Convolutional Neural Networks

IE643 - Lectures 17 & 18

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CNN - GoogLeNet

Going deeper with convolutions

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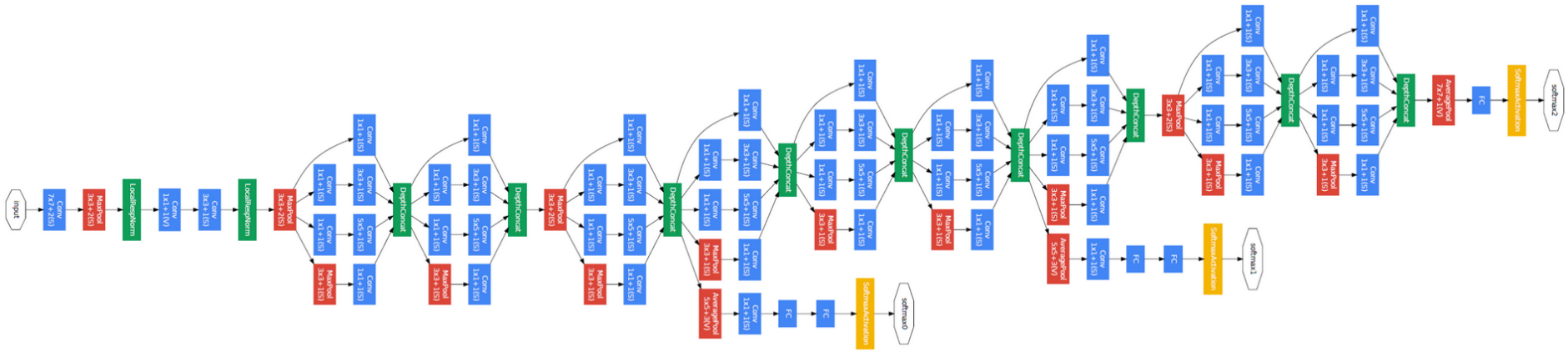
CNN - GoogLeNet

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Table : GoogLeNet incarnation of the Inception architecture

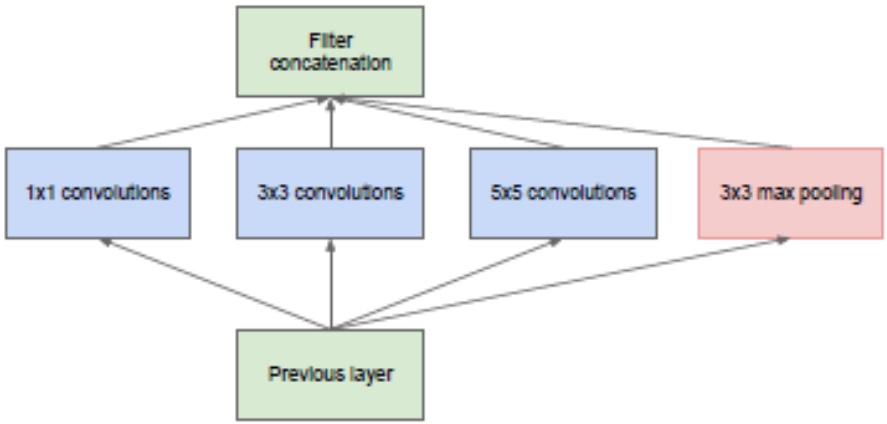
CNN - GoogLeNet



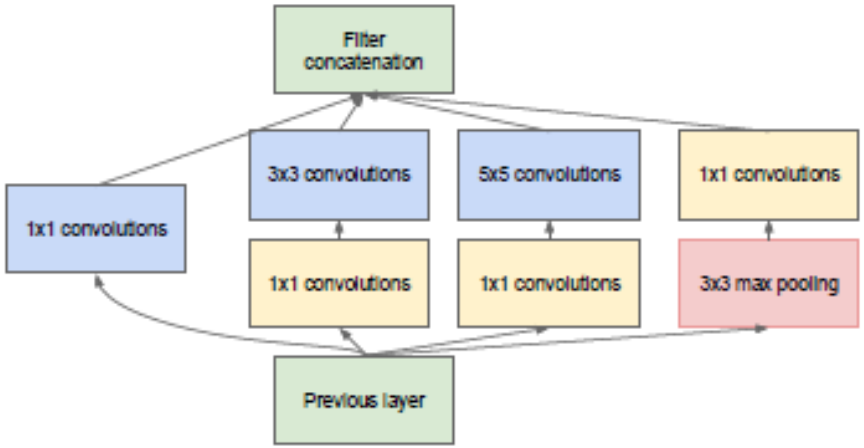
GoogLeNet Network (From Left to Right)

- Testing is a bit complicated: involves 7 models, 144 crops per image, softmax probabilities averaged over all crops
- Achieved $\sim$ **93.3%** accuracy on ILSVRC 2014 Classification Challenge

CNN - GoogLeNet



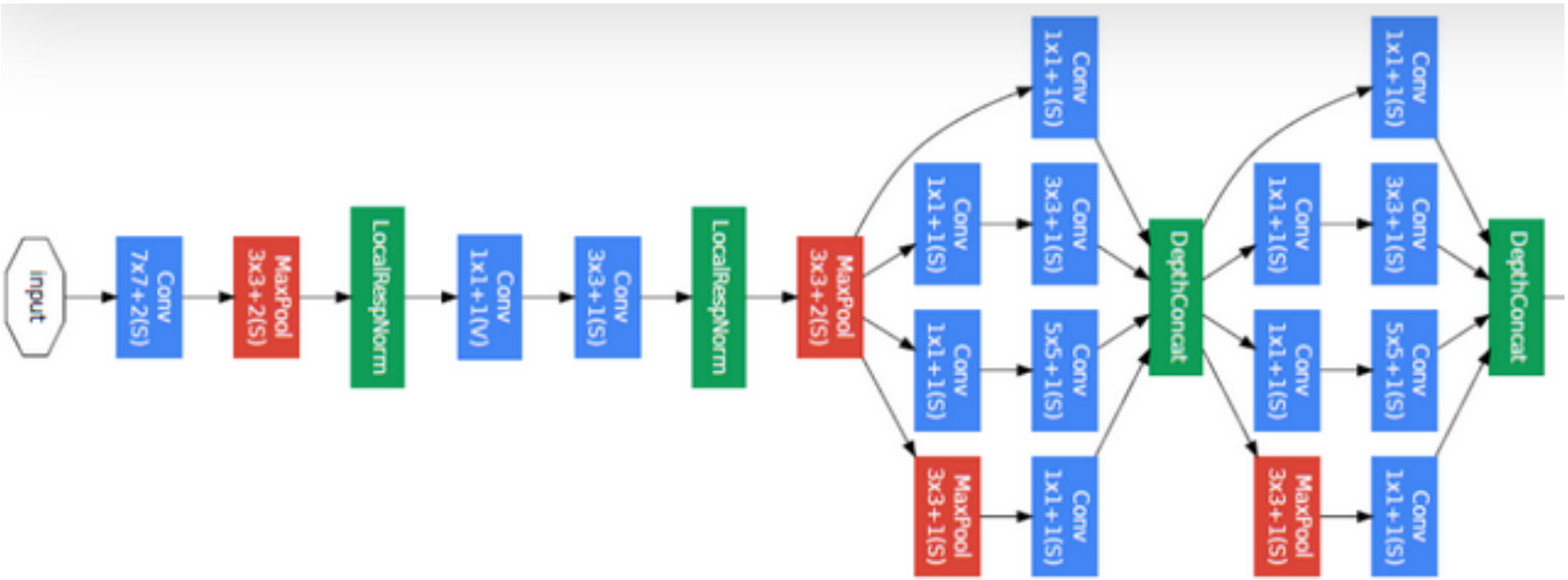
(a) Inception module, naïve version



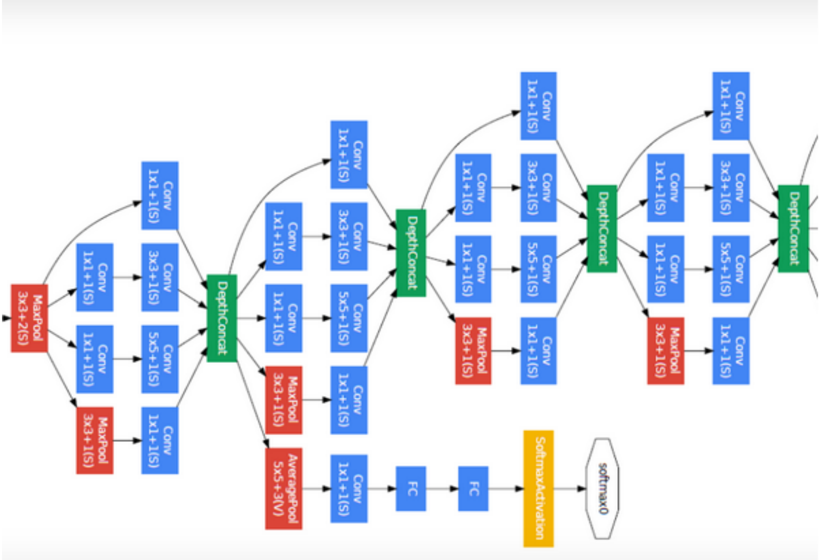
(b) Inception module with dimension reductions

