# Training CNNs with Selective Allocation of Channels

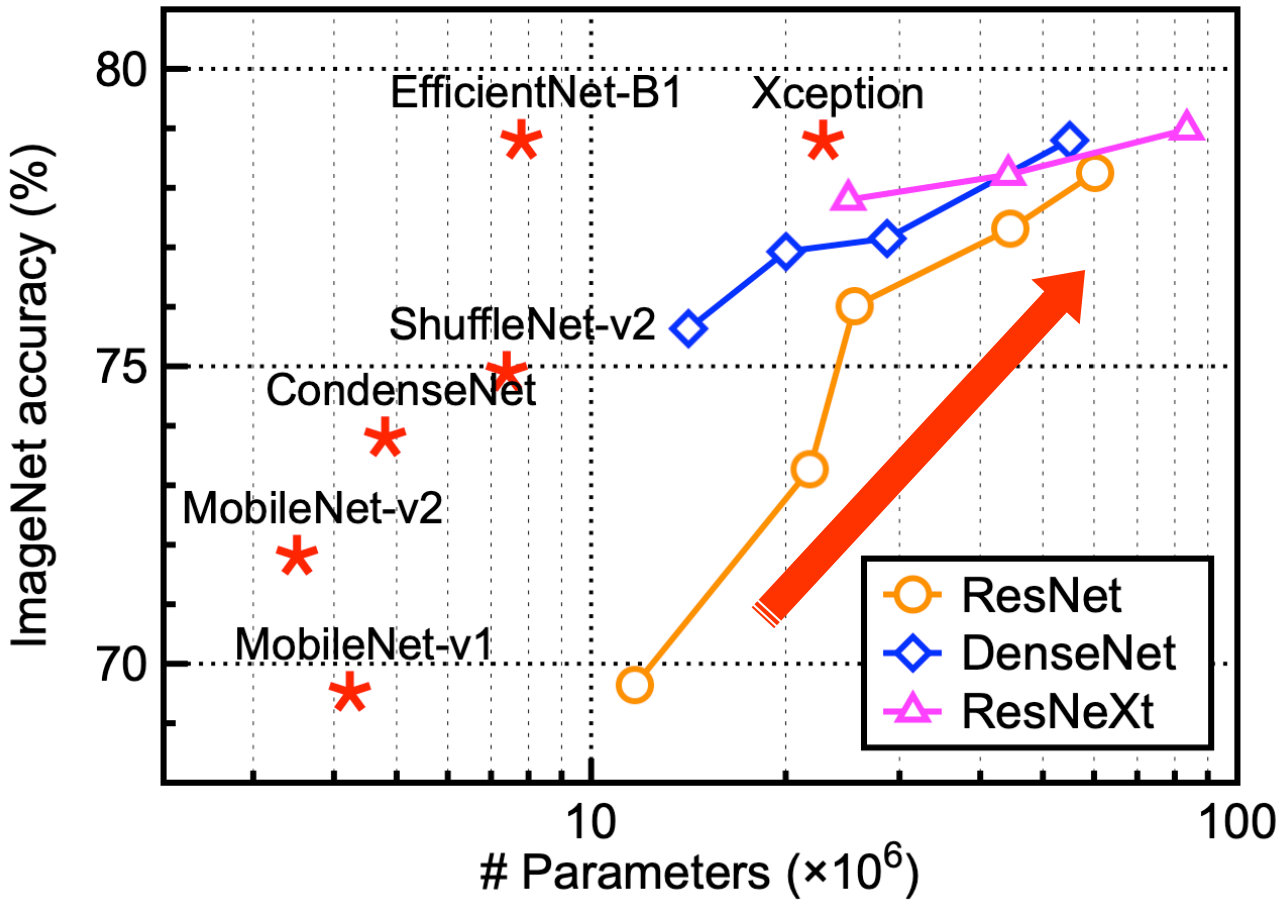
Jongheon Jeong[1] Jinwoo Shin[1,2]

[1] Korea Advanced Institute of Science and Technology (KAIST)
[2] AITRICS

ICML 2019

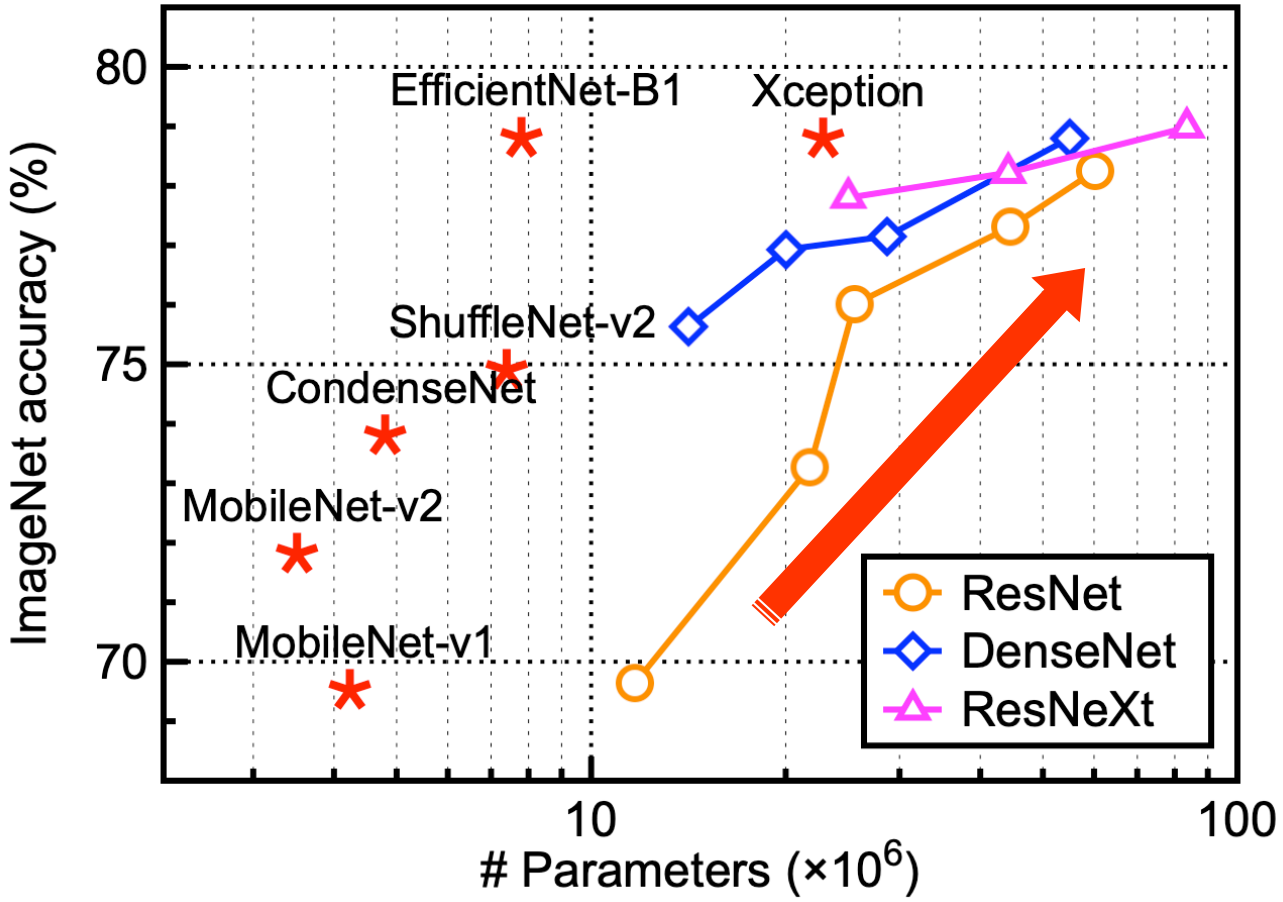
# Recent Advances in CNN Architectures

- Larger model, better accuracy → "efficient" architecture design



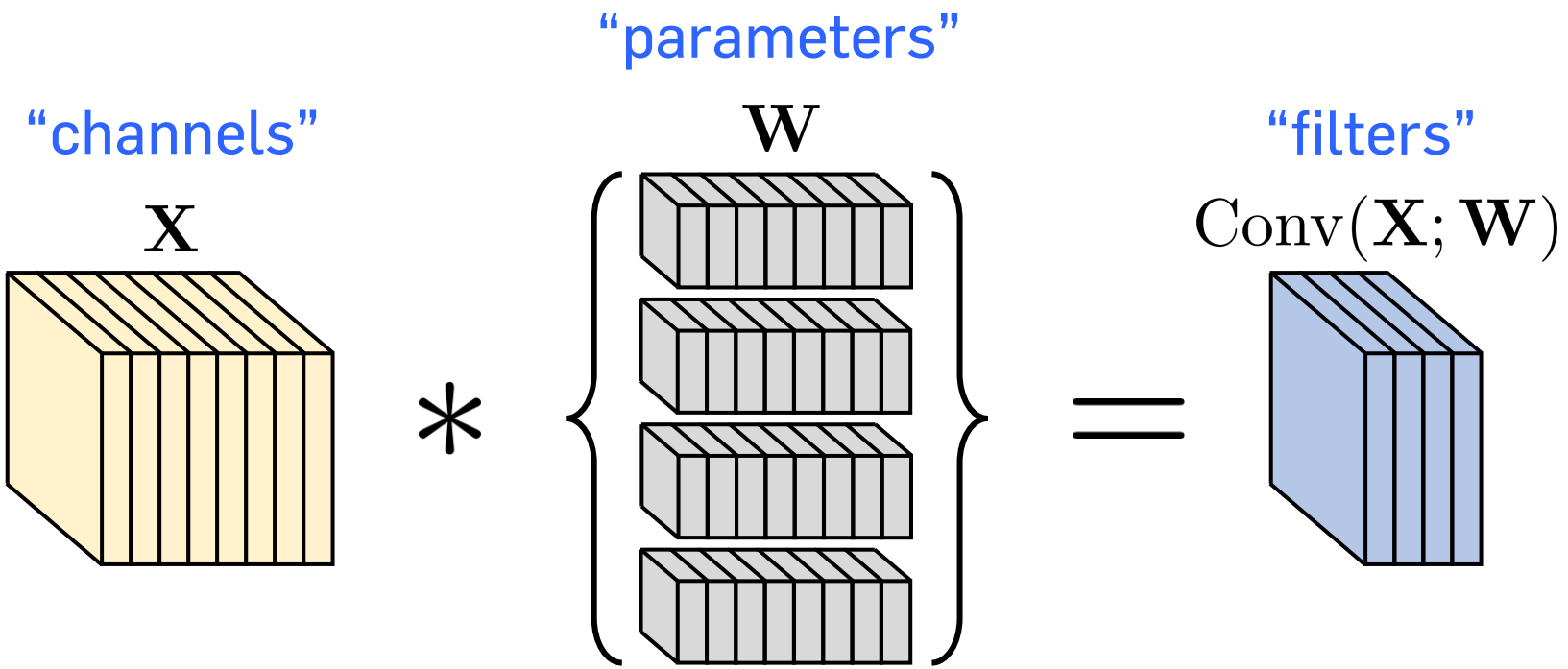
# Recent Advances in CNN Architectures

- Larger model, better accuracy → "efficient" architecture design
- **Motivation**: Current CNN design typically focus on static layers



