NEURAL NETWORK ARCHITECTURES

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Megvii Technology

Outline

- CNN review
- General idea
- Architecture design
- Neural architecture search (NAS)

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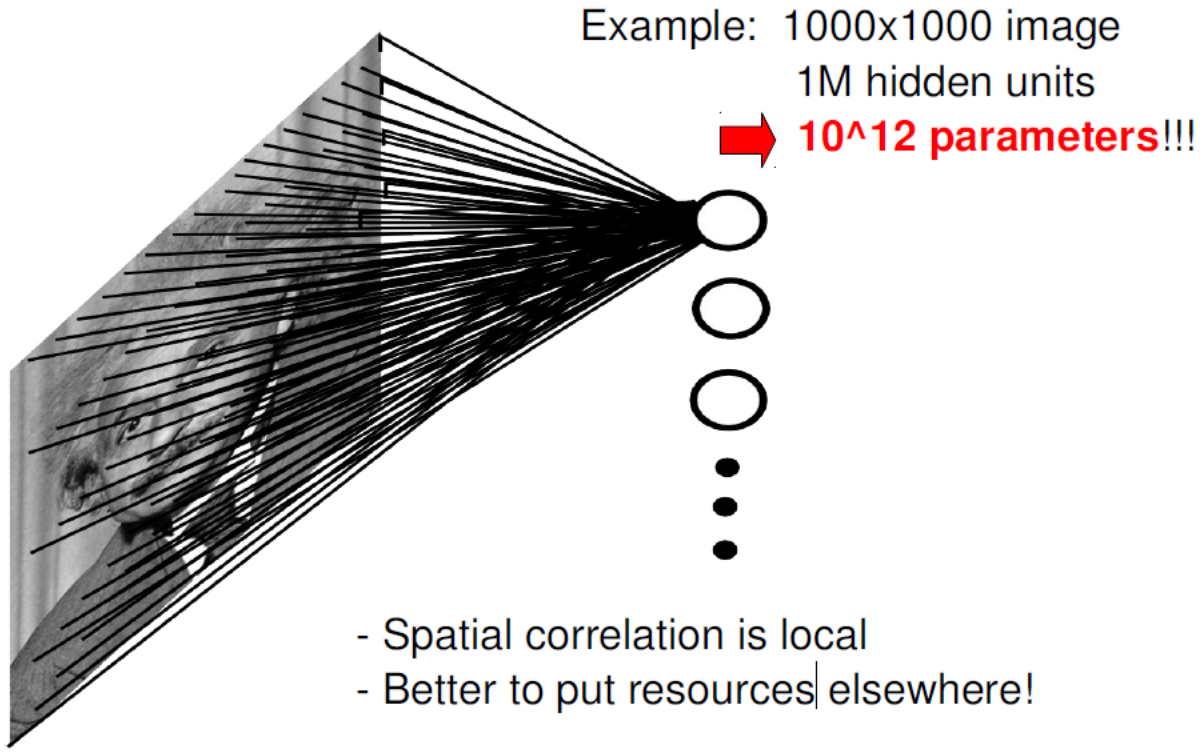
Deep Neural Networks on Images

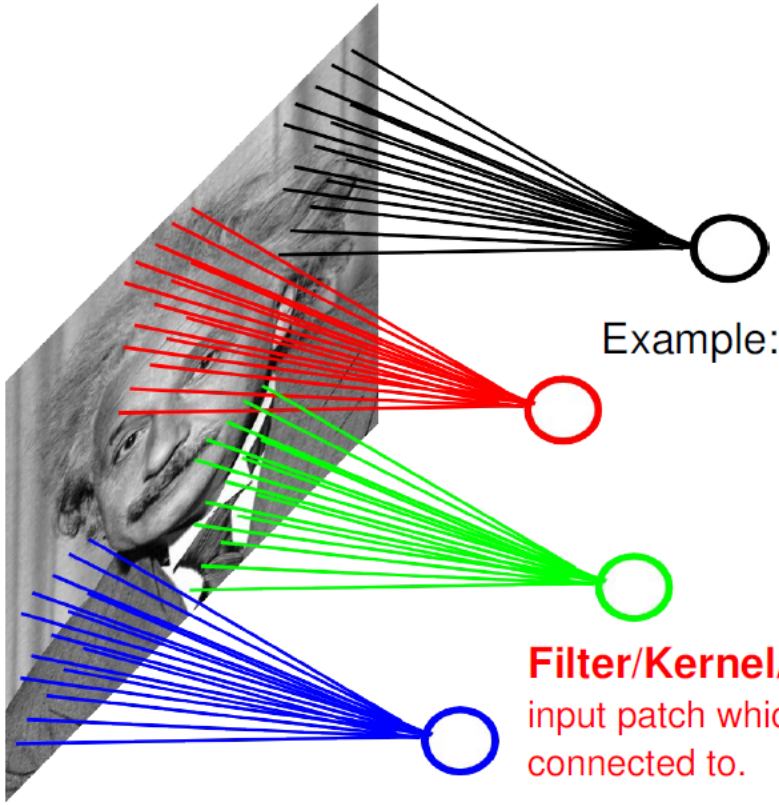
- How to apply a neural network on 2D or 3D inputs?

Fully-connected Net



Locally-connected Net

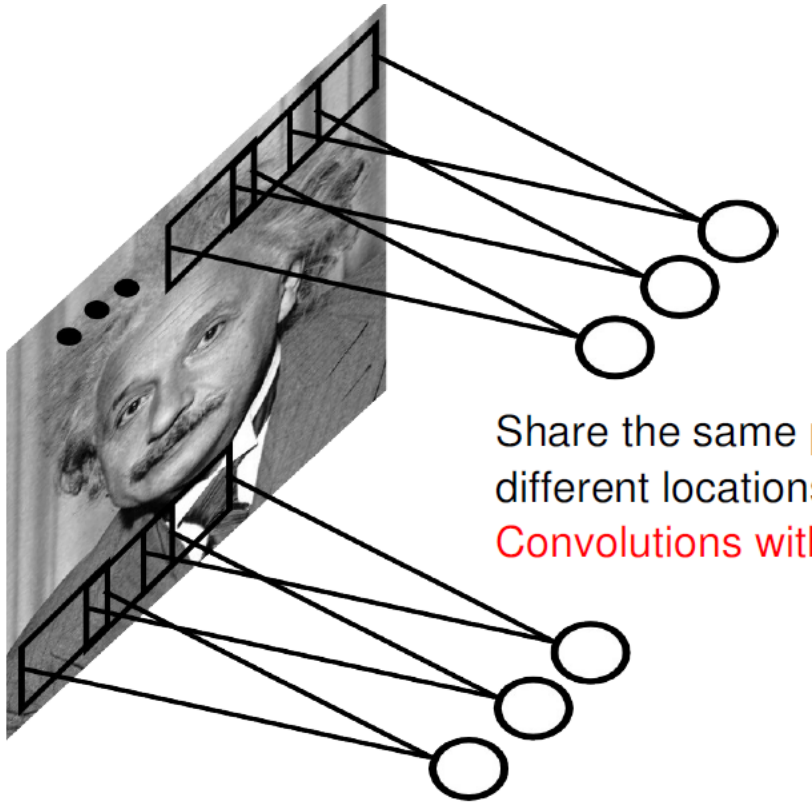
STATIONARITY?
Statistics are similar at different locations (translation invariance)



Example: 1000x1000 image
1M hidden units
Filter size: 10x10
100M parameters

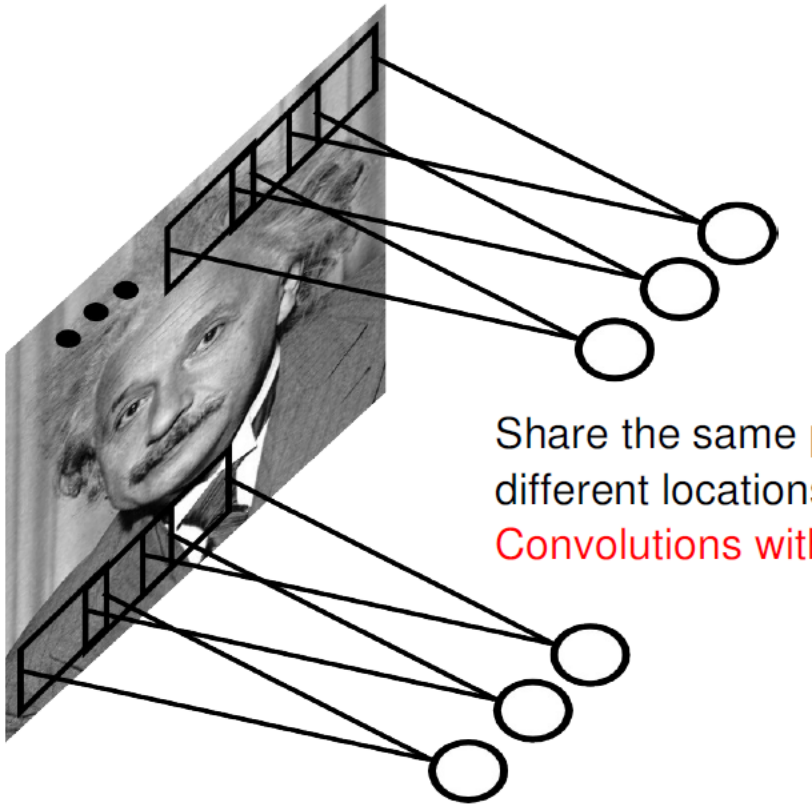
Filter/Kernel/Receptive field:
input patch which the hidden unit is connected to.

Convolutional Net



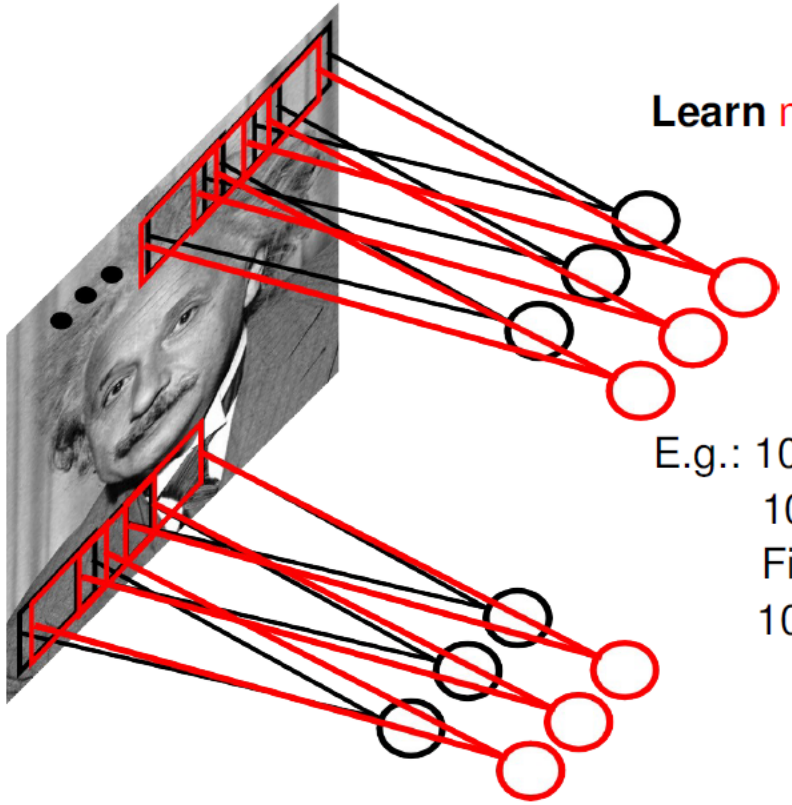
Share the same parameters across different locations:
Convolutions with learned kernels

Convolutional Net (cont'd)



Share the same parameters across different locations:
Convolutions with learned kernels

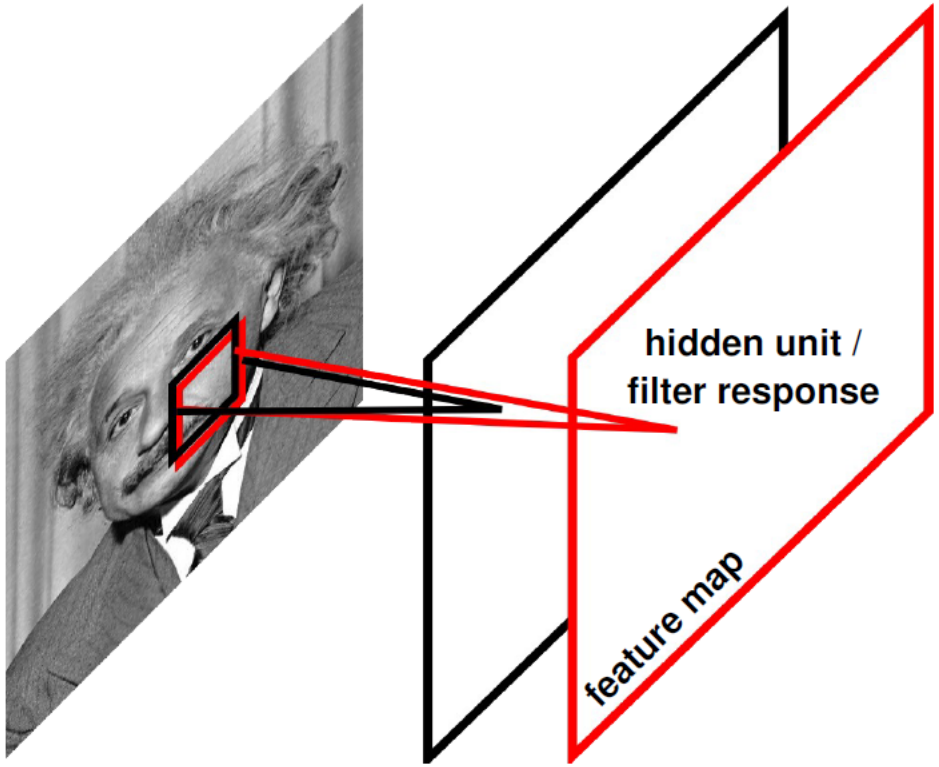
Convolutional Net (cont'd)



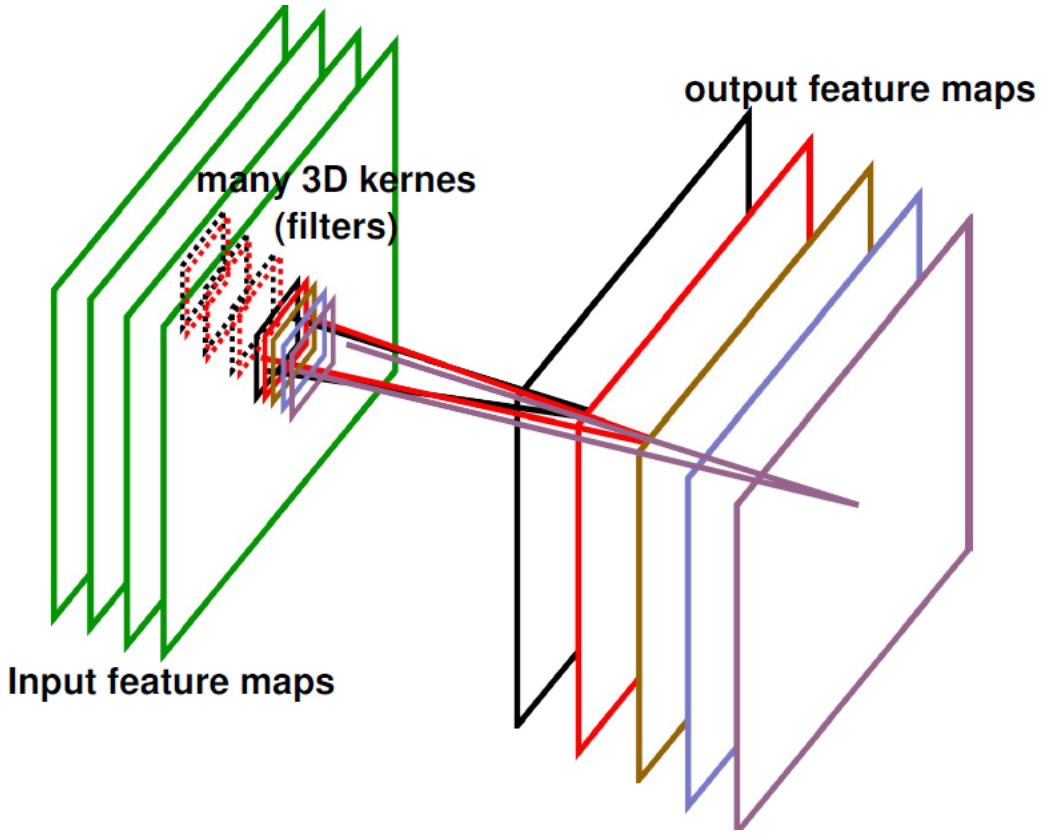
Learn multiple filters.

E.g.: 1000x1000 image
100 Filters
Filter size: 10x10
10K parameters

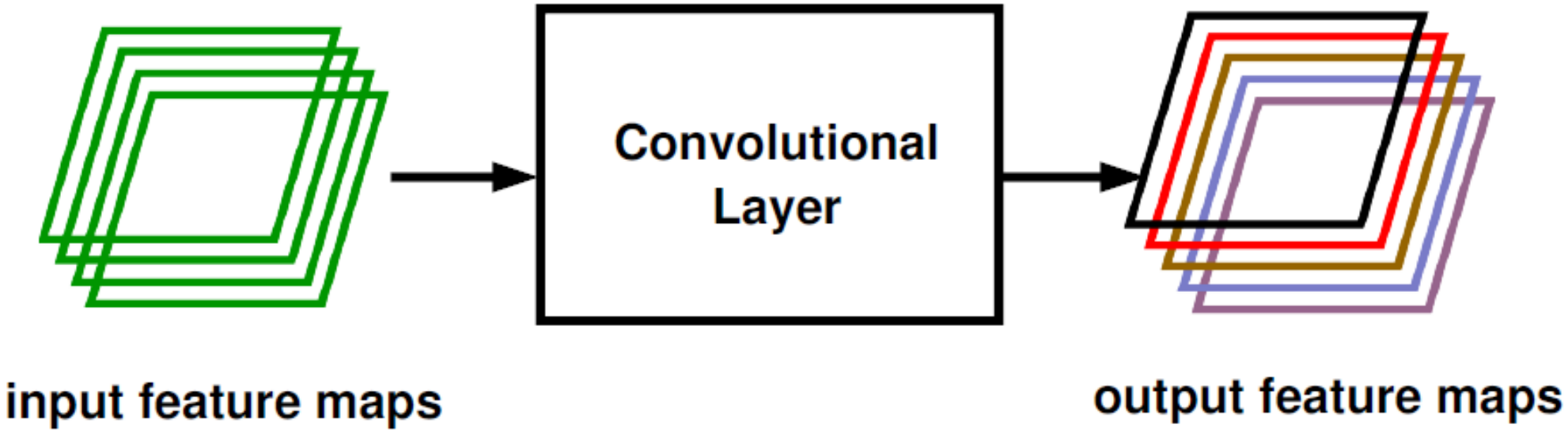
Convolutional Net (cont'd)



Convolutional Layer



Convolutional Layer (cont'd)



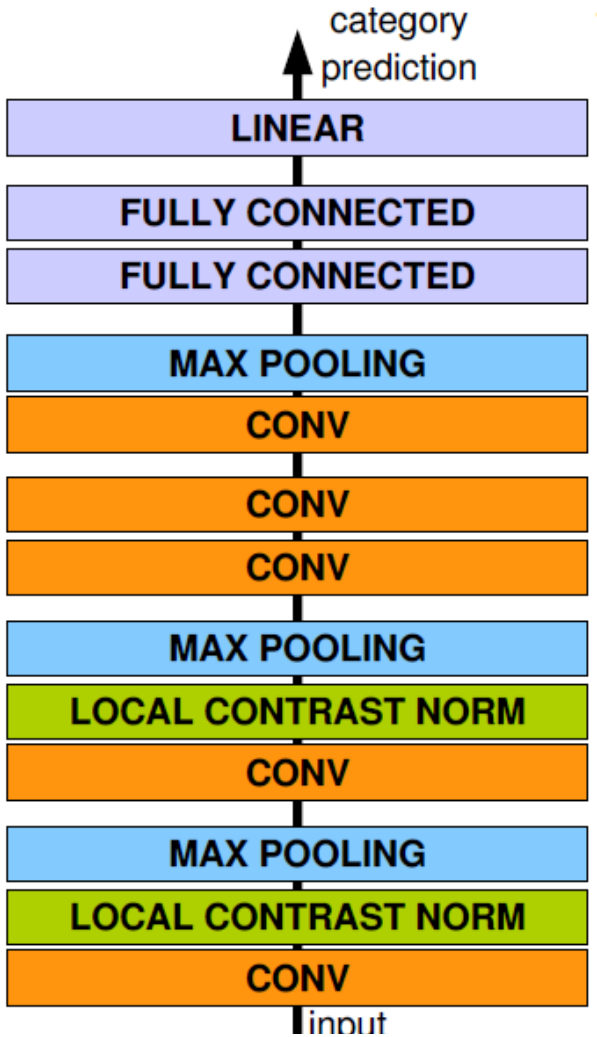
Summary: Key Ideas of Convolutional Nets

- A standard neural net applied to images:
  - *scales quadratically with the size of the input*
  - *does not leverage stationarity*

- Solution:
  - *connect each hidden unit to a small patch of the input*
  - *share the weight across hidden units*

- This is called: convolutional network.