Figure 2: Inception module

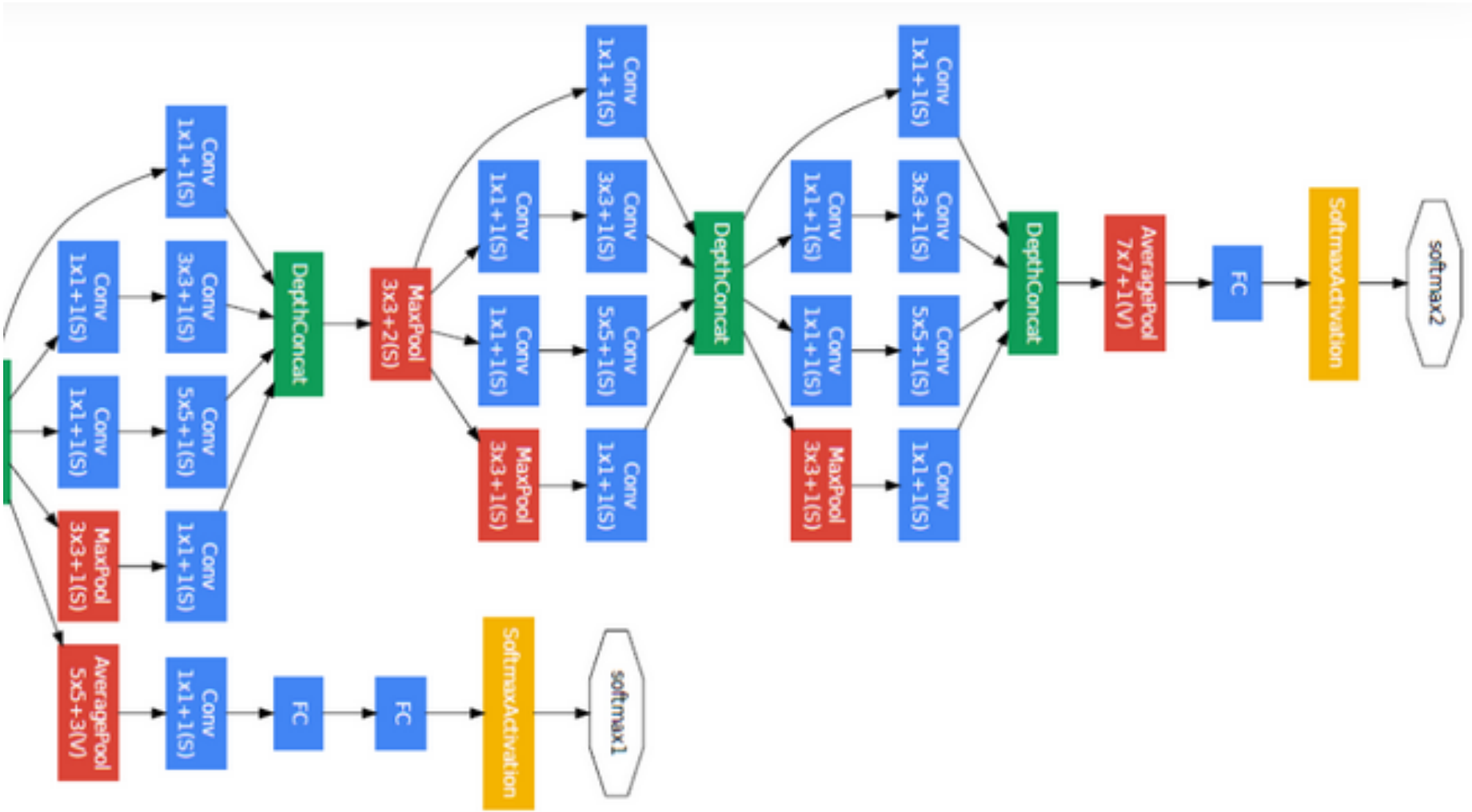
CNN - GoogLeNet



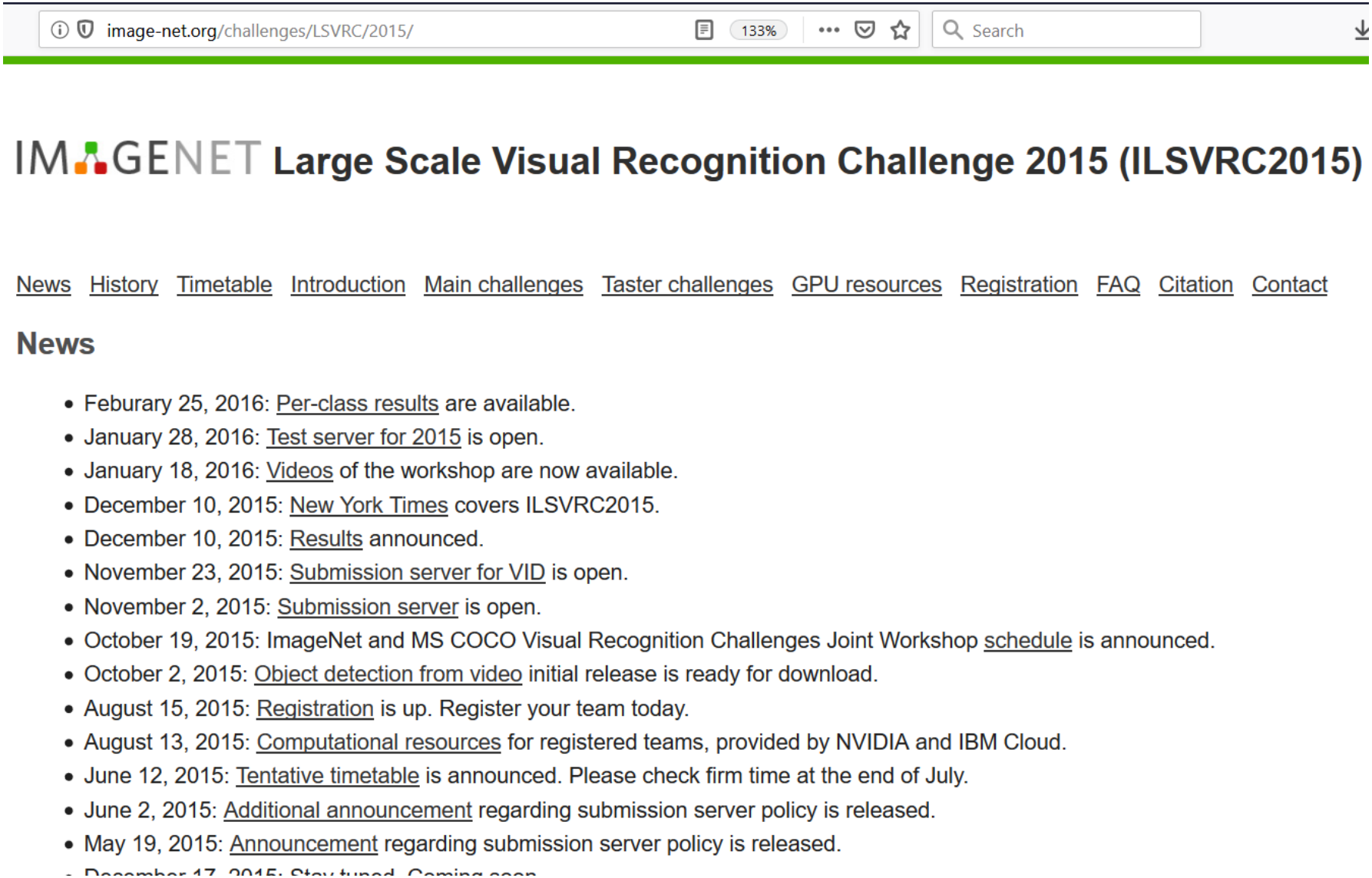
CNN - GoogLeNet



CNN - GoogLeNet



ILSVRC 2015 Challenge



ILSVRC 2015 Challenge

1. Two main competitions:
    I. Object detection for 200 fully labeled categories.
    II. Object localization for 1000 categories.
2. Two taster competitions **New**:
    I. Object detection from video for 30 fully labeled categories
    II. Scene classification for 401 categories.

CNN - ResNet

Deep Residual Learning for Image Recognition

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CNN - ResNet

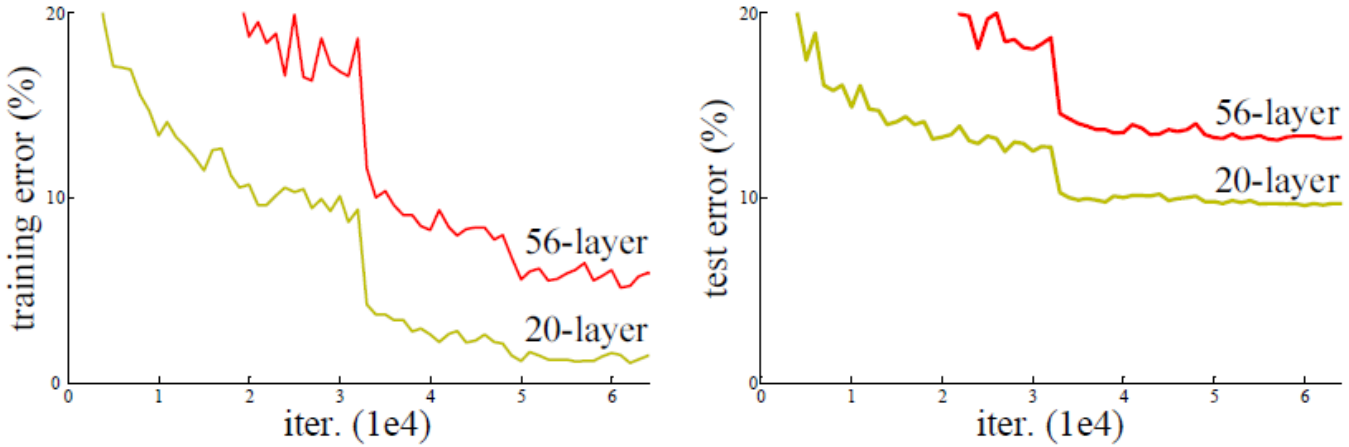
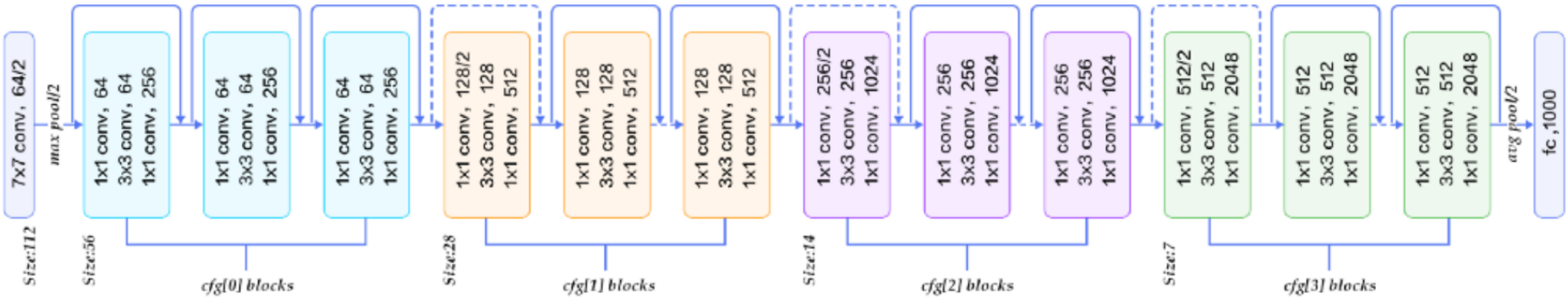


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

CNN - ResNet



- Testing involves 6 models, multiple crops per image, softmax probabilities averaged over all crops
- ResNet-152 Achieved $\sim$ **97%** accuracy on ILSVRC 2015 Classification Challenge

CNN - ResNet

- **Aim**: To model a map $\mathcal{H} : I \rightarrow S$
- I can denote the input space or some suitable intermediate representation space.
- S can denote the output space or some suitable intermediate representation space.

CNN - ResNet

- **Idea**: To model $\mathcal{H}$ using $\mathcal{H}(x) = \mathcal{F}(x) + Wx$ and learn $\mathcal{F}$ and W.
- If I and S are of same dimensions, W can be considered (or hypothesized) to be the identity, hence the aim reduces to learning $\mathcal{F}$.

CNN - ResNet

- **Motivation**: Learning the actual map $\mathcal{H}$ is difficult.
- **Hope**: Can we ease the task by focusing the learning task related to $\mathcal{F}$ and then use the original input to get back $\mathcal{H}$.
- **Caveat**: Learning $\mathcal{F}$ is also not that easy! (Exploit deep nets to learn $\mathcal{F}$)

CNN - ResNet

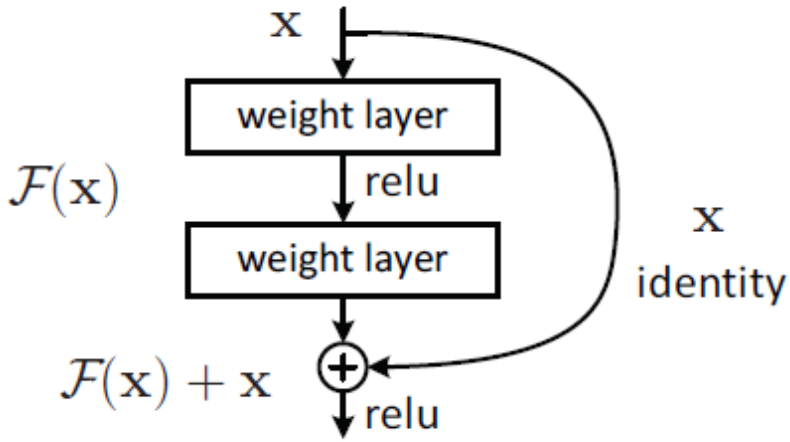


Figure 2. Residual learning: a building block.

CNN - ResNet

model	top-1 err.	top-5 err.
VGG-16 [41]	28.07	9.33
GoogLeNet [44]	-	9.15
PReLU-net [13]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	**21.43**	**5.71**

Table 3. Error rates (%, **10-crop** testing) on ImageNet validation. VGG-16 is based on our test. ResNet-50/101/152 are of option B that only uses projections for increasing dimensions.