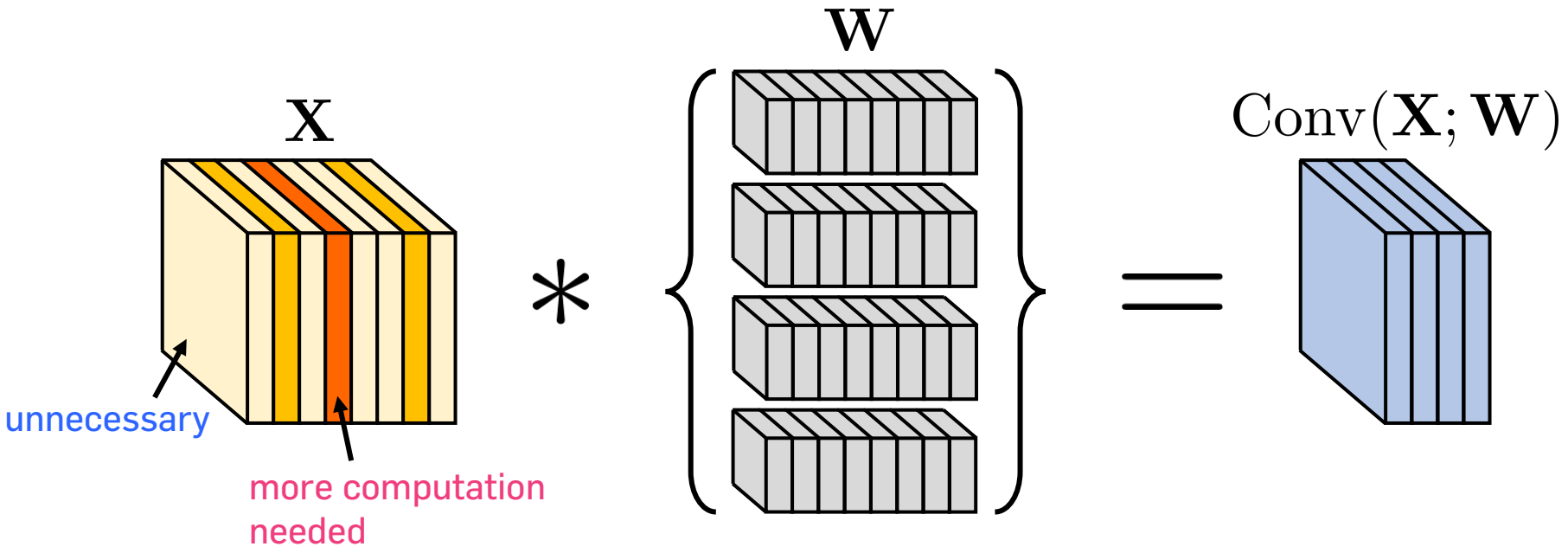
# “Static” Layers?

- Current convolutional layers allocate parameters uniformly across channels
- “Static”: The allocation is **fixed** until the end of training



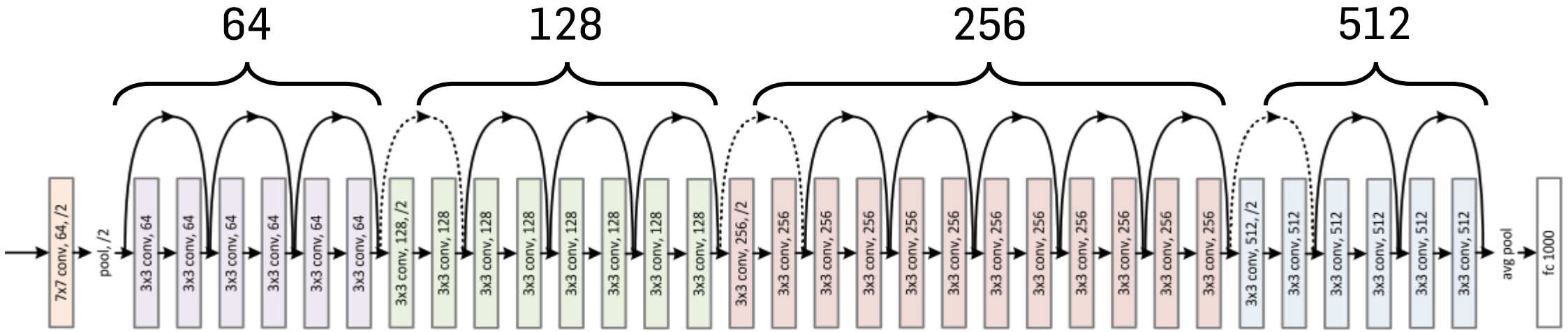
# Channel Inefficiency in “Static” CNNs

- Current convolutional layers allocate parameters uniformly across channels
- “Static”: The allocation is **fixed** until the end of training
- What if the layer contains unnecessary channels to compute?
  - The parameters allocated for those channels can hardly utilized



# Channel Inefficiency in “Static” CNNs

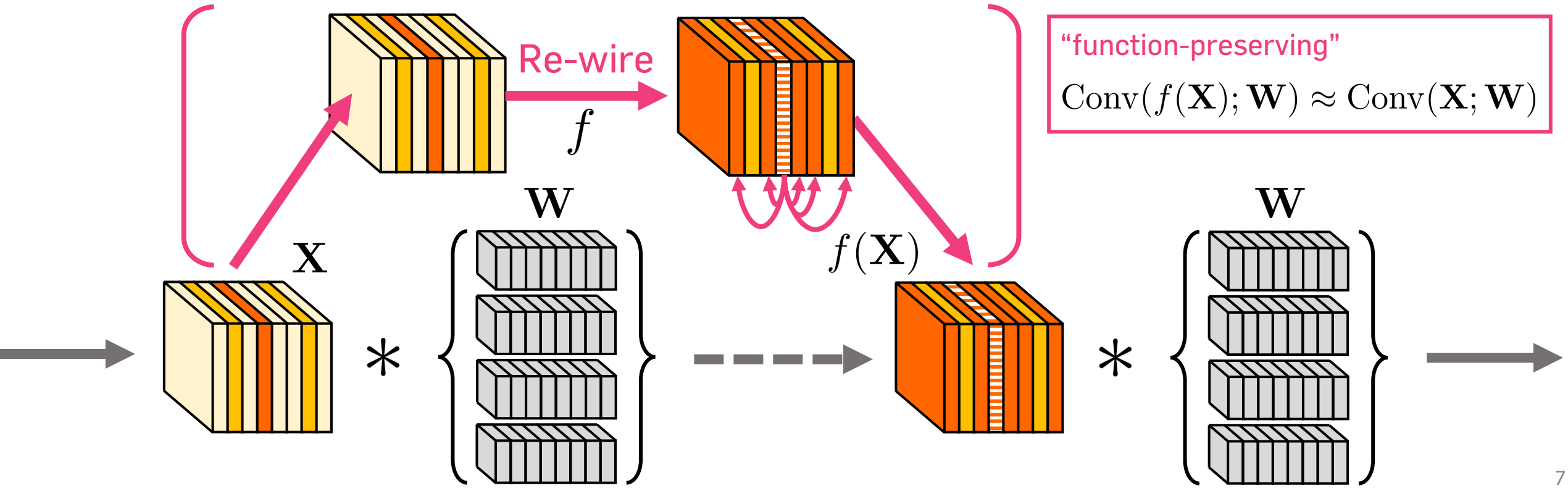
- Current convolutional layers allocate parameters uniformly across channels
- “Static”: The allocation is **fixed** until the end of training
- What if the layer contains unnecessary channels to compute?
  - The parameters allocated for those channels can hardly utilized
- Moreover, # channels are usually set without much care in recent CNNs
  - **Can we utilize them in training for efficiency?** 🤔




* Source: He et al. “Deep Residual Learning for Image Recognition”, CVPR 2016

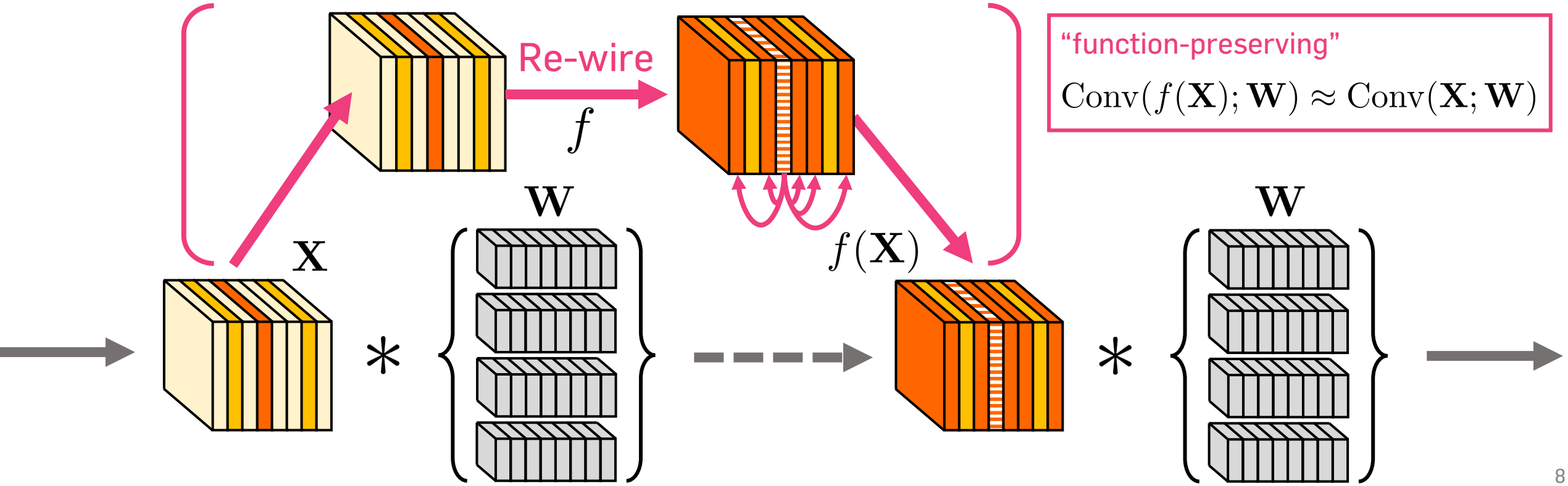
# Framework: Training with “Dynamic” Re-wiring