Conv Architecture Example (AlexNet)



Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012

Outline

- CNN review
- General idea
- Architecture design
- Neural architecture search (NAS)

Architecture Design

- What?
  - *Network topology*
  - *Layer functions*
  - *Hyper-parameters*
  - *Optimization algorithms*

  ...
- Why?
  - *Difficult to determine the optimal structures*
  - *Requirements of different applications, datasets or limitations*

Architecture Design (cont'd)

- How?
  - *Manually*
  - *Automatically*

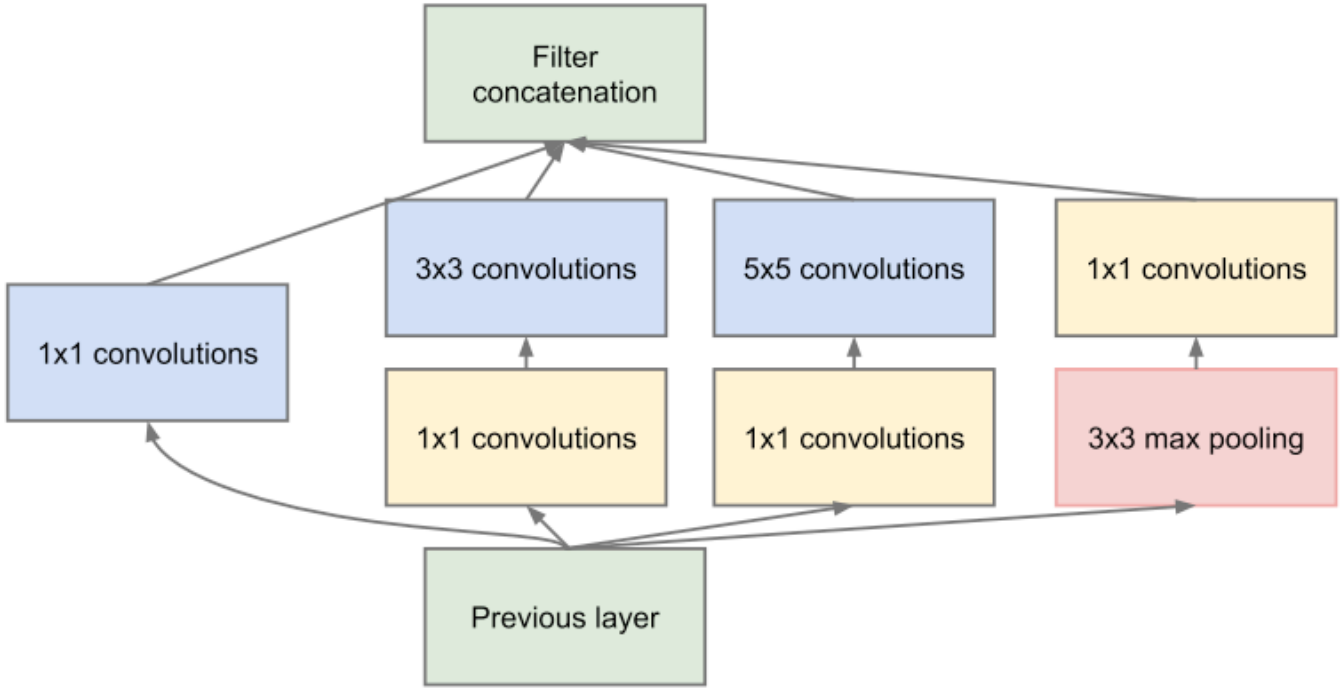
- Objective
  - *Representation capability*
  - *Robustness, anti-overfitting*
  - *Computation or parameter efficiency*
  - *Ease of optimization*
  - *…*

Outline

- CNN review
- General idea
- Architecture design
  - *Tensor decomposition*
  - *Channel operations*
  - *Spatial operations*
  - *Skip connections*
  - *Attention blocks*
  - *Normalization*
  - *Inference efficiency*
  - *Training*
  - *Bilinear feature*
- Neural architecture search

Tensor Decomposition

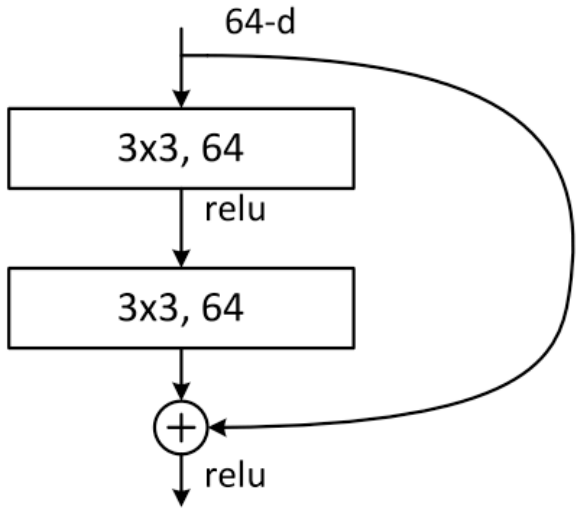
- 1x1 + KxK
  - *GoogleNet*

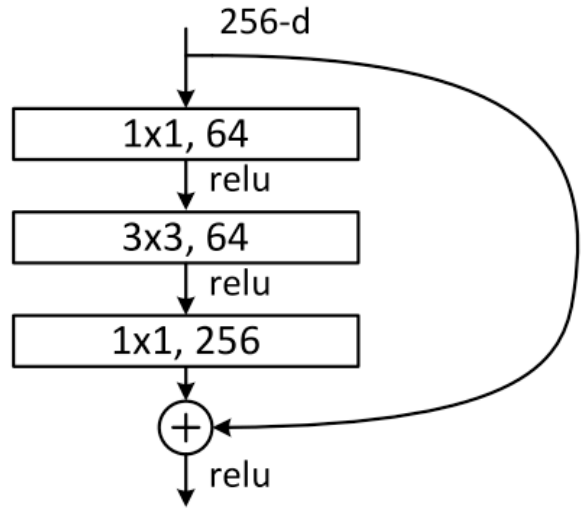


Szegedy, Christian, et al. "Going deeper with convolutions." Cvpr, 2015.

Tensor Decomposition

- 1x1 + KxK + 1x1
  - *Bottlenecks*

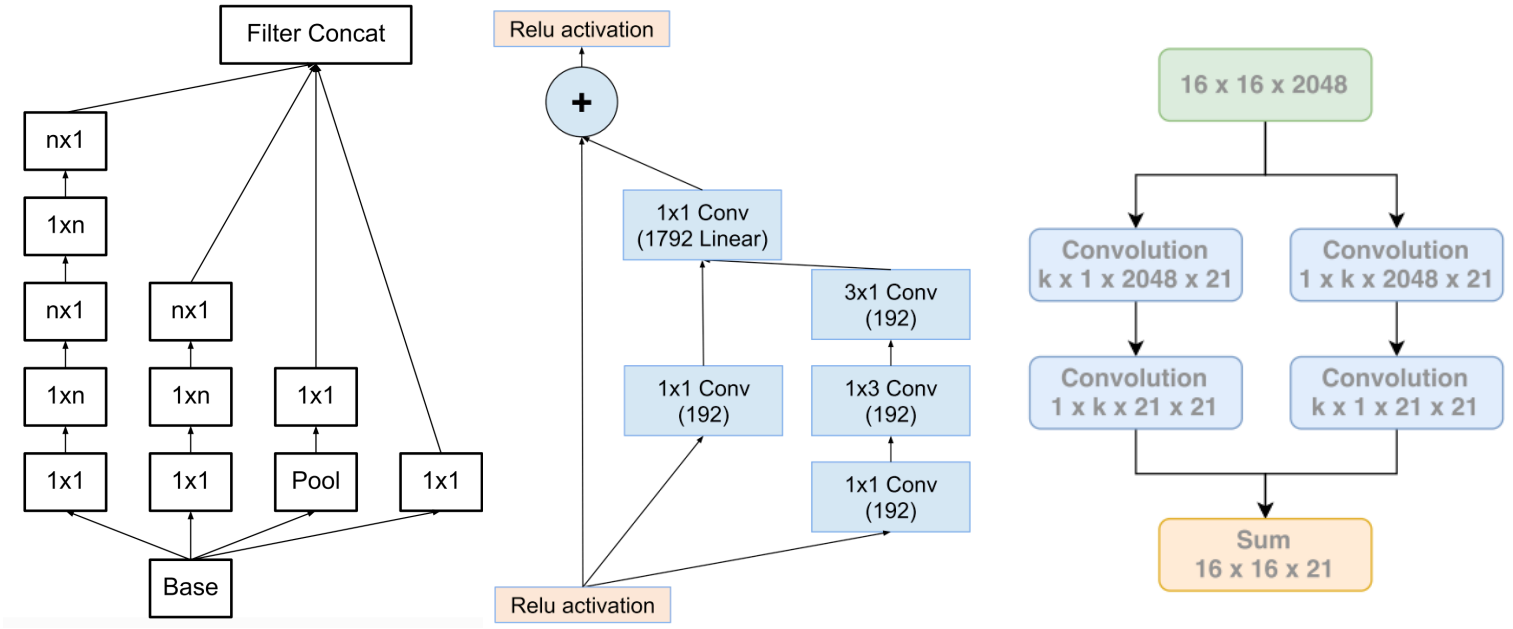




He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition.

Tensor Decomposition

- 1xM + Mx1
  - *Inception v3, v4*
  - *“Large kernel matters”*



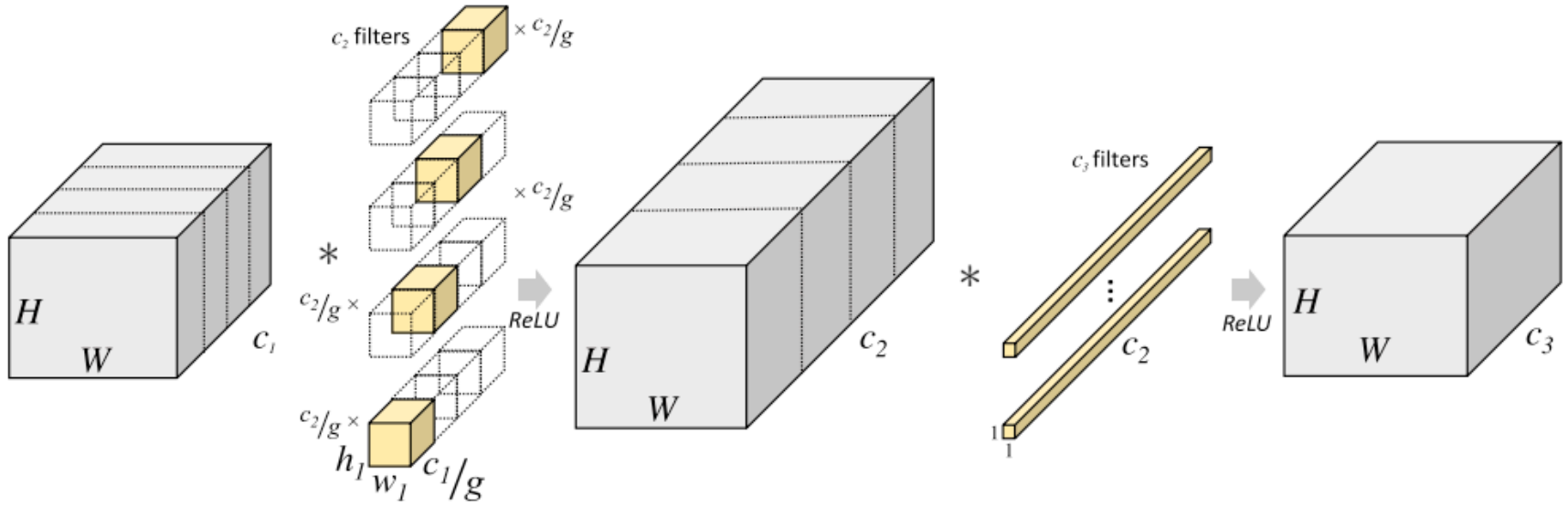
Szegedy, Christian, et al. "Rethinking the inception architecture for computer vision." *Cvpr*. 2016.

Szegedy, Christian, et al. "Inception-v4, inception-resnet and the impact of residual connections on learning." *AAAI*. Vol. 4. 2017.

Peng, Chao, et al. "Large Kernel Matters--Improve Semantic Segmentation by Global Convolutional Network.” *Cvpr 2017*

Tensor Decomposition

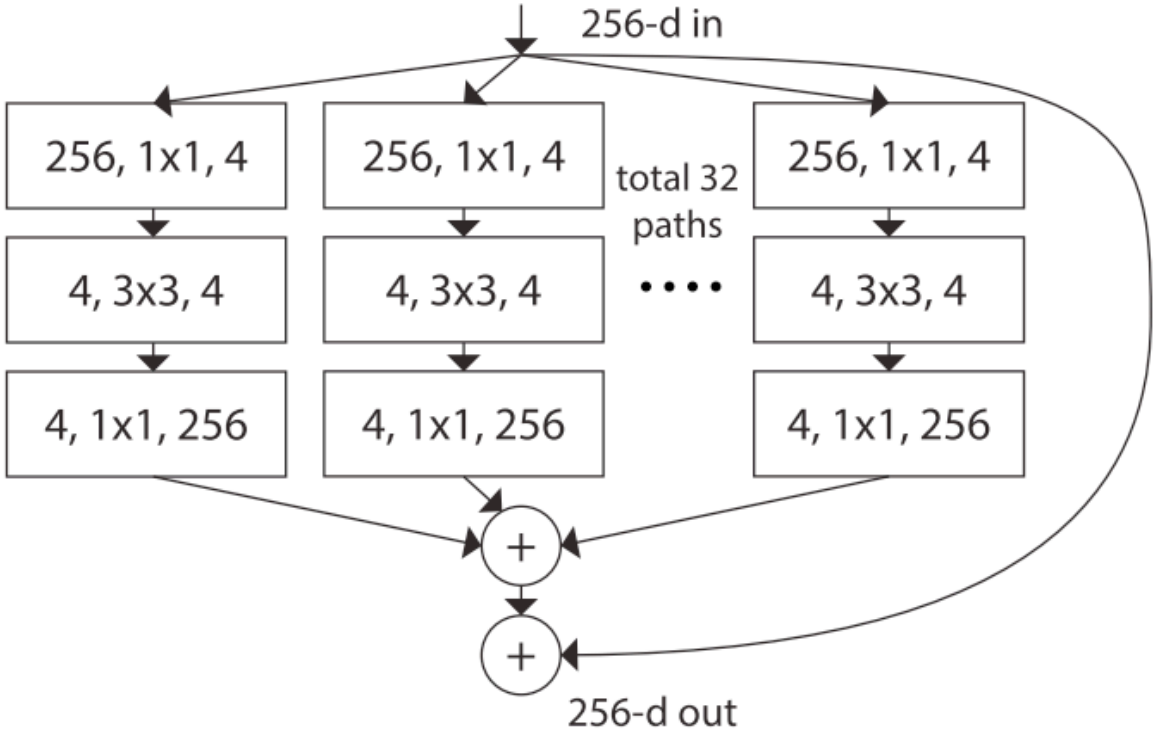
- GConv + 1x1
  - *DeepRoots*



Ioannou, Yani, et al. "Deep roots: Improving CNN efficiency with hierarchical filter groups." (2017).

Tensor Decomposition

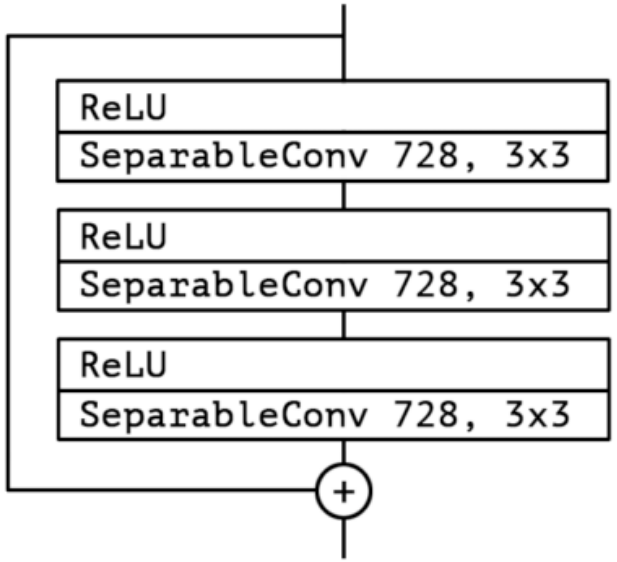
- 1x1 + GConv + 1x1
  - *ResNeXt*

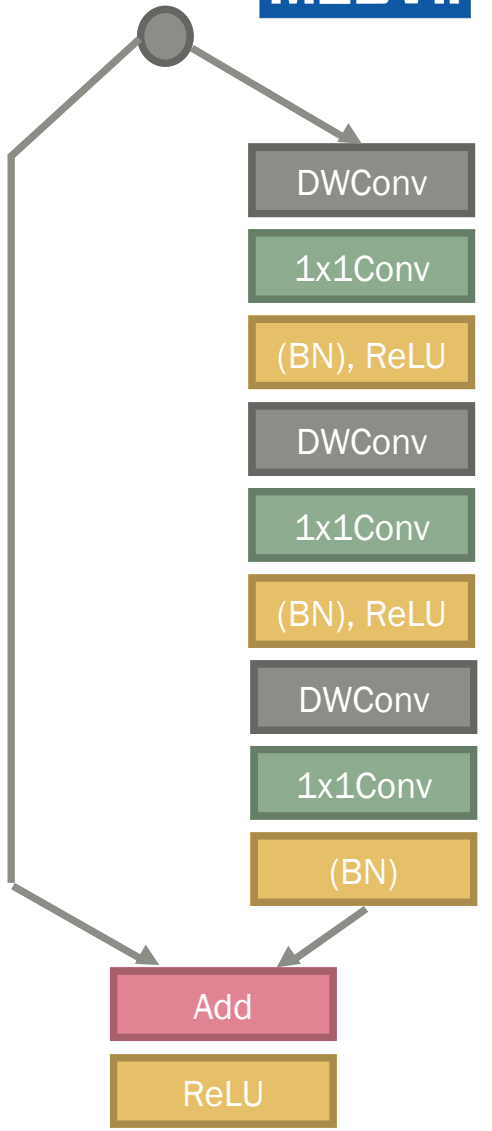


Xie, Saining, et al. "Aggregated residual transformations for deep neural networks." *(CVPR)*

Tensor Decomposition

- DWConv + 1x1
  - *Xception*
  - *Light-head DET*
  - *Waterfall Xception*





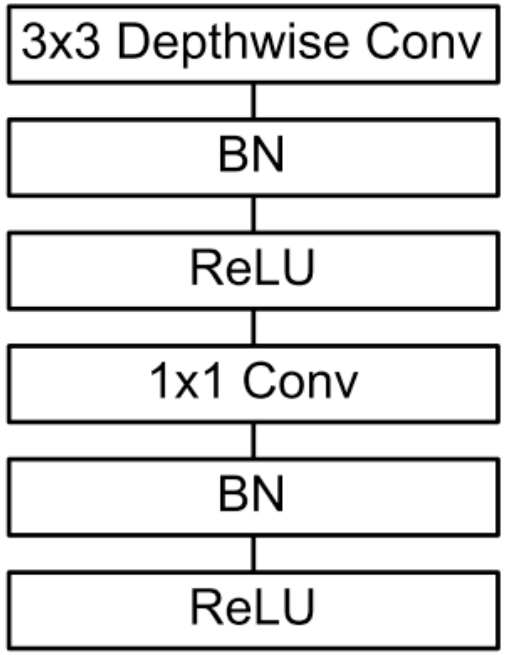
- Applications
  - *Large RF required (e.g. segmentation)*

Chollet, François. "Xception: Deep learning with depthwise separable convolutions."

Li, Zeming, et al. "Light-Head R-CNN: In Defense of Two-Stage Object Detector."

Tensor Decomposition

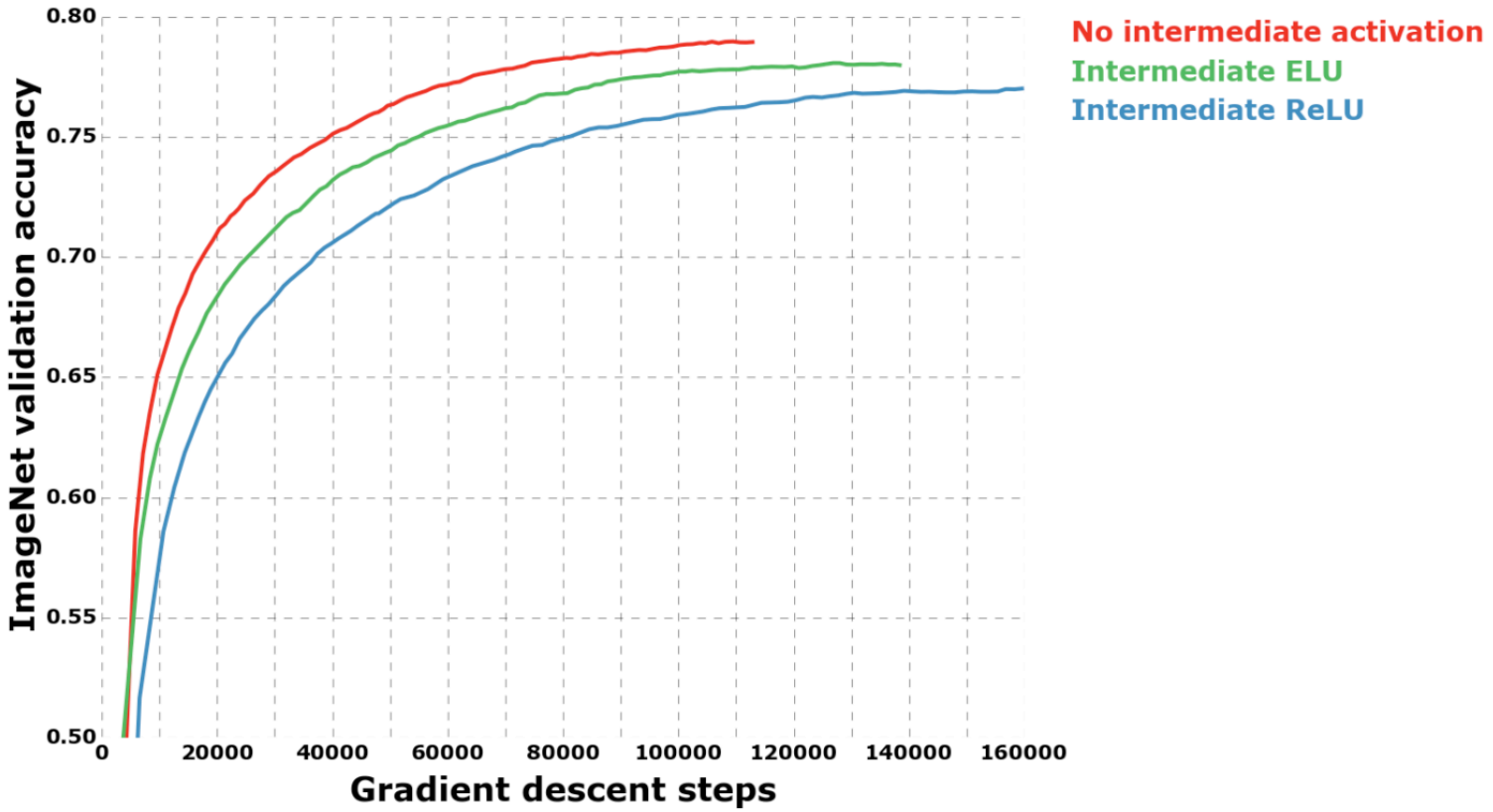
- DWConv + 1x1
  - *MobileNet v1*



Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications."

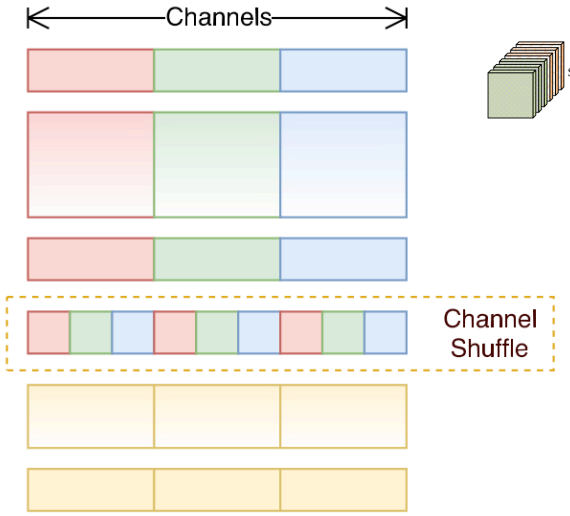
Tensor Decomposition

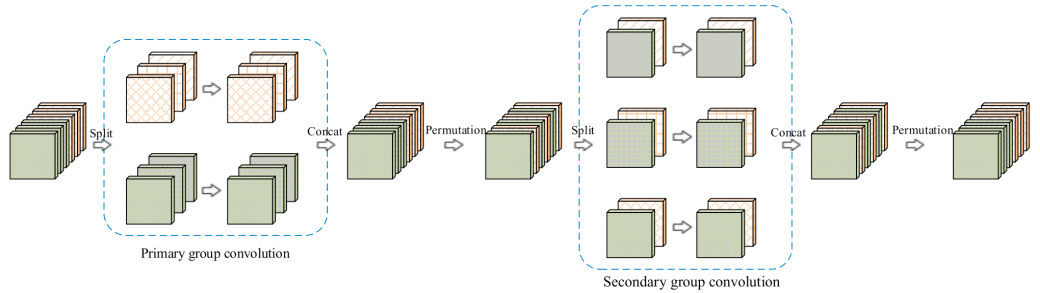
- Some details
  - *With/without BN?*
  - *With/without ReLU?*

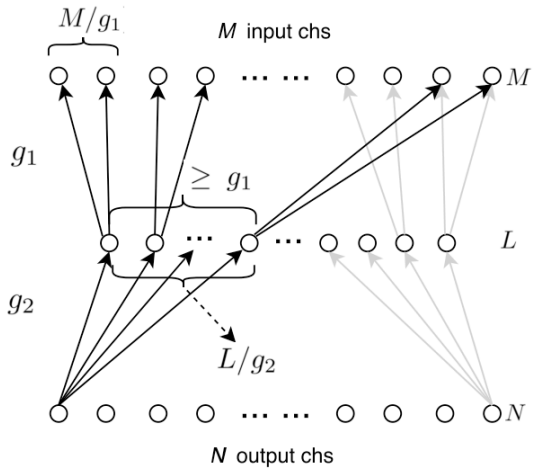


Channel Shuffle

- GConv + Channel Shuffle
  - *ShuffleNet*
  - *IGCNet*
  - *CLCNet*







Zhang, X.*, Zhou, X.*, Lin, M. and Sun, J., 2017. Shufflenet: An extremely efficient convolutional neural network for mobile devices

Zhang, Dong-Qing. "clcNet: Improving the Efficiency of Convolutional Neural Network using Channel Local Convolutions."