CNN - ResNet

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43†
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

CNN - DenseNet

Densely Connected Convolutional Networks

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CNN - DenseNet

- **Aim**: To facilitate flow of gradients from last layers to the initial layers **avoiding vanishing gradient** issue.
- A densenet block is designed which can facilitate the flow of gradients.

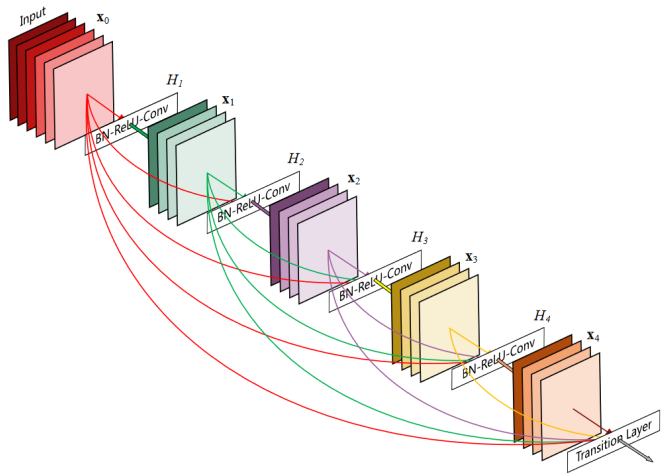

Figure : A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

- In each densenet block of L layers, the ℓ-th layer $(0 \leq \ell \leq L-1)$ receives feature maps from **all the previous** $\ell - 1$ **layers**.
- Hence there would be $\frac{L(L+1)}{2}$ feature maps in the densenet block.

CNN - DenseNet

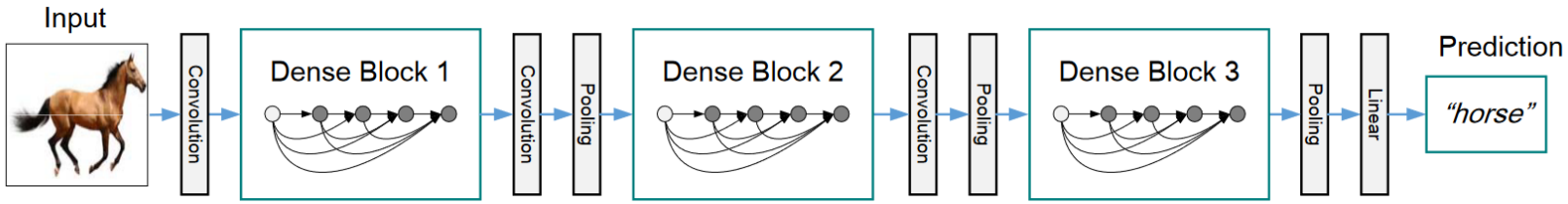

Figure : A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

- At ℓ-th layer the operation would be of the form:

$$M_\ell = H_\ell[M_0; M_1; \ldots; M_{\ell-1}]$$

where $[M_0; M_1; \ldots; M_{\ell-1}]$ denotes concatenation of feature maps $M_0, M_1, \ldots, M_{\ell-1}$ at corresponding layers.

- H_ℓ is composition of Batch normalization, ReLU and 3×3 convolution.

$$H_\ell(M) = \text{Conv}_{3\times3}(ReLU(BN(M))), \ell \in \{0, 1, \ldots, L-1\}.$$

CNN - DenseNet

Batch Norm Operation

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.

Ref: S. Ioffe and C. Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. http://arxiv.org/abs/1502.03167

CNN - DenseNet

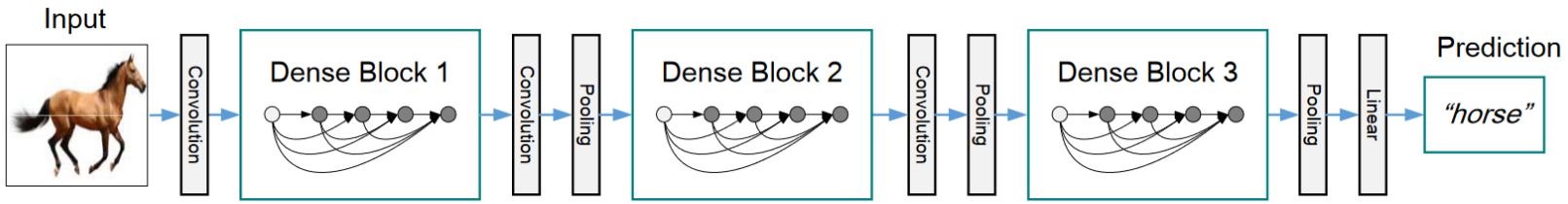

Figure : A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

- The densely connected layers are grouped to form **dense blocks**.
- The convolution and pooling layers between the dense blocks are called **transition layers**.
- At transition layers, the following operations are done:

$$H_{\text{trans}}(M) = \text{AvgPool}_{2\times 2}(\text{Conv}_{1\times 1}(BN(M)))$$

CNN - DenseNet

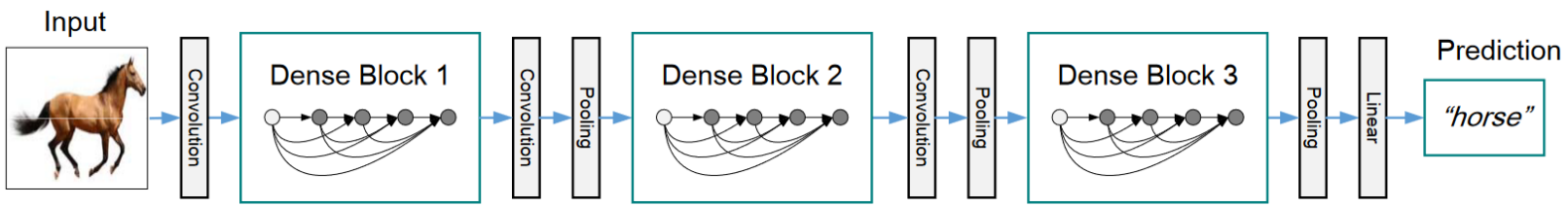

Figure : A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

- If each layer in dense block outputs k feature maps, then the input to the ℓ-th layer in the dense block is $k_0 + k * (\ell - 1)$.
- k_0 is the number of channels at the input layer.
- Thus the number of feature maps at each layer in a dense block is controlled by a factor k called the growth rate.
- k can typically be a small number. (e.g. $k = 12$)

CNN - DenseNet

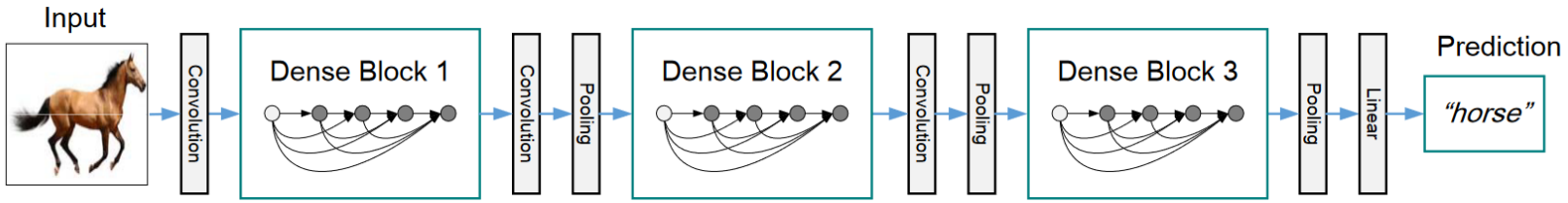

Figure : A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

Other heuristics:

- In DenseNet-B, H_ℓ a bottleneck layer of 1×1 convolution precedes the 3×3 convolution:

$$H_\ell(M) = \text{Conv}_{3\times3}(\text{Conv}_{1\times1}(ReLU(BN(M))))$$

CNN - DenseNet

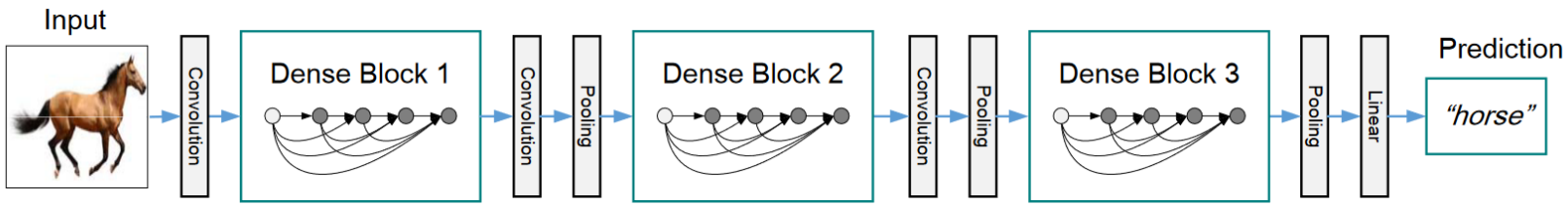

Figure : A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

Other heuristics:

- Compression introduced at transition layer where only $\lfloor \theta m \rfloor, \theta \in (0, 1]$ to pass on only a fraction of total m feature maps produced at the dense block.

CNN - DenseNet

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112 × 112	7 × 7 conv, stride 2			
Pooling	56 × 56	3 × 3 max pool, stride 2			
Dense Block (1)	56 × 56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56 × 56	1 × 1 conv			
	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28 × 28	1 × 1 conv			
	14 × 14	2 × 2 average pool, stride 2			
Dense Block (3)	14 × 14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14 × 14	1 × 1 conv			
	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1 × 1	7 × 7 global average pool			
		1000D fully-connected, softmax			

Table : DenseNet architectures for ImageNet. The growth rate for all the networks is $k = 32$. Note that each "conv" layer shown in the table corresponds the sequence BN-ReLU-Conv.

CNN - DenseNet

Method	Depth	Params	C10	C10+	C100	C100+	SVHN
Network in Network [22]	-	-	10.41	8.81	35.68	-	2.35
All-CNN [32]	-	-	9.08	7.25	-	33.71	-
Deeply Supervised Net [20]	-	-	9.69	7.97	-	34.57	1.92
Highway Network [34]	-	-	-	7.72	-	32.39	-
FractalNet [17]	21	38.6M	10.18	5.22	35.34	23.30	2.01
with Dropout/Drop-path	21	38.6M	7.33	4.60	28.20	23.73	1.87
ResNet [11]	110	1.7M	-	6.61	-	-	-
ResNet (reported by [13])	110	1.7M	13.63	6.41	44.74	27.22	2.01
ResNet with Stochastic Depth [13]	110	1.7M	11.66	5.23	37.80	24.58	1.75
	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	-	-	-	-	1.64
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	1.79
DenseNet ($k = 12$)	100	7.0M	**5.77**	**4.10**	**23.79**	**20.20**	1.67
DenseNet ($k = 24$)	100	27.2M	**5.83**	**3.74**	**23.42**	**19.25**	**1.59**
DenseNet-BC ($k = 12$)	100	0.8M	**5.92**	4.51	**24.15**	22.27	1.76
DenseNet-BC ($k = 24$)	250	15.3M	**5.19**	**3.62**	**19.64**	**17.60**	1.74
DenseNet-BC ($k = 40$)	190	25.6M	-	**3.46**	-	**17.18**	-

Table : Error rates (%) on CIFAR and SVHN datasets. k denotes network's growth rate. Results that surpass all competing methods are **bold** and the overall best results are **blue**. "+" indicates standard data augmentation (translation and/or mirroring). $*$ indicates results run by ourselves. All the results of DenseNets without data augmentation (C10, C100, SVHN) are obtained using Dropout. DenseNets achieve lower error rates while using fewer parameters than ResNet. Without data augmentation, DenseNet performs better by a large margin.