- Idea: Incorporating **function-preserving operations** **on channels** 💡
- A re-wiring operation $f$ can be called at any time in training



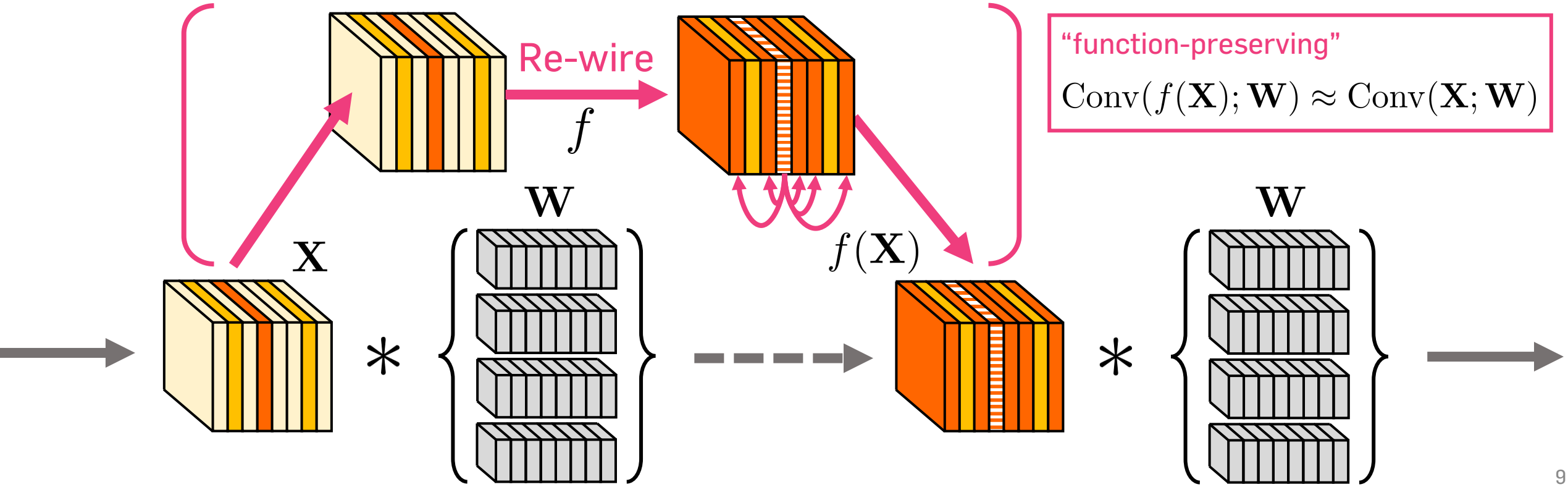
# Framework: Training with “Dynamic” Re-wiring

- Idea: Incorporating **function-preserving operations** **on channels** 💡
- A re-wiring operation $f$ can be called at any time in training
  - Connectivity is updated without affecting the overall training



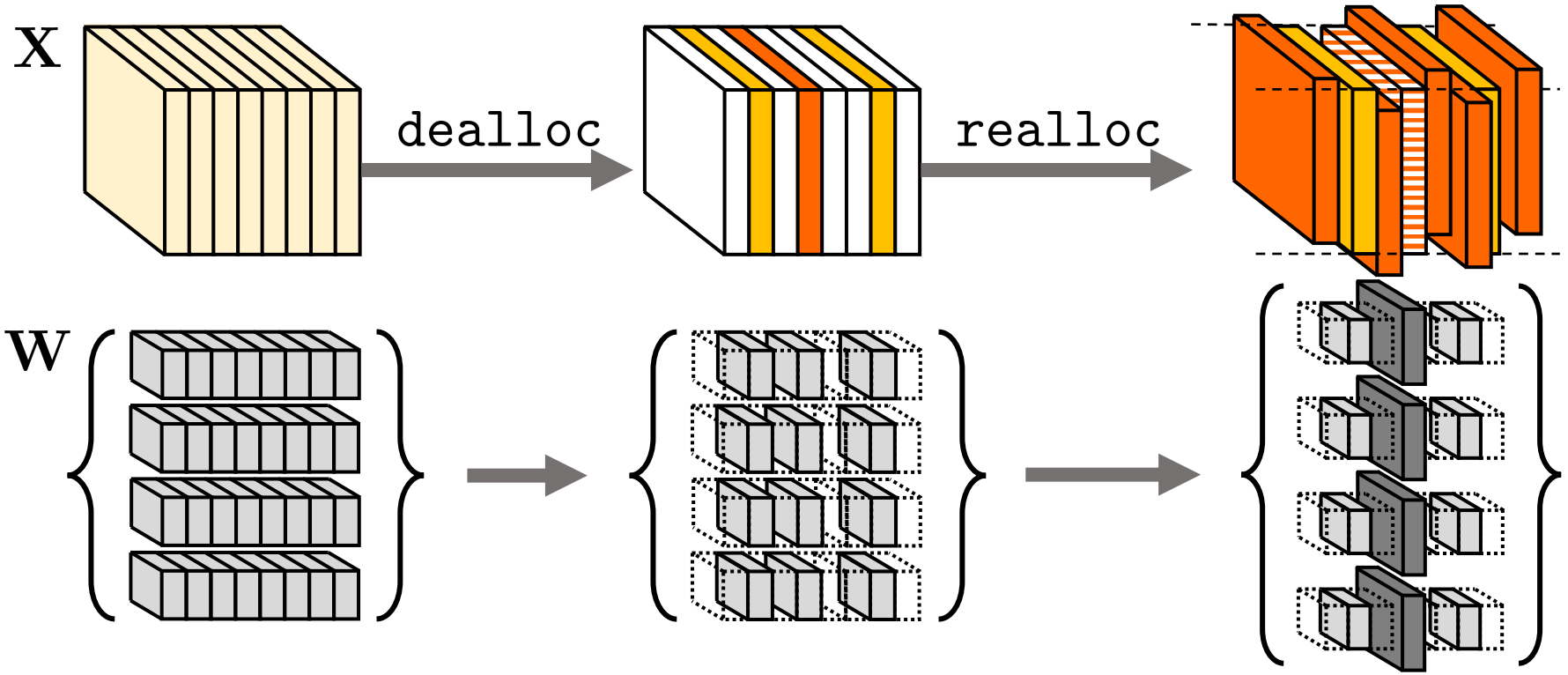
# Framework: Training with “Dynamic” Re-wiring

- Idea: Incorporating **function-preserving operations** **on channels** 💡
- A re-wiring operation $f$ can be called at any time in training
  - Connectivity is updated without affecting the overall training
  - Manipulation on **channels** rather than **parameters** → architecture-agnostic



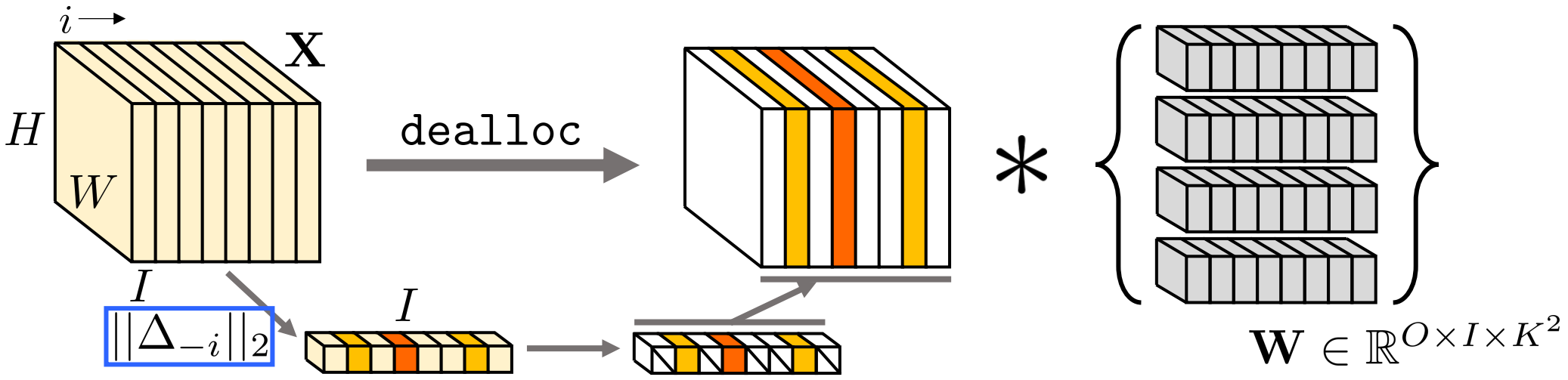
# Selective Convolutional Layer

- Idea: Incorporating **function-preserving operations** on channels 💡
- **Two re-wiring operations**: `dealloc` & `realloc`
  1. `dealloc`: Release unimportant channels → pruning parameters
  2. `realloc`: Replicate important channels → re-using the pruned parameter



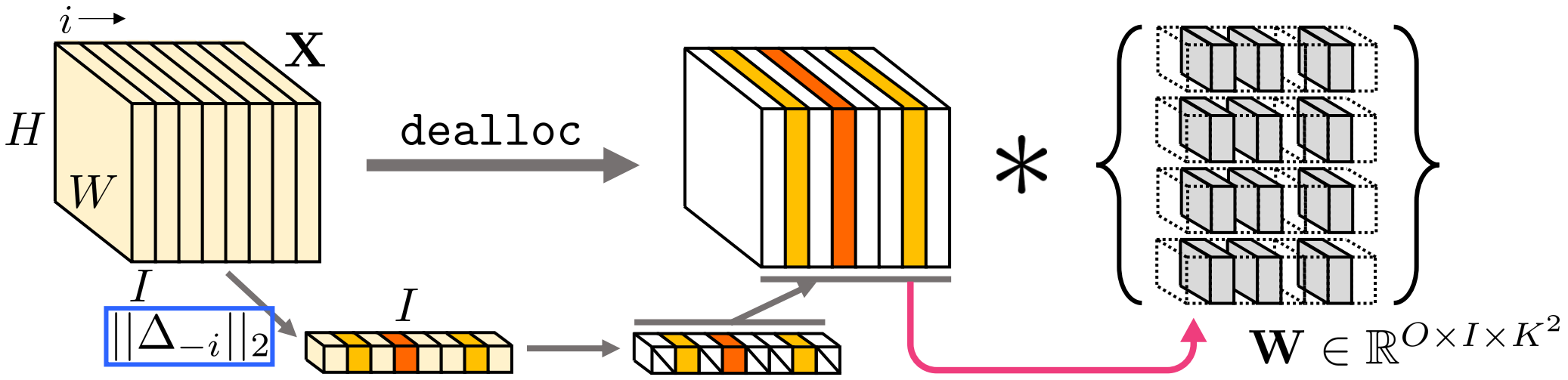
# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  1. **Channel de-allocation (`dealloc`)**: Release "unimportant" channels
     - Drops unimportant channels based on a measure $||\Delta_{-i}||_2$ we defined



