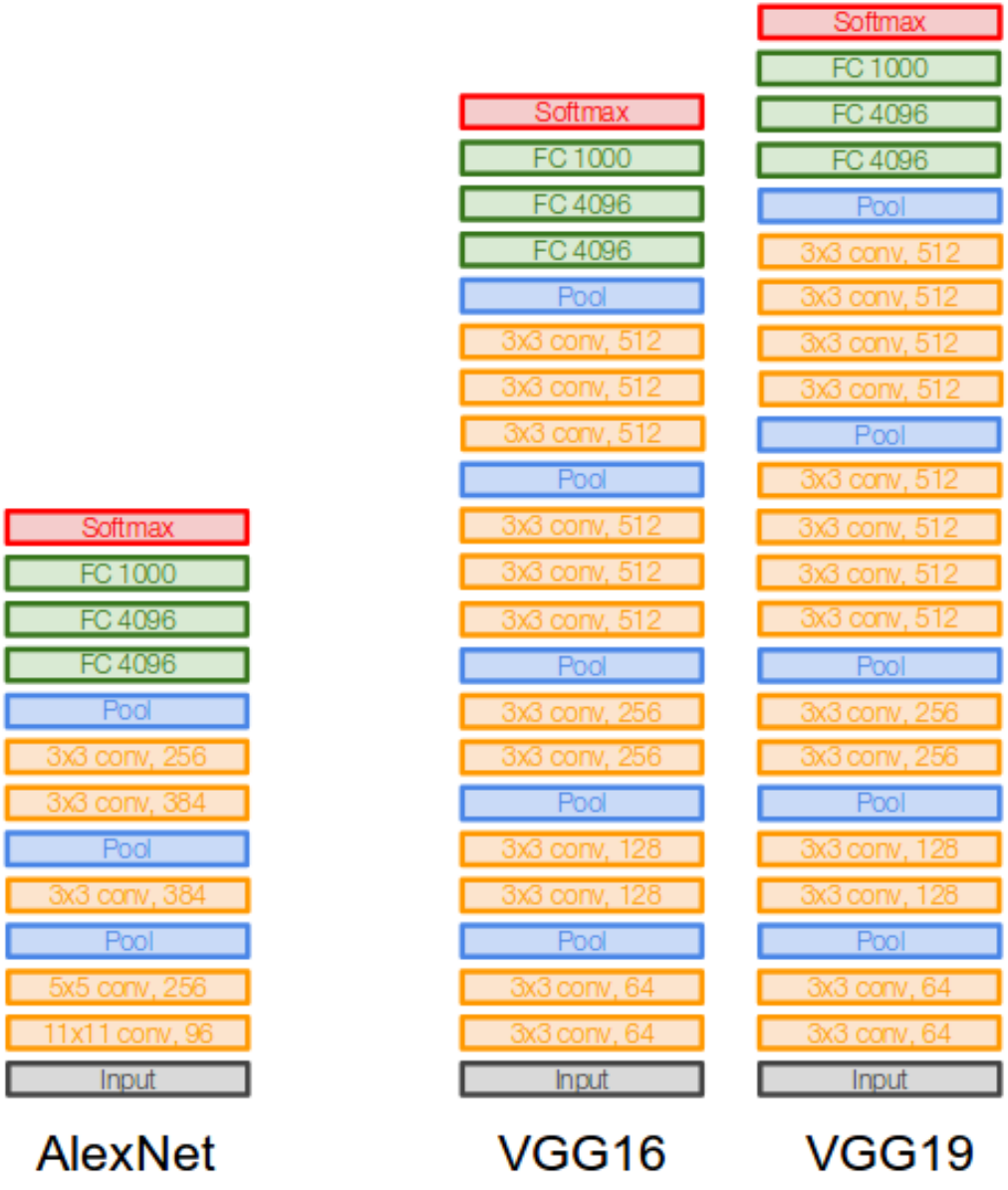
Batch norm properties

- Speeds up training
- Improves generalization
- Is usually used before nonlinearity
- In case of convolutional networks normalization and scale/shift coefficients are shared over spatial dimensions
- Typical sequences of layers in CNNs are Conv-BN-Relu or BN-Relu-Conv