CNN - EfficientNet

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Mingxing Tan Quoc V. Le

CNN - EfficientNet

- A layer i in a CNN can be written as:

$$Y_i = F_i(X_{i_{\langle H_i, W_i, C_i \rangle}})$$

  where F_i is the operation on an input feature map X_i of dimensions $H_i \times W_i \times C_i$ to get the output feature map Y_i.
- **Note:** X_i and Y_i are tensors.
- Hence a CNN $\mathcal{N}$ can be written as:

$$\mathcal{N} = F_k(F_{k-1}(\ldots F_2(F_1(X_1))\ldots)).$$

CNN - EfficientNet

- A layer i in a CNN can be written as:

$$Y_i = F_i(X_{i_{\langle H_i, W_i, C_i \rangle}})$$

  where F_i is the operation on an input feature map X_i of dimensions $H_i \times W_i \times C_i$ to get the output feature map Y_i.

- (H_i, W_i) is called **resolution**.
- C_i (number of channels) is called **width**.
- If an operation F_i is possibly repeated L_i times, L_i is called **network length** or **depth**.

CNN - EfficientNet

We will use an equivalent notation to write the CNN $\mathcal{N}$:

$$\begin{aligned}\mathcal{N} &= F^{L_k}_{k\langle H_k, W_k, C_k\rangle} \odot F^{L_{k-1}}_{k-1\langle H_{k-1}, W_{k-1}, C_{k-1}\rangle} \odot \ldots \odot F^{L_1}_{1\langle H_1, W_1, C_1\rangle} \\ &= \bigodot_{j=1,2,\ldots,k} F^{L_j}_{j\langle H_j, W_j, C_j\rangle}.\end{aligned}$$

CNN - EfficientNet

Optimization problem:

$$\max_{d,w,r} \quad Accuracy(\mathcal{N}(d,w,r))$$

$$s.t. \quad \mathcal{N}(d,w,r) = \bigodot_{i=1\ldots s} \hat{\mathcal{F}}_i^{d\cdot\hat{L}_i}{}_{\langle r\cdot\hat{H}_i, r\cdot\hat{W}_i, w\cdot\hat{C}_i\rangle}$$

$$\text{Memory}(\mathcal{N}) \leq \text{target\_memory}$$

$$\text{FLOPS}(\mathcal{N}) \leq \text{target\_flops}$$

CNN - EfficientNet

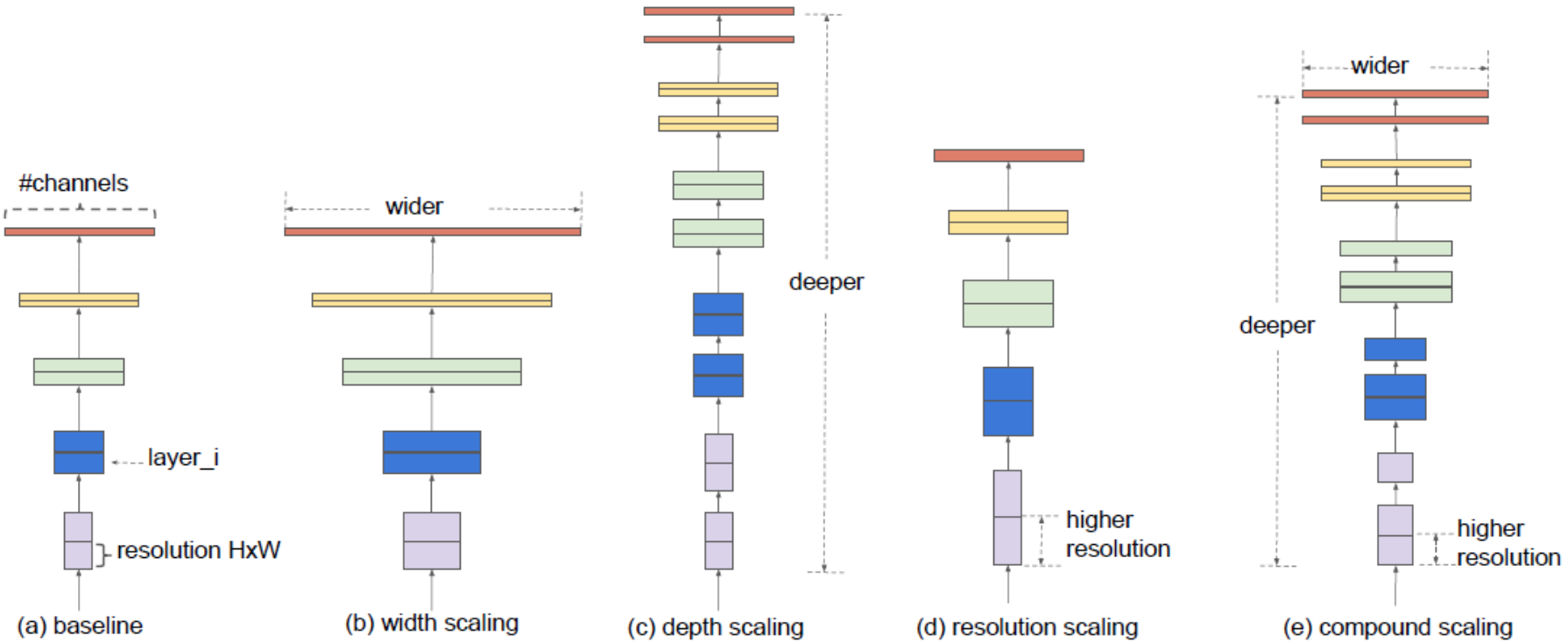

Figure . **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

CNN - EfficientNet

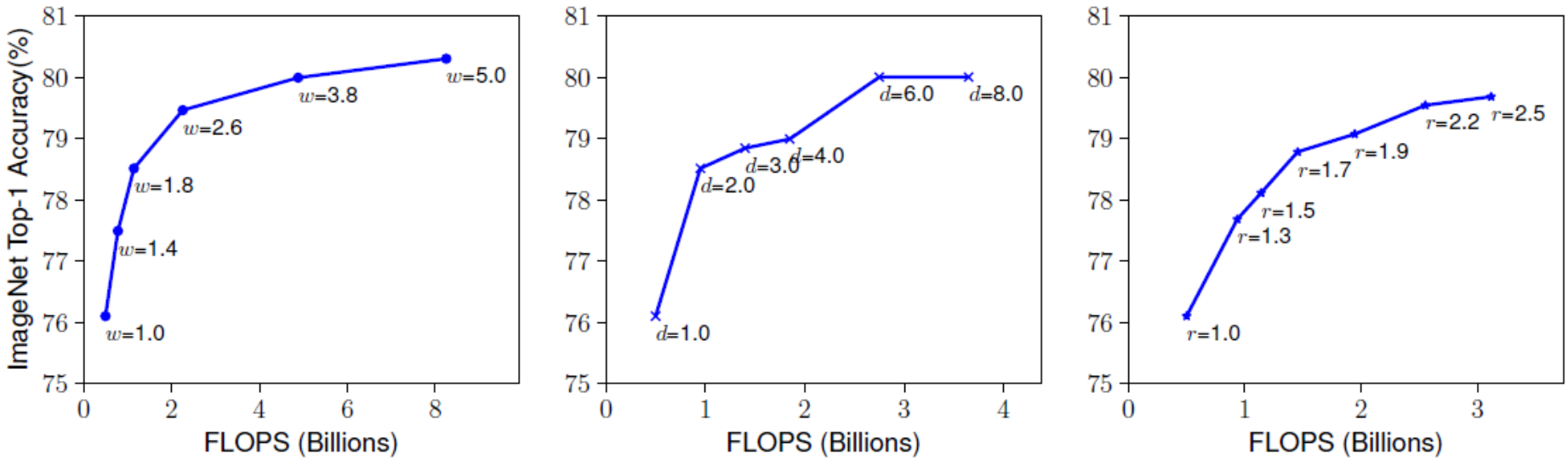

Figure . **Scaling Up a Baseline Model with Different Network Width (w), Depth (d), and Resolution (r) Coefficients.** Bigger networks with larger width, depth, or resolution tend to achieve higher accuracy, but the accuracy gain quickly saturate after reaching 80%, demonstrating the limitation of single dimension scaling.

CNN - EfficientNet

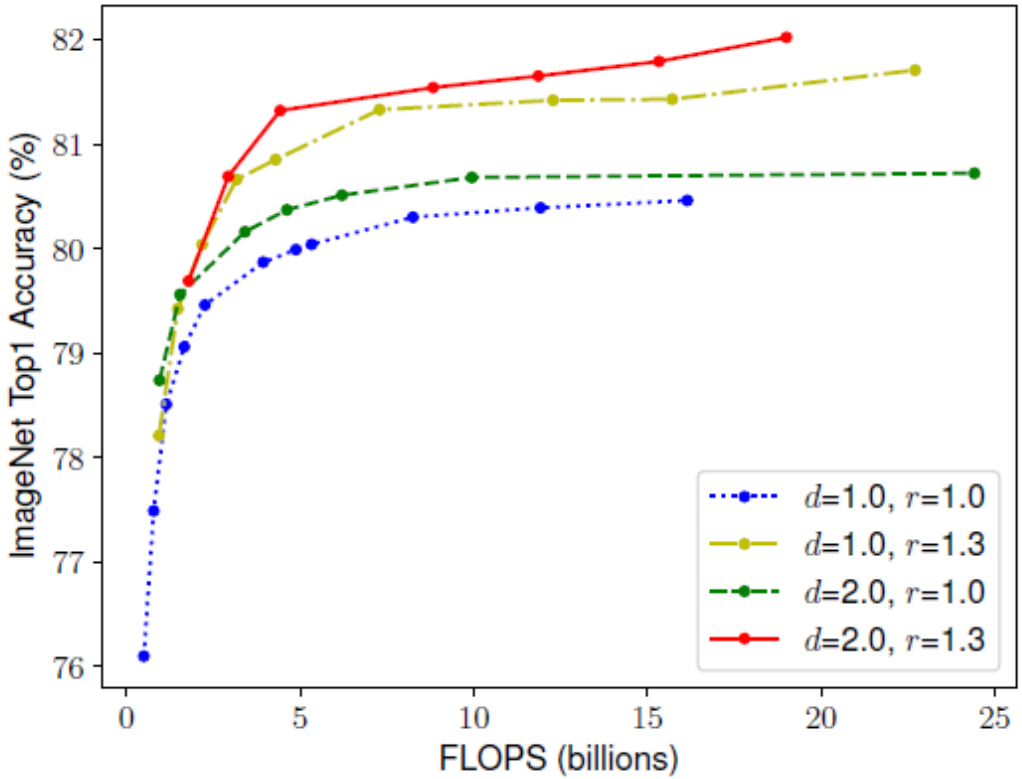

Figure. **Scaling Network Width for Different Baseline Networks**. Each dot in a line denotes a model with different width coefficient (w). The first baseline network (d=1.0, r=1.0) has 18 convolutional layers with resolution 224x224, while the last baseline (d=2.0, r=1.3) has 36 layers with resolution 299x299.