Zhang, T., et al. Interleaved Group Convolutions for Deep Neural Networks

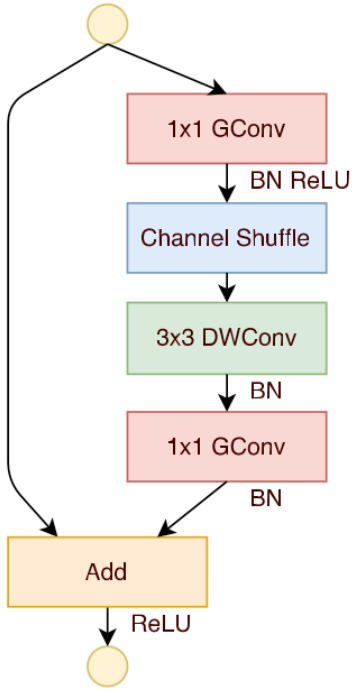
Channel Shuffle

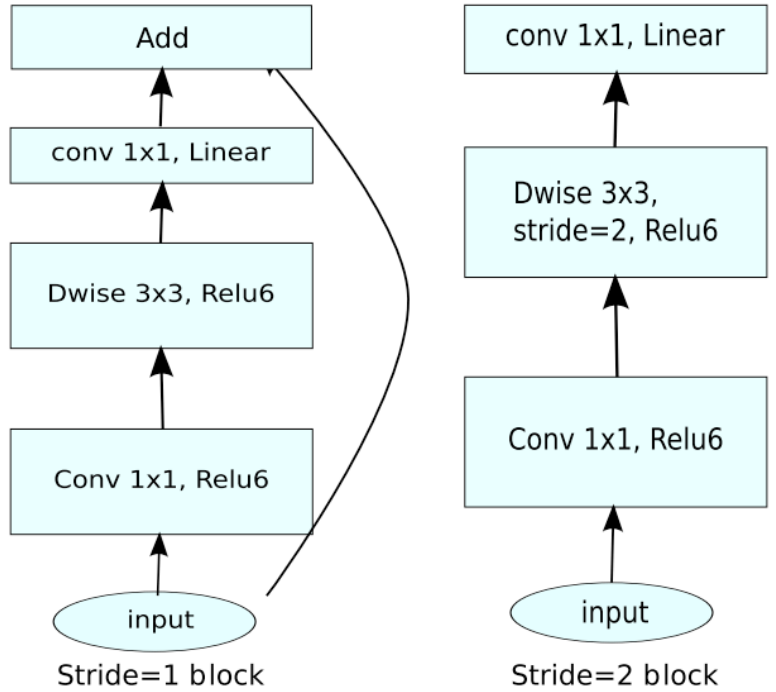
- Network configuration
  - *"fast downsampling"*

Layer	Output size	KSize	Stride	Repeat	Output channels (g groups)				
					$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 8$
Image	224×224				3	3	3	3	3
Conv1	112×112	3×3	2	1	24	24	24	24	24
MaxPool	56×56	3×3	2						
Stage2[1]	28×28		2	1	144	200	240	272	384
	28×28		1	3	144	200	240	272	384
Stage3	14×14		2	1	288	400	480	544	768
	14×14		1	7	288	400	480	544	768
Stage4	7×7		2	1	576	800	960	1088	1536
	7×7		1	3	576	800	960	1088	1536
GlobalPool	1×1	7×7							
FC					1000	1000	1000	1000	1000
Complexity[2]					143M	140M	137M	133M	137M

Bottleneck vs. Inverted Bottleneck

- MobileNet v2
  - *Linear bottleneck*
  - *Inverted residual*
  - *ReLU6*





Sandler, Mark, et al. "Inverted Residuals and Linear Bottlenecks: Mobile Networks for Classification, Detection and Segmentation."

Bottleneck vs. Inverted Bottleneck

- Trick in MobileNet v2

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$28^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times k$	conv2d 1x1	-	k	-	

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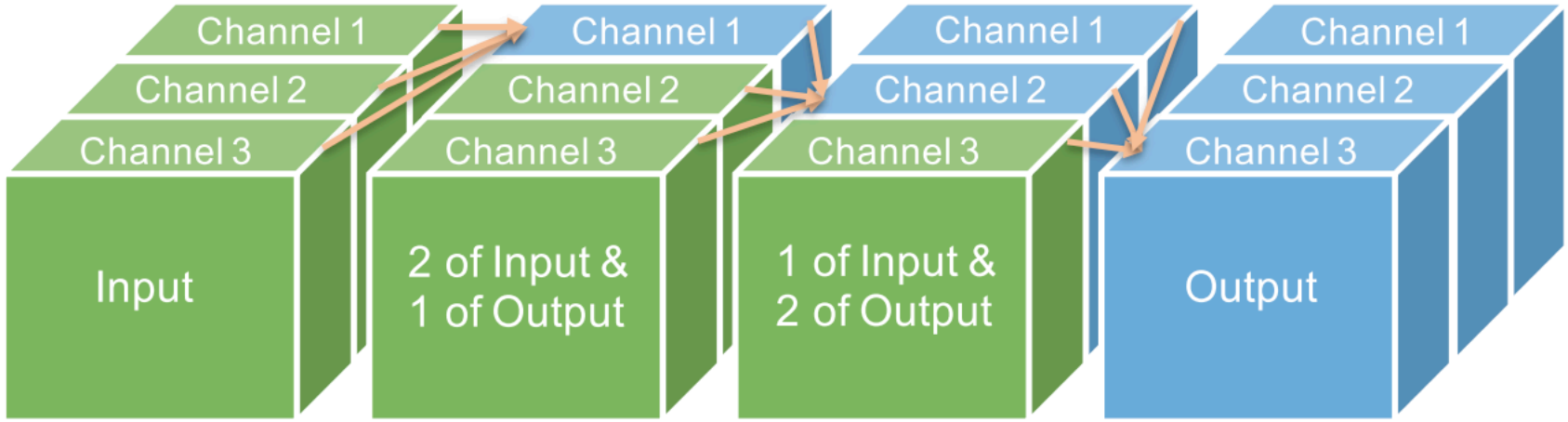
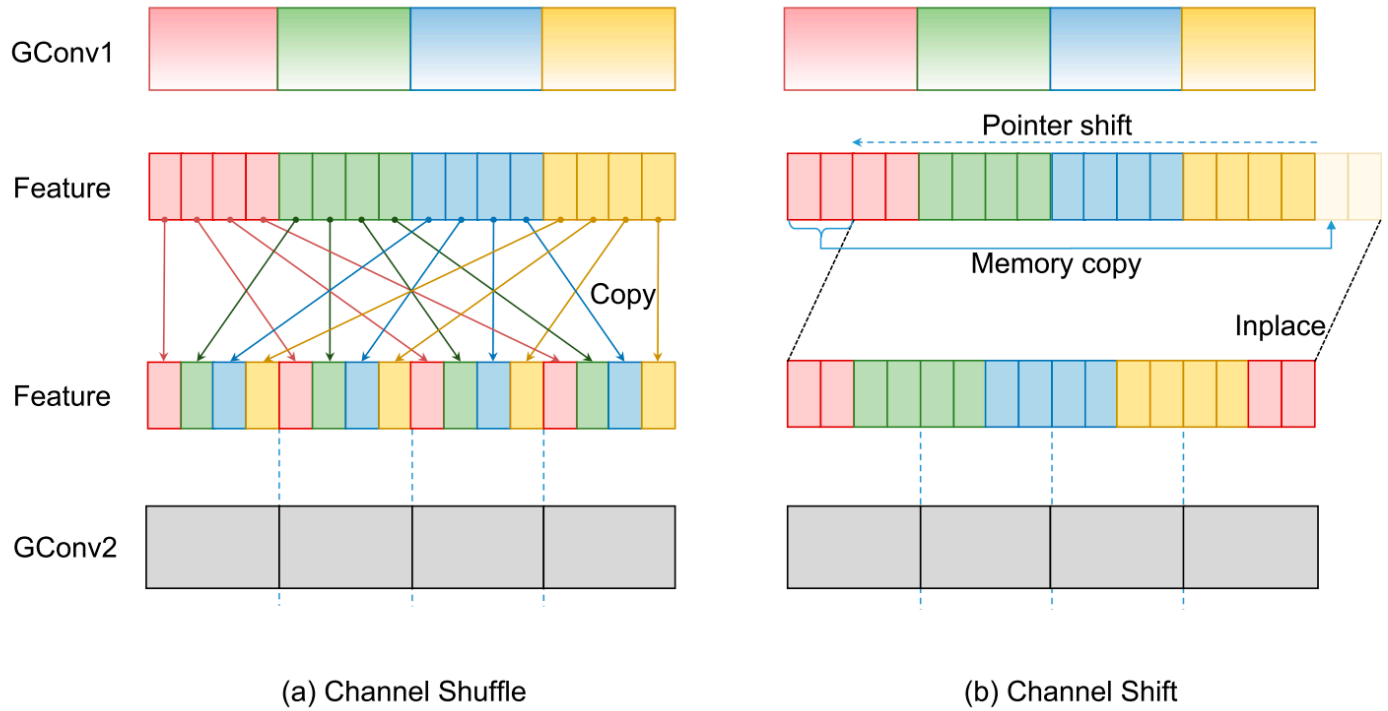
Channel Shift



Qiao, Siyuan, et al. "Gradually Updated Neural Networks for Large-Scale Image Recognition."

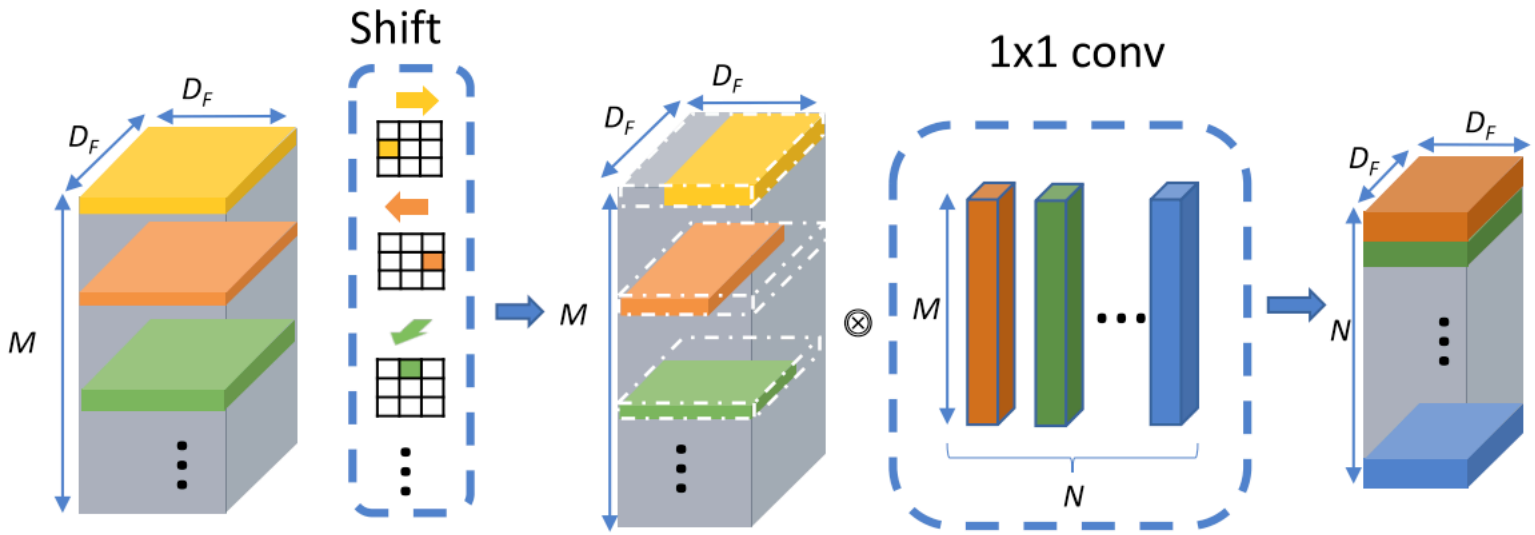
Channel Shift



Zhong, Huasong, et al. "Shift-based Primitives for Efficient Convolutional Neural Networks."

Spatial Operators

- “Shift” operator

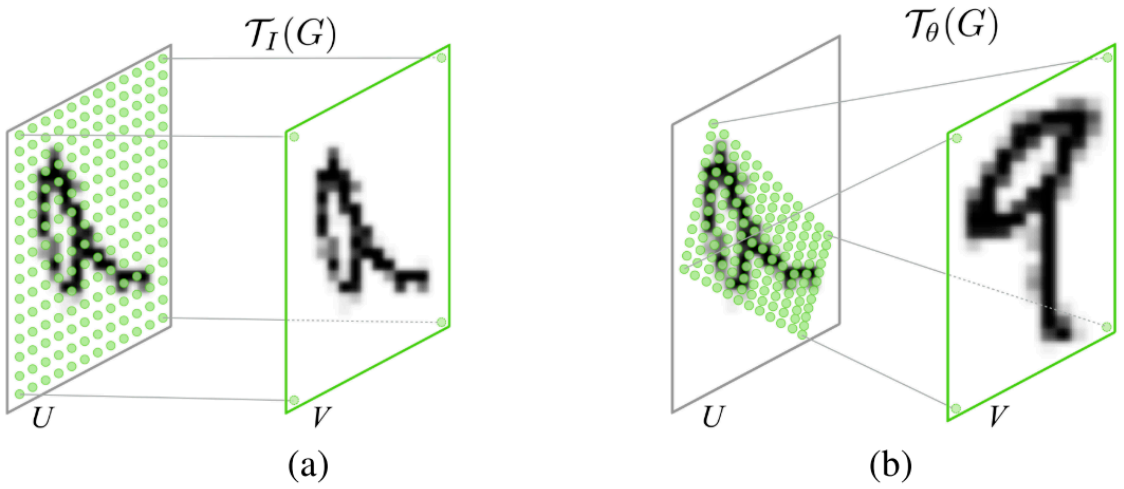


Wu, Bichen, et al. "Shift: A Zero FLOP, Zero Parameter Alternative to Spatial Convolutions."

Spatial Operators

- Spatial transformer networks (STN)

$$V_i^c = \sum_n^H \sum_m^W U_{nm}^c k(x_i^s - m; \Phi_x) k(y_i^s - n; \Phi_y) \quad \forall i \in [1 \dots H'W'] \quad \forall c \in [1 \dots C]$$

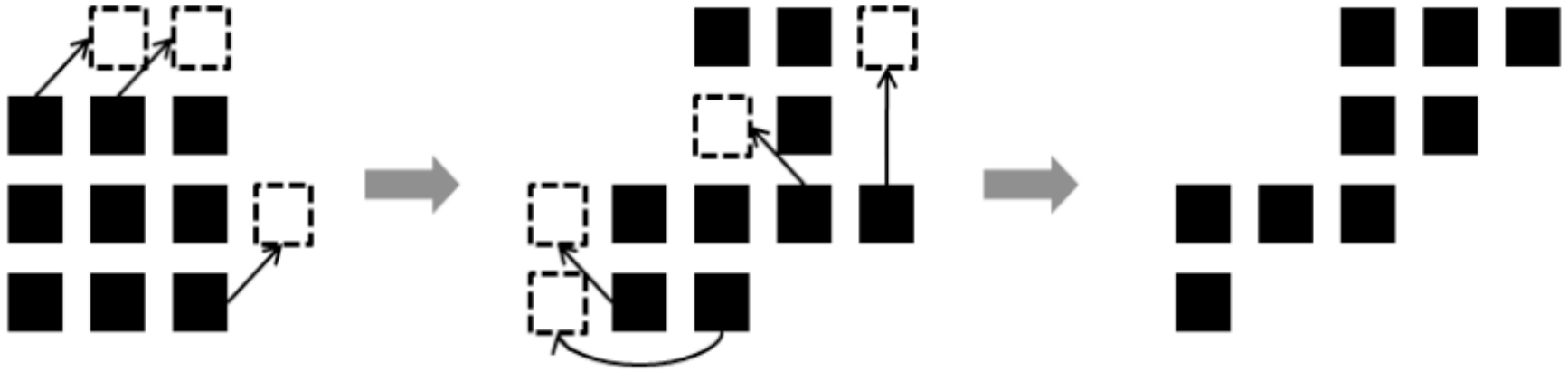


$$V_i^c = \sum_n^H \sum_m^W U_{nm}^c \max(0, 1 - |x_i^s - m|) \max(0, 1 - |y_i^s - n|)$$

Jaderberg, Max, Karen Simonyan, and Andrew Zisserman. "Spatial transformer networks."

Spatial Operators

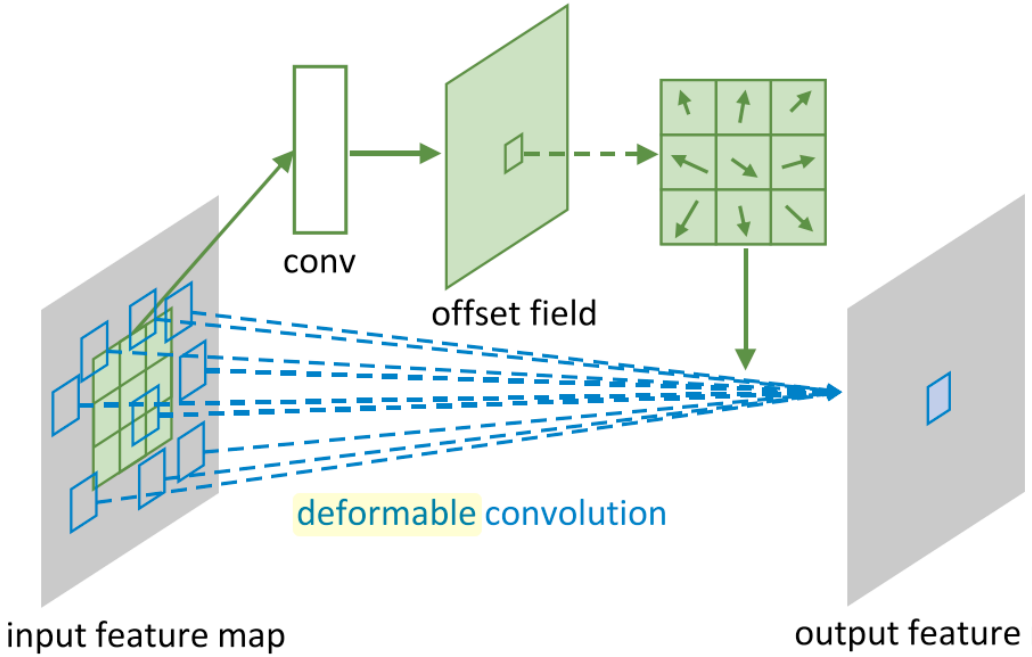
- Irregular convolution



Ma, Jiabin, Wei Wang, and Liang Wang. "Irregular Convolutional Neural Networks."

Spatial Operators

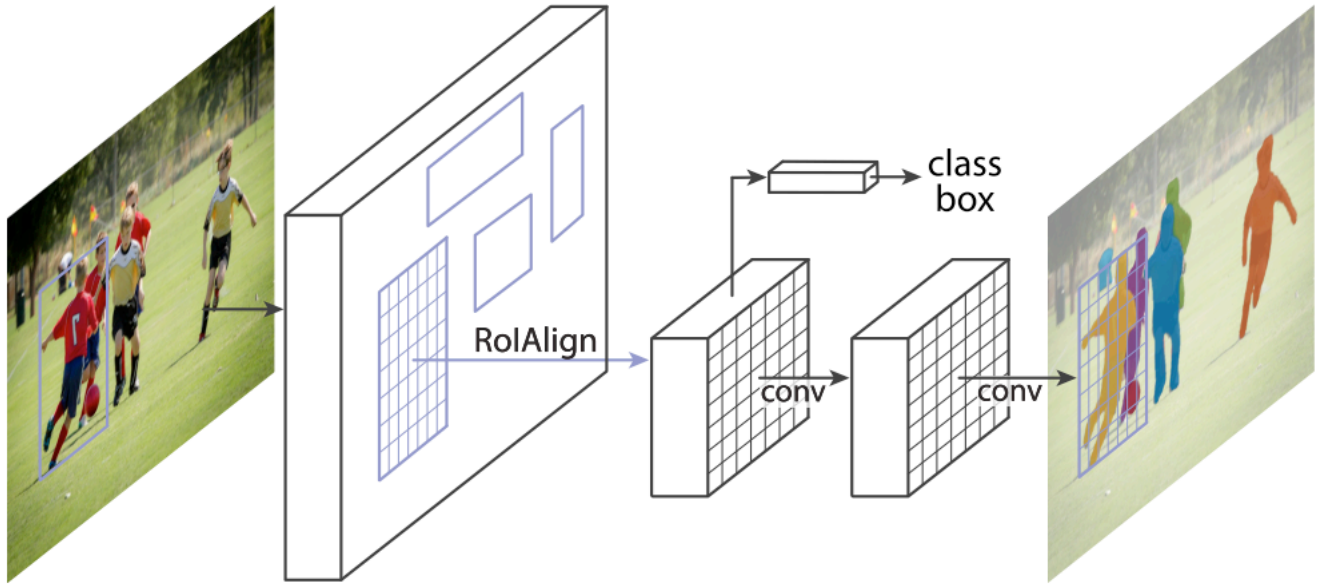
- Deformable Convolution/Pooling



Dai, Jifeng, et al. "Deformable convolutional networks."

Spatial Operators

- ROIPooling
- ROIAlign



Girshick, Ross. "Fast r-cnn."

He, Kaiming, et al. "Mask r-cnn."

Spatial Operators

- Upsampling
  - *Deconvolution*
  - *Resize*
  - *“Reshape”*
  - *Unpooling*

  ...