ImageNet competition results



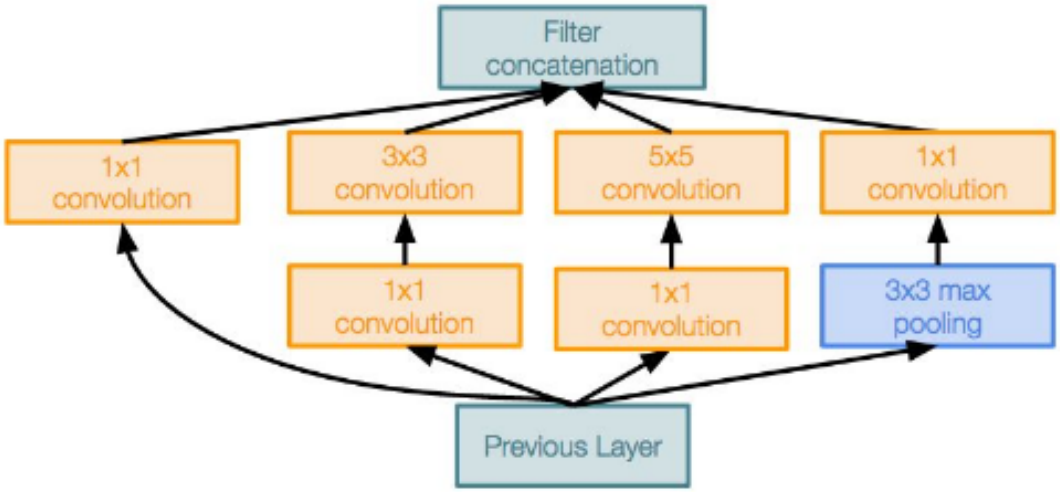
VGG


Softmax
FC 1000
FC 4096
FC 4096
Pool
3x3 conv, 256
3x3 conv, 384
Pool
3x3 conv, 384
Pool
5x5 conv, 256
11x11 conv, 96
Input
AlexNet
Softmax
FC 1000
FC 4096
FC 4096
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 256
3x3 conv, 256
Pool
3x3 conv, 128
3x3 conv, 128
Pool
3x3 conv, 64
3x3 conv, 64
Input
VGG16
Softmax
FC 1000
FC 4096
FC 4096
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 256
3x3 conv, 256
Pool
3x3 conv, 128
3x3 conv, 128
Pool
3x3 conv, 64
3x3 conv, 64
Input
VGG19

VGG - details

- 3*3 filters, padding 1, stride 1
- Dropout + averaging at test time
- 138 M params