CNN - EfficientNet

- **Optimization problem:**

$$\max_{d,w,r} \quad Accuracy(\mathcal{N}(d,w,r))$$

$$s.t. \quad \mathcal{N}(d,w,r) = \bigodot_{i=1\ldots s} \hat{\mathcal{F}}_i^{d\cdot\hat{L}_i}{}_{\langle r\cdot\hat{H}_i, r\cdot\hat{W}_i, w\cdot\hat{C}_i\rangle}$$

$$\text{Memory}(\mathcal{N}) \leq \text{target\_memory}$$

$$\text{FLOPS}(\mathcal{N}) \leq \text{target\_flops}$$

- **Parameter selection:**

$$\text{depth: } d = \alpha^\phi$$

$$\text{width: } w = \beta^\phi$$

$$\text{resolution: } r = \gamma^\phi$$

$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

CNN - EfficientNet

Parameter selection procedure:

- STEP 1: we first fix $\phi = 1$, assuming twice more resources available, and do a small grid search of α, β, γ In particular, we find the best values for EfficientNet-B0 are $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$, under constraint of $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$.
- STEP 2: we then fix α, β, γ as constants and scale up baseline network with different ϕ to obtain EfficientNet-B1 to B7

CNN - EfficientNet

Table . **EfficientNet Performance Results on ImageNet** (Russakovsky et al., 2015). All EfficientNet models are scaled from our baseline EfficientNet-B0 using different compound coefficient ϕ . ConvNets with similar top-1/top-5 accuracy are grouped together for efficiency comparison. Our scaled EfficientNet models consistently reduce parameters and FLOPS by an order of magnitude (up to 8.4x parameter reduction and up to 16x FLOPS reduction) than existing ConvNets.

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	**77.1%**	**93.3%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**79.1%**	**94.4%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**80.1%**	**94.9%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.6%**	**95.7%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**82.9%**	**96.4%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.6%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.0%**	**96.8%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.3%**	**97.0%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

R-CNN (Fast version)

Fast R-CNN

Ross Girshick
Microsoft Research

R-CNN (Fast version)

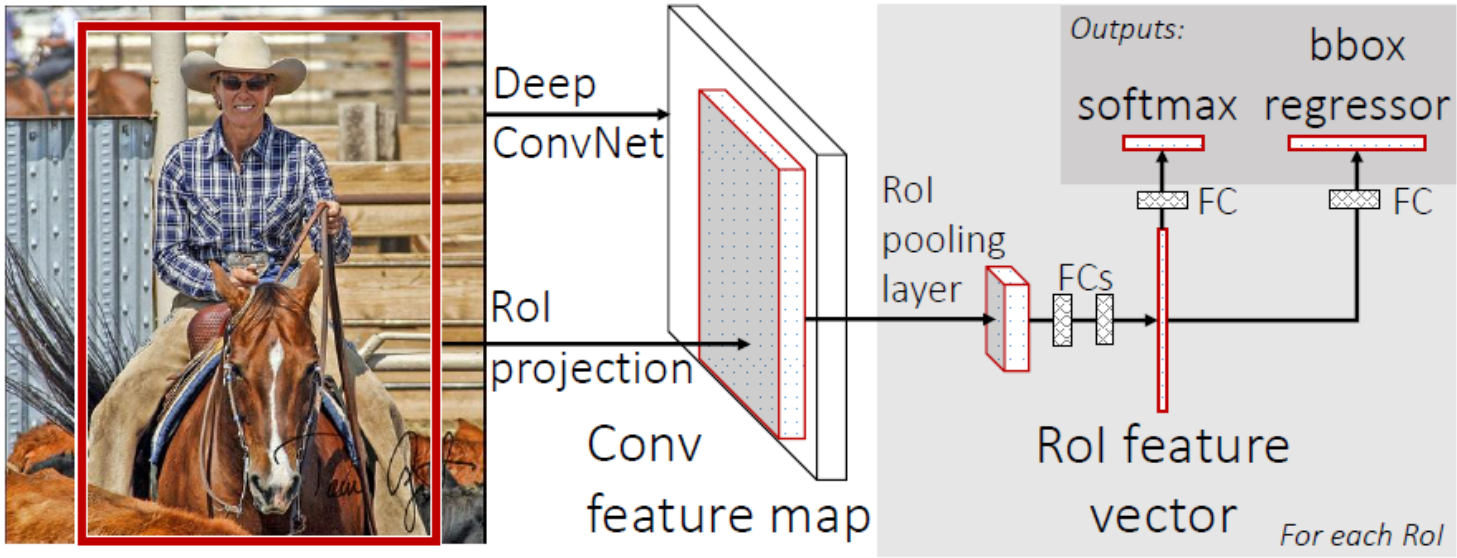

Figure 1. Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets. The architecture is trained end-to-end with a multi-task loss.

R-CNN (Fast version)

- The whole image is first processed by deep convolution networks to produce a conv feature map.
- For each Region of Interest (RoI) proposal, a RoI pooling layer extracts a fixed length feature vector from the feature map.
- Each such feature vector is then fed into sequence of fully connected layers with two output layers.
- The two output layers correspond to object detection and region of interest prediction

R-CNN (Fast version)

- RoI is quantified using (r, c, h, w) where (r, c) represent the top left corner and h, w represent the height and width of regions
- Conv feature map can be constructed from any pre-trained network like Alex Net, VGG Net, etc.

R-CNN (Fast version)

- Two Output Layers:
  - Predict the object class
  - Predict the RoI box
- Loss functions?

R-CNN (Fast version)

- Loss functions
  - $L_{objclass} = L(O_p, O_t)$
  - O_p, O_t represent the predicted class and true class
  - Cross-entropy used for $L_{objclass}$
  - $L_{RoIBox} = L((r_p, c_p, h_p, w_p), (r_t, c_t, h_t, w_t))$
  - (r_p, c_p, h_p, w_p), (r_t, c_t, h_t, w_t) represent predicted and true RoI parameters.
  - Smooth L1 loss used for L_{RoIBox}

$$L_{RoIBox} = L1_{sm}(r_p - r_t) + L1_{sm}(c_p - c_t) + L1_{sm}(h_p - h_t) + L1_{sm}(w_p - w_t)$$

$$L1_{sm}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{else.} \end{cases}$$

- Total Loss: $L = L_{objclass} + \lambda L_{RoIBox}$
- Guess on λ value used?

R-CNN (Fast version)

- Mini-batch SGD used for training
- Testing: Multiple RoI should be sampled and the network is used for predicting the confidence scores and RoI predictions relative to each sampled RoI.

R-CNN (Fast version)

method	train set	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	persn	plant	sheep	sofa	train	tv	mAP
SPPnet BB [11]†	07 \ diff	73.9	72.3	62.5	51.5	44.4	74.4	73.0	74.4	42.3	73.6	57.7	70.3	74.6	74.3	54.2	34.0	56.4	56.4	67.9	73.5	63.1
R-CNN BB [10]	07	73.4	77.0	63.4	45.4	**44.6**	75.1	78.1	79.8	40.5	73.7	62.2	79.4	78.1	73.1	64.2	**35.6**	66.8	67.2	70.4	**71.1**	66.0
FRCN [ours]	07	74.5	78.3	69.2	53.2	36.6	77.3	78.2	82.0	40.7	72.7	67.9	79.6	79.2	73.0	69.0	30.1	65.4	70.2	75.8	65.8	66.9
FRCN [ours]	07 \ diff	74.6	**79.0**	68.6	57.0	39.3	79.5	**78.6**	81.9	**48.0**	74.0	67.4	80.5	80.7	74.1	69.6	31.8	67.1	68.4	75.3	65.5	68.1
FRCN [ours]	07+12	**77.0**	78.1	**69.3**	**59.4**	38.3	**81.6**	**78.6**	**86.7**	42.8	**78.8**	**68.9**	**84.7**	**82.0**	**76.6**	**69.9**	31.8	**70.1**	**74.8**	**80.4**	70.4	**70.0**

Table 1. **VOC 2007 test** detection average precision (%). All methods use VGG16. Training set key: **07**: VOC07 trainval, **07 \ diff**: **07** without "difficult" examples, **07+12**: union of **07** and VOC12 trainval. †SPPnet results were prepared by the authors of [11].

method	train set	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	persn	plant	sheep	sofa	train	tv	mAP
BabyLearning	Prop.	77.7	73.8	62.3	48.8	45.4	67.3	67.0	80.3	41.3	70.8	49.7	79.5	74.7	78.6	64.5	36.0	69.9	55.7	70.4	61.7	63.8
R-CNN BB [10]	12	79.3	72.4	63.1	44.0	44.4	64.6	66.3	84.9	38.8	67.3	48.4	82.3	75.0	76.7	65.7	35.8	66.2	54.8	69.1	58.8	62.9
SegDeepM	12+seg	**82.3**	75.2	67.1	50.7	**49.8**	71.1	69.6	88.2	42.5	71.2	50.0	85.7	76.6	81.8	69.3	**41.5**	**71.9**	62.2	73.2	**64.6**	67.2
FRCN [ours]	12	80.1	74.4	67.7	49.4	41.4	74.2	68.8	87.8	41.9	70.1	50.2	86.1	77.3	81.1	70.4	33.3	67.0	63.3	77.2	60.0	66.1
FRCN [ours]	07++12	82.0	**77.8**	**71.6**	**55.3**	42.4	**77.3**	**71.7**	**89.3**	**44.5**	**72.1**	**53.7**	**87.7**	**80.0**	**82.5**	**72.7**	36.6	68.7	**65.4**	**81.1**	62.7	**68.8**

Table 2. **VOC 2010 test** detection average precision (%). BabyLearning uses a network based on [17]. All other methods use VGG16. Training set key: **12**: VOC12 trainval, **Prop.**: proprietary dataset, **12+seg**: **12** with segmentation annotations, **07++12**: union of VOC07 trainval, VOC07 test, and VOC12 trainval.

method	train set	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	persn	plant	sheep	sofa	train	tv	mAP
BabyLearning	Prop.	78.0	74.2	61.3	45.7	42.7	68.2	66.8	80.2	40.6	70.0	49.8	79.0	74.5	77.9	64.0	35.3	67.9	55.7	68.7	62.6	63.2
NUS_NIN_c2000	Unk.	80.2	73.8	61.9	43.7	**43.0**	70.3	67.6	80.7	41.9	69.7	51.7	78.2	75.2	76.9	65.1	**38.6**	**68.3**	58.0	68.7	63.3	63.8
R-CNN BB [10]	12	79.6	72.7	61.9	41.2	41.9	65.9	66.4	84.6	38.5	67.2	46.7	82.0	74.8	76.0	65.2	35.6	65.4	54.2	67.4	60.3	62.4
FRCN [ours]	12	80.3	74.7	66.9	46.9	37.7	73.9	68.6	87.7	41.7	71.1	51.1	86.0	77.8	79.8	69.8	32.1	65.5	63.8	76.4	61.7	65.7
FRCN [ours]	07++12	**82.3**	**78.4**	**70.8**	**52.3**	38.7	**77.8**	**71.6**	**89.3**	**44.2**	**73.0**	**55.0**	**87.5**	**80.5**	**80.8**	**72.0**	35.1	**68.3**	**65.7**	**80.4**	**64.2**	**68.4**

Table 3. **VOC 2012 test** detection average precision (%). BabyLearning and NUS_NIN_c2000 use networks based on [17]. All other methods use VGG16. Training set key: see Table 2, **Unk.**: unknown.

