# Convolution with even-sized kernels and symmetric padding

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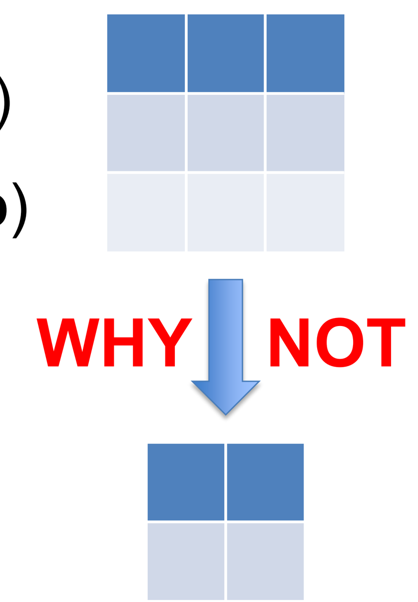
Paper Code

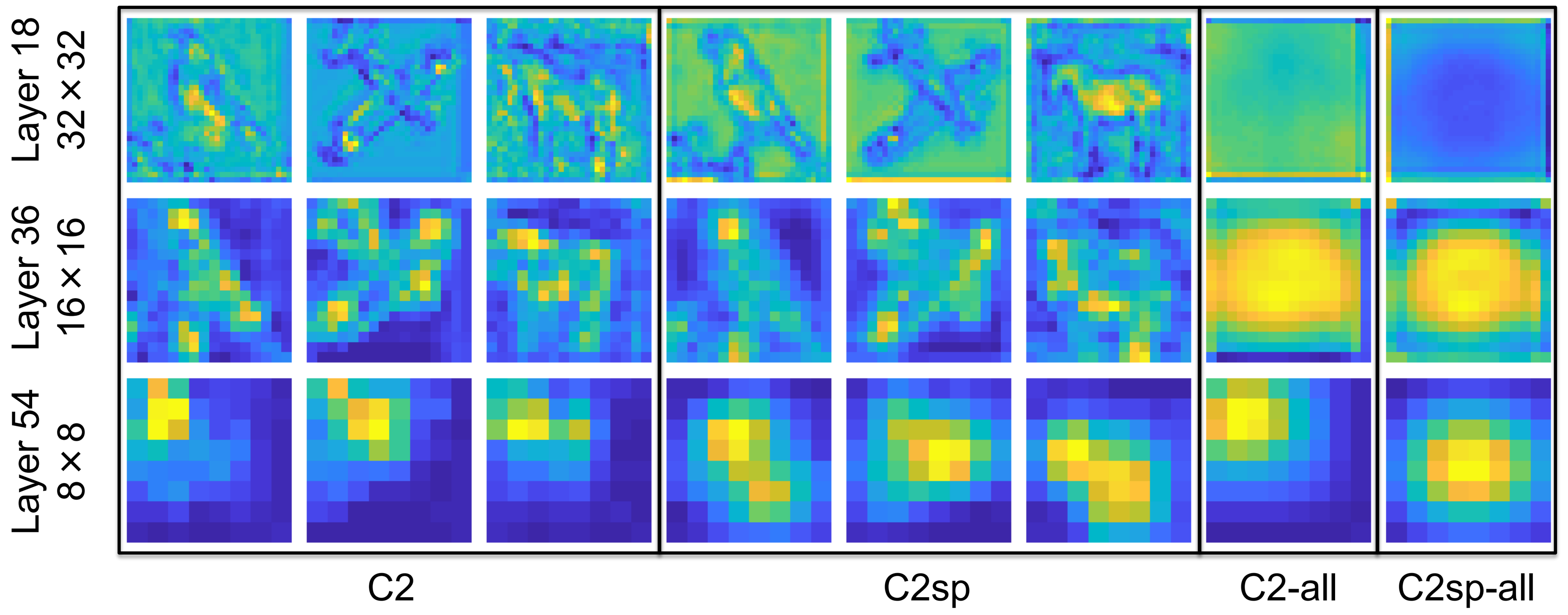
## TL;DR

- Exploration of convolution kernel sizes (C2, C3, C4, C5)
- Quantify the shift problem in even-sized kernels (C2, C4)
- Proposing symmetric padding convolutions (**C2sp, C4sp**)
- The advantages of this approach:
  + Improved classification accuracy (CIFAR, ImageNet)
  + Improved image quality of GANs (CIFAR, LSUN, CelebA-HQ)
  − Less parameters, FLOPs, training memory and time