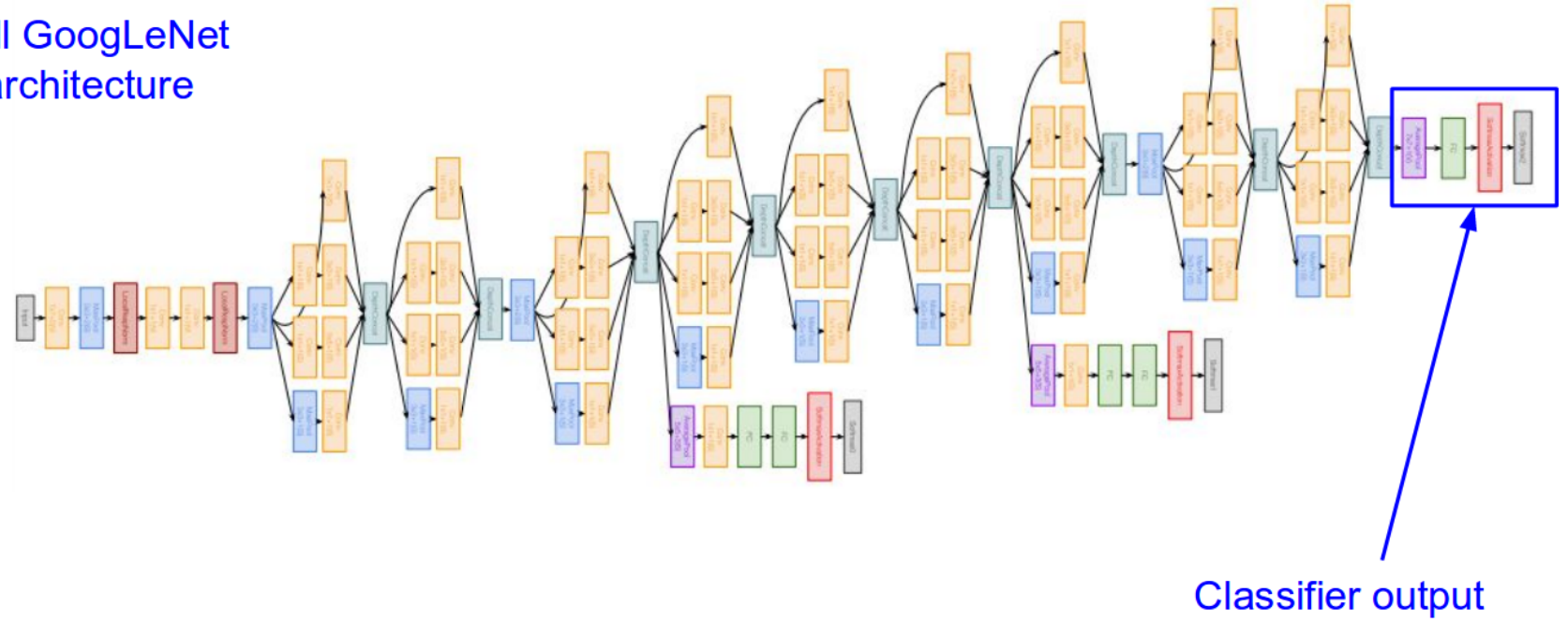
GoogLeNet



Inception module

GoogLeNet

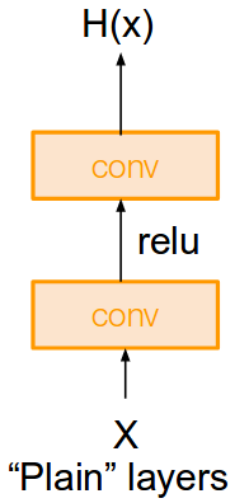
Full GoogLeNet architecture

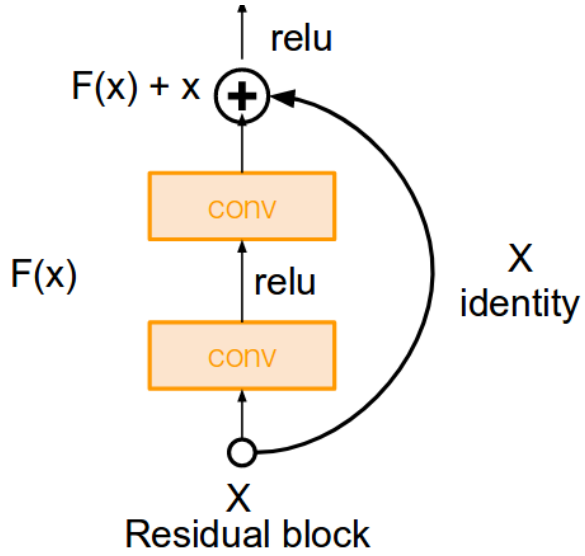