R-CNN (Faster version)

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

Shaoqing Ren* **Kaiming He** **Ross Girshick** **Jian Sun**

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{v-shren, kahe, rbg, jiansun}@microsoft.com

R-CNN (Faster version)

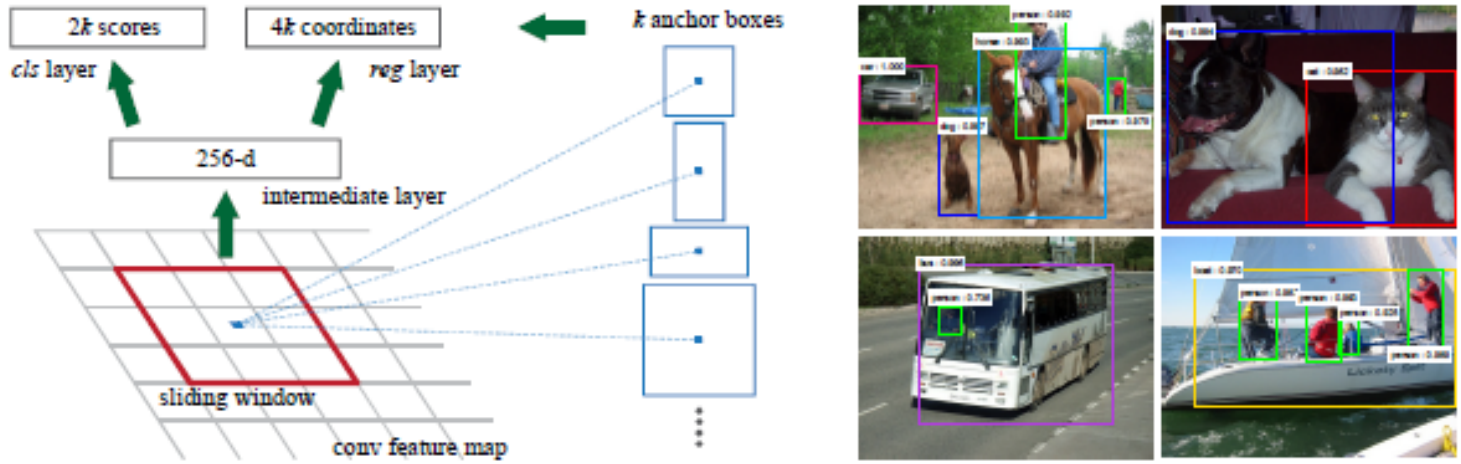


Figure 1: **Left**: Region Proposal Network (RPN). **Right**: Example detections using RPN proposals on PASCAL VOC 2007 test. Our method detects objects in a wide range of scales and aspect ratios.

R-CNN (Faster version)

- Proposed Region Proposal Networks (RPN)
- Essentially similar to fast R-CNN
- Anchors used in training which overlap with the true RoI boxes
- This leads to some form of robustness in prediction
- Weight sharing between RPNs and Fast R-CNNs employed

R-CNN (Faster version)

Table 1: Detection results on **PASCAL VOC 2007 test set** (trained on VOC 2007 trainval). The detectors are Fast R-CNN with ZF, but using various proposal methods for training and testing.

train-time region proposals		**test-time region proposals**		
method	# boxes	method	# proposals	mAP (%)
SS	2k	SS	2k	58.7
EB	2k	EB	2k	58.6
RPN+ZF, shared	2k	RPN+ZF, shared	300	**59.9**

R-CNN (Faster version)

Table 2: Detection results on **PASCAL VOC 2007 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07+12": union set of VOC 2007 trainval and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2k. †: this was reported in [5]; using the repository provided by this paper, this number is higher (68.0±0.3 in six runs).

method	# proposals	data	mAP (%)	time (ms)
SS	2k	07	66.9†	1830
SS	2k	07+12	70.0	1830
RPN+VGG, unshared	300	07	68.5	342
RPN+VGG, shared	300	07	69.9	**198**
RPN+VGG, shared	300	07+12	**73.2**	**198**

Table 3: Detection results on **PASCAL VOC 2012 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07++12": union set of VOC 2007 trainval+test and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2k. †: `http://host.robots.ox.ac.uk:8080/anonymous/HZJTQA.html`. ‡: `http://host.robots.ox.ac.uk:8080/anonymous/YNPLXB.html`

method	# proposals	data	mAP (%)
SS	2k	12	65.7
SS	2k	07++12	68.4
RPN+VGG, shared†	300	12	67.0
RPN+VGG, shared‡	300	07++12	**70.4**

More CNN architectures...

3D CNN

3D Convolutional Neural Networks for Human Action Recognition

Shuiwang Ji, Wei Xu, Ming Yang, *Member*, *IEEE*, and Kai Yu, *Member*, *IEEE*

3D CNN

Figure: Video as sequence of image frames†

† https://www.cctvsg.net/frame-rate/

3D CNN

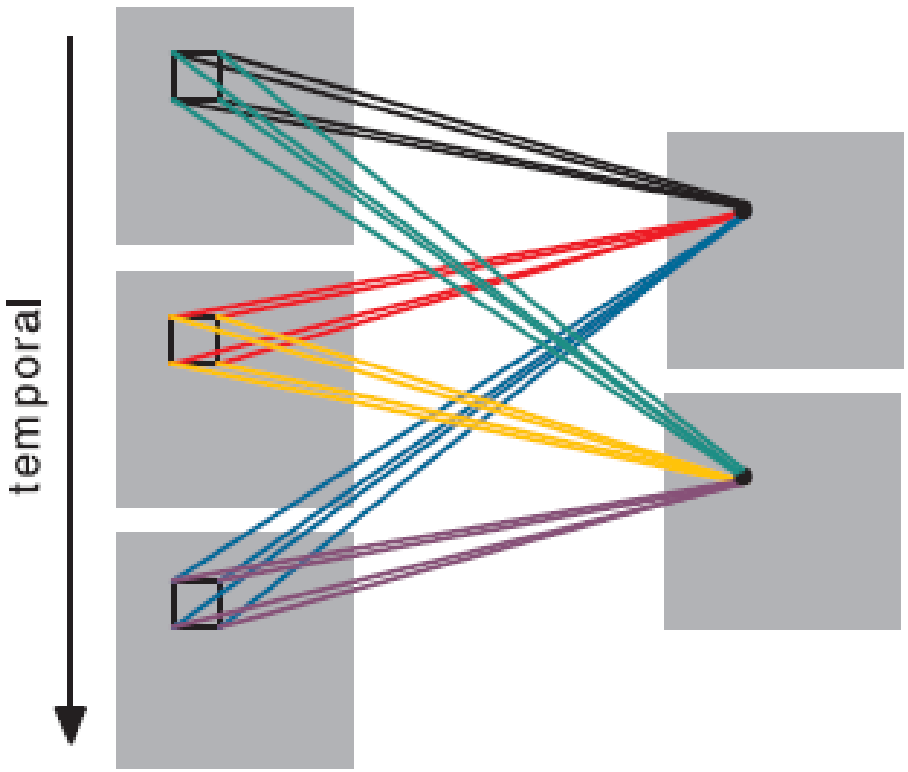


Fig. 2. Extraction of multiple features from contiguous frames. Multiple 3D convolutions can be applied to contiguous frames to extract multiple features. As in Fig. 1, the sets of connections are color-coded so that the shared weights are in the same color. Note that all six sets of connections do not share weights, resulting in two different feature maps on the right.

3D CNN

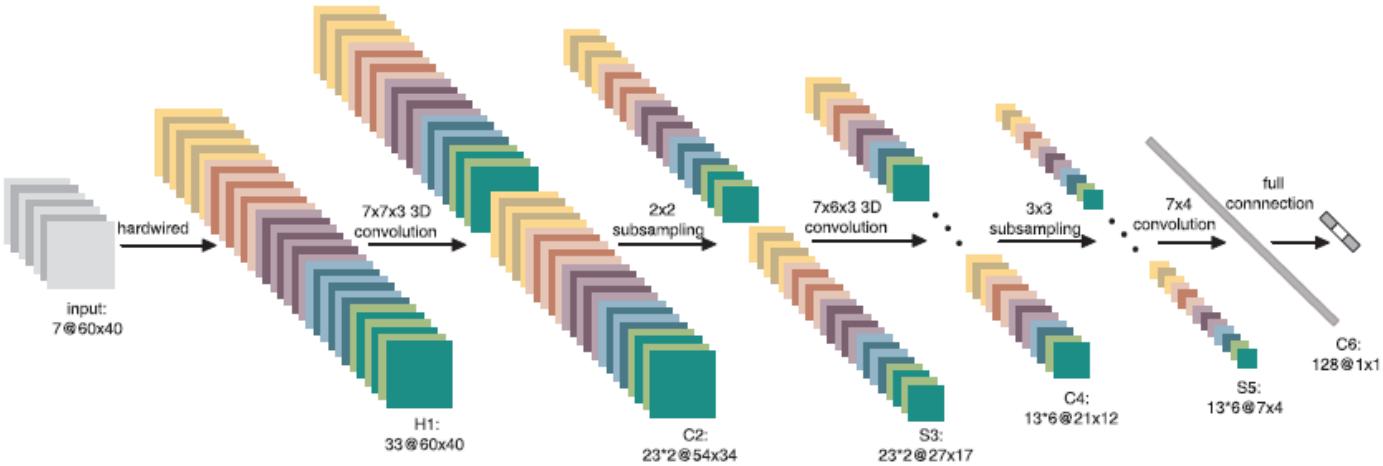


Fig. 3. A 3D CNN architecture for human action recognition. This architecture consists of one hardwired layer, three convolution layers, two subsampling layers, and one full connection layer. Detailed descriptions are given in the text.

3D CNN

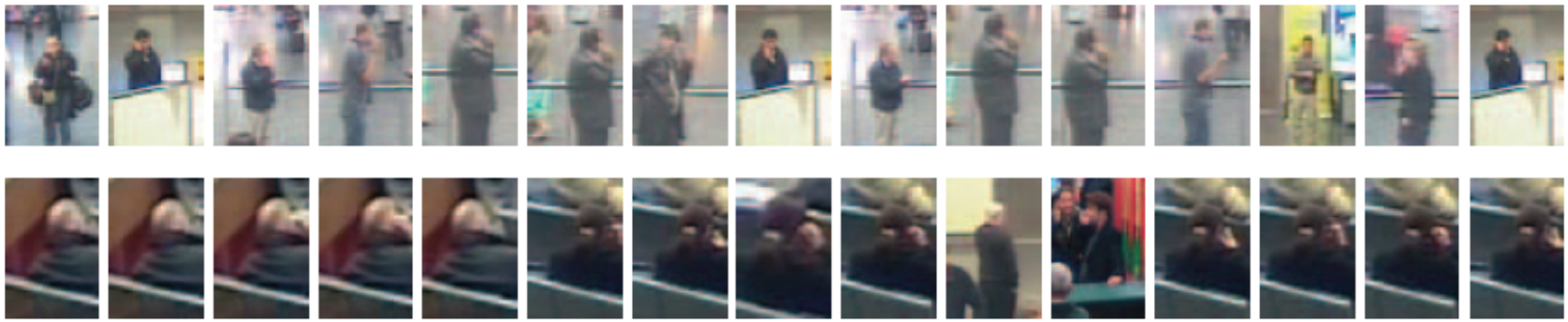


Fig. 10. Sample actions in the CellToEar class. The top row shows actions that are correctly recognized by the combined 3D CNN model, while the bottom row shows those that are misclassified by the model.

3D CNN

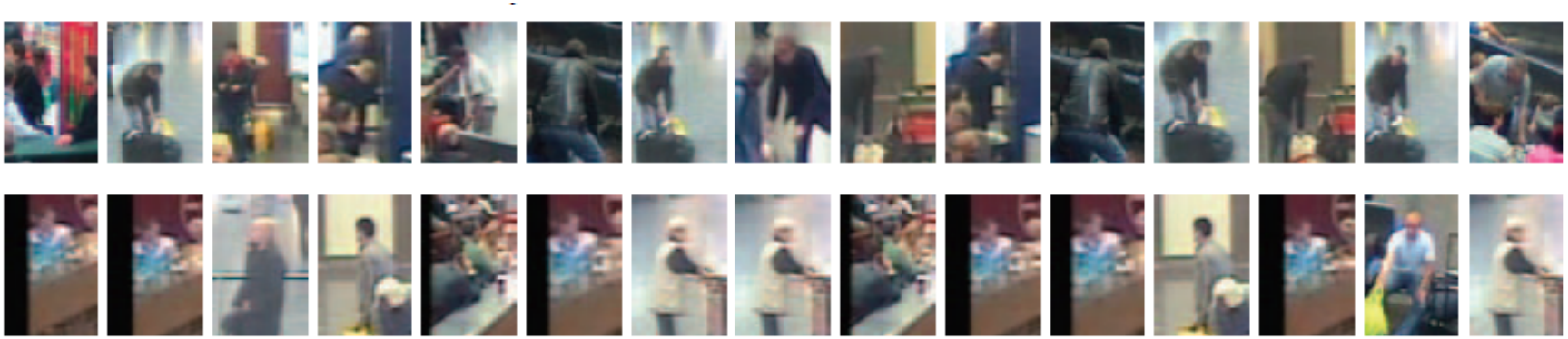


Fig. 11. Sample actions in the ObjectPut class. The top row shows actions that are correctly recognized by the combined 3D CNN model, while the bottom row shows those that are misclassified by the model.