Spatial Operators

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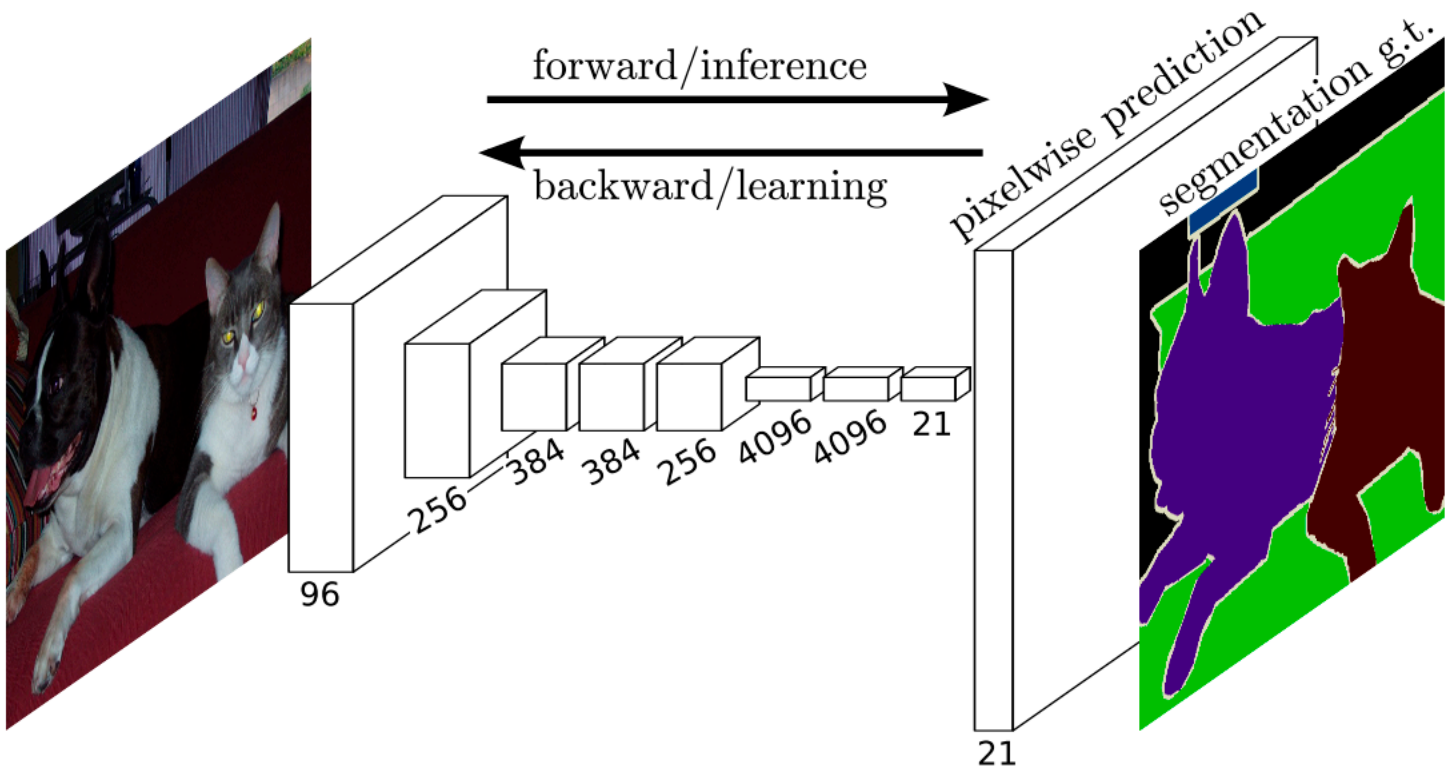
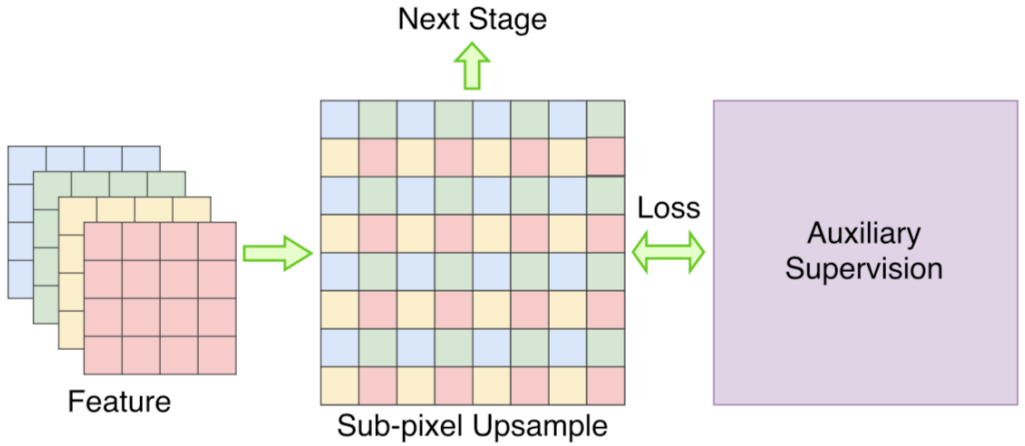
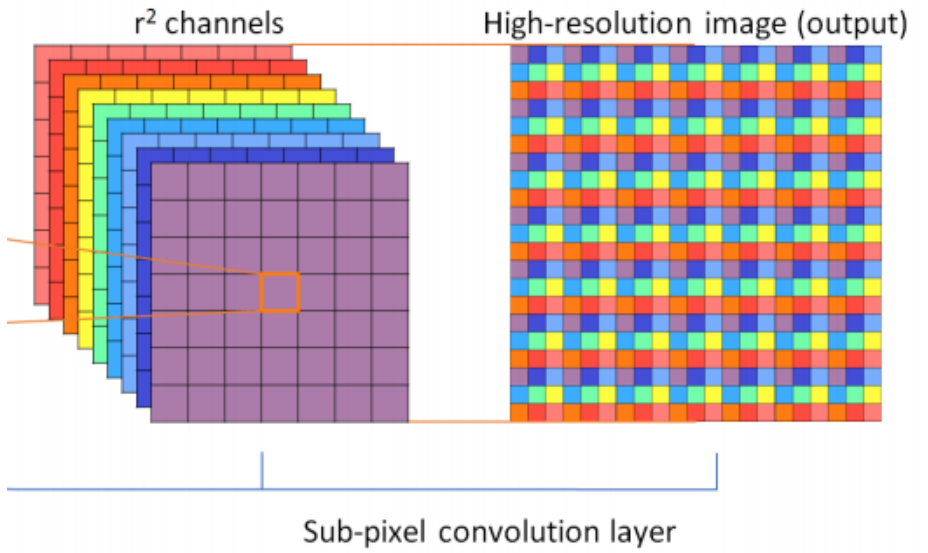


Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation."

Spatial Operators

- Upsampling
  - *Deconvolution*
  - *Resize*
  - *“Reshape”*
  - *Unpooling*
  - …





Shi, W., et al. Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network. (2016)

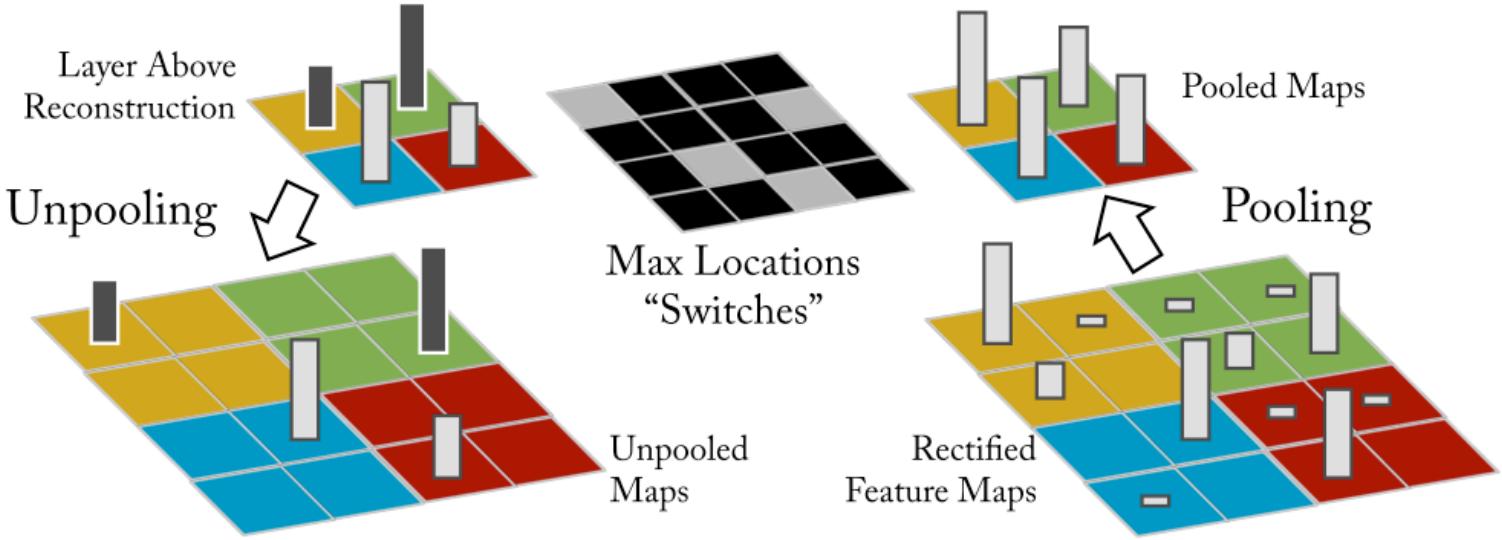
Aitken, A., et al.: Checkerboard 684 artifact free sub-pixel convolution: A note on sub-pixel convolution, resize convolution and convolution resize. (2017)

Zhenli Zhang, et al. ExFuse: Enhancing Feature Fusion for Semantic Segmentation.

Spatial Operators

- Upsampling
  - *Deconvolution*
  - *Resize*
  - *“Reshape”*
  - *Unpooling*

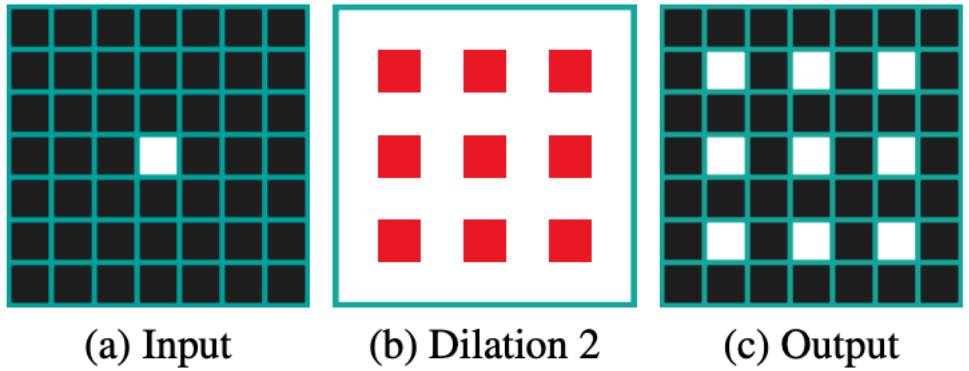
  ...

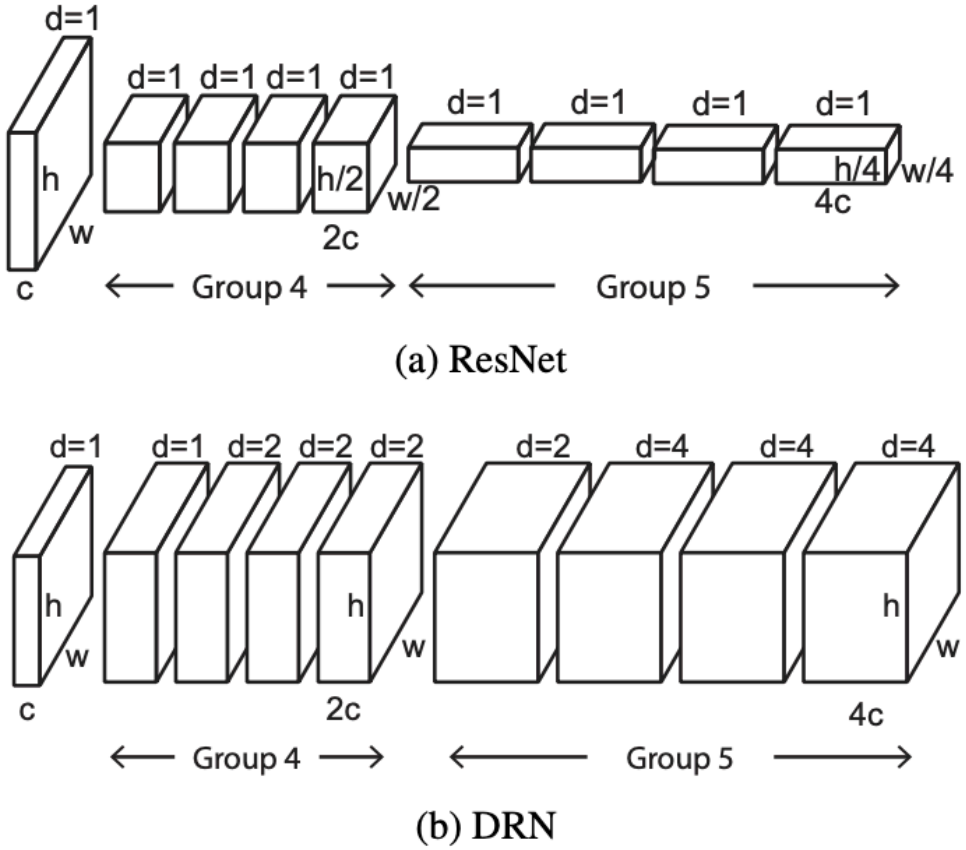


Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." *European conference on computer vision.*

Spatial Operators

- Dilated convolutions

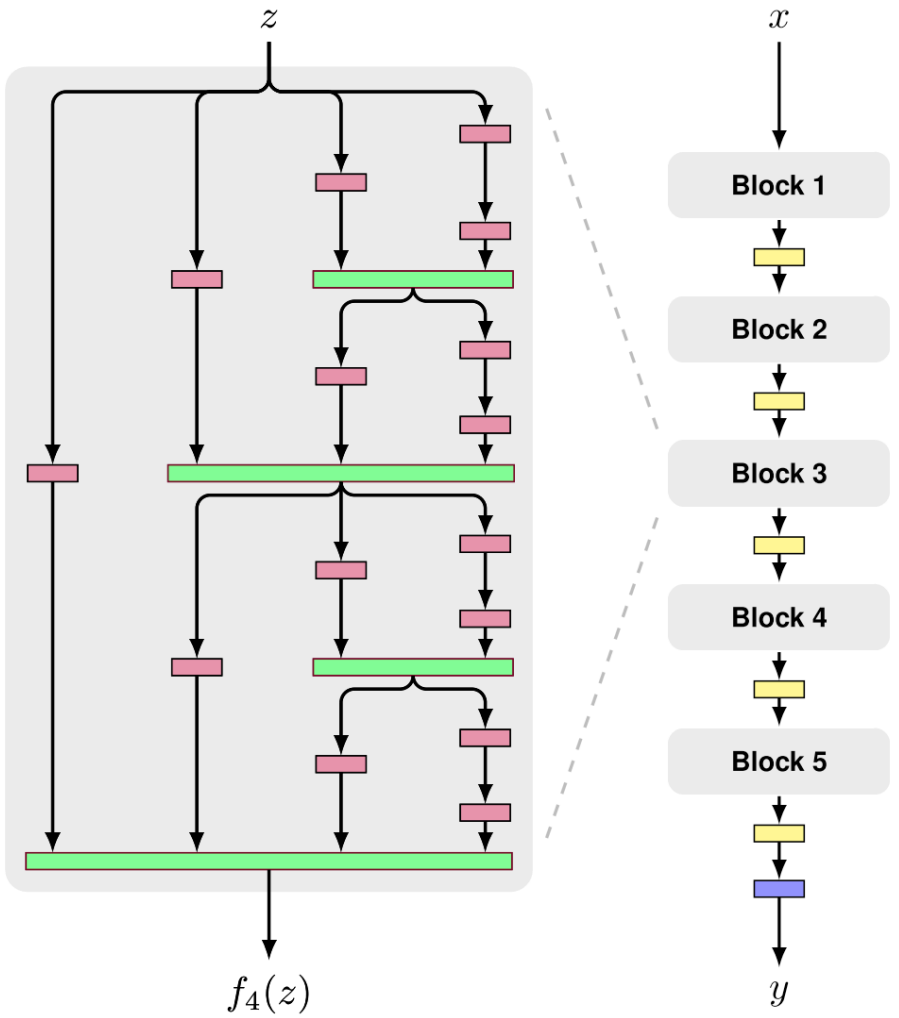




Yu, Fisher, Vladlen Koltun, and Thomas Funkhouser. "Dilated residual networks."

Skip Connections

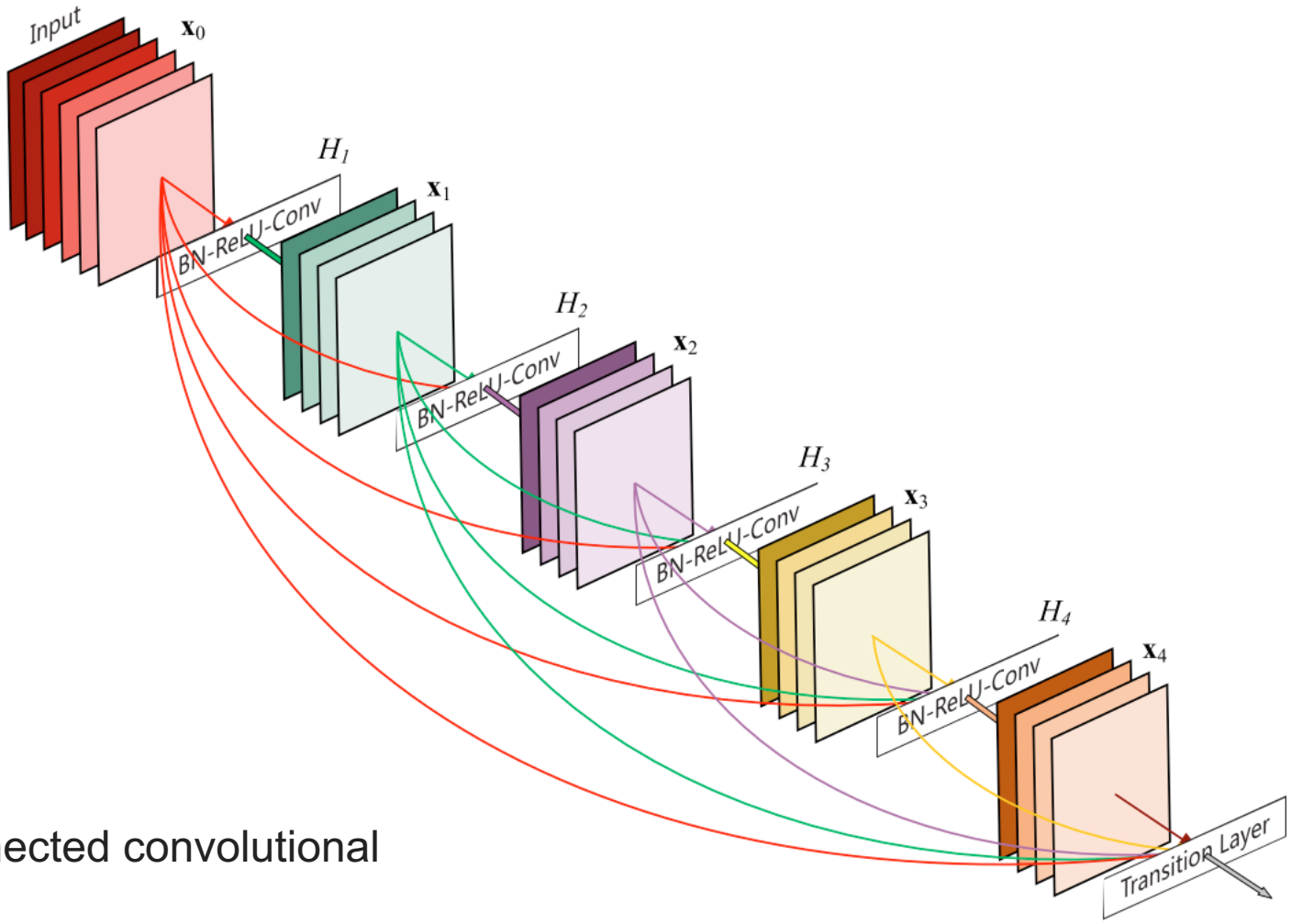
- ResNet-like models
- FractalNet



Larsson, Gustav, Michael Maire, and Gregory Shakhnarovich. "Fractalnet: Ultra-deep neural networks without residuals."

Skip Connections

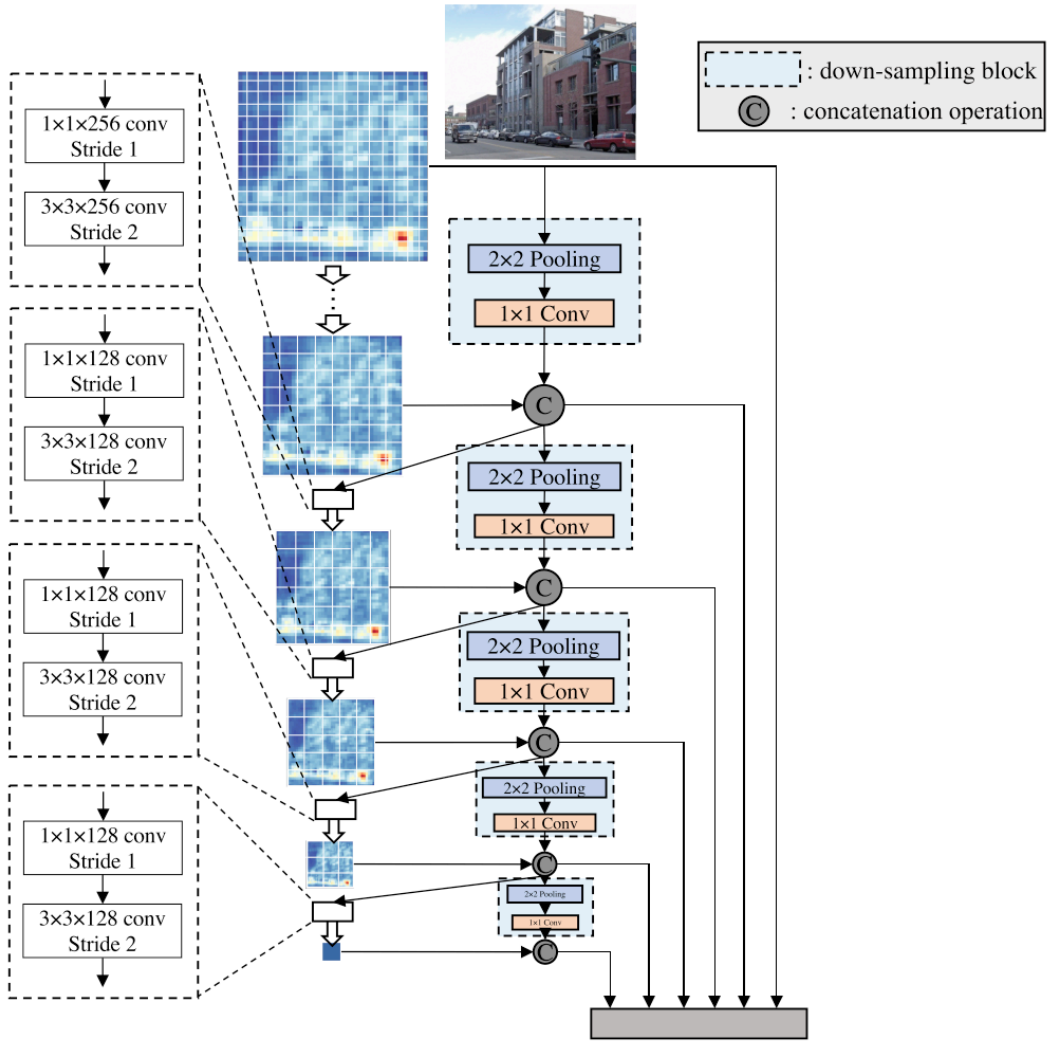
- DenseNet



Huang, Gao, et al. "Densely connected convolutional networks." *CVPR 2017.*

Skip Connections

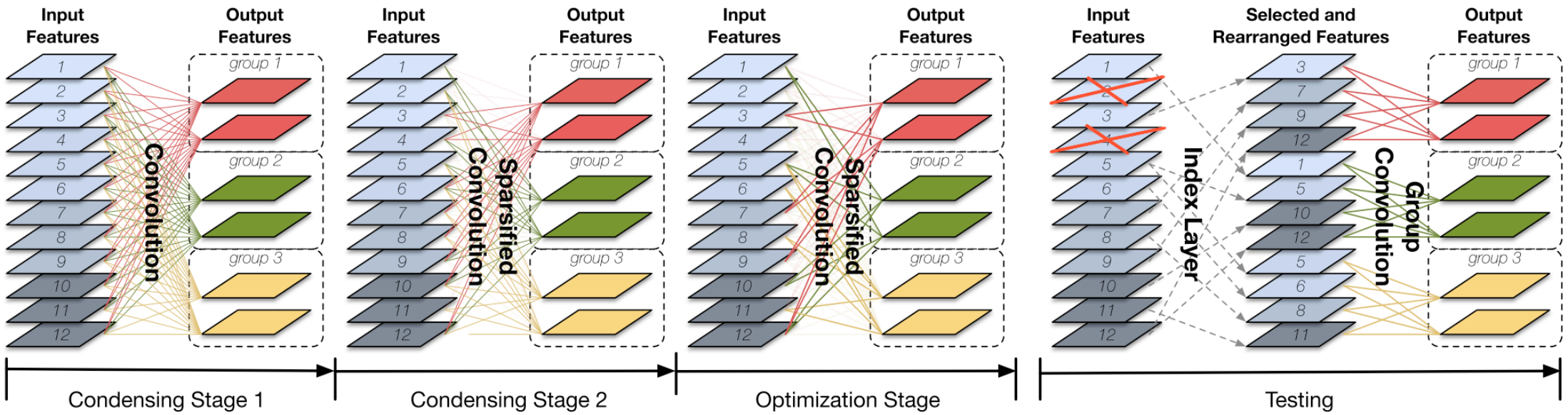
- DenseNet Applications
  - *DSOD*



Shen, Zhiqiang, et al. "Dsod: Learning deeply supervised object detectors from scratch." ICCV 2017

Skip Connections

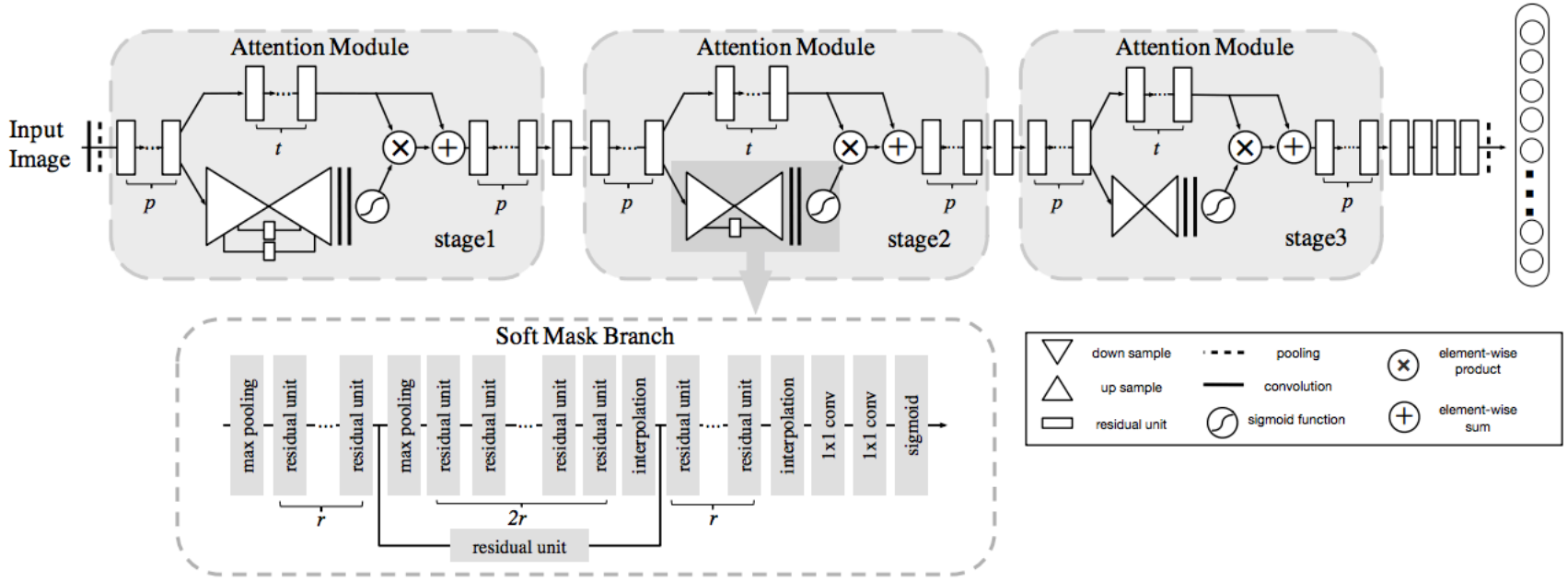
- DenseNet Optimizations
  - *CondenseNet*



Huang, Gao, et al. "CondenseNet: An Efficient DenseNet using Learned Group Convolutions."

