Constructing Fast Network through Deconstruction of Convolution

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Goal

CNN has achieved outstanding accuracy with deeper and wider networks

Can we make fast CNN with smaller resources while retaining accuracy?

How to make a fast network

- *Reduce FLOPs*
  - Grouped or depthwise convolution
  - Network pruning

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- *Reduce memory access*
  - Reduce spatial convolutions

- *Maximize utilization of accessed memory*
  - Use 1x1 convolutions

How to make a fast network

- *Reduce FLOPs*
  - Grouped or depthwise convolution
  - Use 1x1 convolutions
- *R*
- *M*

Key Idea

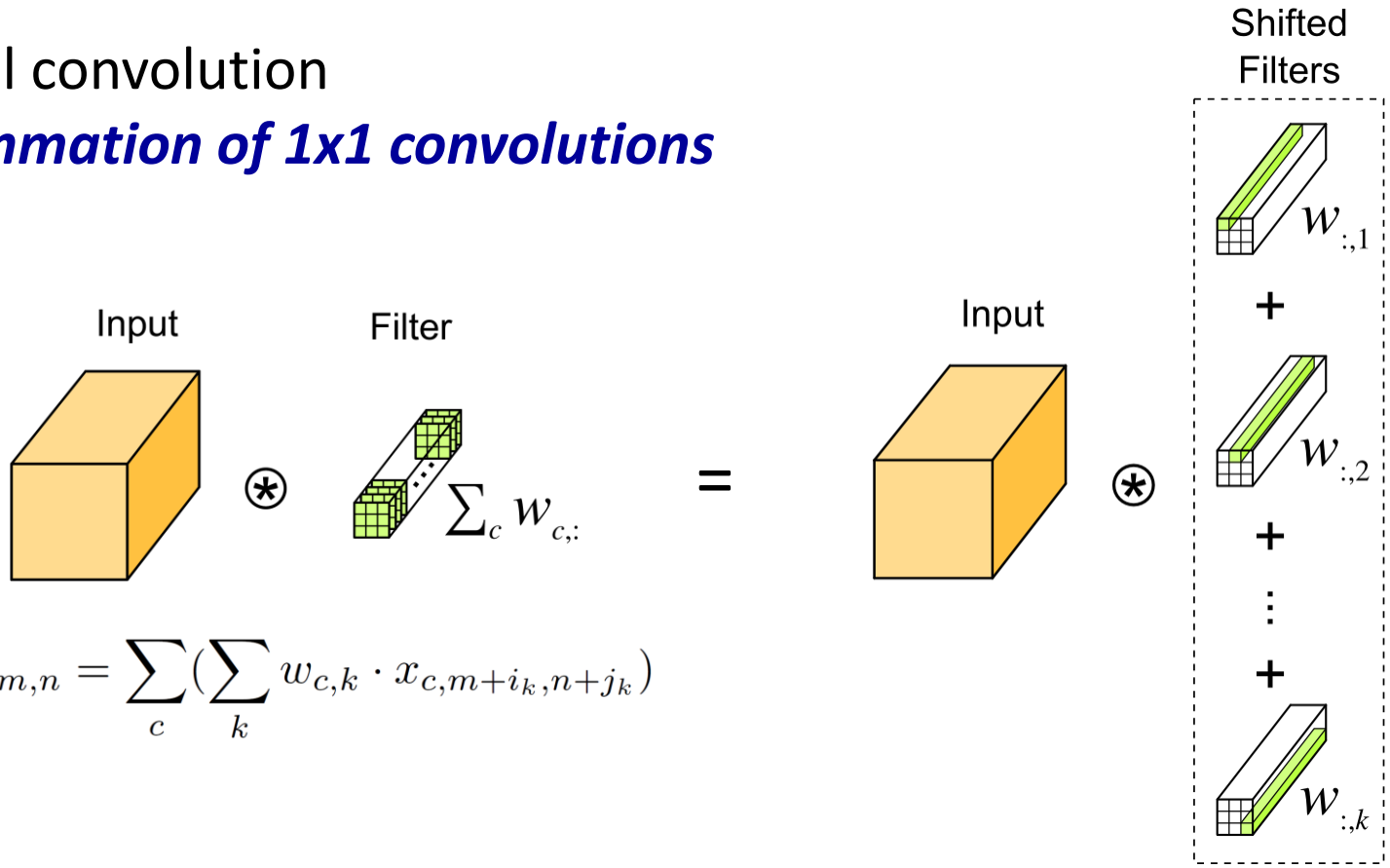
Deconstruct spatial convolution

into atomic operations

Deconstruction of convolution (1/3)