3D CNN

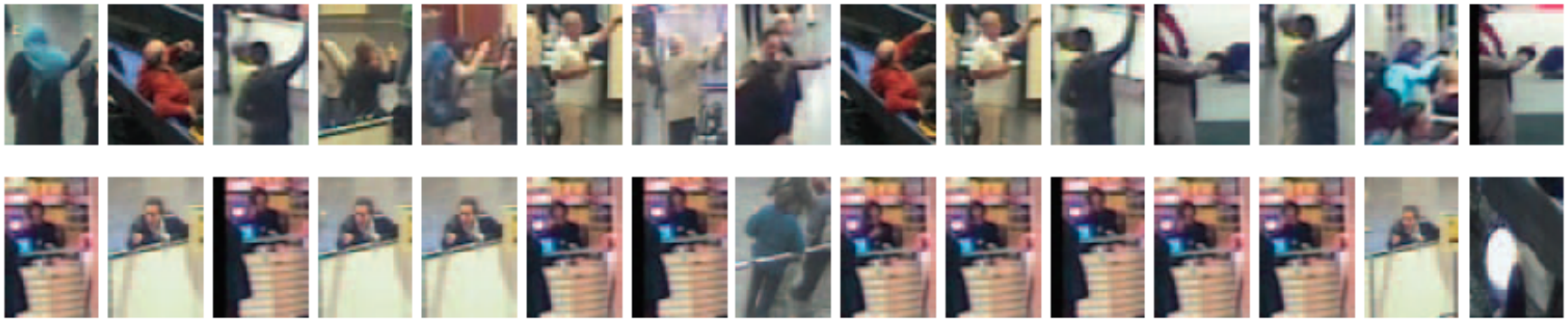


Fig. 12. Sample actions in the Pointing class. The top row shows actions that are correctly recognized by the combined 3D CNN model, while the bottom row shows those that are misclassified by the model.

CNN for 3D Modeling

Render for CNN: Viewpoint Estimation in Images Using CNNs Trained with Rendered 3D Model Views

Hao Su*, Charles R. Qi*, Yangyan Li, Leonidas J. Guibas
Stanford University

CNN for 3D Modeling

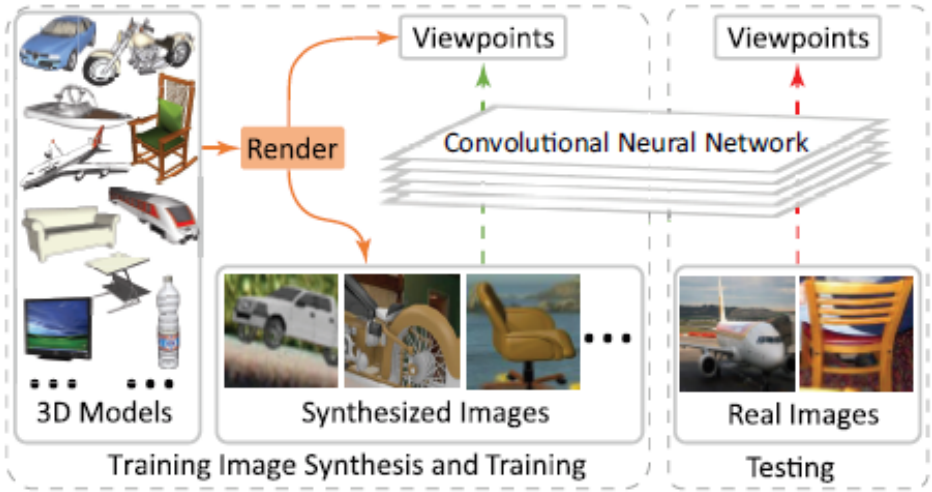


Figure 1. **System overview.** We synthesize training images by overlaying images rendered from large 3D model collections on top of real images. CNN is trained to map images to the ground truth object viewpoints. The training data is a combination of real images and synthesized images. The learned CNN is applied to estimate the viewpoints of objects in real images. Project homepage is at https://shapenet.cs.stanford.edu/projects/RenderForCNN

CNN for 3D Modeling

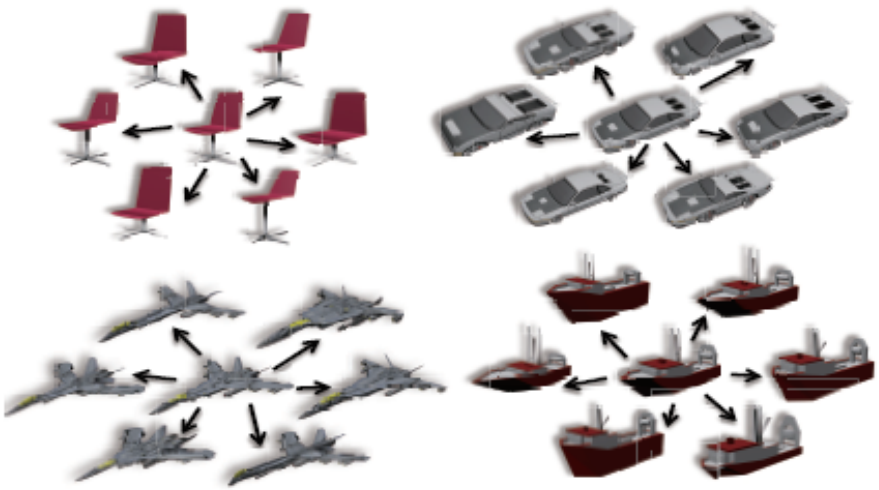


Figure 2. **3D model set augmentation by symmetry-preserving deformation.**

CNN for 3D Modeling

Figure 3. **Synthetic image examples.** Three example images are shown for each of the 12 classes from PASCAL 3D+.

CNN for 3D Modeling

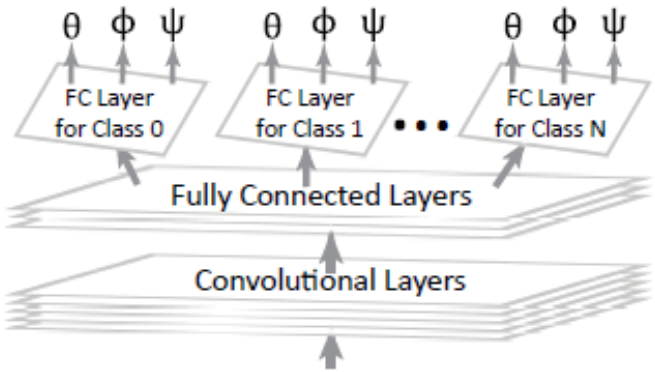


Figure 4. **Network architecture**[2]. Our network includes shared feature layers and class-dependent viewpoint estimation layers.

CNN for 3D Modeling

- Goal: To predict the viewpoint of an object in an image
- Viewpoint is with respect to the camera
- Viewpoint characterized by three parameters (θ, ϕ, ψ) denoting the azimuth, elevation and in-plane rotation angles.
- Opensource ShapeNet† used

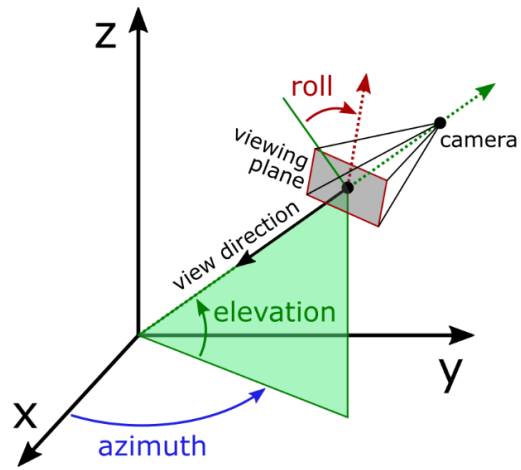


Figure: Azimuth, elevation and roll of camera viewpoint.‡

† https://www.shapenet.org/

‡ https://matplotlib.org/stable/api/toolkits/mplot3d/view_angles.html

CNN for 3D Modeling

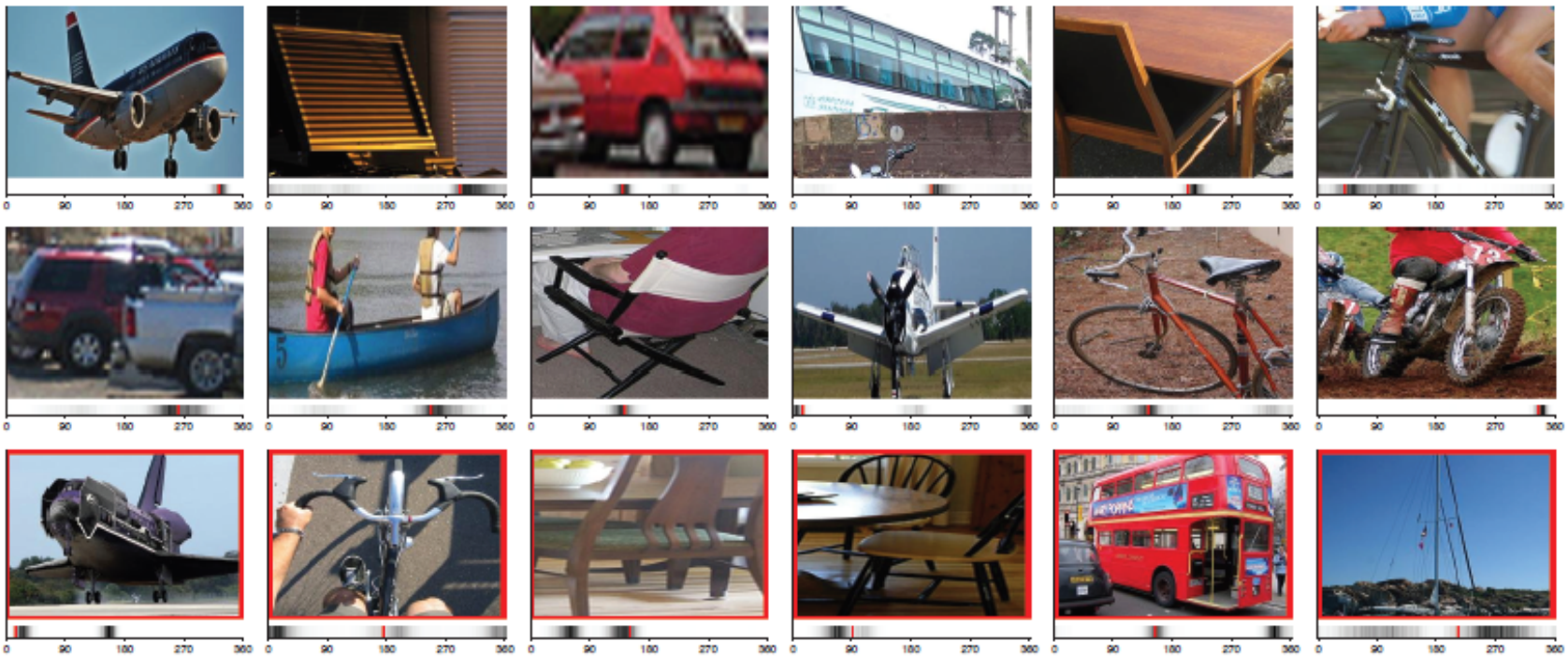


Figure 10. **Viewpoint estimation example results.** The bar under each image indicates the 360-class confidences (black means high confidence) corresponding to $0^\circ \sim 360^\circ$ (with object facing towards us as 0° and rotating clockwise). The red vertical bar indicates the ground truth. The first two rows are positive cases, the third row is negative case (with red box surrounding the image).