Attention Blocks

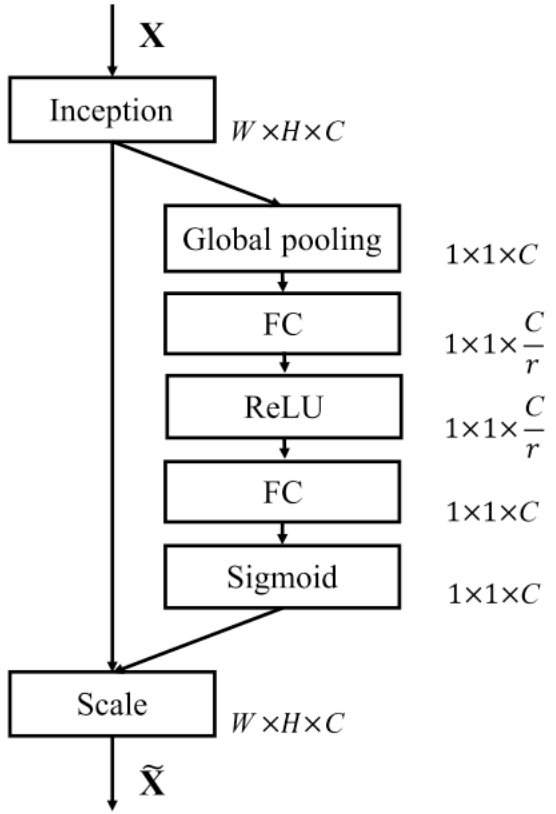
- Spatial attention
  - *Residual Attention Net*



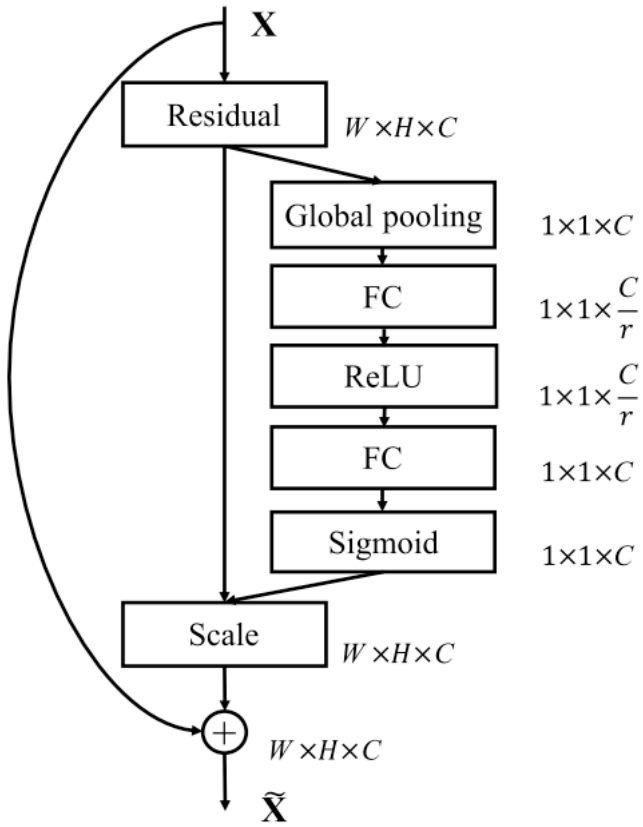
Wang, Fei, et al. "Residual attention network for image classification."

Attention Blocks

- Channel Attention
  - *SENet*
  - *With/without BN?*
- Applications
  - *Recommended*



SE-Inception Module

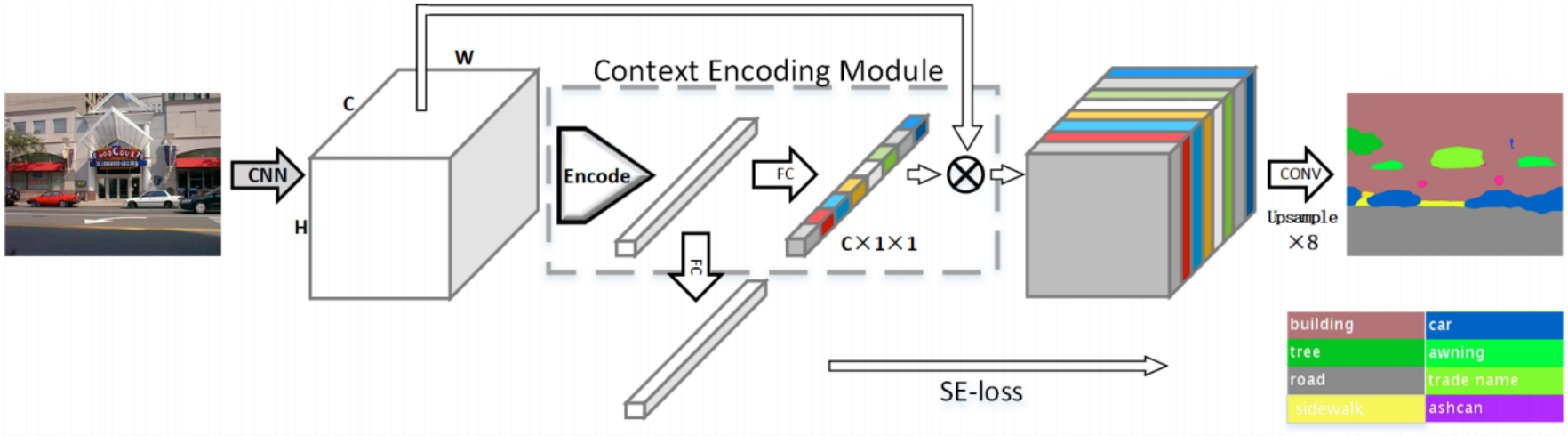


SE-ResNet Module

Hu, Jie, Li Shen, and Gang Sun. "Squeeze-and-excitation networks."

Attention Blocks

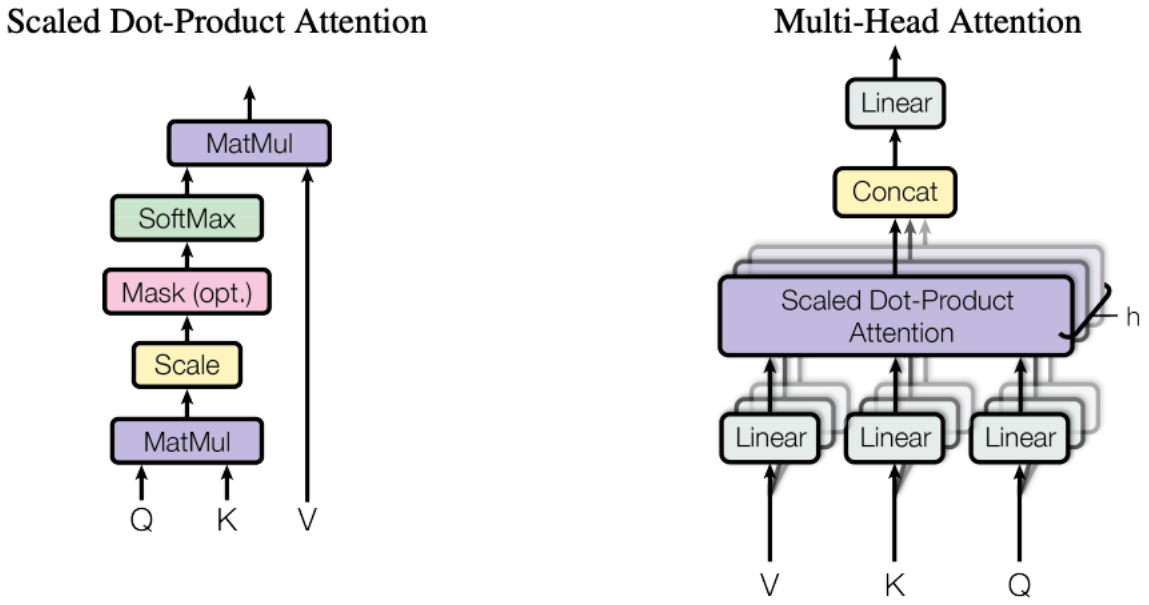
- Applications
  - *EncNet*



Hang Zhang, et al. Context Encoding for Semantic Segmentation

Attention Blocks

- Transformer



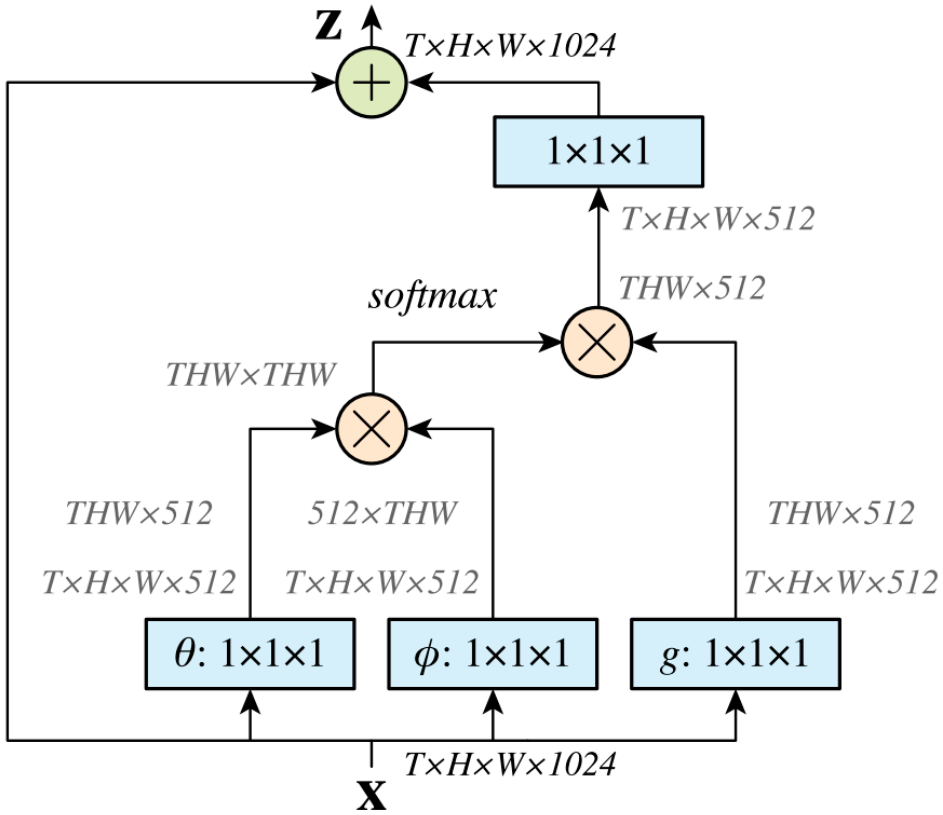
$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Vaswani, Ashish, et al. "Attention is all you need."

Attention Blocks

- Non-local network

$$\mathbf{y}_i = \frac{1}{\mathcal{C}(\mathbf{x})} \sum_{\forall j} f(\mathbf{x}_i, \mathbf{x}_j) g(\mathbf{x}_j).$$



Wang, Xiaolong, et al. "Non-local neural networks."

Normalization

- Batch Normalization/Batch Renormalization
- Multi-GPU Batch Normalization
- Layer Normalization
- Weight Normalization
- Gradient Normalization
- Group Normalization

...

Normalization

- Batch Normalization/Batch Renormalization
- Multi-GPU Batch Normalization
- Layer Normalization
- Weight Normalization
- Gradient Normalization
- Group Normalization

...

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

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

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

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

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

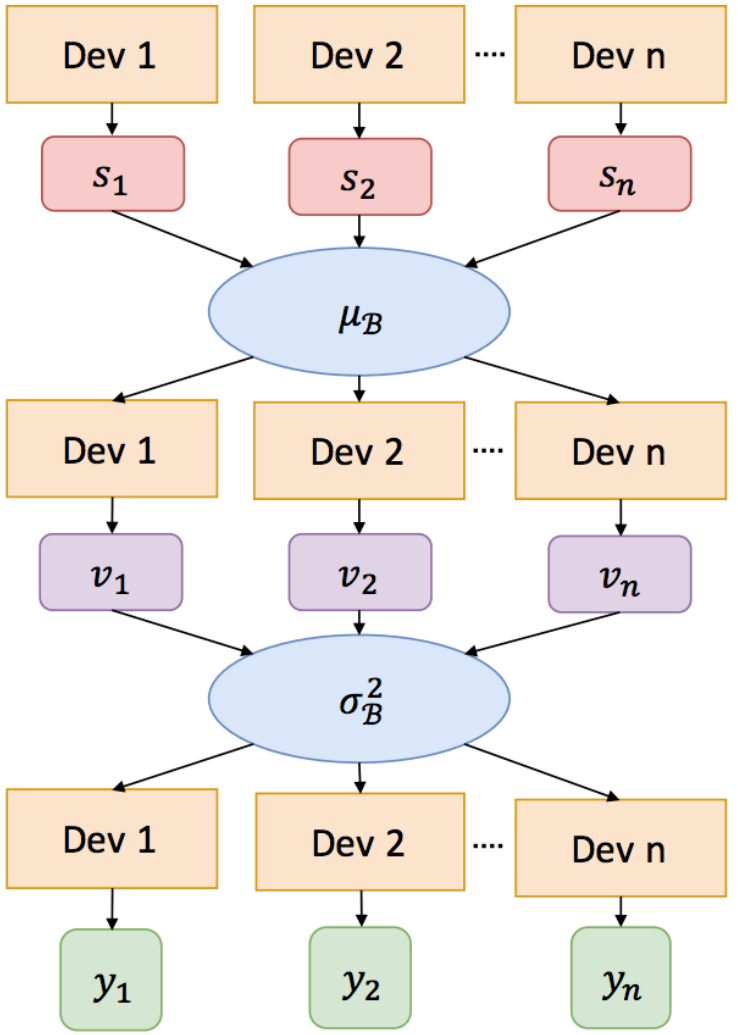
$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Ioffe, Sergey, and Christian Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift."
Ioffe, Sergey. "Batch renormalization: Towards reducing minibatch dependence in batch-normalized models."

Normalization

- Batch Normalization/Batch Renormalization
- Multi-GPU Batch Normalization
- Layer Normalization
- Weight Normalization
- Gradient Normalization
- Group Normalization

...

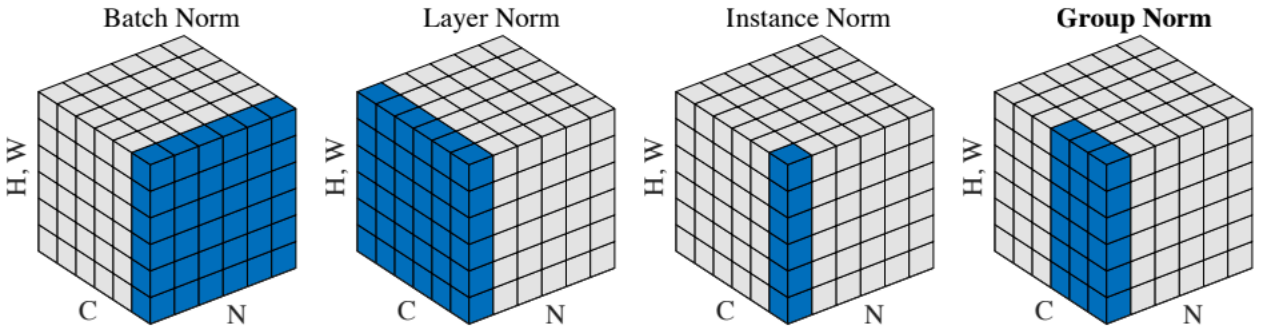


Peng, Chao, et al. "MegDet: A Large Mini-Batch Object Detector."

Normalization

- Batch Normalization/Batch Renormalization
- Multi-GPU Batch Normalization
- Layer Normalization
- Weight Normalization
- Gradient Normalization
- Group Normalization

...



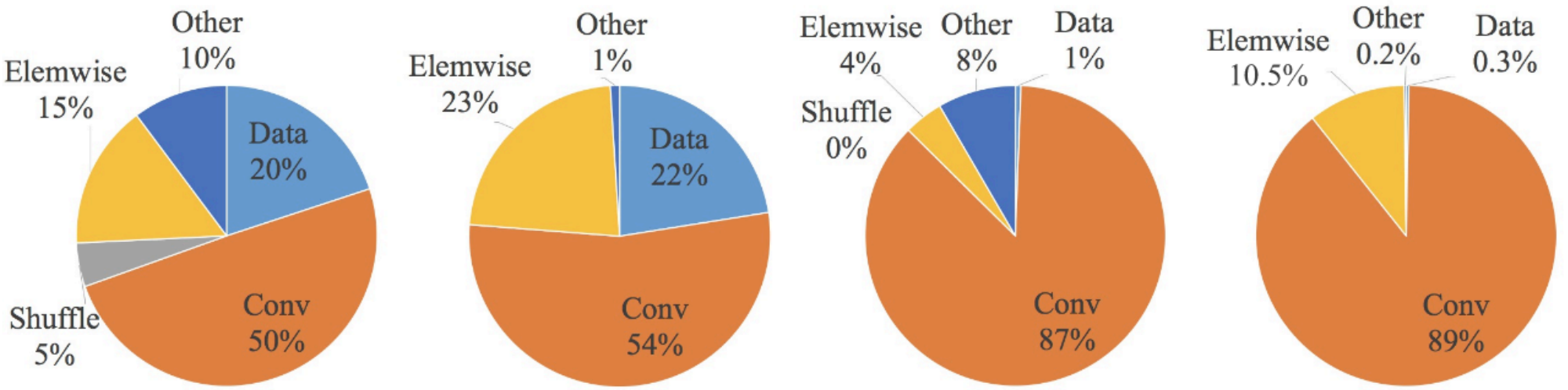
Yuxin Wu, et al. Group normalization

Normalization

- Best practice
  - *Large batch: BN*
  - *Small batch: Multi-gpu BN > GN/BRN > BN/LN*
  - *Weight/meta network: LN/WN*
  - *GAN/Multi-task: Gradient normalization*

Inference Efficiency

- Actual running time
  - *Convolutions and elementwise operators*



Inference Efficiency

- Structure efficiency
  - *Convolutional kernel shape*

		GPU (Batches/sec.)			CPU (Images/sec.)		
Input size	Channel (c) when c1=c2	c=128	c=256	c=512	c=32	c=64	c=128
56x56	c1=c2	1480	723	232	76.2	21.7	5.3
	c1=2c2	1296	586	206	72.9	20.5	5.1
	c1=6c2	876	489	189	69.1	17.9	4.6
	c1=12c2	748	392	163	57.6	15.1	4.4
28x28	c1=c2	2314	1504	765	263.9	82.6	23.3
	c1=2c2	2239	1401	675	212.8	78.5	22.6
	c1=6c2	1931	1075	573	198.8	75.5	20.7
	c1=12c2	1646	975	521	194.9	72.5	19.5

Inference Efficiency

- Structure efficiency
  - *Group convolutions*

		GPU (Batches/sec.)			CPU (Images/sec.)		
Input size	Channel (c) when g=1	c=128	c=256	c=512	c=64	c=128	c=256
56x56	g=1	2451	1289	437	40.0	10.2	2.3
	g=2	1725	873	341	35.0	9.5	2.2
	g=4	1026	644	338	32.9	8.7	2.1
	g=8	634	445	230	27.8	7.5	1.8
28x28	g=1	3546	2523	1404	146.8	44.3	10.6
	g=2	2650	1874	976	137.4	42.2	10.2
	g=4	1766	1265	717	137.2	39.4	10.1
	g=8	1097	807	499	122.9	33.9	9.6

Inference Efficiency

- Structure efficiency
  - *Fragments*

		GPU (Batches/sec.)			CPU (Images/sec.)		
Input size	Channel (c) for 1-fragment	c=128	c=256	c=512	c=64	c=128	c=256
56x56	1-fragment	2446	1274	434	40.2	10.1	2.3
	2-fragment-series	1790	909	336	38.6	10.1	2.2
	4-fragment-series	752	745	349	38.4	10.1	2.3
	2-fragment-parallel	1537	803	320	33.4	9.1	2.2
	4-fragment-parallel	691	572	292	35.0	8.4	2.1
28x28	1-fragment	3572	2508	1377	169.8	44.3	9.4
	2-fragment-series	2377	1763	960	155.3	42.9	9.1
	4-fragment-series	1269	1134	776	156.3	41.9	9.4
	2-fragment-parallel	2097	1587	887	146.2	40.7	8.7
	4-fragment-parallel	1045	974	651	144.5	40.3	8.5