Insight

- Spatial convolution
  = ***Summation of 1x1 convolutions***



$$y_{m,n} = \sum_c (\sum_k w_{c,k} \cdot x_{c,m+i_k,n+j_k})$$

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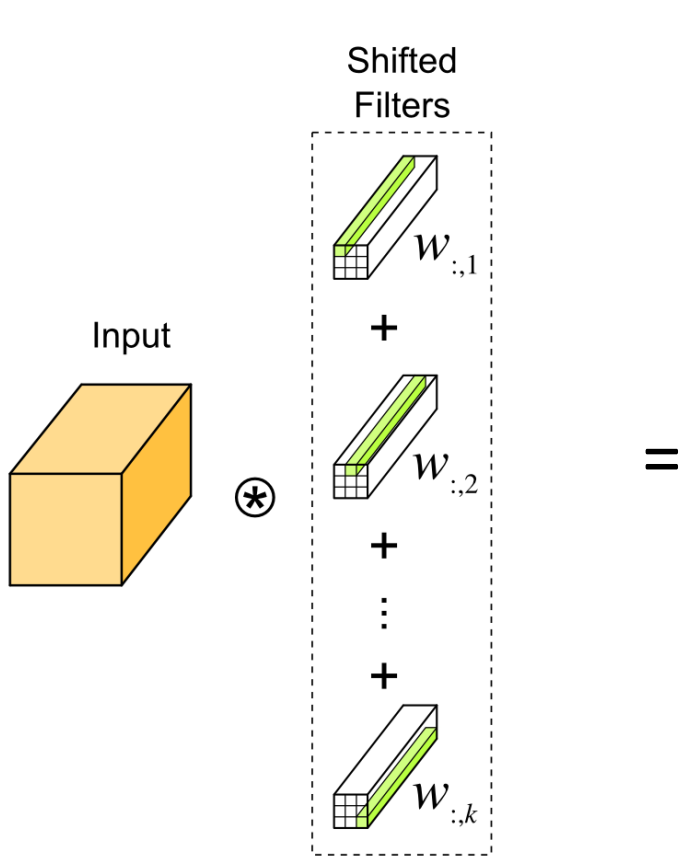
Deconstruction of convolution (2/3)

Shift Inputs *instead of filters*



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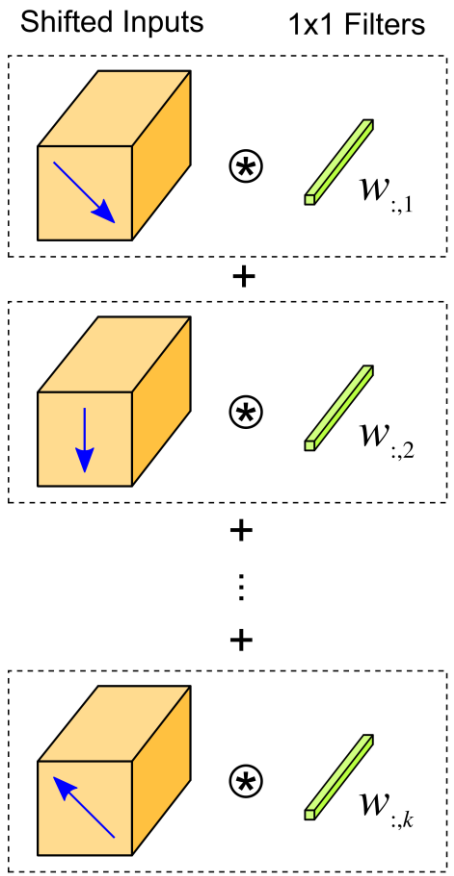

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Deconstruction of convolution (3/3)