# Selective Convolutional Layer

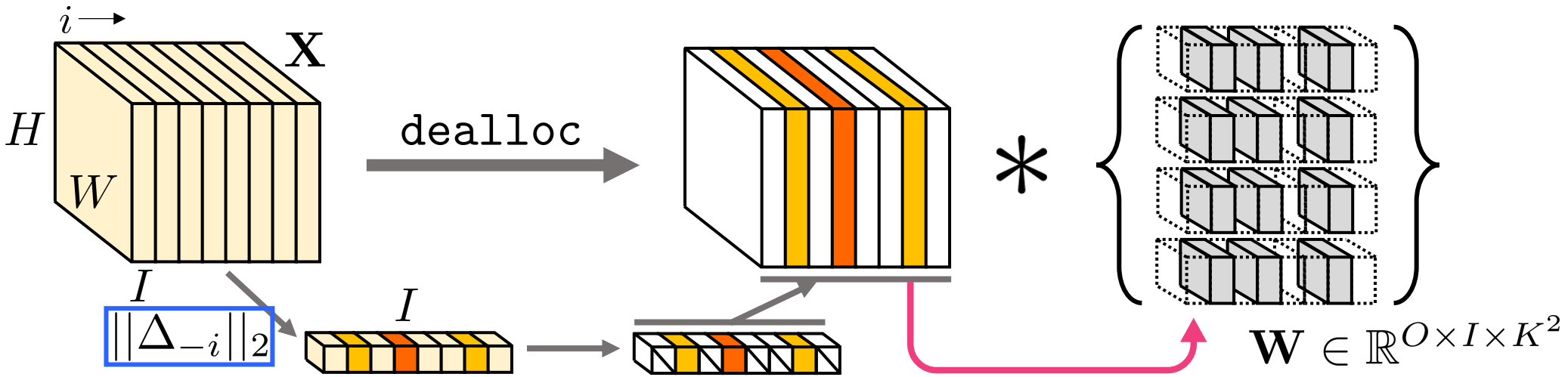
- Two operations during training: `dealloc` & `realloc`
  1. **Channel de-allocation (`dealloc`)**: Release "unimportant" channels
     - Drops unimportant channels based on a measure $||\Delta_{-i}||_2$ we defined
     - Equivalent to pruning parameters corresponding to the de-allocated channels



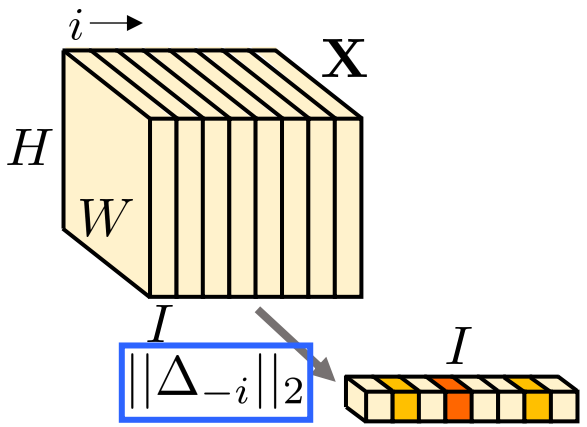
# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  1. **Channel de-allocation (`dealloc`)**: Release "unimportant" channels
     - Drops unimportant channels based on a measure $||\Delta_{-i}||_2$ we defined
     - Equivalent to pruning parameters corresponding to the de-allocated channels
     - Key point: `dealloc` has to be **function-preserving**:

$$\text{Conv}(\texttt{dealloc}(\mathbf{X}); \mathbf{W}) \approx \text{Conv}(\mathbf{X}; \mathbf{W})$$



# Selective Convolutional Layer




- Two operations during training: `dealloc` & `realloc`
  - Key point: `dealloc` has to be **function-preserving**

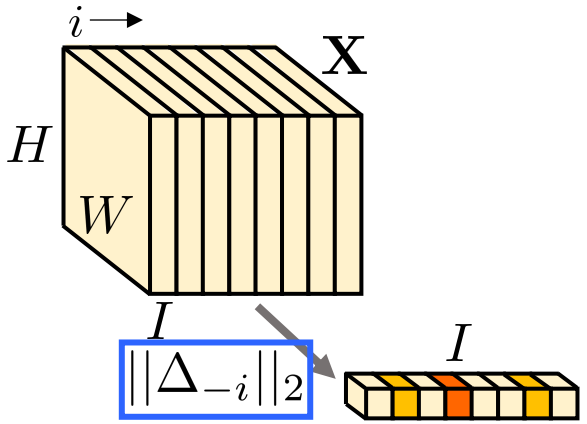
$$\text{Conv}(\texttt{dealloc}(\mathbf{X}); \mathbf{W}) \approx \text{Conv}(\mathbf{X}; \mathbf{W})$$

  - We measure expected channel damage for channel importance

$$\Delta_{-i} := \frac{1}{HW} \sum_{h,w} \mathbb{E}_{\mathbf{X}}[\underbrace{\text{Conv}(\mathbf{X}; \mathbf{W})}_{\text{original}} - \underbrace{\text{Conv}(\mathbf{X}; \mathbf{W}_{-i})}_{\text{after pruning channel } i}]_{:,h,w} \in \mathbb{R}^O$$

    - Difference after pruning channel $i$ → function-preserving property
    - The value is averaged over the spatial dimension $h, w$
    - $\Delta \in \mathbb{R}^{I \times O}$: Expected Channel Damage Matrix (ECDM)

# Selective Convolutional Layer




- Two operations during training: `dealloc` & `realloc`
  - Key point: `dealloc` has to be **function-preserving**

    $$\text{Conv}(\texttt{dealloc}(\mathbf{X}); \mathbf{W}) \approx \text{Conv}(\mathbf{X}; \mathbf{W})$$

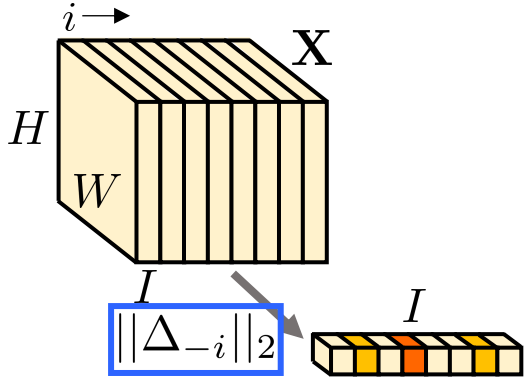
  - We measure expected channel damage for channel importance

$$\Delta_{-i} := \frac{1}{HW} \sum_{h,w} \mathbb{E}_{\mathbf{X}}[\underbrace{\text{Conv}(\mathbf{X}; \mathbf{W})}_{\text{original}} - \underbrace{\text{Conv}(\mathbf{X}; \mathbf{W}_{-i})}_{\text{after pruning channel } i}]_{:,h,w} \in \mathbb{R}^O$$

    - Difference after pruning channel $i$ → function-preserving property
    - The value is averaged over the spatial dimension $h, w$
    - $\Delta \in \mathbb{R}^{I \times O}$: Expected Channel Damage Matrix (ECDM)

  - Challenge: Computing $\Delta_{-i}$ requires a marginalization over $\mathbf{X}$ 🤔

# Selective Convolutional Layer

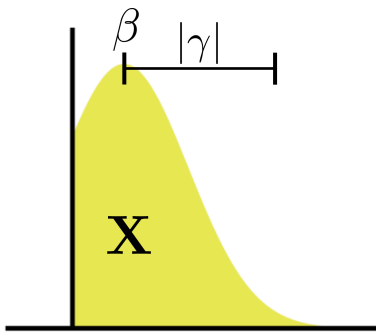



- Two operations during training: `dealloc` & `realloc`
  - We measure expected channel damage for channel importance

$$\Delta_{-i} := \frac{1}{HW} \sum_{h,w} \mathbb{E}_{\mathbf{X}}[\underbrace{\text{Conv}(\mathbf{X}; \mathbf{W})}_{\text{original}} - \underbrace{\text{Conv}(\mathbf{X}; \mathbf{W}_{-i})}_{\text{after pruning channel } i}]_{:,h,w} \in \mathbb{R}^O$$

  - Challenge: Computing $\Delta_{-i}$ requires a marginalization over $\mathbf{X}$ 🤔

- Idea: Use a BatchNorm layer to approximate $\Delta_{-i}$ 💡
  1. $\text{BatchNorm}(x) \sim \mathcal{N}(\beta, \gamma^2)$: $\beta, \gamma$ are BatchNorm parameters
  2. $\mathbf{X} = \text{ReLU}(\text{BN}(\mathbf{Y}))$: A common design in modern CNNs



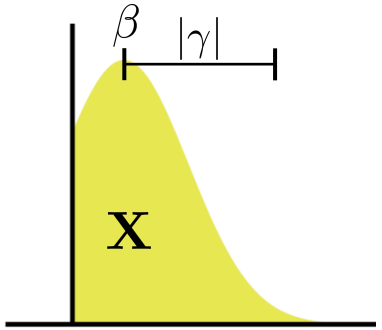

$$\Delta_{-i} \approx \underbrace{\left( |\gamma_i| \phi_{\mathcal{N}}\left(\frac{\beta_i}{|\gamma_i|}\right) + \beta_i \Phi_{\mathcal{N}}\left(\frac{\beta_i}{|\gamma_i|}\right) \right)}_{\text{activity level}} \cdot \underbrace{\sum_{k=1}^{K^2} \mathbf{W}_{i,:,k}}_{\text{magnitude}}$$

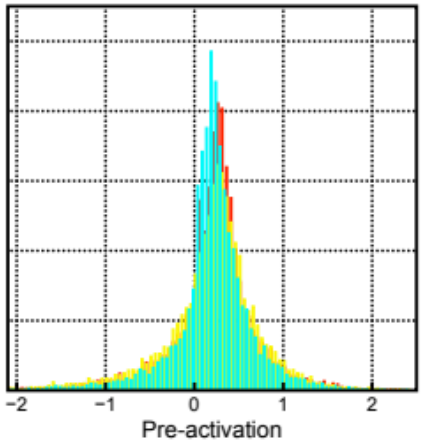
p.d.f. c.d.f.