Left Ventricle Segmentation

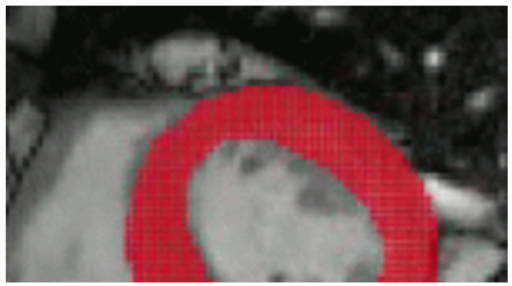
Cardiac Atlas Project

Studies Challenges Resources Publications

LEFT VENTRICULAR SEGMENTATION CHALLENGE

Establishing ground truth consensus segmentation images from automated methods

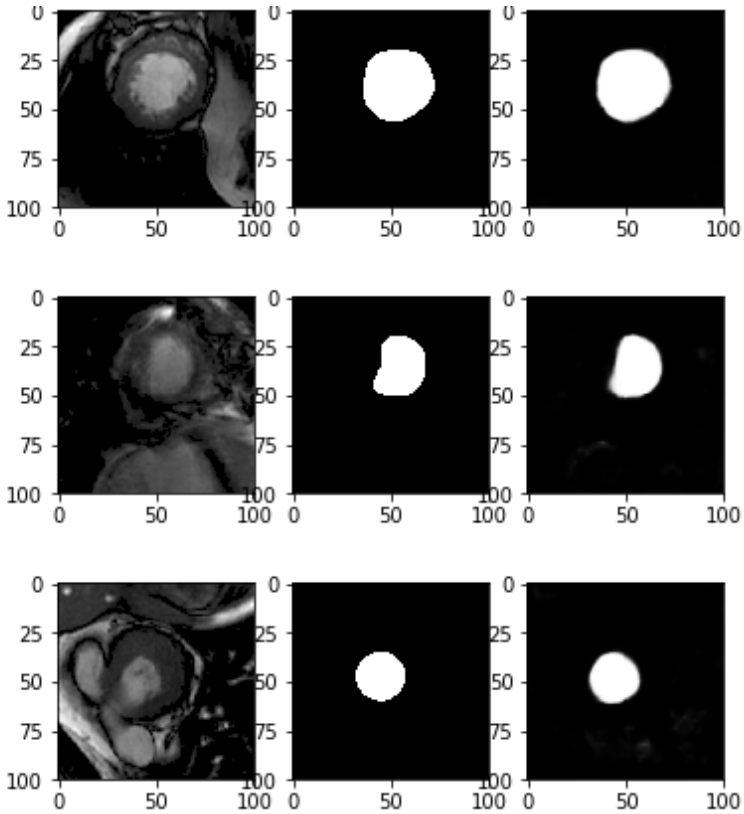
About



One major challenge for developing a 4D segmentation algorithm is the lack of available large set of ground truth that are defined for the whole cardiac frames and slices. Initiated from the 2011 LV Segmentation Challenge that was held for the 2011 STACOM Workshop, we have started up a larger collaborative project to establish the ground truth or the consensus segmentation images for myocardium. The segmentation challenge is therefore set to open for new algorithms to participate. We aim to establish consensus segmentation images from a large set of data. We used modified STAPLE method to generate the consensus images from the contributing participants (raters). However, before the consensus images can be robustly established, we need a lot of participants, which are semi or fully automated segmentation methods. The more people join this work, the better the consensus images. Everybody can participate in this work, particularly for students and researchers in the field of fully automatic

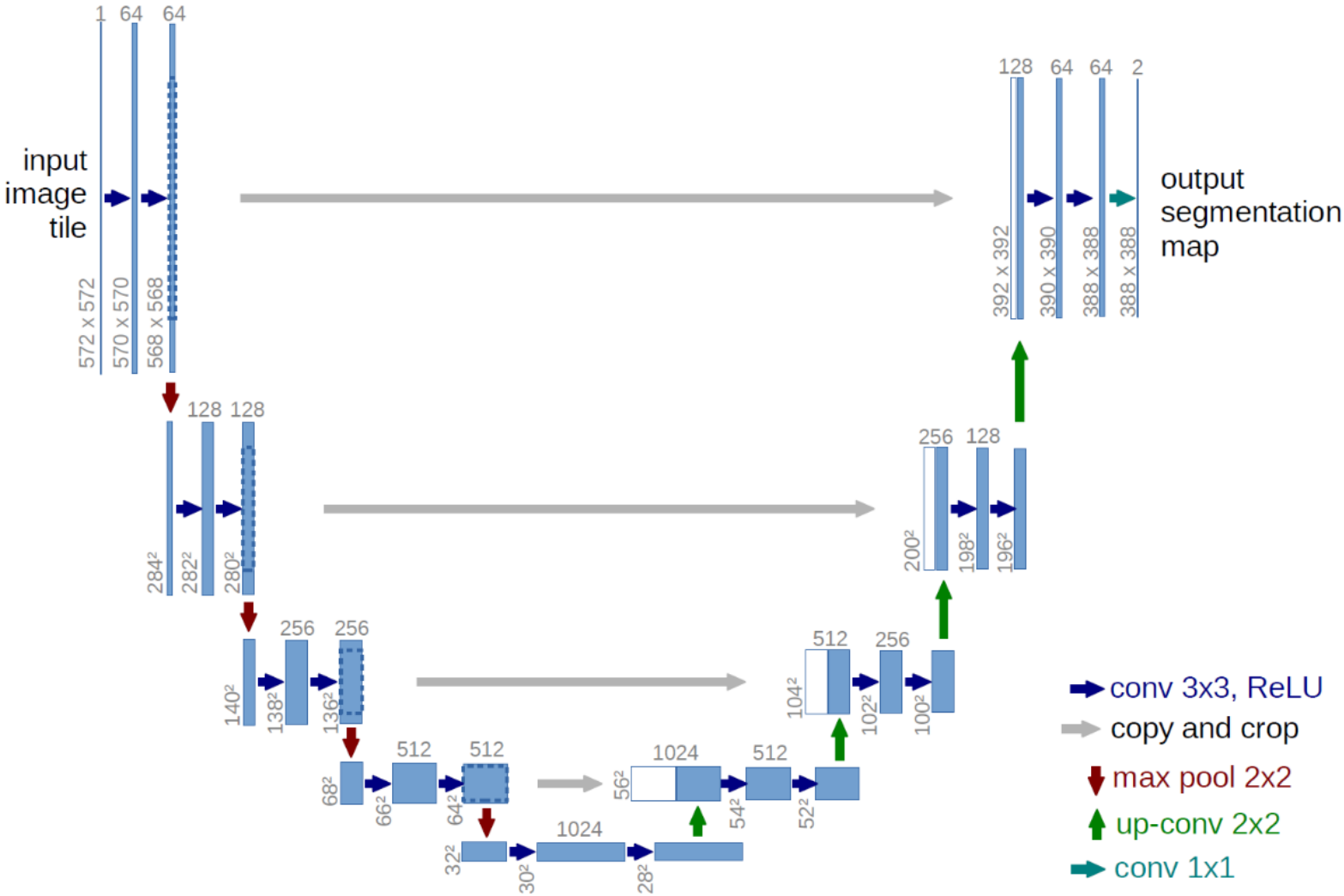
http://www.cardiacatlas.org/challenges/lv-segmentation-challenge/

Left Ventricle Segmentation



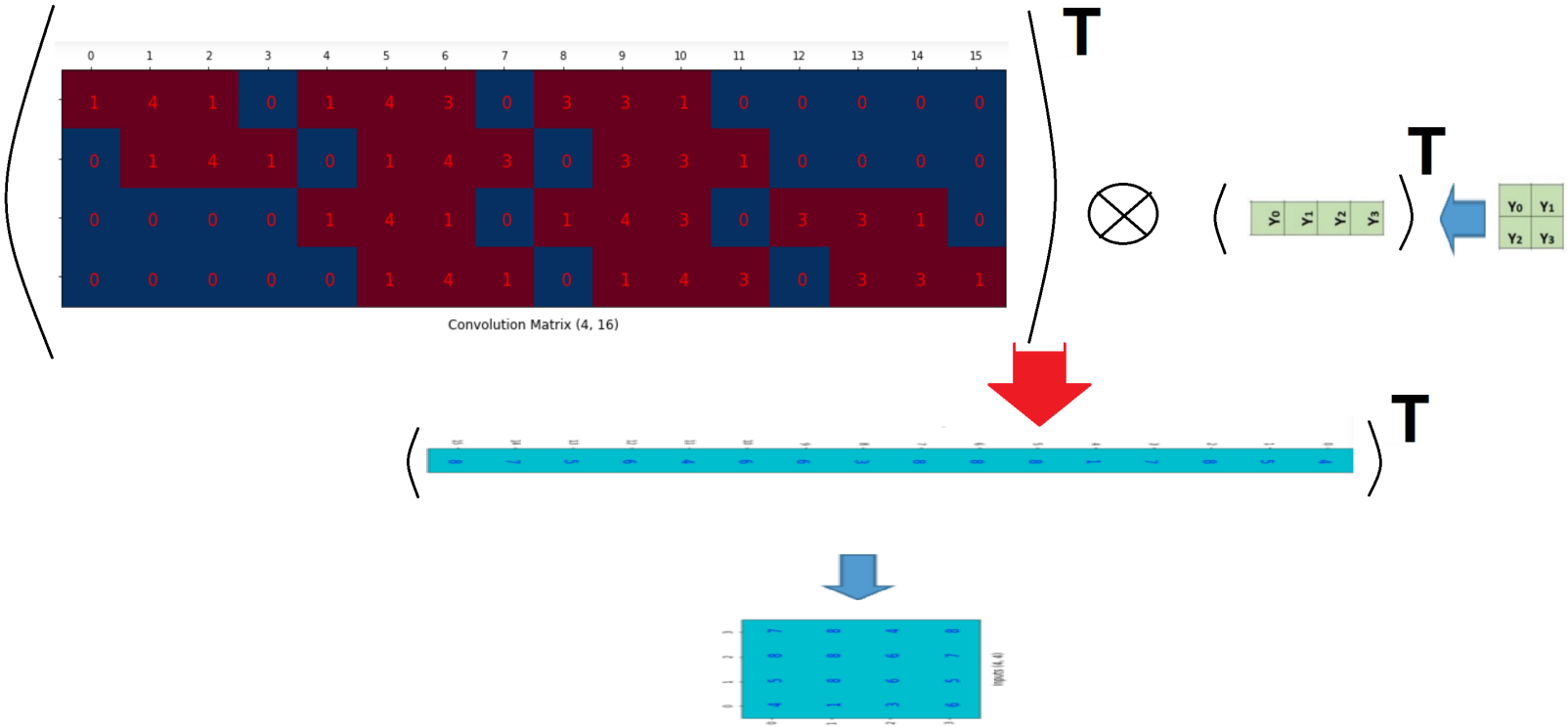
Ventricle of Human Heart	Mask indicating ventricle location	Predicted Mask

U-Net†



† U-Net: Convolutional Networks for Biomedical Image Segmentation. O. Ronneberger, P. Fischer, T. Brox. MICCAI, 2015.

U-Net: Upsampling



Upsampling operation (or Transpose Convolution)
Source: medium.com. towardsdatascience.com