If we can ***share shifted inputs,***

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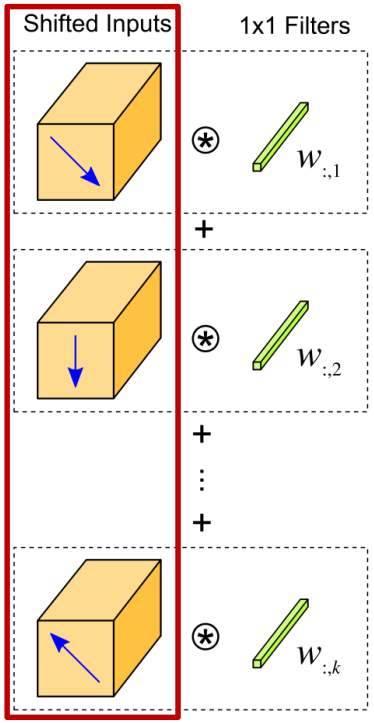

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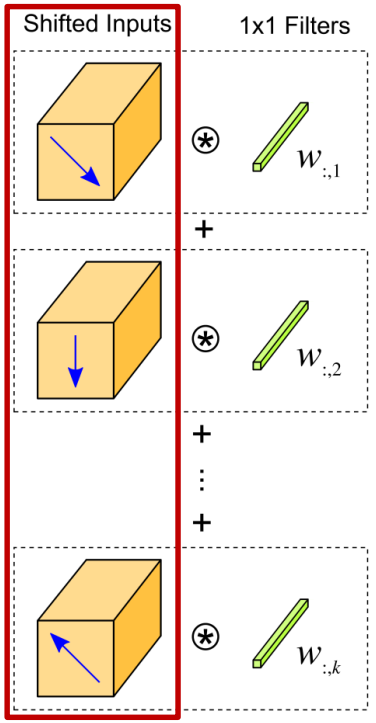
Deconstruction of convolution (3/3)

If we can ***share shifted inputs,***

– *Reduce FLOPs & memory access*

Share shifted inputs



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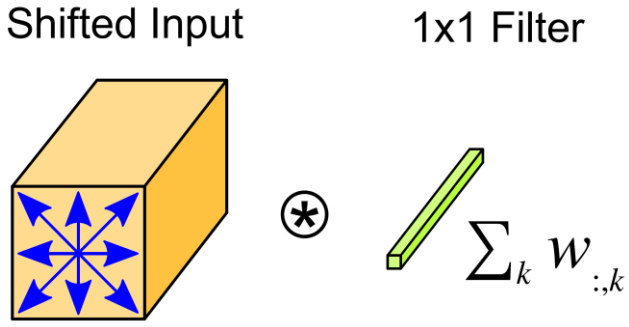

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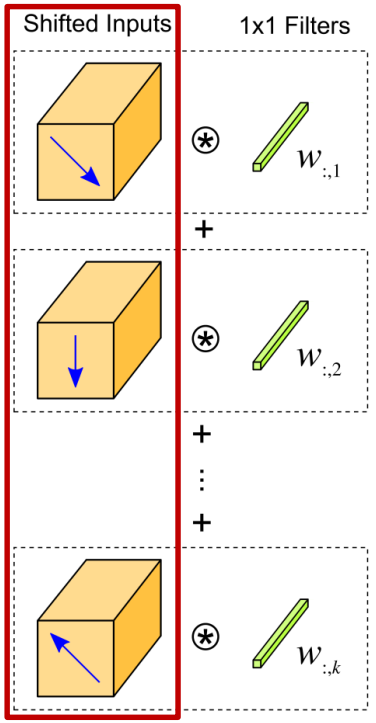
Deconstruction of convolution (3/3)

If we can ***share shifted inputs,***

- *Reduce FLOPs & memory access*
- But, *expressive power is limited* *if shifting to one direction*

Share shifted inputs



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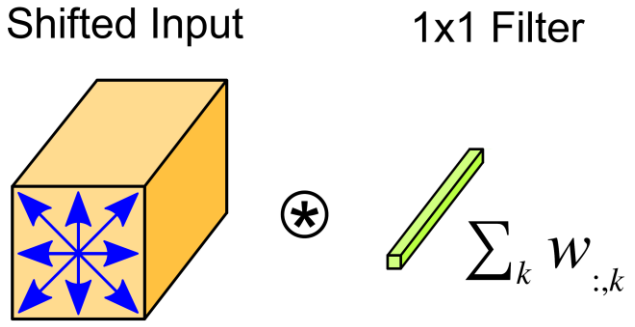