# Selective Convolutional Layer

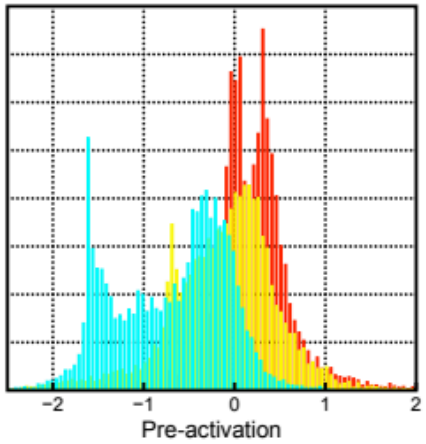
- Two operations during training: `dealloc` & `realloc`
  - Challenge: Computing $\Delta_{-i}$ requires a marginalization over $\mathbf{X}$ 🤔

- Idea: Use a BatchNorm layer to approximate $\Delta_{-i}$ 💡
  1. $\mathrm{BatchNorm}(x) \sim \mathcal{N}(\beta, \gamma^2)$: $\beta, \gamma$ are BatchNorm parameters
  2. $\mathbf{X} = \mathrm{ReLU}(\mathrm{BN}(\mathbf{Y}))$: A common design in modern CNNs
- **Are those assumptions realistic in practice?**

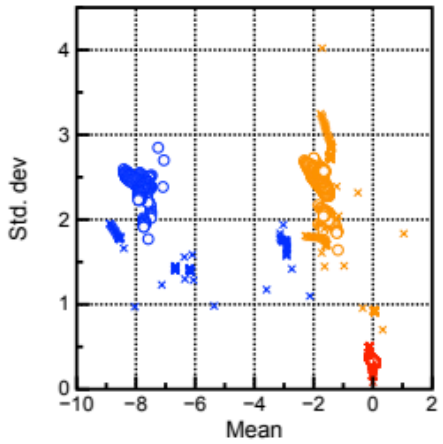


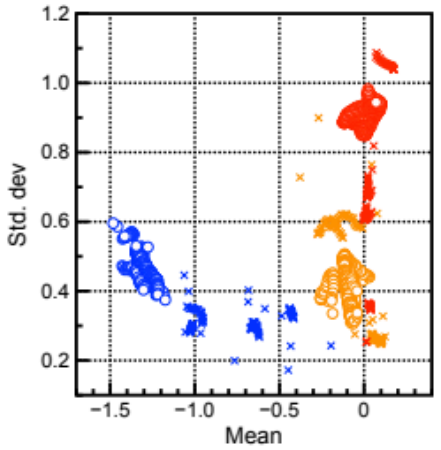

(a) Non-boundary pixels




(b) Boundary pixels




(c) Initialized randomly

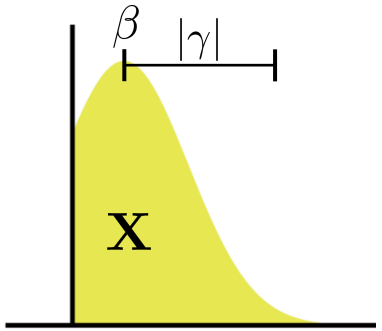


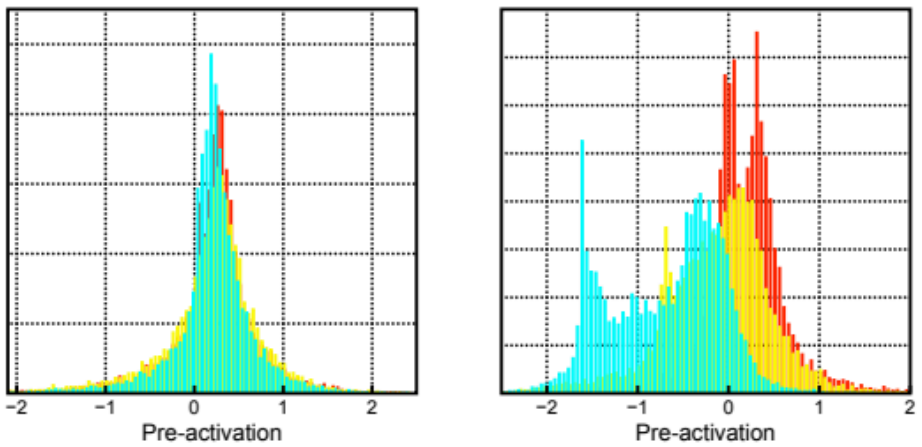

(d) Trained to converge

# Selective Convolutional Layer

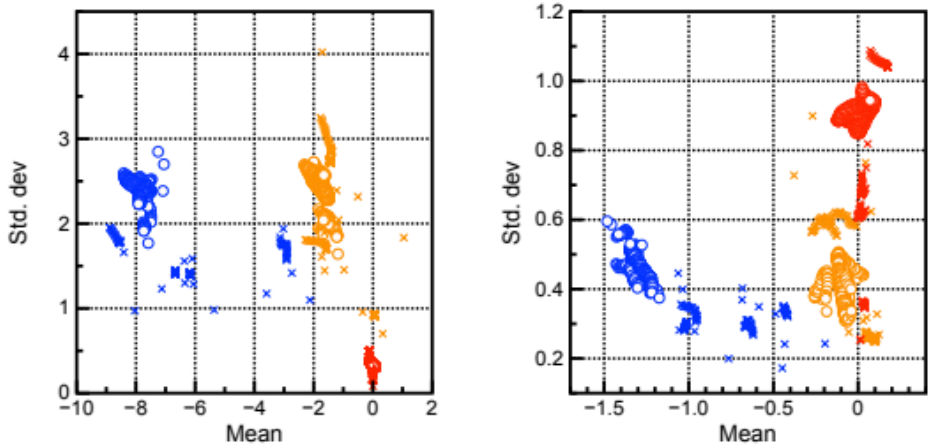
- Two operations during training: `dealloc` & `realloc`
  - Challenge: Computing $\Delta_{-i}$ requires a marginalization over $\mathbf{X}$ 🤔

- **Are those assumptions realistic in practice?**
  1. For a fixed channel, most of the pixel distributions are unimodal (a)
  2. The means and variances are clustered for each channel (d)
  3. The trend still exists even the model re-initialized (c, d)




(a) Non-boundary pixels (b) Boundary pixels

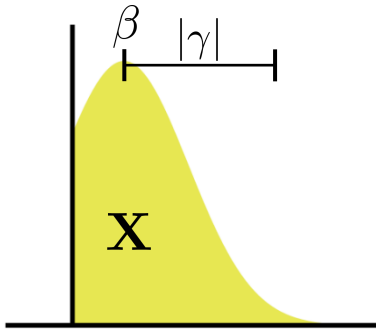


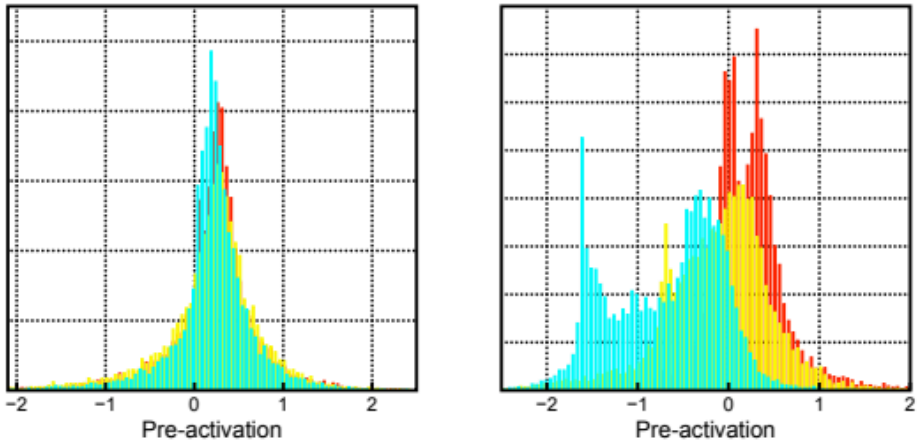

(c) Initialized randomly (d) Trained to converge

# Selective Convolutional Layer

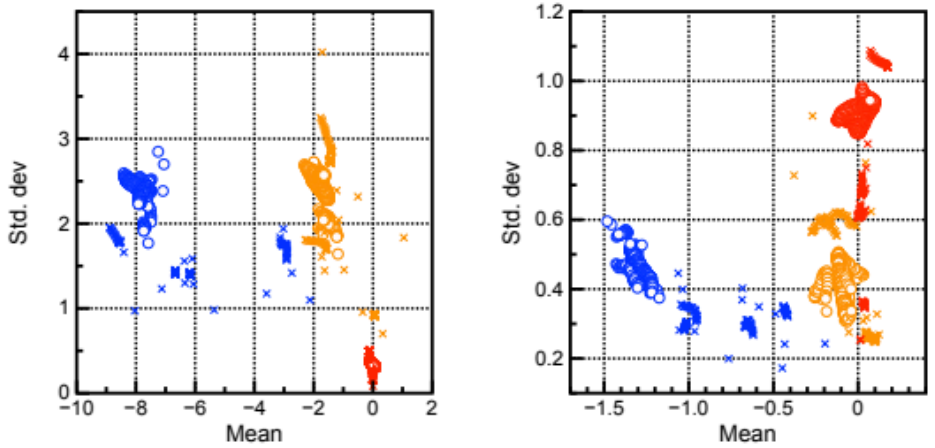
- Two operations during training: `dealloc` & `realloc`
  - Challenge: Computing $\Delta_{-i}$ requires a marginalization over $\mathbf{X}$ 🤔

- **Are those assumptions realistic in practice?**
  - Two properties of CNN can be responsible:
    1. CLT from the **linear, weighted summing nature** of convolution
    2. **Translation-equivariance** of convolution on spatial dimensions