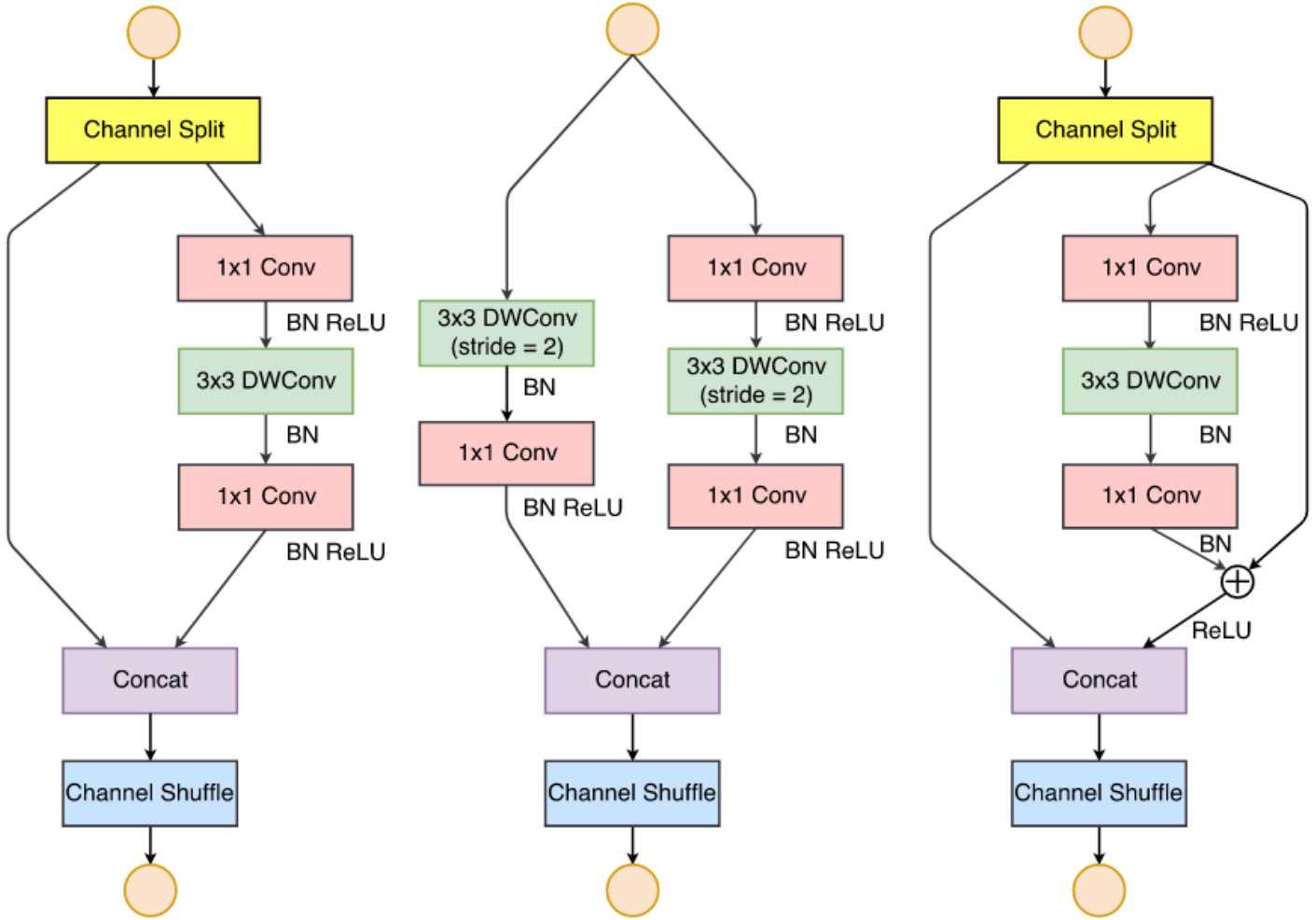
Inference Efficiency

- Structure efficiency
  - *ReLUs and residual-adds*

		GPU (Batches/sec.)			CPU (Images/sec.)		
Input size	Channel (c)	c=32	c=64	c=128	c=32	c=64	c=128
56x56	bottleneck	2427	2066	1436	56.7	16.9	5.0
	bottleneck (without shortcut)	2647	2256	1735	61.9	18.8	5.2
	bottleneck (without ReLU)	2672	2121	1458	57.3	18.2	5.1
	bottleneck (without shortcut and ReLU)	2842	2376	1782	66.3	20.2	5.4
28x28	bottleneck	2927	3120	2845	261.1	74.7	21.6
	bottleneck (without shortcut)	3032	3499	3102	274.0	79.7	23.5
	bottleneck (without ReLU)	3137	3562	2905	274.7	76.1	22.4
	bottleneck (without shortcut and ReLU)	3342	3719	3118	284.9	81.6	24.3

ShuffleNet v2

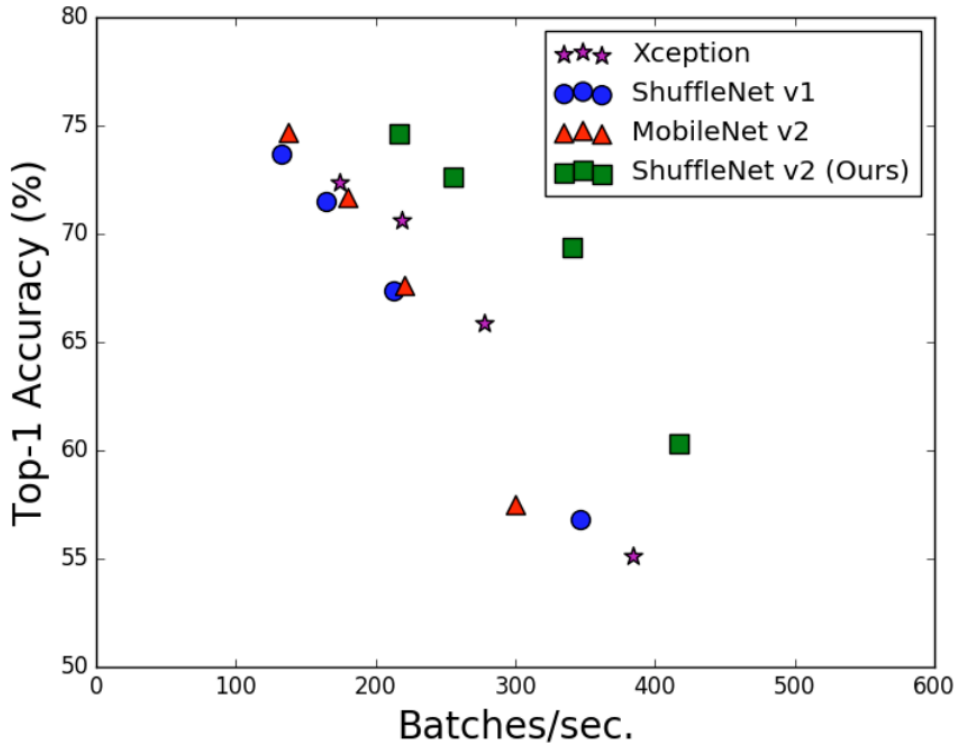
- Inference-efficient structure

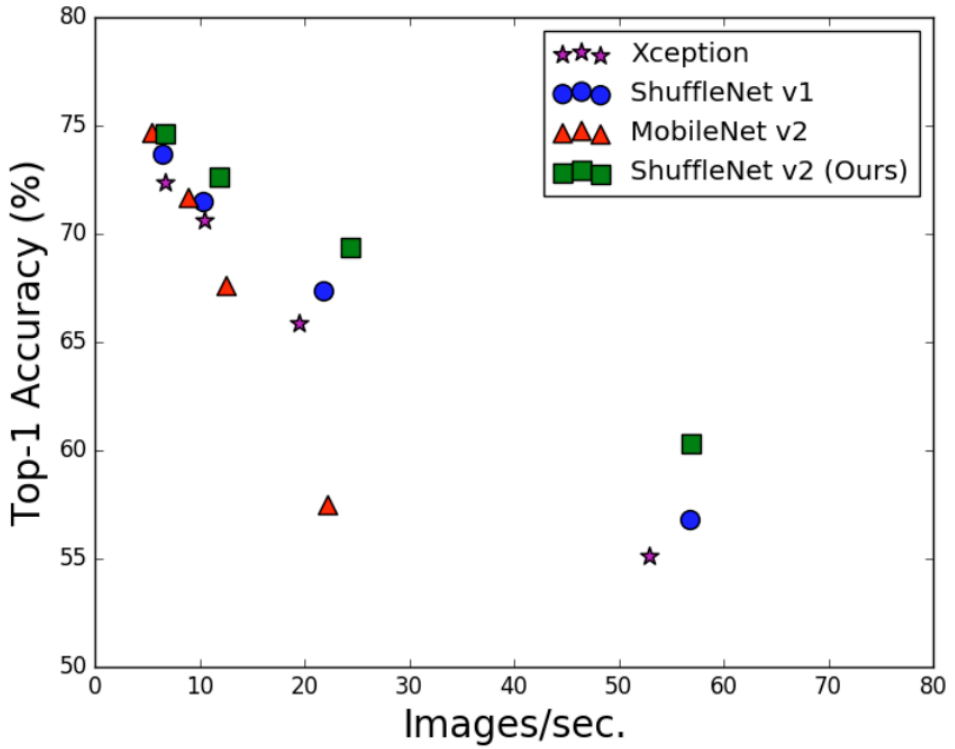


Ninging Ma, Xiangyu Zhang, Jian Sun. ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture Design

ShuffleNet v2

- Better accuracy/actual speed trade-offs





ShuffleNet v2

- Known issues
  - *Limited RF*
- Applications
  - *Classification-oriented tasks*
  - *GPU efficiency*
  - *Competition (not sure)*

Model	mmAP (%)		GPU Speed (Batches/sec.)	
FLOPs	300M	500M	300M	500M
Xception	31.3	32.9	25.3	20.8
ShuffleNet v1	29.9	32.9	19.0	15.0
MobileNet v2	30.0	30.6	23.5	18.0
ShuffleNet v2 (ours)	31.8	33.3	**27.3**	**21.8**
ShuffleNet v2* (ours)	**33.0**	**34.8**	21.3	16.5

Large Batch Training

- Distributed training
  - *Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour*
  - *Extremely Large Minibatch SGD: Training ResNet-50 on ImageNet in 15 Minutes*
  - *ImageNet Training in Minutes*

Large Batch Training

- Equivalence rules
  - *Linear scaling rule (lr and wc)*

> ***Linear Scaling Rule:*** *When the minibatch size is multiplied by k, multiply the learning rate by k.*

  - *Batch normalization vs. batch size*
  - *Warm up*
  - *Momentum correction*

Goyal, Priya, et al. "Accurate, large minibatch SGD: training imagenet in 1 hour."

Large Batch Training

- Learning rate vs. batch size

$$
\begin{aligned}
g &= \frac{\epsilon}{1-m}\left(\frac{N}{B}-1\right) \\
&\approx \frac{\epsilon N}{B(1-m)}
\end{aligned}
$$

Smith, Samuel L., Pieter-Jan Kindermans, and Quoc V. Le. "Don't Decay the Learning Rate, Increase the Batch Size."

Large Batch Training

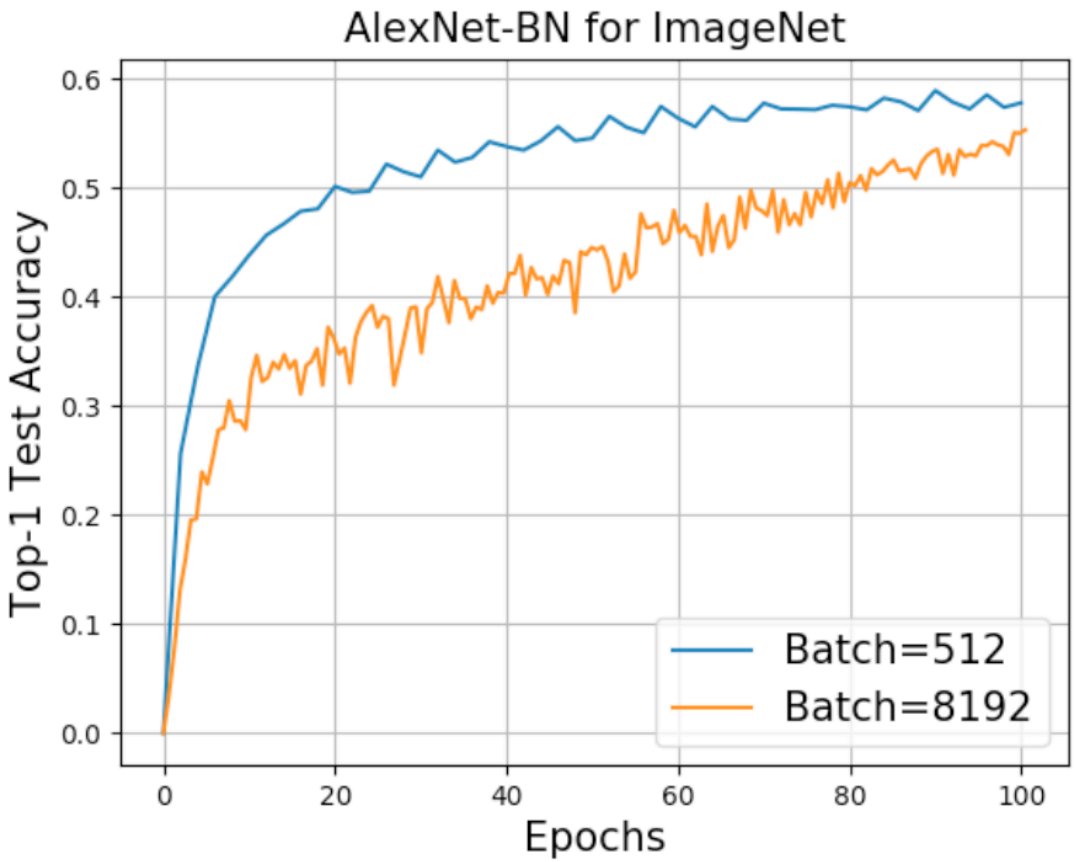
- Layer-wise Adaptive Rate Scaling (LARS)

Algorithm 1 SGD with LARS. Example with weight decay, momentum and polynomial LR decay.

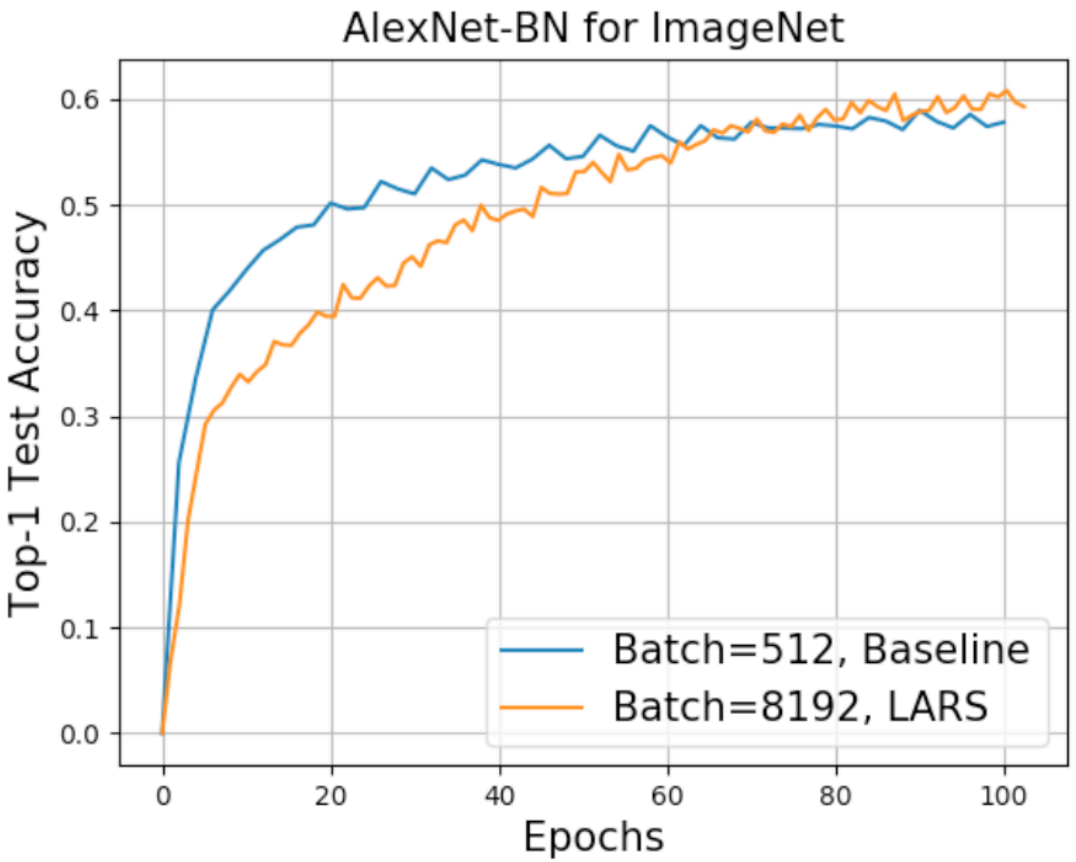
Parameters: base LR γ_0, momentum m, weight decay β, LARS coefficient η, number of steps T
Init: $t = 0, v = 0$. Init weight w_0^l for each layer l
while $t < T$ for each layer l **do**
$g_t^l \leftarrow \nabla L(w_t^l)$ (obtain a stochastic gradient for the current mini-batch)
$\gamma_t \leftarrow \gamma_0 * \left(1 - \frac{t}{T}\right)^2$ (compute the global learning rate)
$\lambda^l \leftarrow \frac{||w_t^l||}{||g_t^l|| + \beta||w_t^l||}$ (compute the local LR λ^l)
$v_{t+1}^l \leftarrow m v_t^l + \gamma_{t+1} * \lambda^l * (g_t^l + \beta w_t^l)$ (update the momentum)
$w_{t+1}^l \leftarrow w_t^l - v_{t+1}^l$ (update the weights)
end while

Yang You, et al. LARGE BATCH TRAINING OF CONVOLUTIONAL NETWORKS

Large Batch Training



(a) Training without LARS

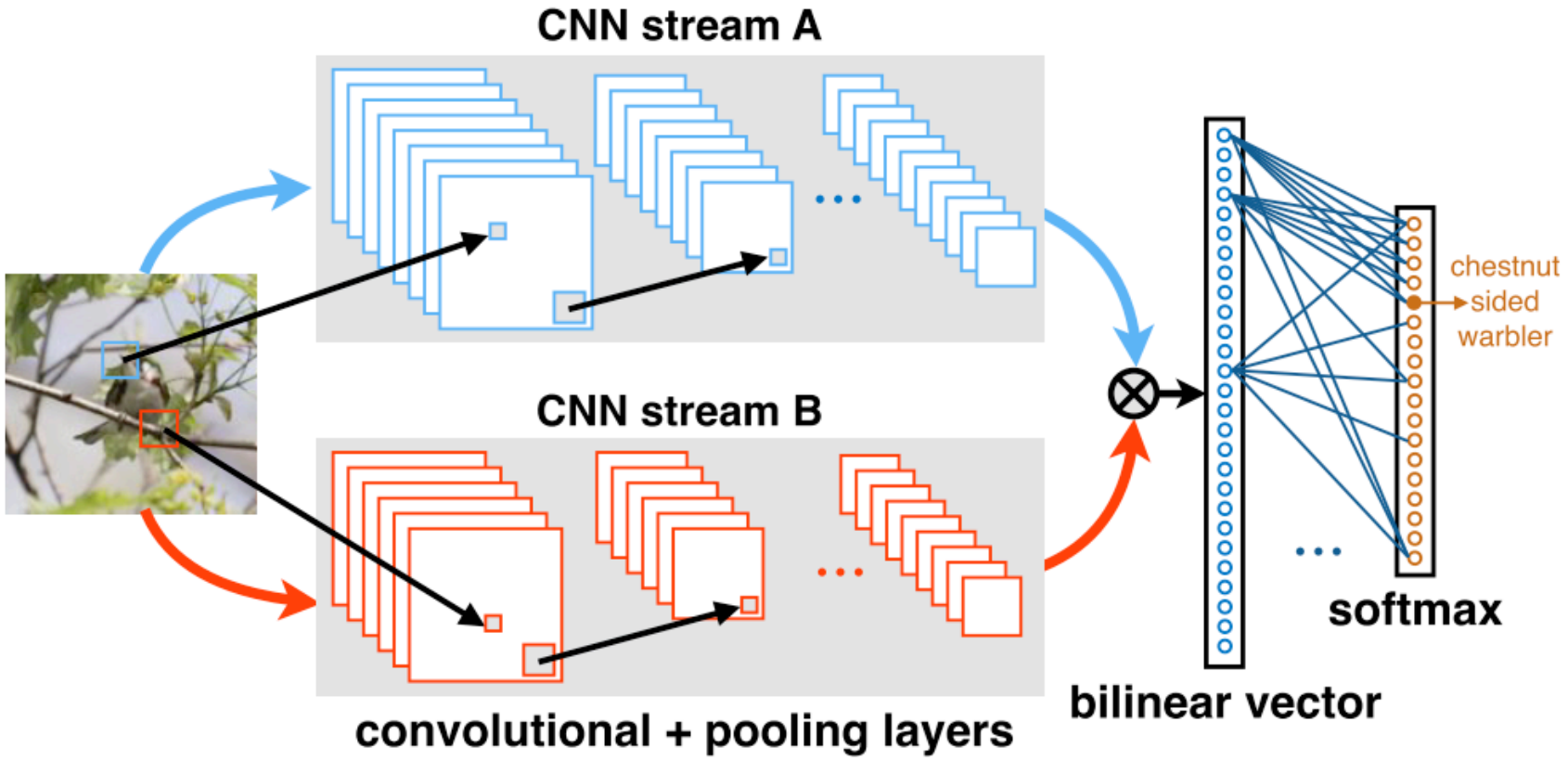


(b) Training with LARS

Large Batch Training

- Trend
  - *Higher performance*
  - *Flexibility*

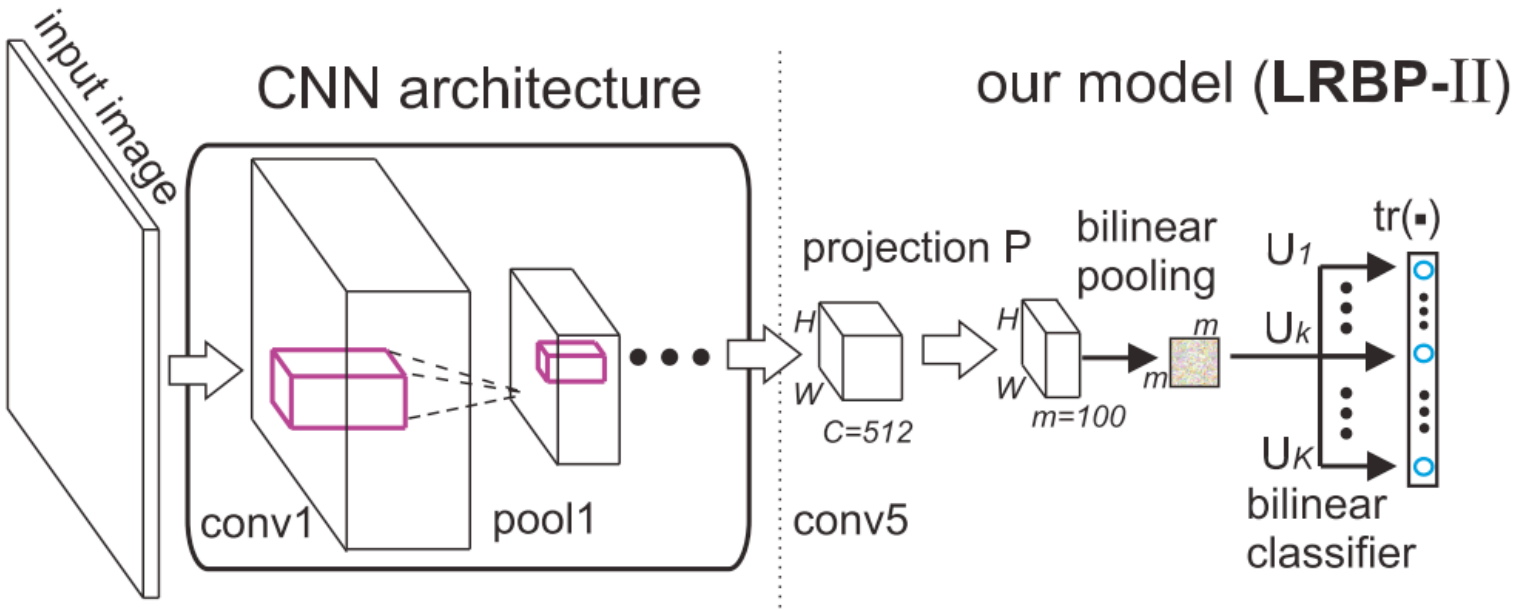
Bilinear Feature



Lin, Tsung-Yu, Aruni RoyChowdhury, and Subhransu Maji. "Bilinear cnn models for fine-grained visual recognition."