GoogleNet - details

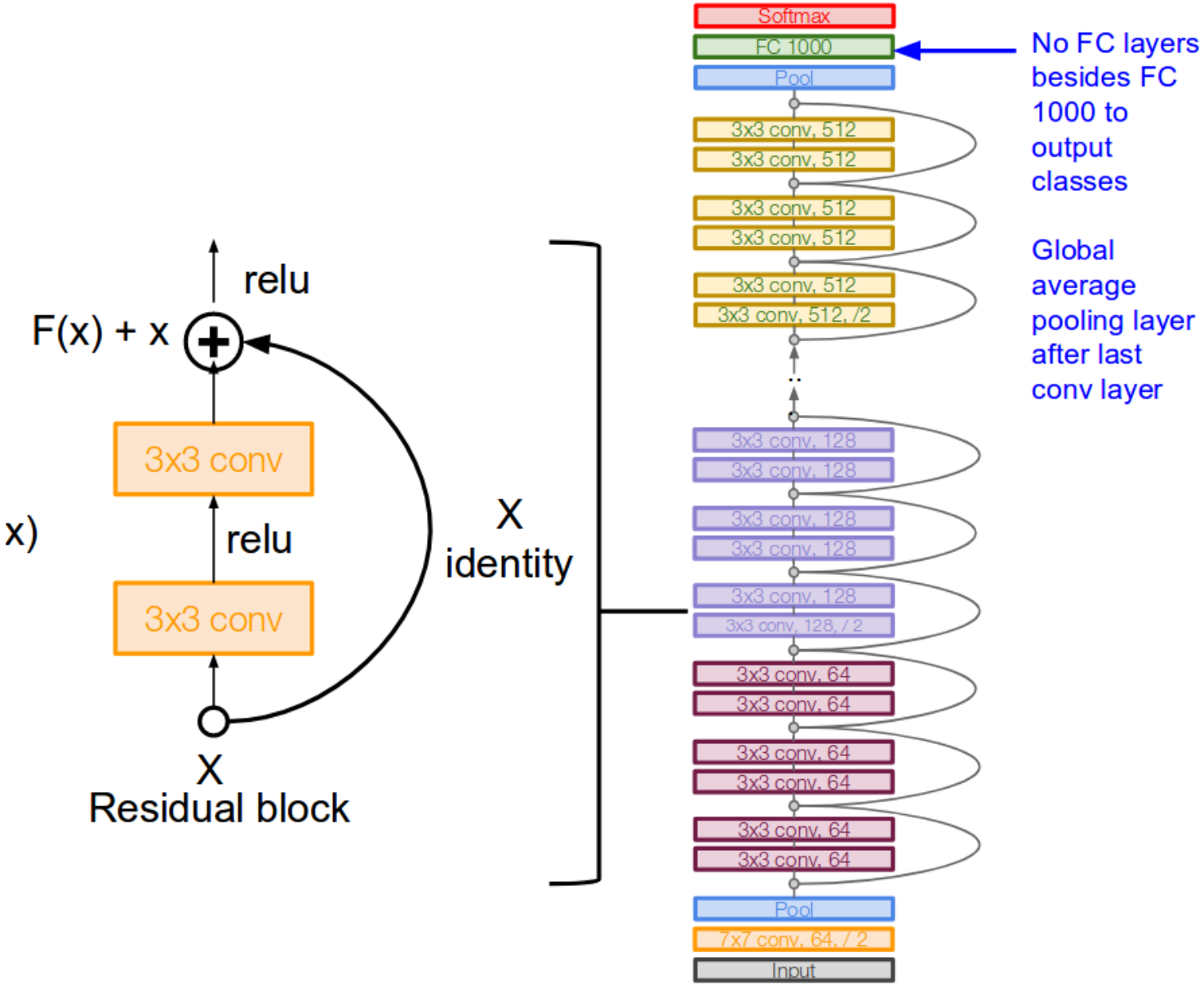
- No fully connected layers at the end
- 5M parameters
- ILSVRC14 classification winner (6.7% top 5 error)
- 22 layers