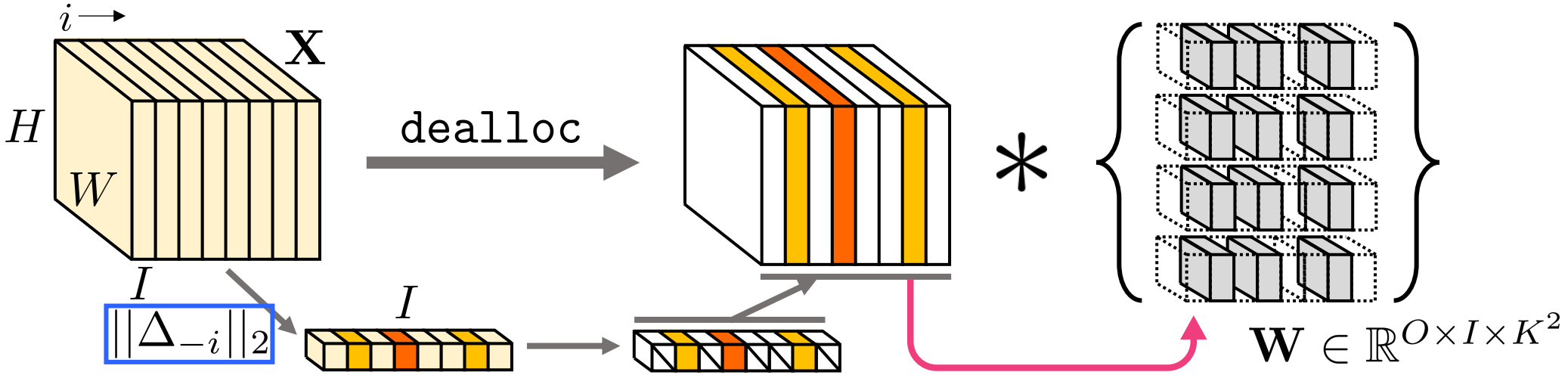

(a) Non-boundary pixels (b) Boundary pixels




(c) Initialized randomly (d) Trained to converge

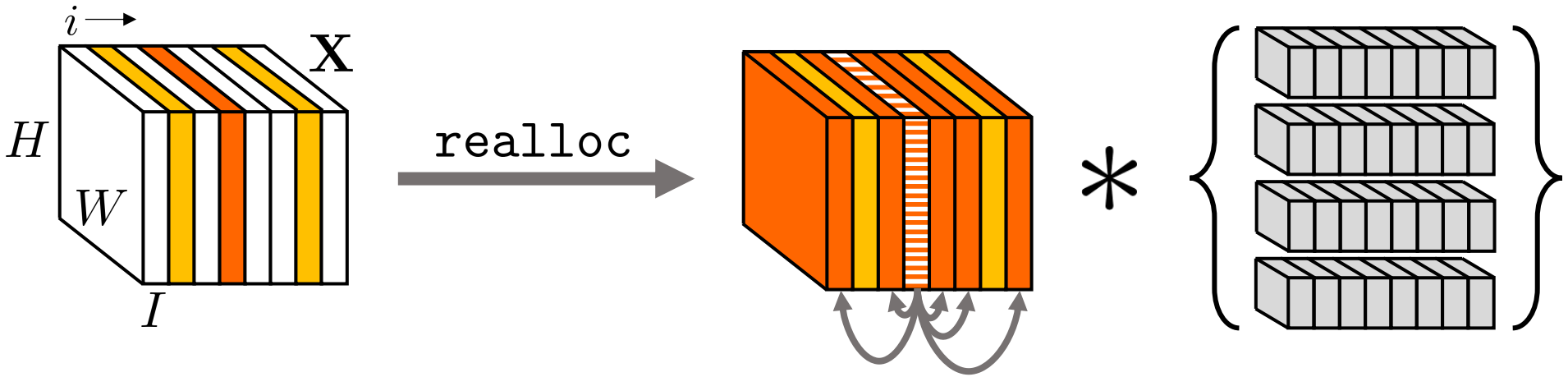
# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  1. **Channel de-allocation (`dealloc`)**: Release "unimportant" channels
     - Drops unimportant channels based on a measure $||\Delta_{-i}||_2$ we defined
     - Equivalent to pruning parameters corresponding to the de-allocated channels
     - Key point: `dealloc` has to be **function-preserving**



# Selective Convolutional Layer

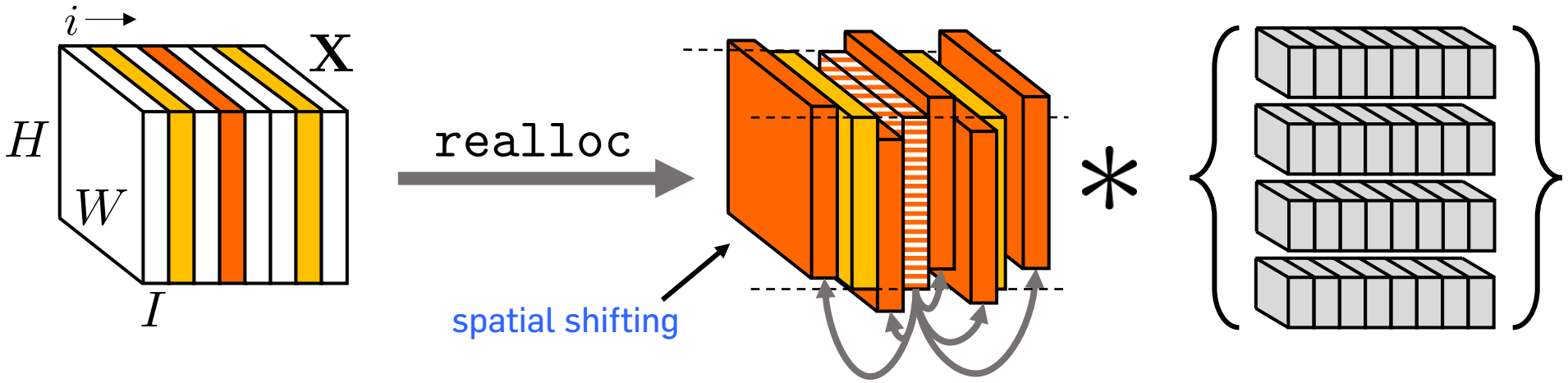
- Two operations during training: `dealloc` & `realloc`
  2. **Channel re-allocation (`realloc`)**: Replicate "important" channels into the released area




- Channels with high $||\Delta_{-i}||_2$ are copied into the de-allocated channels
- Challenge: Naïvely copying a channel in does **NOT** give any benefit 🤔
  - Due to the **linearity** of convolutional layers
  - A convolutional filter will see the exact same patch of the two images

# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  2. **Channel re-allocation (`realloc`)**: Replicate "important" channels into the released area




- Channels with high $||\Delta_{-i}||_2$ are copied, but with spatial shifting bias $b = (b^h, b^w)$ (learnable)

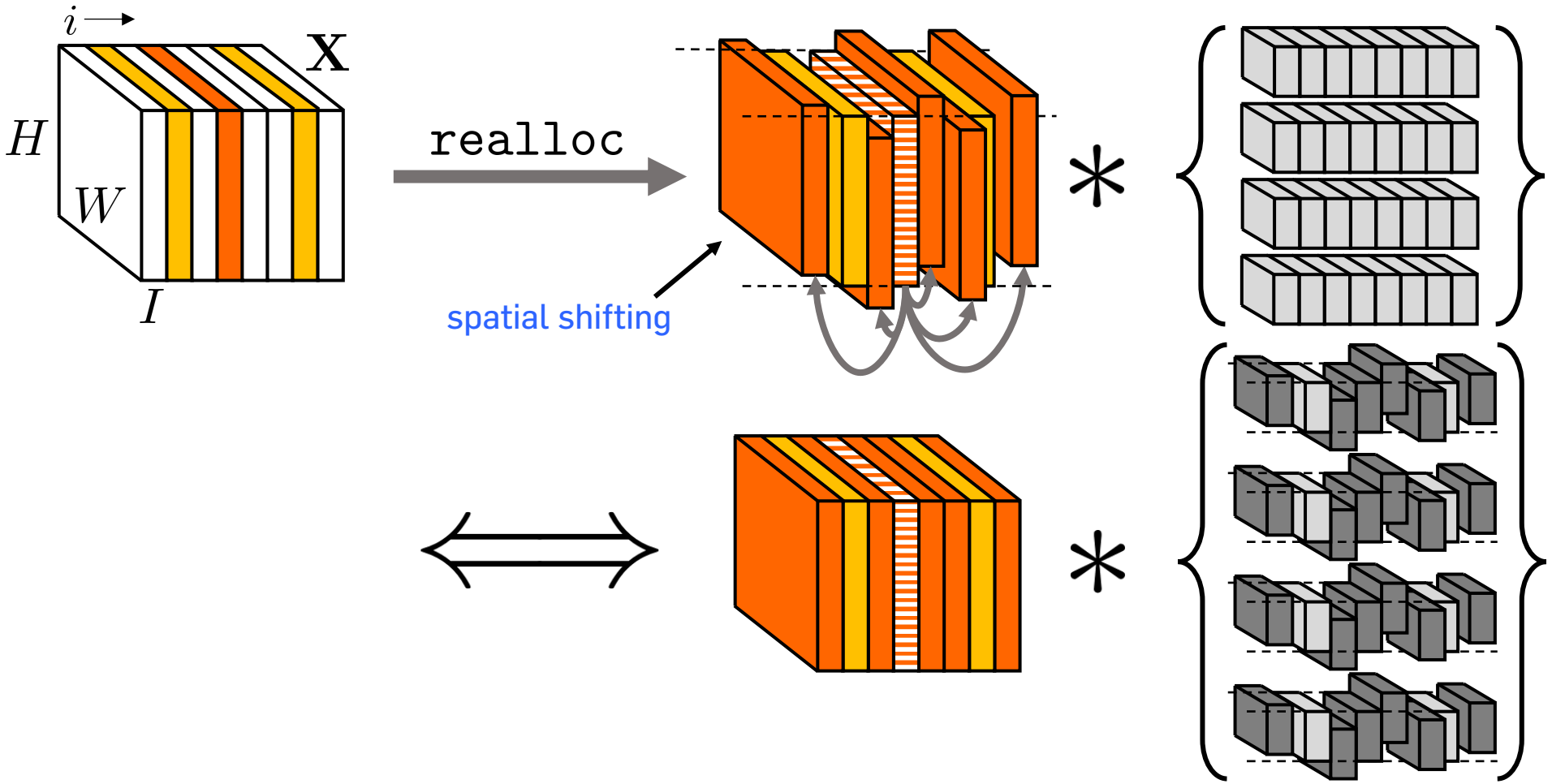
$$\text{shift}\,(\mathbf{X}, b)_{x,y} := \sum_{n=1}^{H}\sum_{m=1}^{W} \mathbf{X}_{n,m}$$

"bilinear interpolation kernel"

$$\times \max\left(0, 1 - |x - n + b^h|\right) \times \max\left(0, 1 - |y - m + b^w|\right)$$