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Deconstruction of convolution (3/3)

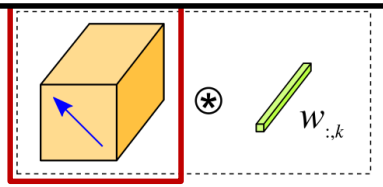
If we can ***share shifted inputs,***

- *Reduce FLOPs & memory access*
- But, *exp*

Key Challenge

How to shift inputs?

Share shifted inputs



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Our approach

- ***Active Shift Layer (ASL)***
  1. Use *depthwise shift*

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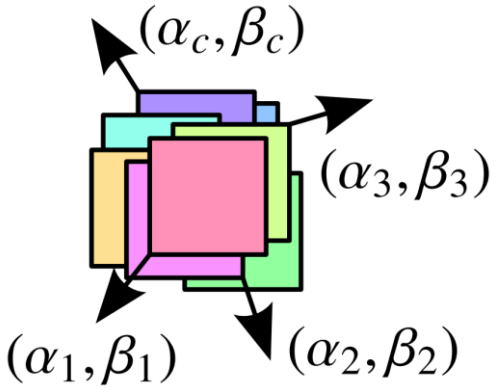

- ***Active Shift Layer (ASL)***
  1. Use *depthwise shift*
  2. *Introduce new shift parameters for each channel*

$$\theta_s = \{(\alpha_c, \beta_c) | 1 \leq c \leq C\}$$

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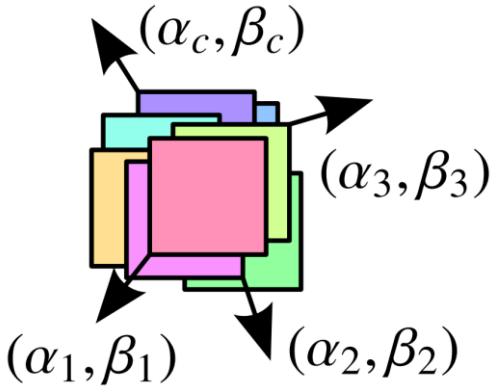

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  3. *Expand to non-integer shift* using interpolation

$$\begin{aligned}\tilde{x}_{c,m+\alpha_c,n+\beta_c} =& Z_c^1 \cdot (1-\Delta\alpha_c) \cdot (1-\Delta\beta_c) + Z_c^3 \cdot \Delta\alpha_c \cdot (1-\Delta\beta_c) \\ &+ Z_c^2 \cdot (1-\Delta\alpha_c) \cdot \Delta\beta_c + Z_c^4 \cdot \Delta\alpha_c \cdot \Delta\beta_c, \\ \Delta\alpha_c = \alpha_c - \lfloor\alpha_c\rfloor&, \Delta\beta_c = \beta_c - \lfloor\beta_c\rfloor,\end{aligned}$$

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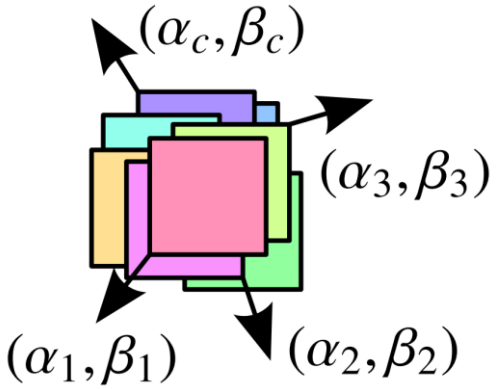