## Problem Formulation

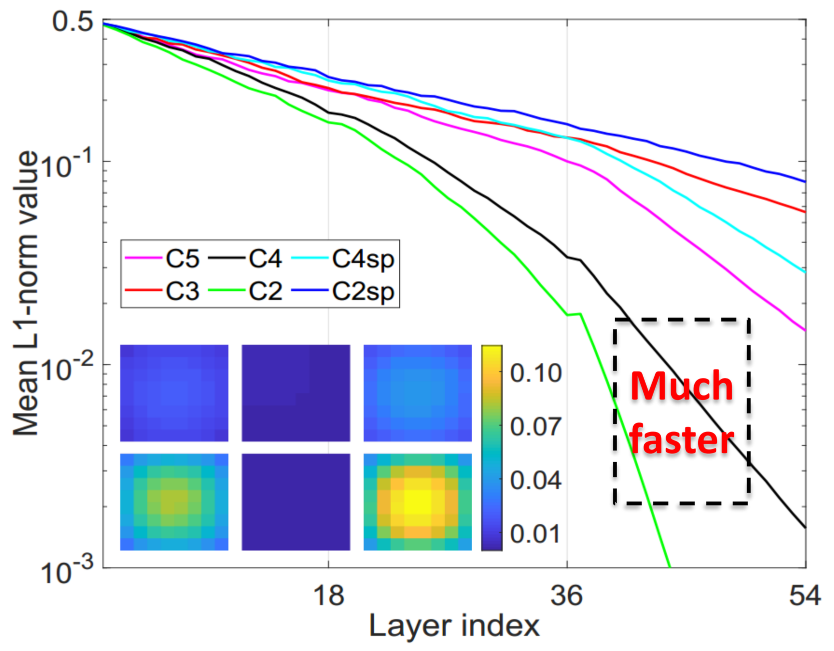
- Even-sized kernels: rarely adopted, inferior to C3
  - No central point, resulting in 0.5 pixel shift for each convolution layer
  - The shift is cumulative in deep nets, small feature maps:




- The information erosion of padding
  - Zero-padding erode the information

$$Q_n = \frac{1}{hw}\sum_{p\in h\times w}|\mathcal{F}_n(p)|,\ Q_n < Q_{n-1}$$

  - **Asymmetry accelerates the erosion**
  - Provides explanations for degradation in deep CNNs (e.g., ResNet paper)



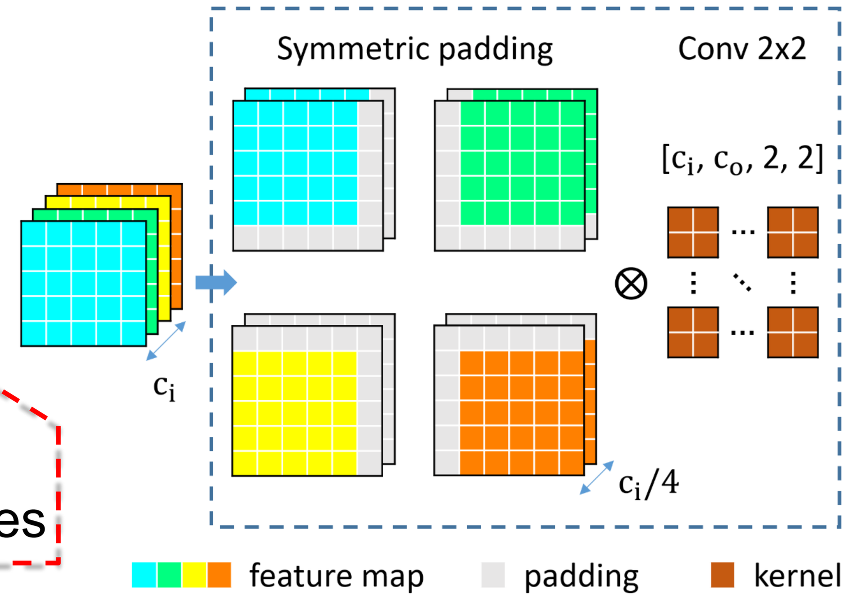

## Symmetric Padding

- Introducing symmetry by group-padding strategy
  - **Asymmetry input → Symmetry output**