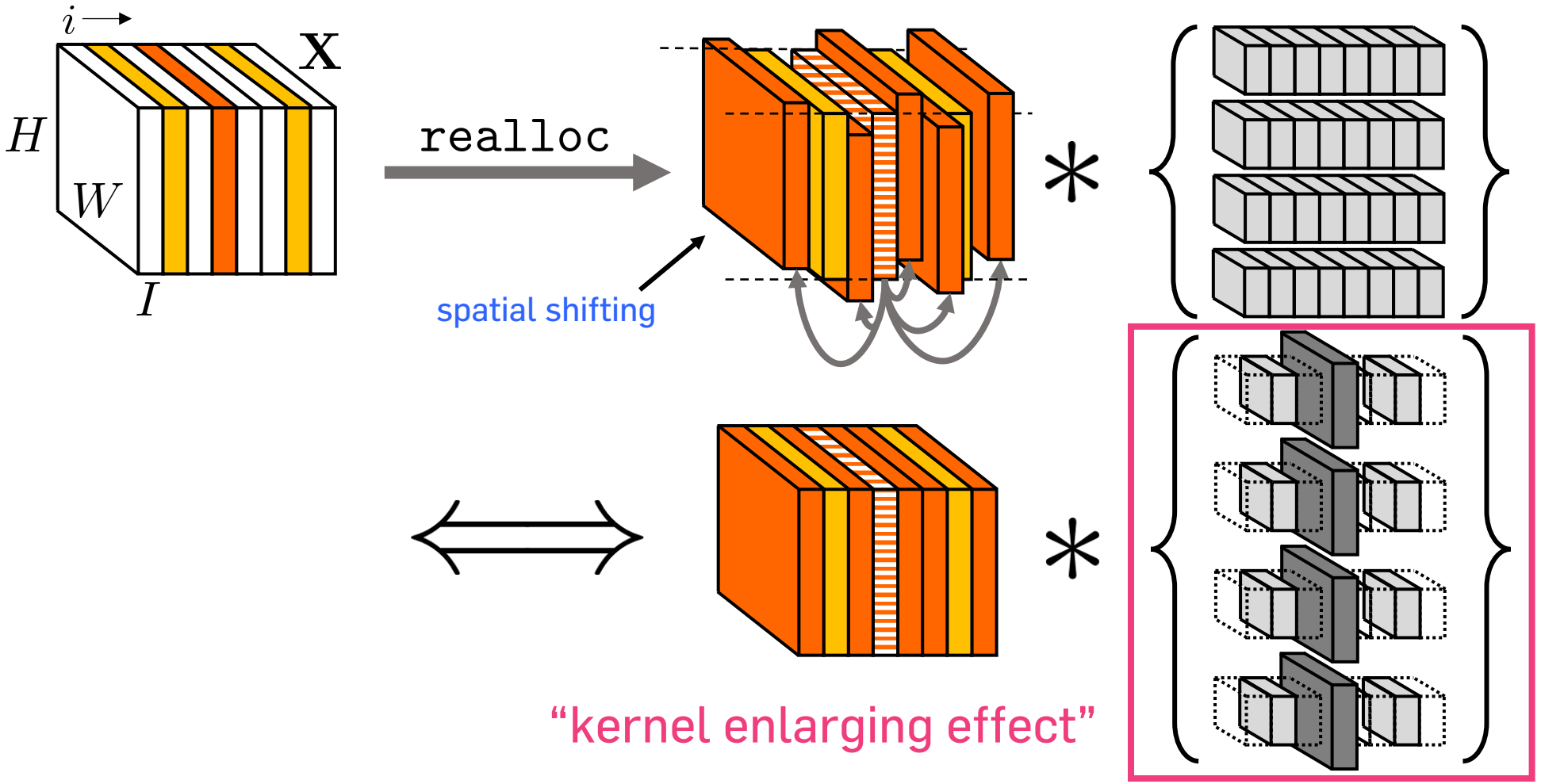
# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  2. **Channel re-allocation (`realloc`)**: Replicate "important" channels into the released area



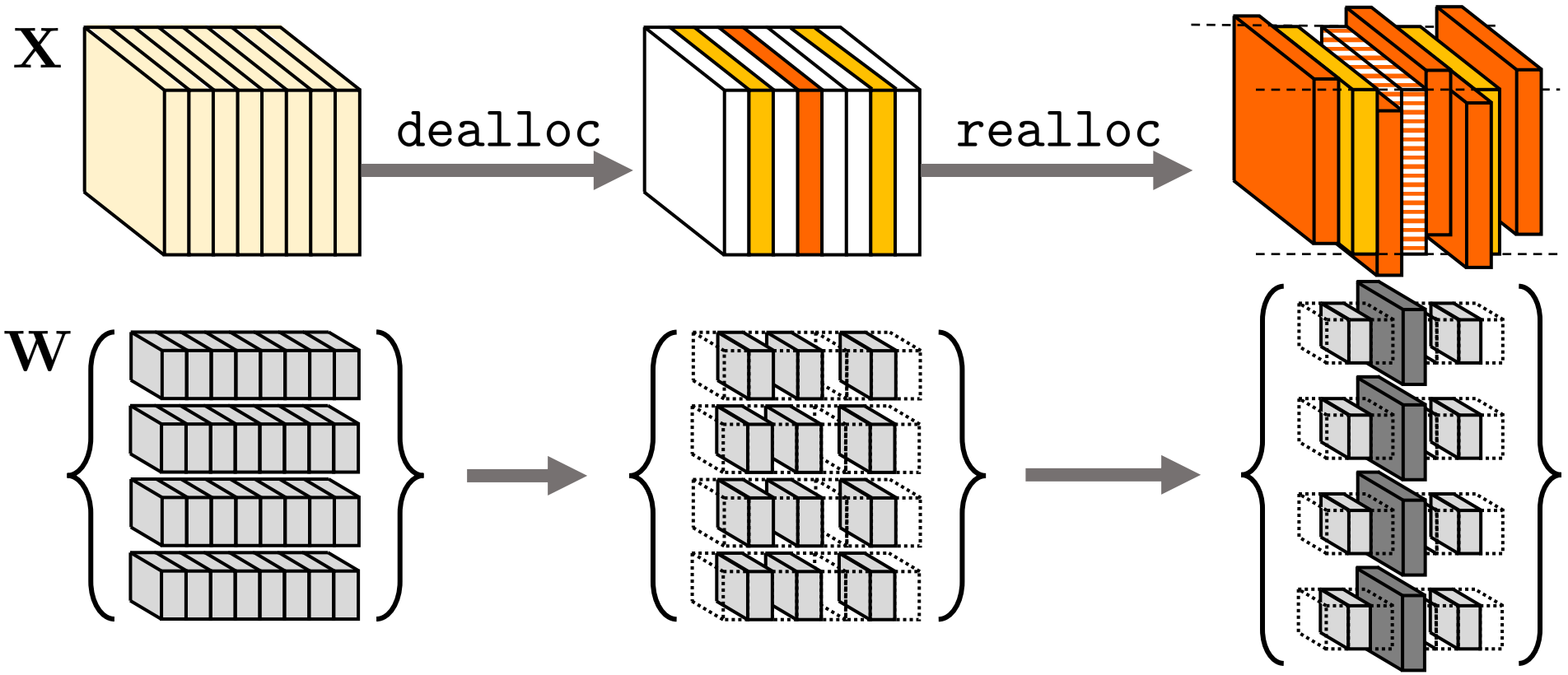
# Selective Convolutional Layer

- Two operations during training: `dealloc` & `realloc`
  2. **Channel re-allocation (`realloc`)**: Replicate "important" channels into the released area



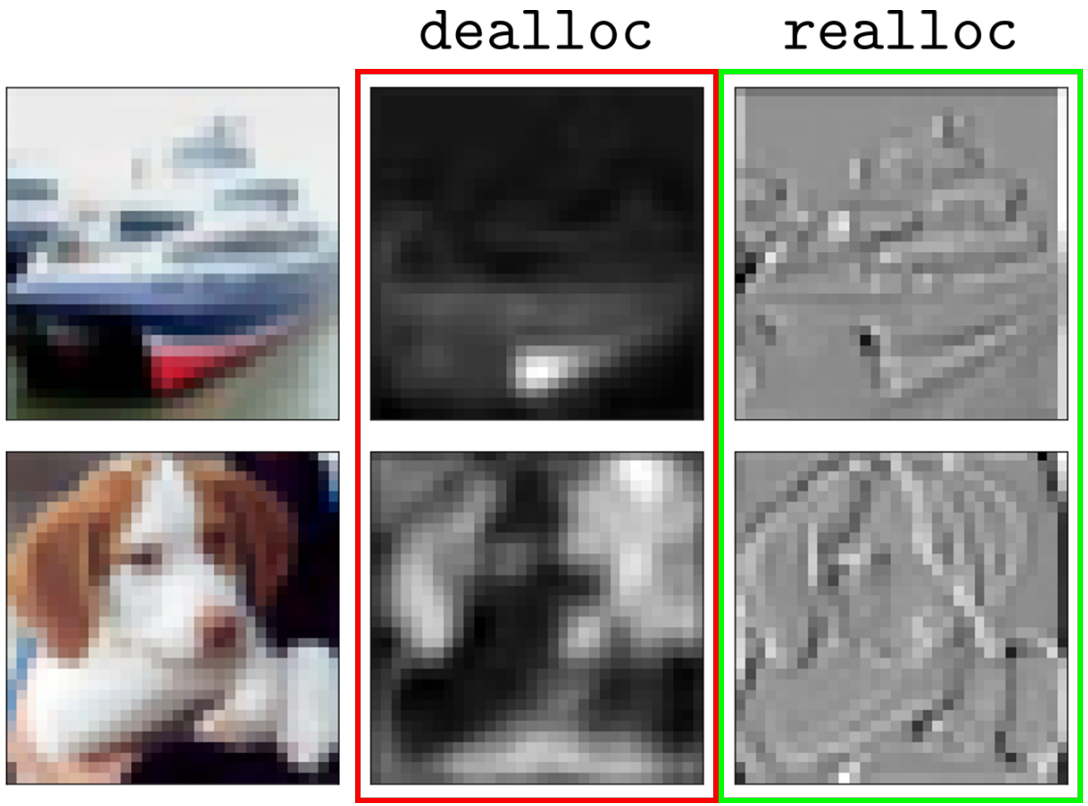
# Selective Convolutional Layer

- Framework: Incorporating **re-wiring operations** in training
- Two operations during training: `dealloc` & `realloc`
- Dynamic re-wiring of parameters → selective kernel expansion