ResNet

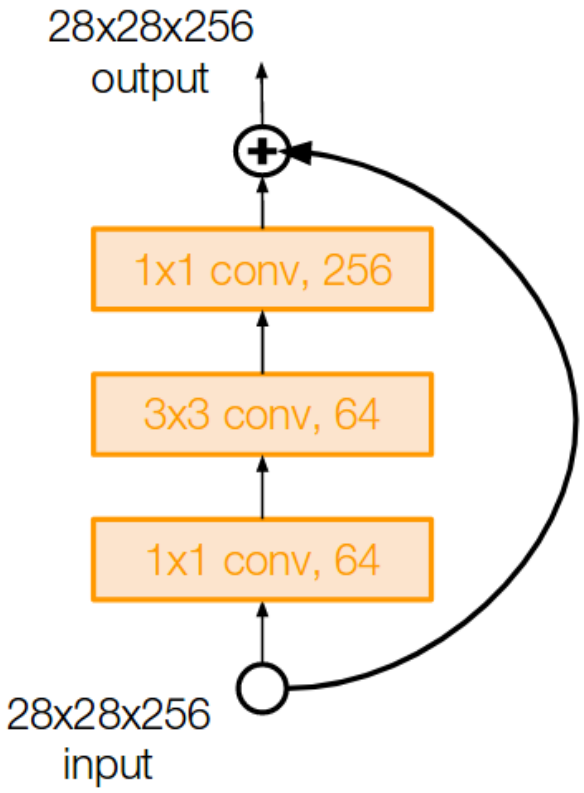

H(x)
conv
relu
conv
X
“Plain” layers


relu
F(x) + x
conv
F(x)
relu
conv
X
identity
X
Residual block

ResNet


relu
F(x) + x
3x3 conv
relu
3x3 conv
x)
X
Residual block
X
identity
Softmax
FC 1000
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128, / 2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
Pool
7x7 conv, 64, / 2
Input
No FC layers besides FC 1000 to output classes
Global average pooling layer after last conv layer