Bilinear Feature

- Low-rank tricks

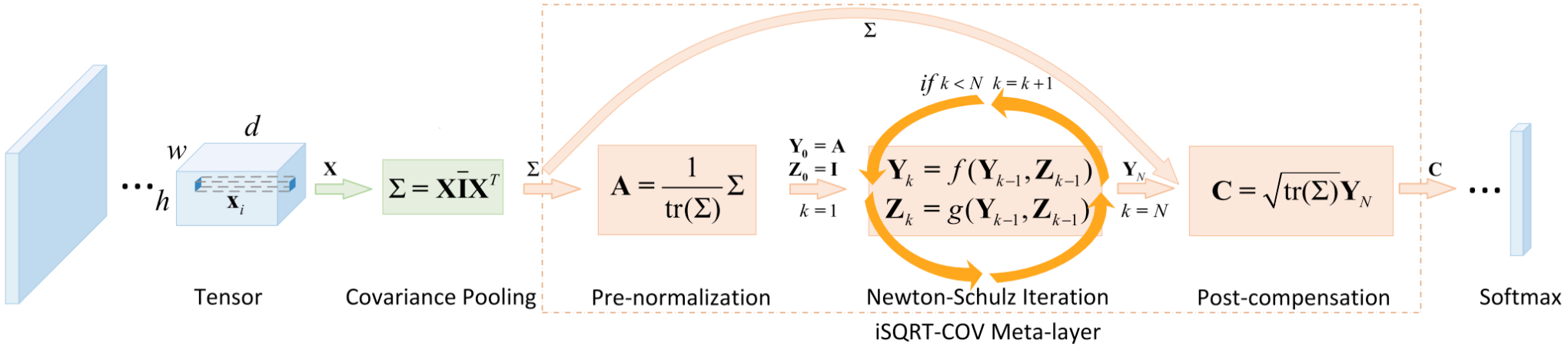


Kong, Shu, and Charless Fowlkes. "Low-rank bilinear pooling for fine-grained classification." *(CVPR)*

Bilinear Feature

- Whitening (SVD, Matrix SQRT, etc.)
  - *MPN-COV*
  - *G2DeNet*
  - *Improved B-CNN*
  - *iSQRT*

Li, Peihua, et al. "Is second-order information helpful for large-scale visual recognition?."
Li, Peihua, et al. "Towards Faster Training of Global Covariance Pooling Networks by Iterative Matrix Square Root Normalization."



Bilinear Feature

- Best practice
  - *Linear 1x1conv + bilinear pooling + classifier*
  - *N^2 > number of classes*
  - *Add whitening if needed*

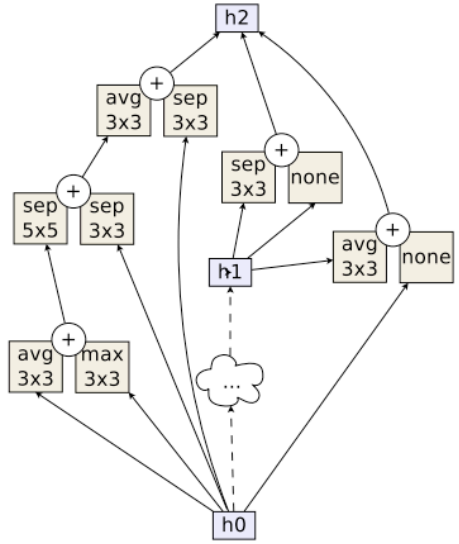
- Pros and cons
  - *Stronger classifier under limited number of feature dimensions*
  - *Unlikely to boost features*
  - *Overfit*

Conclusion: Architecture Design

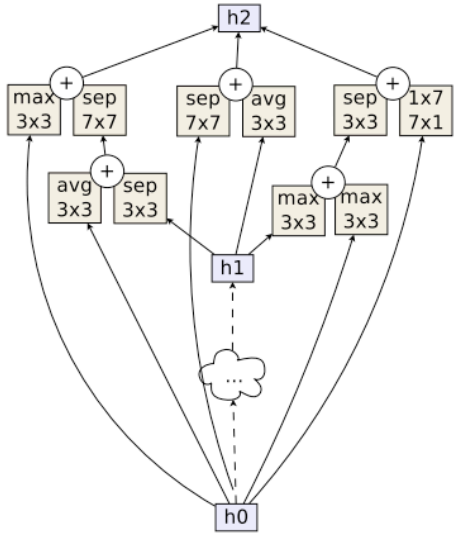
- Task specific
  - *Cls or Loc*
  - *Representation or Receptive Field*
- Shortcut matters!
- Feature reuse
- Attention if needed
- Inference efficiency

Outline

- CNN review
- General idea
- Architecture design
- Neural architecture search


h2
avg 3x3
sep 3x3
sep 5x5
sep 3x3
sep 3x3
none
h1
avg 3x3
none
avg 3x3
max 3x3
...
h0

(a)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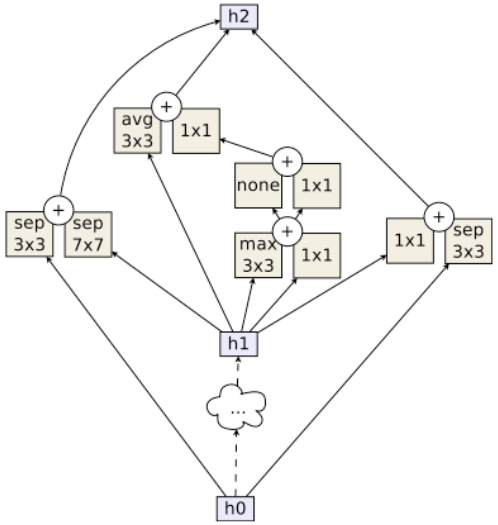
max 3x3
sep 7x7
sep 7x7
avg 3x3
sep 3x3
1x7 7x1
avg 3x3
sep 3x3
max 3x3
max 3x3
h1
...
h0

(b)


h2
avg 3x3
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1x1
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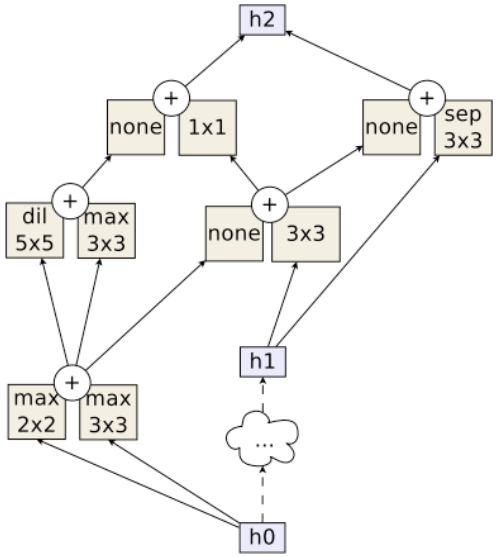
sep 7x7
max 3x3
1x1
1x1
sep 3x3
h1
...
h0

(c)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none
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none
sep 3x3
dil 5x5
max 3x3
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3x3
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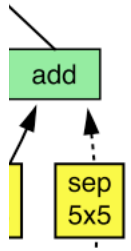
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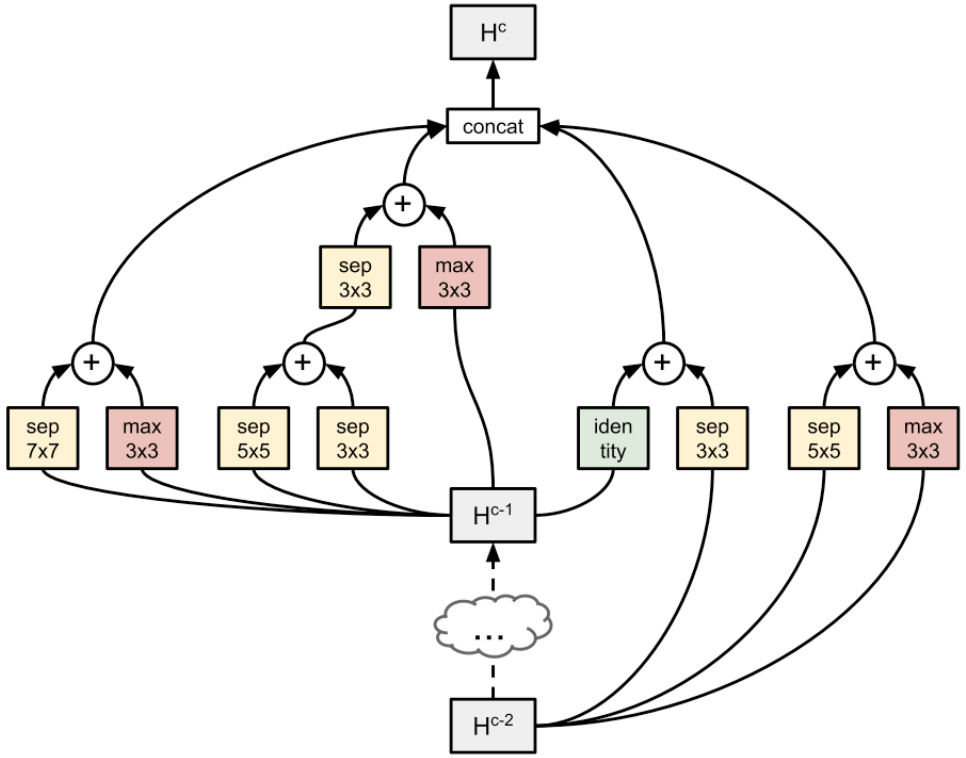
Introduction

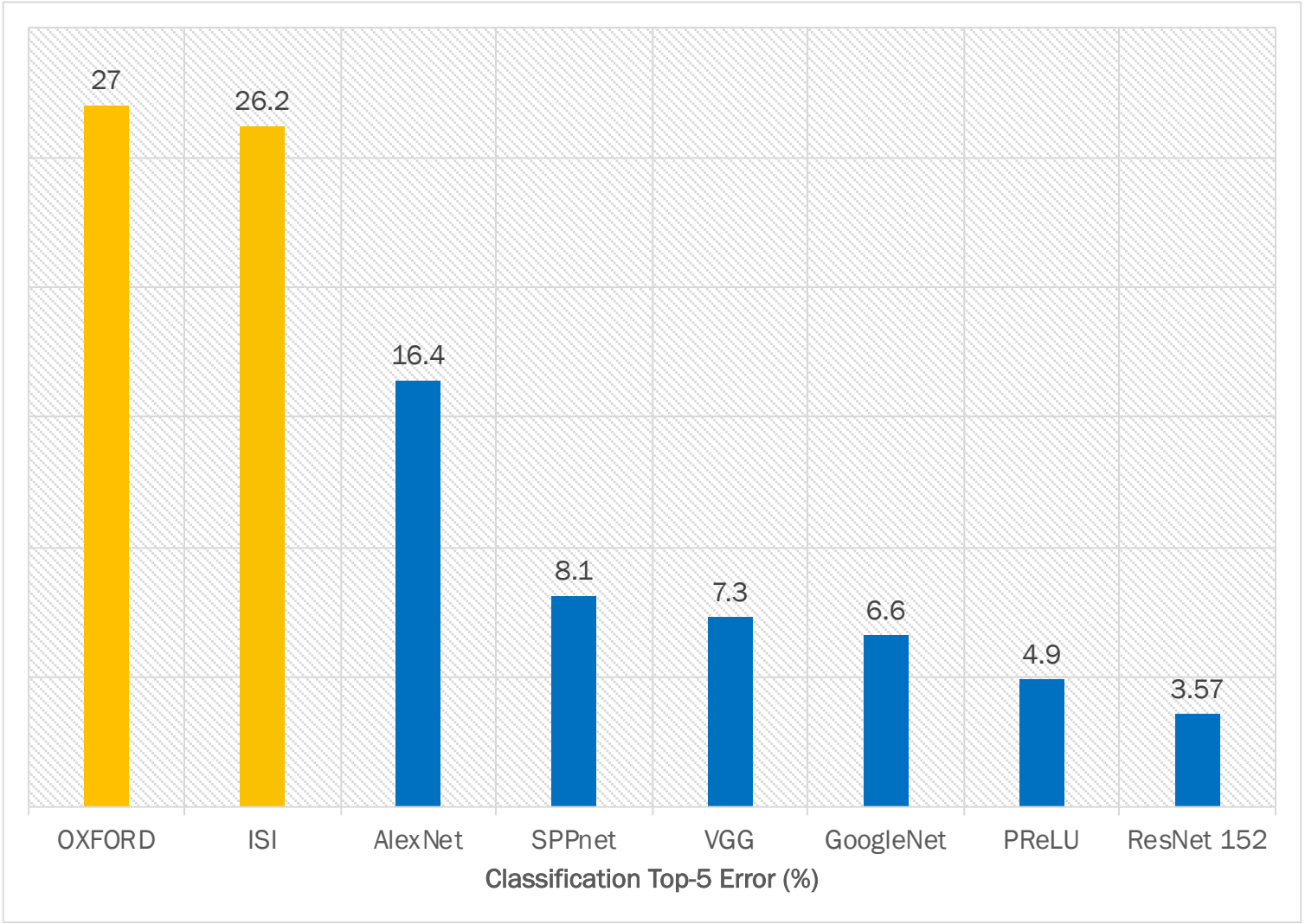
- AutoML
  - *A meta-approach to generate machine learning systems*
  - *Automatically search vs. manually design*

- AutoML for Deep Learning
  - *Neural architecture search (NAS)*
  - *Hyper-parameters turning*
  - *Loss function*
  - *Data augmentation*
  - *Activation function*
  - *Backpropagation*
  - ...



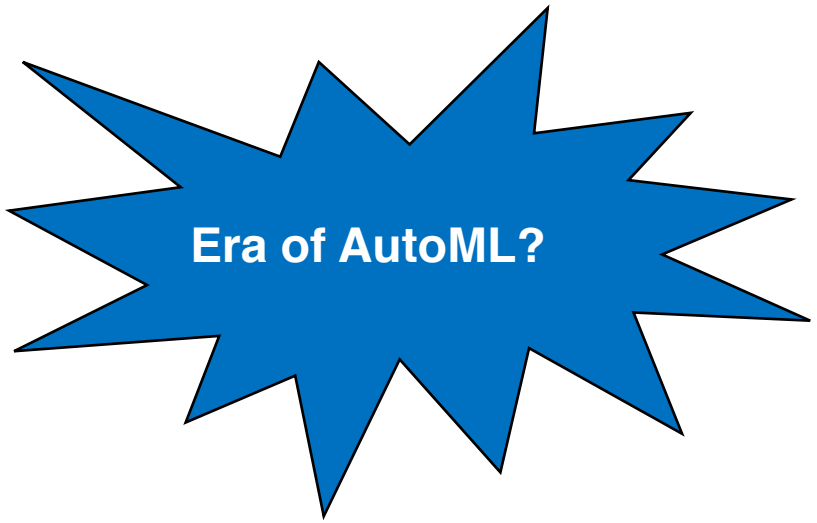
Revolution of AutoML

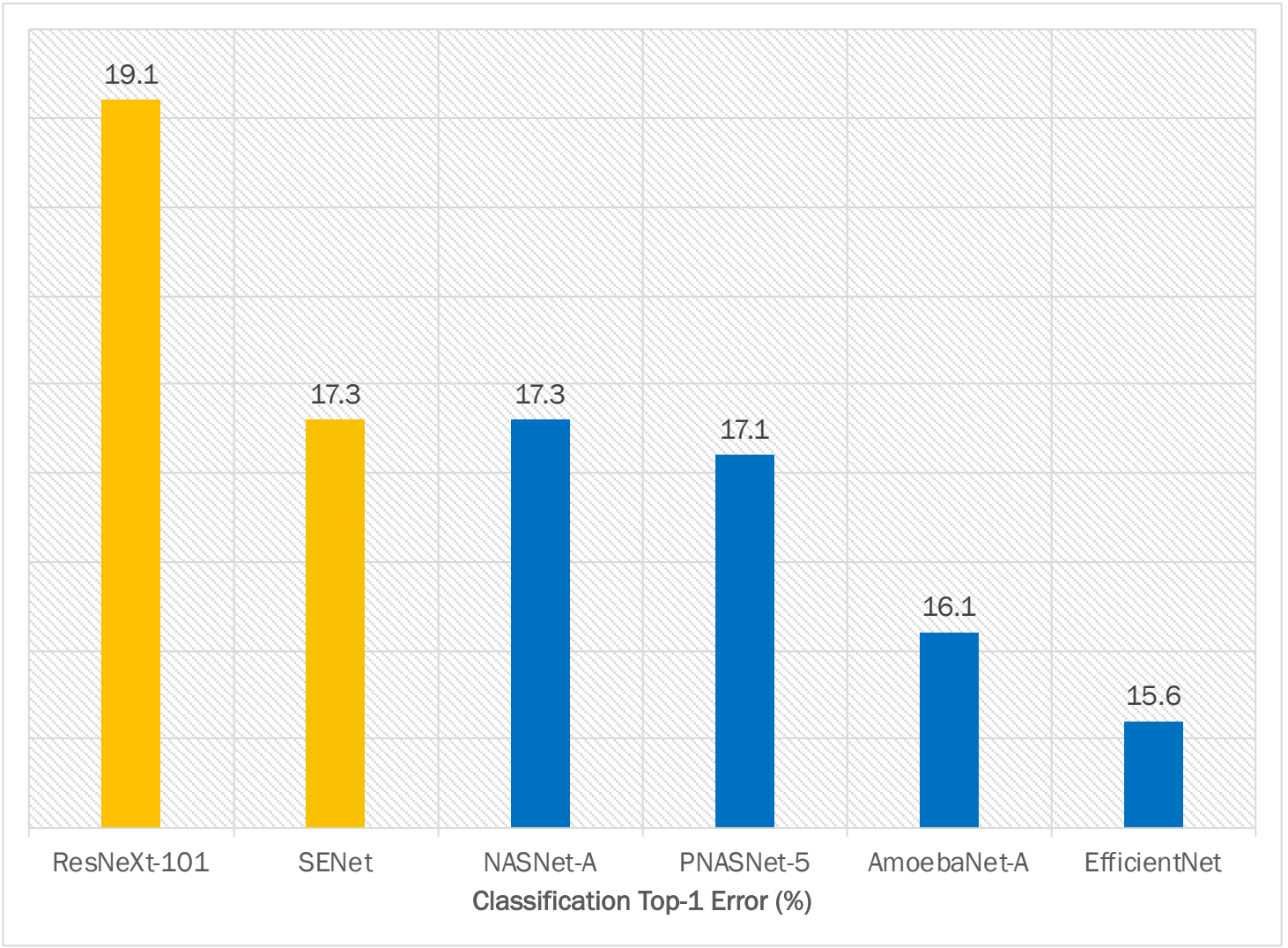
- ImageNet 2012
  - *Hand-craft feature* vs. *deep learning*
- Era of **Deep Learning** begins



Revolution of AutoML (cont'd)

- ImageNet 2017
  - *Manual architecture* vs. *AutoML models*



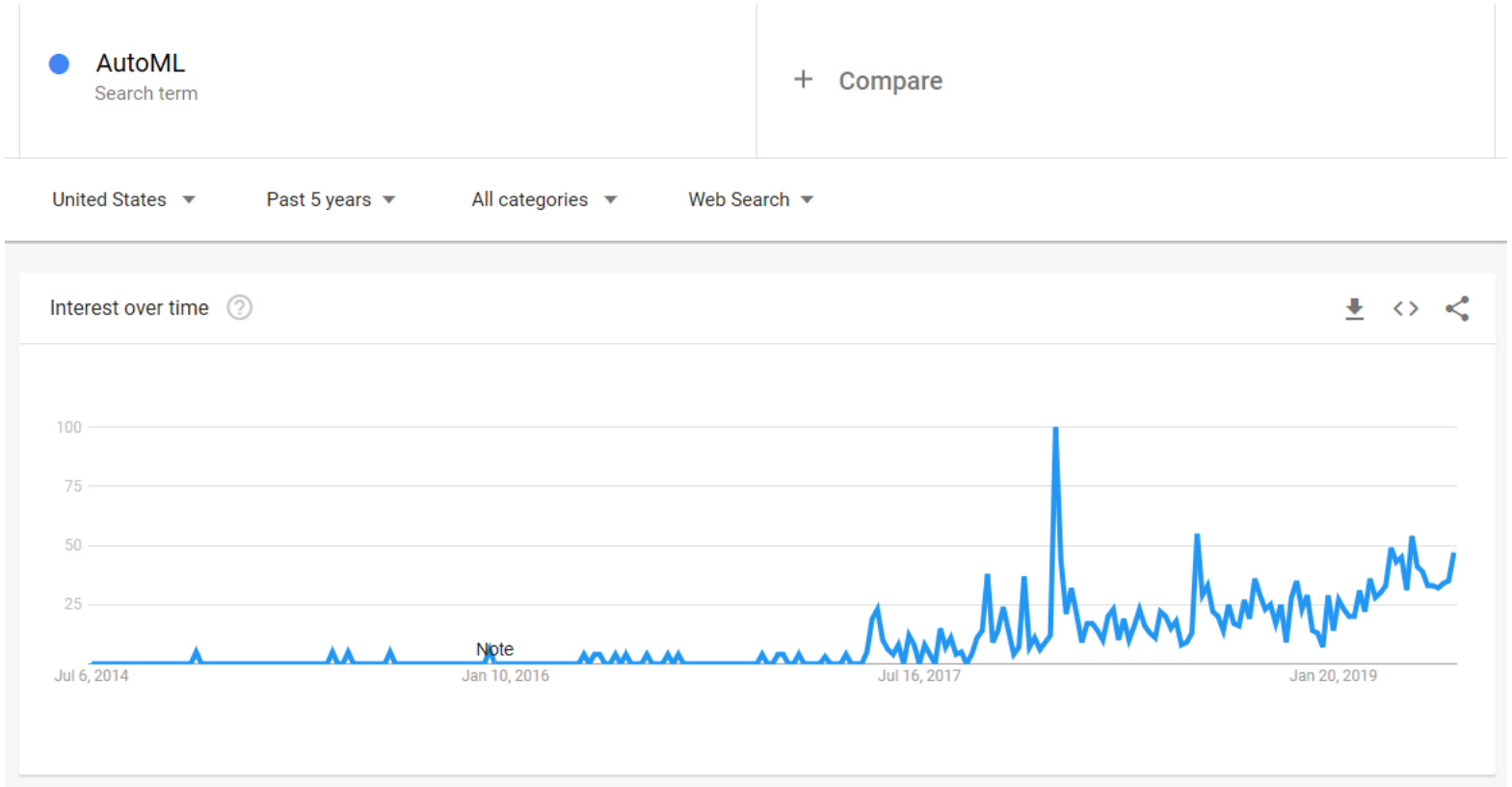


Revolution of AutoML (cont'd)

- Literature
  - *200+ since 2017*

Revolution of AutoML (cont'd)

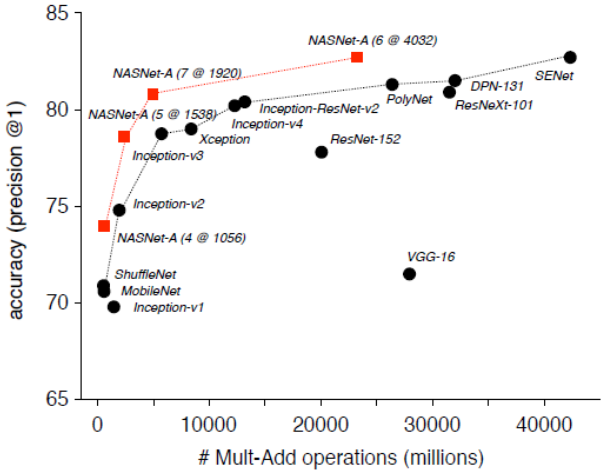
- Literature
  - *200+ since 2017*
- Google Trends

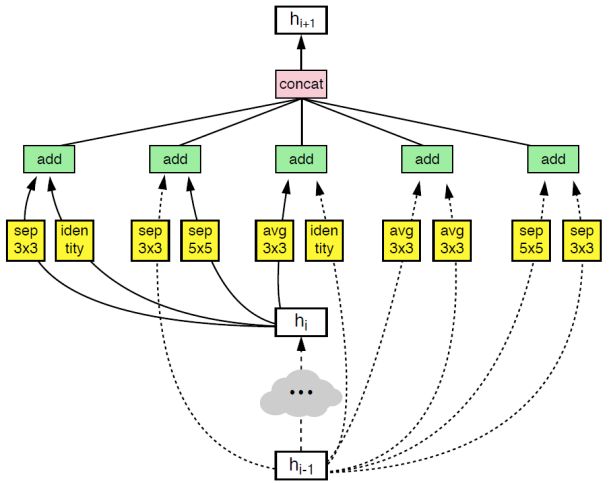


Recent Advances in AutoML (1)

- Surpassing handcraft models
  - *NASNet*

- Keynotes
  - *RNN controller + policy gradient*
  - *Flexible search space*
  - *Proxy task needed*