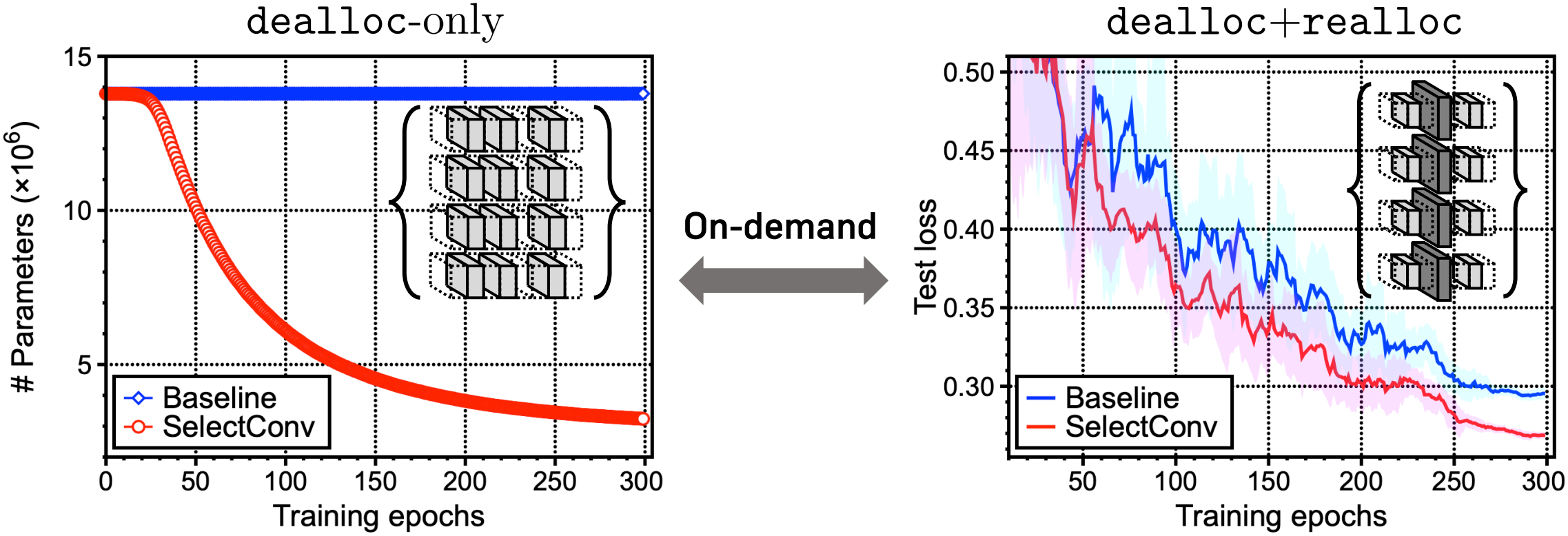
# Selective Convolutional Layer

- Framework: Incorporating **re-wiring operations** in training
- Two operations during training: `dealloc` & `realloc`
- Dynamic re-wiring of parameters → selective kernel expansion



# Selective Convolutional Layer

- Framework: Incorporating **re-wiring operations** in training
- Two operations during training: `dealloc` & `realloc`
- Flexible training: model reduction ⟷ accuracy improvement



# Experiments: Improving Modern CNNs

- Selective convolution can be readily applied to various existing CNNs
- Training each convolutional layer with `dealloc` + `realloc`

| Model | Params | Method | Error rates (%) | | | |
|---|---|---|---|---|---|---|
| | | | CIFAR-10 | CIFAR-100 | Fashion-MNIST | Tiny-ImageNet |
| DenseNet-40 (bottleneck, $k = 12$) | 0.21M | Baseline | 6.62±0.15 | 29.9±0.1 | 5.03±0.07 | 45.8±0.2 |
| | | SelectConv | **6.09**±0.10 **(-8.01%)** | **28.8**±0.1 **(-3.42%)** | **4.73**±0.06 **(-5.96%)** | **44.4**±0.2 **(-3.03%)** |
| DenseNet-100 (bottleneck, $k = 12$) | 1.00M | Baseline | 4.51±0.04 | 22.8±0.3 | 4.70±0.06 | 41.0±0.1 |
| | | SelectConv | **4.29**±0.08 **(-4.88%)** | **22.2**±0.1 **(-2.64%)** | **4.58**±0.05 **(-2.55%)** | **39.9**±0.3 **(-2.78%)** |
| ResNet-164 (bottleneck, pre-act) | 1.66M | Baseline | 4.23±0.15 | 21.3±0.2 | 4.53±0.04 | 37.7±0.4 |
| | | SelectConv | **3.92**±0.14 **(-7.33%)** | **20.9**±0.2 **(-1.97%)** | **4.37**±0.03 **(-3.53%)** | **37.5**±0.2 **(-0.56%)** |
| ResNeXt-29 ($8 \times 64d$) | 33.8M | Baseline | 3.62±0.12 | 18.1±0.1 | 4.40±0.07 | 31.7±0.3 |
| | | SelectConv | **3.39**±0.14 **(-6.36%)** | **17.6**±0.1 **(-2.92%)** | **4.27**±0.06 **(-2.95%)** | **31.4**±0.3 **(-0.88%)** |

- (top) Results on CIFAR-10/100, FMNIST and Tiny-ImageNet
- (right) Results on ImageNet dataset

| Model | Params | Method | Error (%) |
|---|---|---|---|
| DenseNet-121 ($k = 32$) | 7.98M | Baseline | 24.7 |
| | | SelectConv | **24.4** |
| ResNet-50 (bottleneck) | 22.8M | Baseline | 23.9 |
| | | SelectConv | **23.4** |

# Experiments: Improving Modern CNNs

- Selective convolution can be readily applied to various existing CNNs
- Reduction in error rates across all the tested architectures

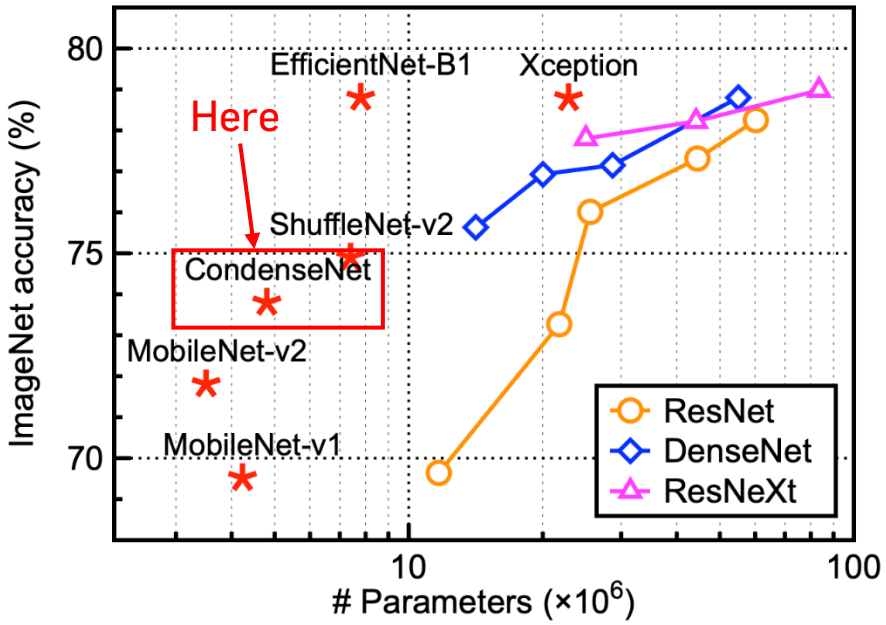
| Model | Params | Method | Error rates (%) CIFAR-10 | CIFAR-100 | Fashion-MNIST | Tiny-ImageNet |
|---|---|---|---|---|---|---|
| DenseNet-40 (bottleneck, $k = 12$) | 0.21M | Baseline | 6.62±0.15 | 29.9±0.1 | 5.03±0.07 | 45.8±0.2 |
| | | SelectConv | **6.09**±0.10 **(-8.01%)** | **28.8**±0.1 **(-3.42%)** | **4.73**±0.06 **(-5.96%)** | **44.4**±0.2 **(-3.03%)** |
| DenseNet-100 (bottleneck, $k = 12$) | 1.00M | Baseline | 4.51±0.04 | 22.8±0.3 | 4.70±0.06 | 41.0±0.1 |
| | | SelectConv | **4.29**±0.08 **(-4.88%)** | **22.2**±0.1 **(-2.64%)** | **4.58**±0.05 **(-2.55%)** | **39.9**±0.3 **(-2.78%)** |
| ResNet-164 (bottleneck, pre-act) | 1.66M | Baseline | 4.23±0.15 | 21.3±0.2 | 4.53±0.04 | 37.7±0.4 |
| | | SelectConv | **3.92**±0.14 **(-7.33%)** | **20.9**±0.2 **(-1.97%)** | **4.37**±0.03 **(-3.53%)** | **37.5**±0.2 **(-0.56%)** |
| ResNeXt-29 ($8 \times 64d$) | 33.8M | Baseline | 3.62±0.12 | 18.1±0.1 | 4.40±0.07 | 31.7±0.3 |
| | | SelectConv | **3.39**±0.14 **(-6.36%)** | **17.6**±0.1 **(-2.92%)** | **4.27**±0.06 **(-2.95%)** | **31.4**±0.3 **(-0.88%)** |

- (top) Results on CIFAR-10/100, FMNIST and Tiny-ImageNet
- (right) Results on ImageNet dataset
  - **Remark**: 23.6% → 23.0% ≈ 51 more layers (official ResNet)

| Model | Params | Method | Error (%) |
|---|---|---|---|
| DenseNet-121 ($k = 32$) | 7.98M | Baseline | 24.7 |
| | | SelectConv | **24.4** |
| ResNet-50 (bottleneck) | 22.8M | Baseline | 23.9 |
| | | SelectConv | **23.4** |

# Experiments: Mobile-targeted Architectures

- Selective convolution can further improve the "already-efficient" CondenseNet-182
- Training with `dealloc` → model compression
- ECDM-based de-allocation outperforms existing dynamic channel pruning scheme
  - Replacing **LGC to SConv** → further compression




| Model (CIFAR-10) | Params | FLOPs | Error (%) |
|---|---|---|---|
| ResNet-1001 | 16.1M | 2,357M | 4.62 |
| WideResNet-28-10 | 36.5M | 5,248M | 4.17 |
| ResNeXt-29 ($16 \times 64d$) | 68.1M | 10,704M | 3.58 |
| VGGNet-Slim [2] | 2.30M | 391M | 6.20 |
| ResNet-164-Slim [2] | 1.10M | 275M | 5.27 |
| CondenseNet-LGC-182 [1] | 4.20M | 513M | 3.76 |
| **CondenseNet-SConv-182** | **3.24M** | **422M** | **3.50** |


[1] Gao Huang et al. Condensenet: An efficient densenet using learned group convolutions. CVPR 2018.
[2] Zhuang Liu et al. Learning efficient convolutional networks through network slimming. ICCV 2017.

# Summary

- A new functionality: channel-selectivity
  - Dynamically choosing channels toward selective expansion of kernels
- We propose selective convolution = convolution + channel-selectivity
  1. **Generic, easy to use**: applicable to any kind of CNN
  2. **Single-pass**: no post-processing/re-training
  3. **On-demand**: accuracy improvement ⟷ model compression
- We define a new metric of channel importance: expected channel damage

Talk@ICML

Paper

GitHub