Bottleneck layers

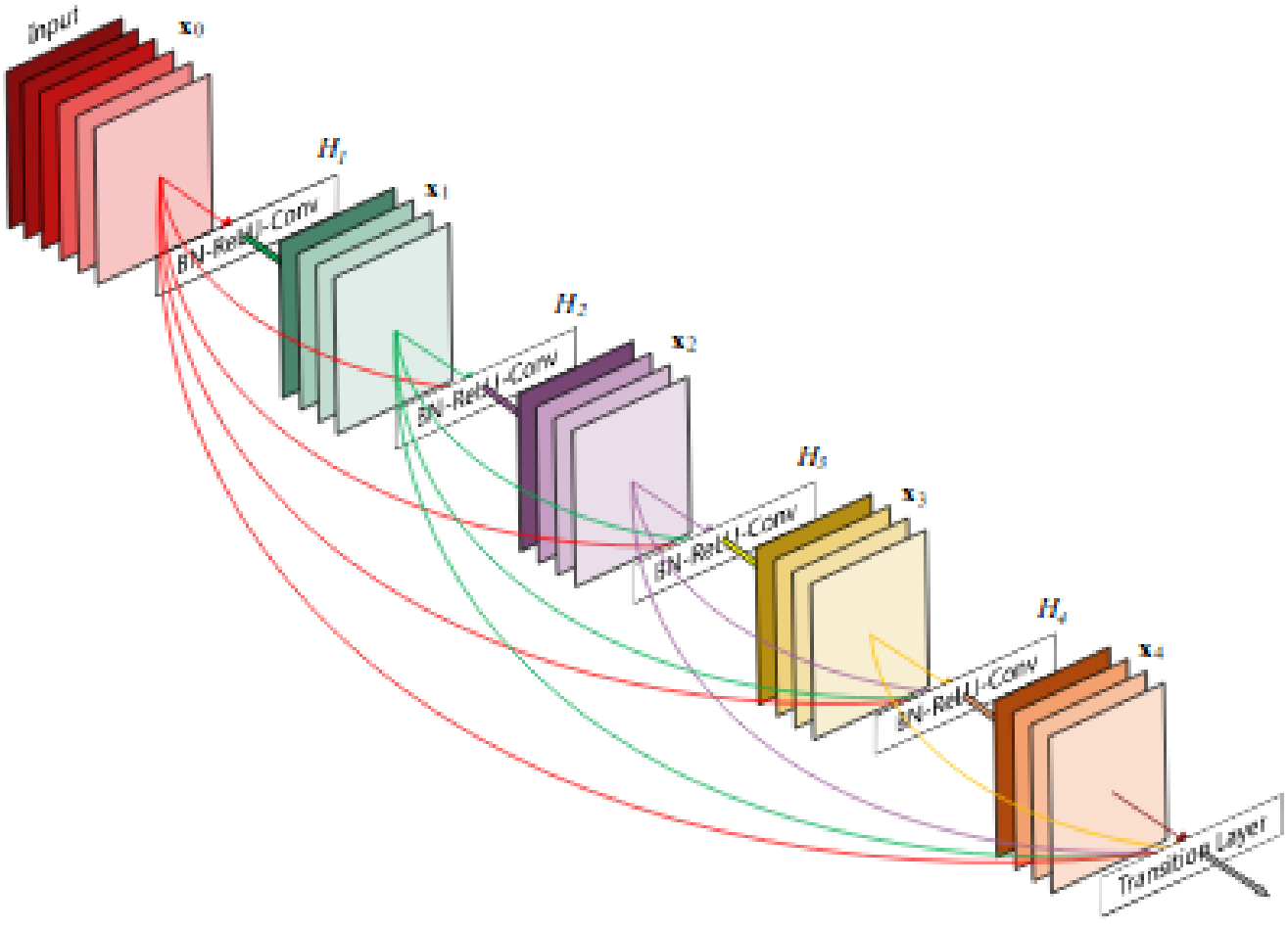


ResNet details

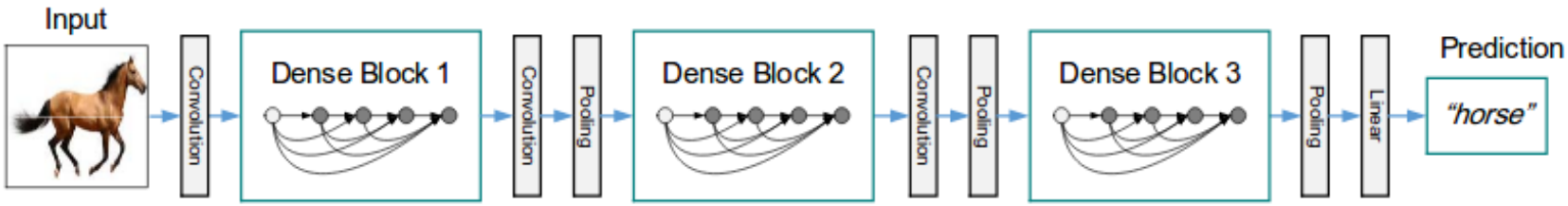
- 34, 50, 101, 152 layers
- Able to train very deep networks without degrading

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

Dense net


Input
$\mathbf{x}_0$
H_1
BN-ReLU-Conv
$\mathbf{x}_1$
H_2
BN-ReLU-Conv
$\mathbf{x}_2$
H_3
BN-ReLU-Conv
$\mathbf{x}_3$
H_4
BN-ReLU-Conv
$\mathbf{x}_4$
Transition Layer

Dense net


Input
Convolution
Dense Block 1
Convolution
Pooling
Dense Block 2
Convolution
Pooling
Dense Block 3
Pooling
Linear
Prediction
"horse"