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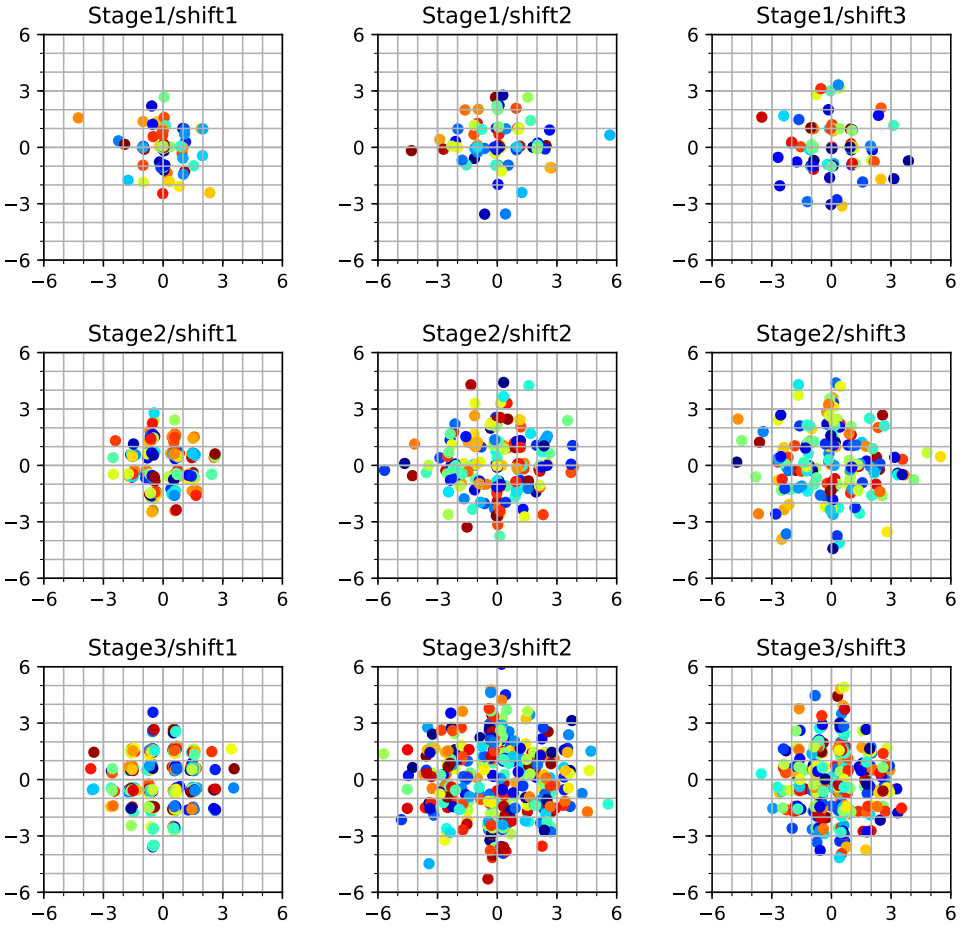
  - *Shift values are differentiable!*

→ *Shift values are trained through network itself*

Example of Learned Shift

Enlarge receptive fields by shifting inputs



Experiment (ImageNet)

- *Better accuracy with the smaller number of parameters*
- *Faster inference time with similar accuracy*

Network	Top-1	Top-5	Param(M)	FLOPs(M)	Inference Time[a] CPU(ms)	GPU(ms)
MobileNetV1[8]	70.6	-	4.2	569	-	-
ShiftNet-A[23]	70.1	89.7	4.1	1.4G	74.1	10.04
MobileNetV2[18]	71.8	**91**	3.47	300	54.7	7.07
AS-ResNet-w68(ours)	**72.2**	90.7	3.42	729	**47.9**	**6.73**
ShuffleNet-×1.5[26]	71.3	-	3.4	292	-	-
MobileNetV2-×0.75	69.8	**89.6**	2.61	209	40.4	6.23
AS-ResNet-w50(ours)	**69.9**	89.3	1.96	404	32.1	6.14
MobileNetV2-×0.5	65.4	86.4	1.95	97	**26.8**	**5.73**
MobileNetV1-×0.5	63.7	-	1.3	149	-	-
SqueezeNet[10]	57.5	80.3	1.2	-	-	-
ShiftNet-B	61.2	83.6	1.1	371	31.8	7.88
AS-ResNet-w32(ours)	**64.1**	**85.4**	0.9	171	**18.7**	**5.37**
ShiftNet-C	58.8	82	0.78	-	-	-

[a]Measured by Caffe [12] using an Intel i7-5930K CPU with a single thread and GTX Titan X (Maxwell). Inference time for MobileNet and ShiftNet (including FLOPs) are measured by using their network description.

Thank you

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