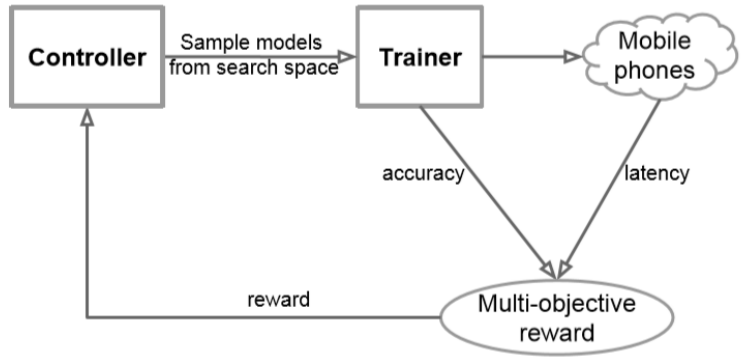


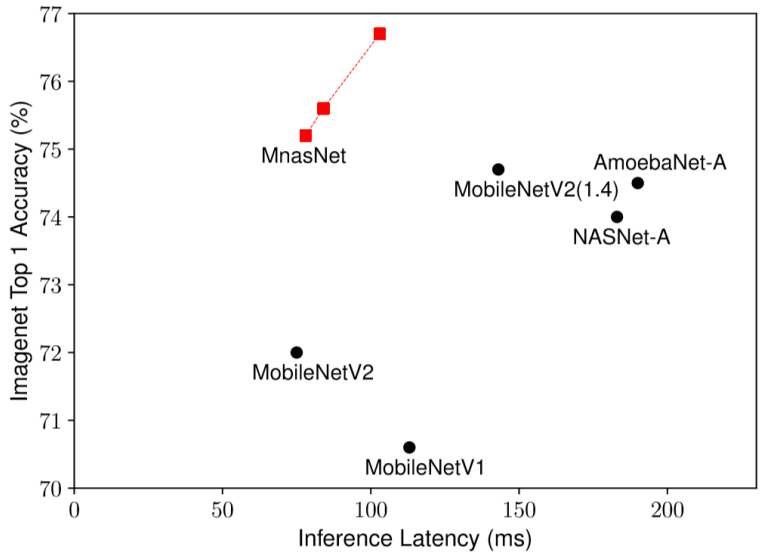
Zoph et al. Learning Transferable Architectures for Scalable Image Recognition
Zoph et al. Neural Architecture Search with Reinforcement Learning

Recent Advances in AutoML (2)

- Search on the target task
  - *MnasNet*

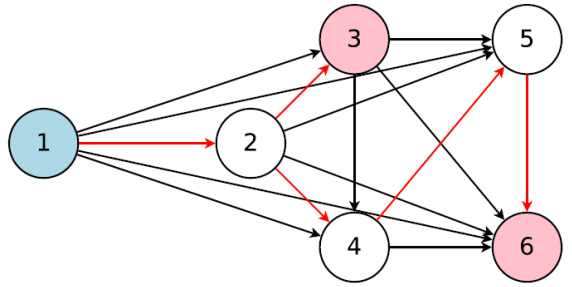
- Keynotes
  - *Search directly on ImageNet*
  - *Platform aware search*
  - *Very costly (thousands of TPU-days)*



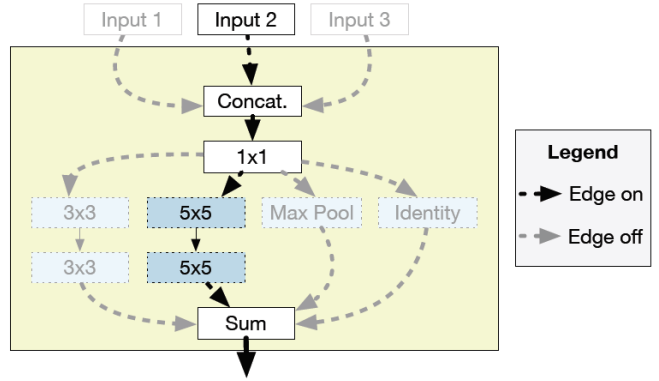


Tan et al. MnasNet: Platform-Aware Neural Architecture Search for Mobile

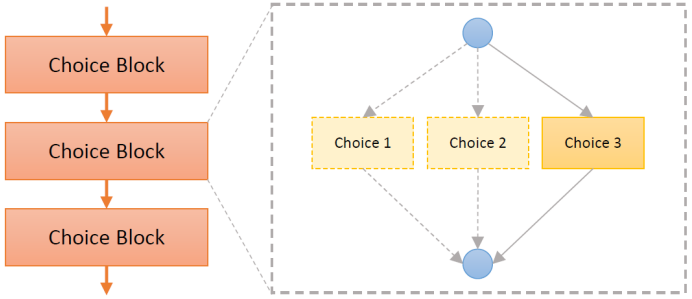
Recent Advances in AutoML (3)



- Weight Sharing for Efficient Search & Evaluation



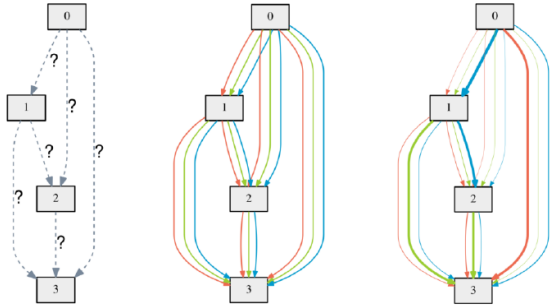
- Keynotes
  - *Super network*
  - *Finetuning & inference only instead of retraining*
  - *Inconsistency in super net evaluation*

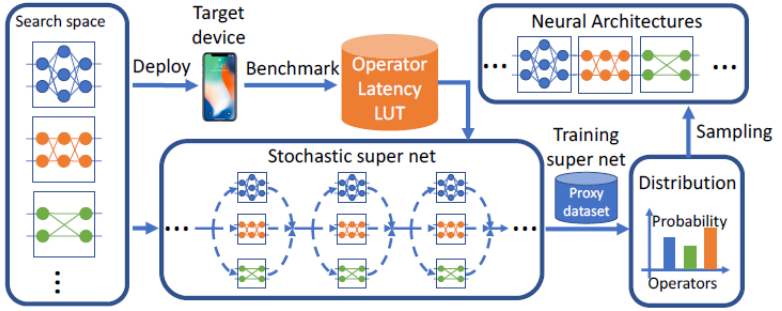


Pham et al. Efficient Neural Architecture Search via Parameter Sharing
Bender et al. Understanding and Simplifying One-Shot Architecture Search
Guo et al. Single Path One-Shot Neural Architecture Search with Uniform Sampling

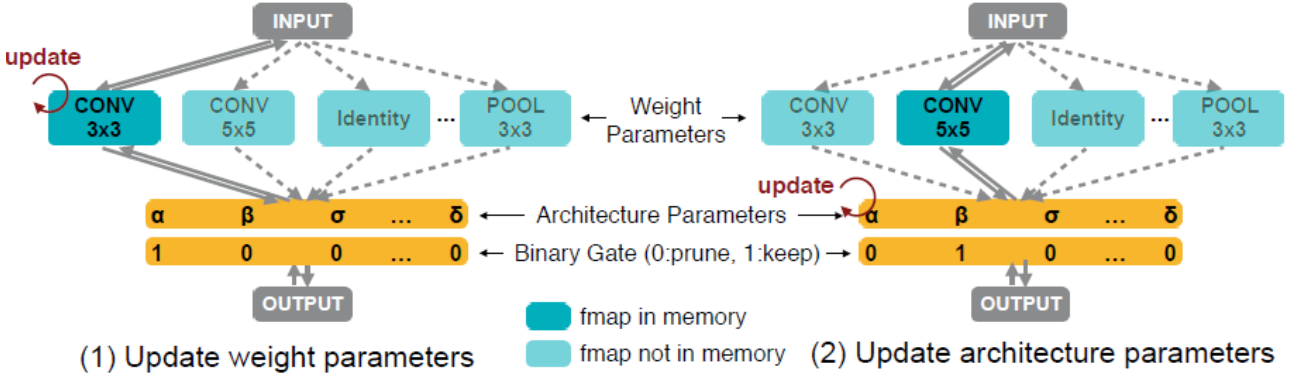
Recent Advances in AutoML (4)

- Gradient-based methods
  - *DARTS*
  - *SNAS, FBNet, ProxylessNAS*





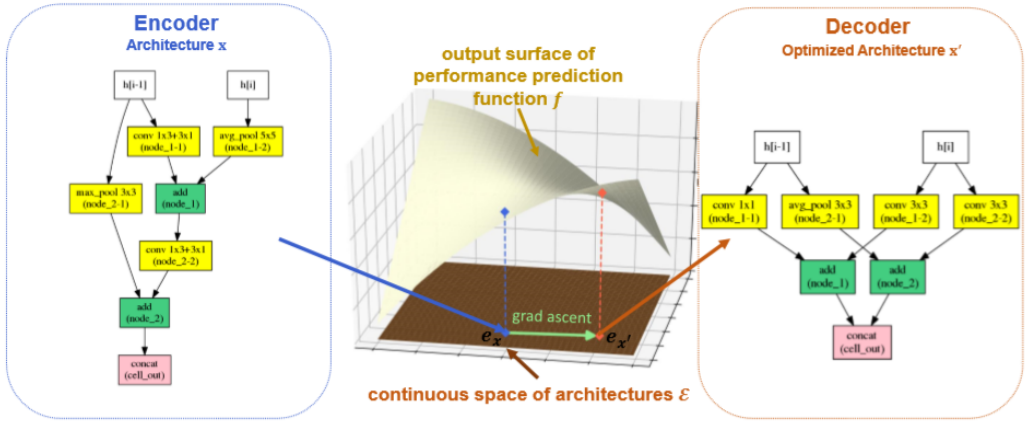
- Keynotes
  - *Joint optimization of architectures and weights*
  - *Weight sharing implied*
  - *Sometimes less flkexible*



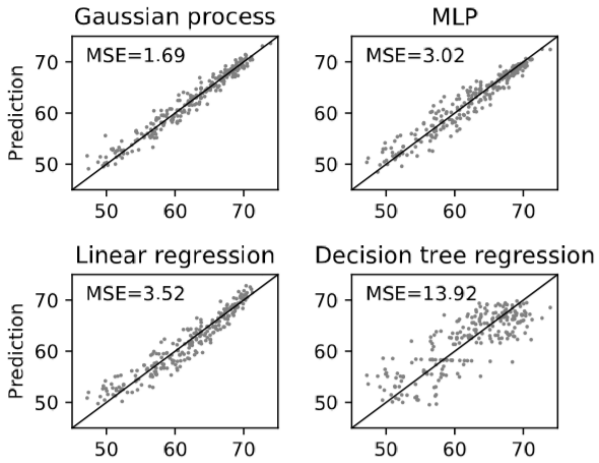
Liu et al. DARTS: Differentiable Architecture Search
Xie et al. SNAS: Stochastic Neural Architecture Search
Cai et al. ProxylessNAS: Direct Neural Architecture Search on Target Task and Hardware
Wu et al. FBNet: Hardware-Aware Efficient ConvNet Design via Differentiable Neural Architecture Search

Recent Advances in AutoML (5)

- Performance Predictor
  - *Neural Architecture Optimization*
  - *ChamNet*



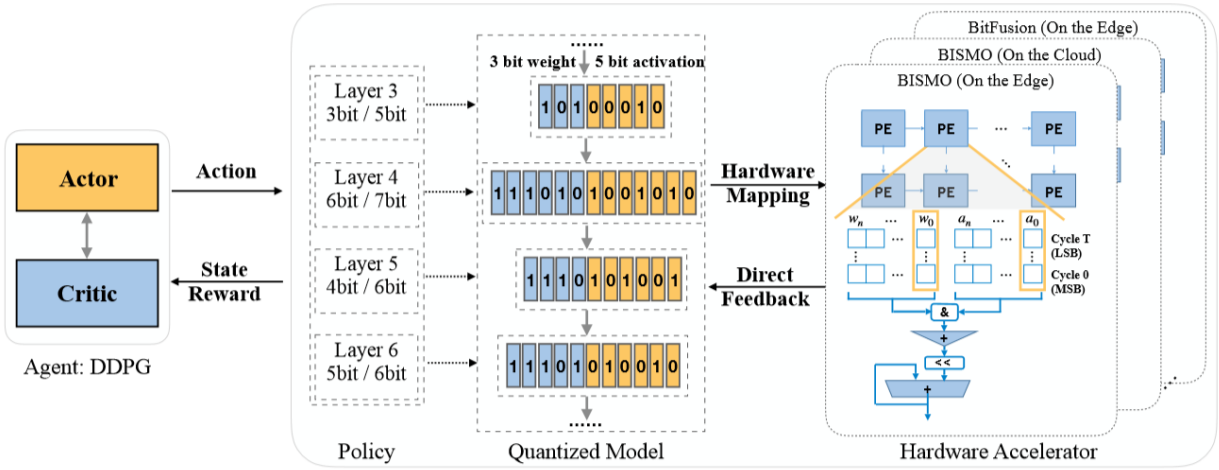
- Keynotes
  - *Architecture encoding*
  - *Performance prediction models*
  - *Cold start problem*



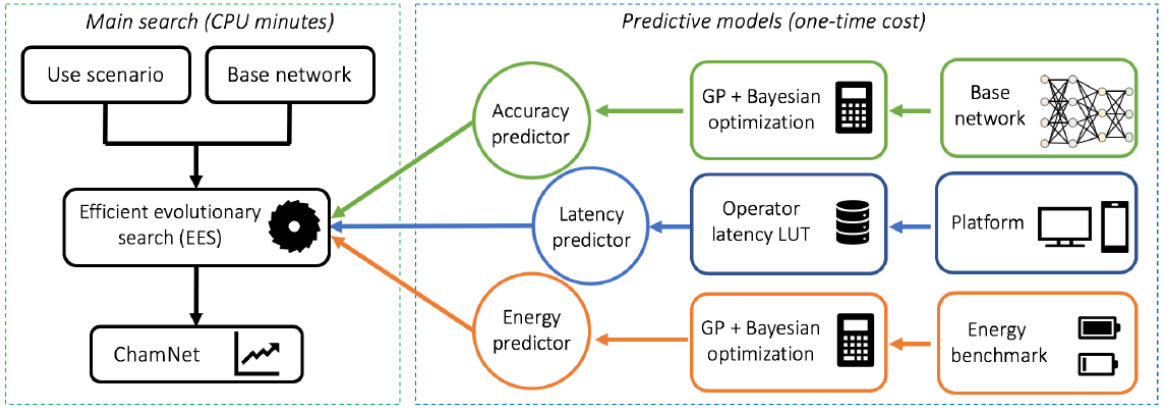
Luo et al. Neural Architecture Optimization
Dai et al. ChamNet: Towards Efficient Network Design through Platform-Aware Model Adaptation

Recent Advances in AutoML (6)

- Hardware-aware Search
  - *Search with complexity budget*
  - *Quantization friendly*
  - *Energy-aware search*
  - ...



- Keynotes
  - *Complexity-aware loss & reward*
  - *Mullti-target search*
  - *Device in the loop*

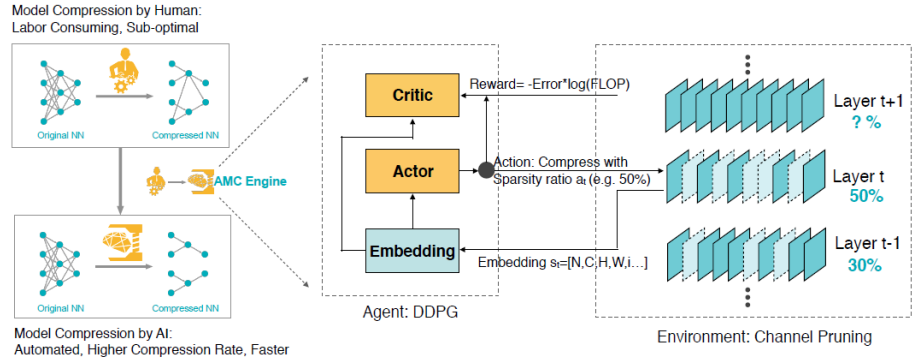


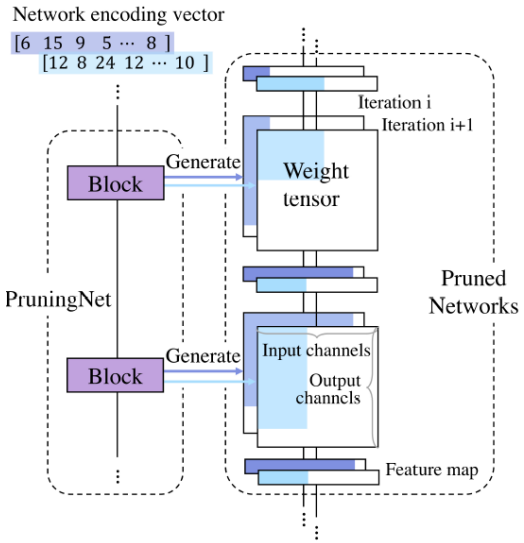
Wu et al. Mixed Precision Quantization of ConvNets via Differentiable Neural Architecture Search
V´eniat et al. Learning Time/Memory-Efficient Deep Architectures with Budgeted Super Networks
Wang et al. HAQ: Hardware-Aware Automated Quantization with Mixed Precision

Recent Advances in AutoML (7)

- AutoML in Model Pruning
  - *NetAdapt*
  - *AMC*
  - *MetaPruning*

- Keynotes
  - *Search for the pruned architecture*
  - *Hyper-parameters like channels, spatial size, …*

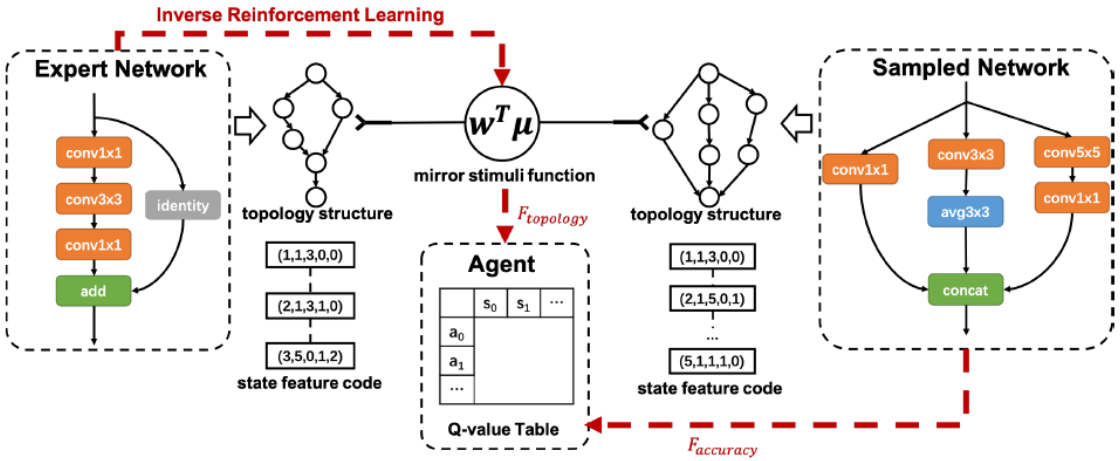




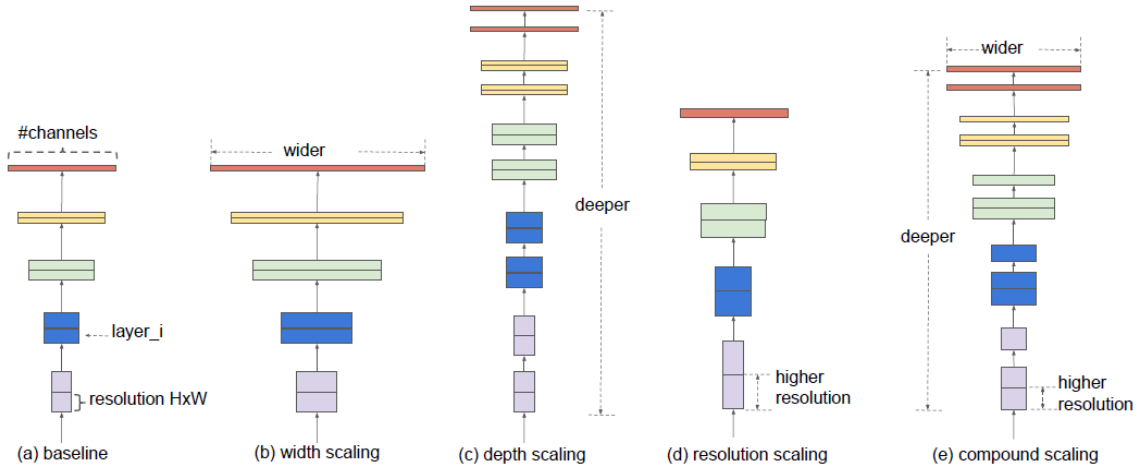
Yang et al. NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications
He et al. AMC: AutoML for Model Compression and Acceleration on Mobile Devices
Liu et al. MetaPruning: Meta Learning for Automatic Neural Network Channel Pruning

Recent Advances in AutoML (8)

- Handcraft + NAS
  - *Human-expert guided search (IRLAS)*
  - *Boosting existing handcraft models (EfficientNet, MobileNet v3)*



- Keynotes
  - *Very competitive performance*
  - *Efficient*
  - *Search space may be restricted*



Howard et al. Searching for MobileNetV3
Tan et al. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks
Guo et al. IRLAS: Inverse Reinforcement Learning for Architecture Search

Recent Advances in AutoML (9)

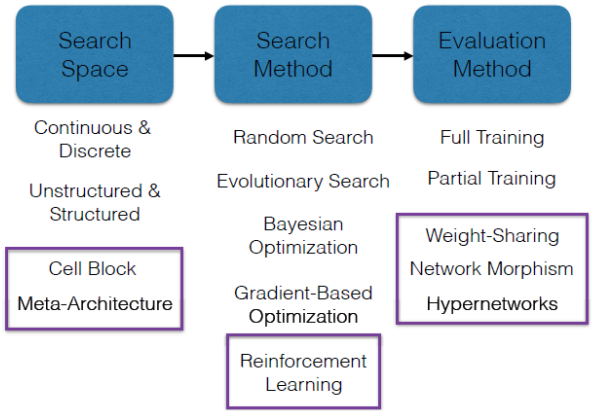
- Varies Tasks
  - *Object Detection*
  - *Semantic Segmentation*
  - *Super-resolution*
  - *Face Recognition*
  - ...
- Not only NAS, search for everything!
  - *Activation function*
  - *Loss function*
  - *Data augmentation*
  - *Backpropagation*
  - ...

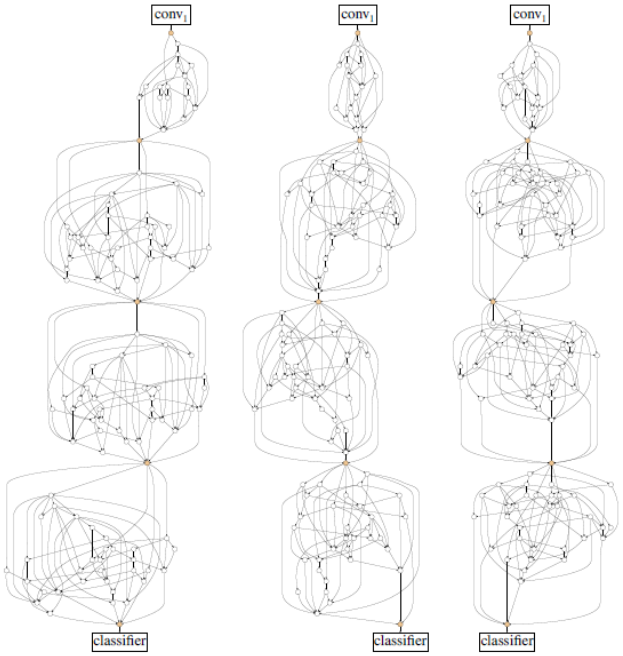
Liu et al. Auto-DeepLab: Hierarchical Neural Architecture Search for Semantic Image Segmentation
Chu et al. Fast, Accurate and Lightweight Super-Resolution with Neural Architecture Search
Ramachandra et al. Searching for Activation Functions
Alber et al. Backprop Evolution

Recent Advances in AutoML (10)

- Rethinking the Effectiveness of NAS
  - *Random search*
  - *Random wire network*

- Keynotes
  - *Reproducibility*
  - *Search algorithm or search space?*
  - *Baselines*





Li et al. Random Search and Reproducibility for Neural Architecture Search
Xie et al. Exploring Randomly Wired Neural Networks for Image Recognition

Summary: Trends and Challenges

- Trends
  - *Efficient & high-performance algorithm*
  - *Flexible search space*
  - *Device-aware optimization*
  - *Multi-task / Multi-target search*

- Challenges
  - *Trade-offs between efficiency, performance and flexibility*
  - *Search space matters!*
  - *Fair benchmarks*
  - *Pipeline search*