Dense net

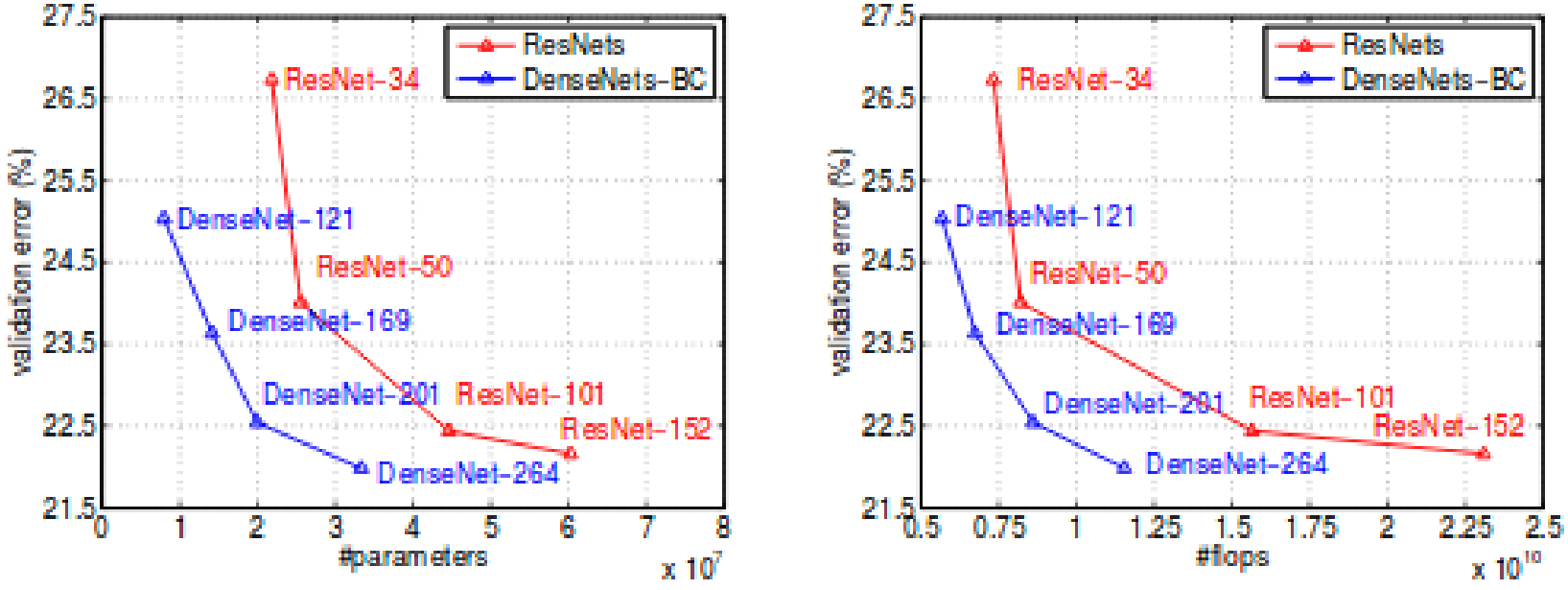


Figure 3: Comparison of the DenseNets and ResNets top-1 error rates (single-crop testing) on the ImageNet validation dataset as a function of learned parameters (*left*) and FLOPs during test-time (*right*).

Dense net

- Dense blocks have such sequences of layers: BN-Relu-Conv1*1-BN-Relu-Conv3*3-Concat
- Transition blocks: BN-Relu-Conv1*1-Pool with transition rate 0.5
- Gradient freely flows backward from the output to the input
- Model with more layers includes model with less layers
- More layers is associated with better training generalization

Dense net results

Method	Depth	Params	C10	C10+	C100	C100+
Network in Network [22]	-	-	10.41	8.81	35.68	-
All-CNN [32]	-	-	9.08	7.25	-	33.71
Deeply Supervised Net [20]	-	-	9.69	7.97	-	34.57
Highway Network [34]	-	-	-	7.72	-	32.39
FractalNet [17]	21	38.6M	10.18	5.22	35.34	23.30
with Dropout/Drop-path	21	38.6M	7.33	4.60	28.20	23.73
ResNet [11]	110	1.7M	-	6.61	-	-
ResNet (reported by [13])	110	1.7M	13.63	6.41	44.74	27.22
ResNet with Stochastic Depth [13]	110	1.7M	11.66	5.23	37.80	24.58
	1202	10.2M	-	4.91	-	-
Wide ResNet [42]	16	11.0M	-	4.81	-	22.07
	28	36.5M	-	4.17	-	20.50
with Dropout	16	2.7M	-	-	-	-
ResNet (pre-activation) [12]	164	1.7M	11.26*	5.46	35.58*	24.33
	1001	10.2M	10.56*	4.62	33.47*	22.71
DenseNet ($k = 12$)	40	1.0M	**7.00**	5.24	**27.55**	24.42
DenseNet ($k = 12$)	100	7.0M	**5.77**	**4.10**	**23.79**	**20.20**
DenseNet ($k = 24$)	100	27.2M	**5.83**	**3.74**	**23.42**	**19.25**
DenseNet-BC ($k = 12$)	100	0.8M	**5.92**	4.51	**24.15**	22.27
DenseNet-BC ($k = 24$)	250	15.3M	**5.19**	**3.62**	**19.64**	**17.60**
DenseNet-BC ($k = 40$)	190	25.6M	-	**3.46**	-	**17.18**