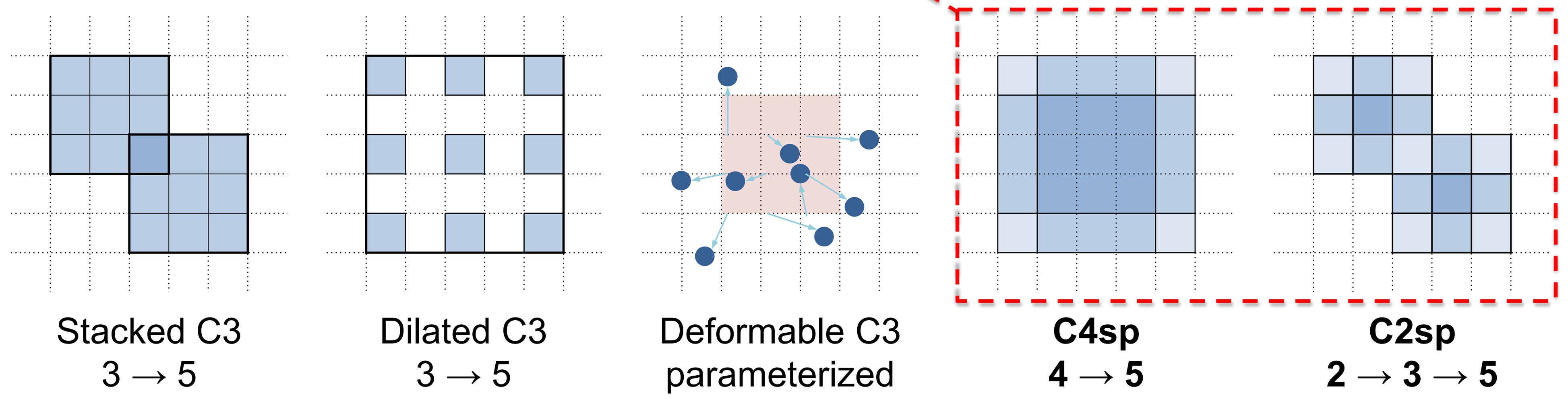
$$\sum_{\delta\in\mathcal{R}} \boldsymbol{\delta} \neq (0,0) \quad \rightarrow \sum_{i=1}^{c_i}\sum_{\delta\in\pi(i)} \boldsymbol{\delta} = (0,0)$$

$\pi(i)$: symmetry padding policy

+ None additional Params/FLOPs
+ Highly extendable to other kernel size
+ Neat implementation in computation libraries

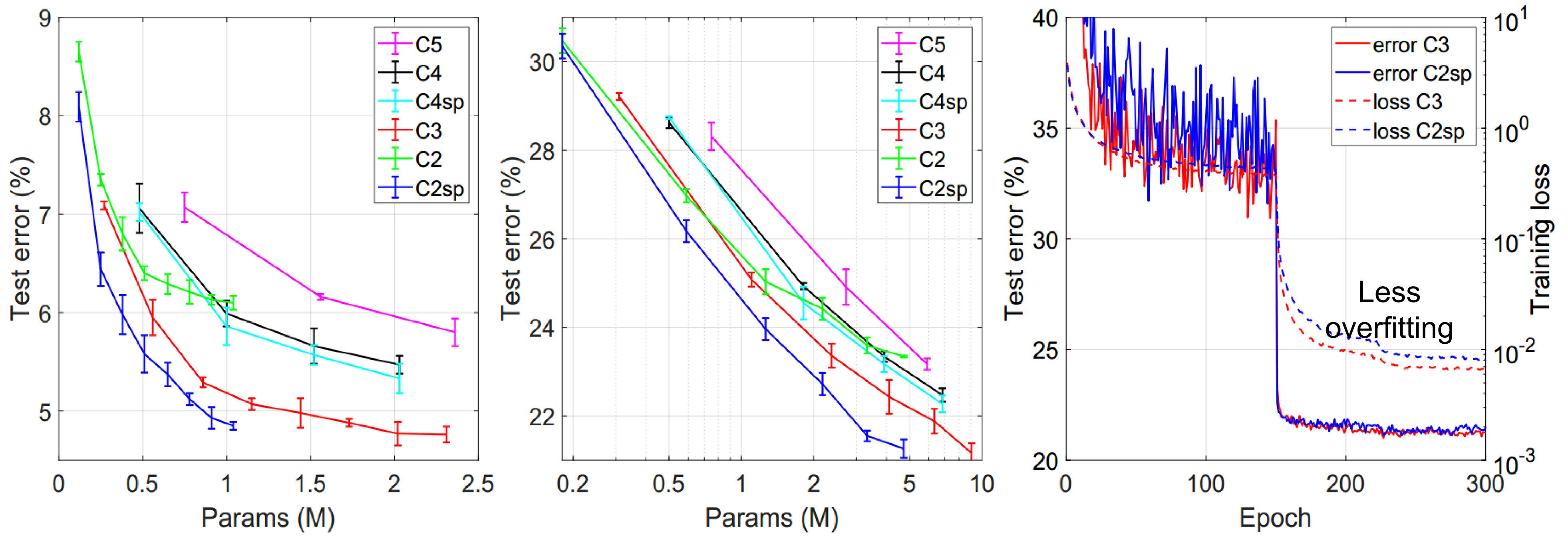



- Expanded reception fields




## Exploration of Kernel Sizes

- Model: ResNet & DenseNet, Dataset: CIFAR10/100
  - C2 is inferior to C3 and saturate much faster as the network deepens
  - **C2sp save 30%-50% parameters and FLOPs compared with C3**
  - Edge effect dominate the information erosion (C4, C5)




## Improved Performance

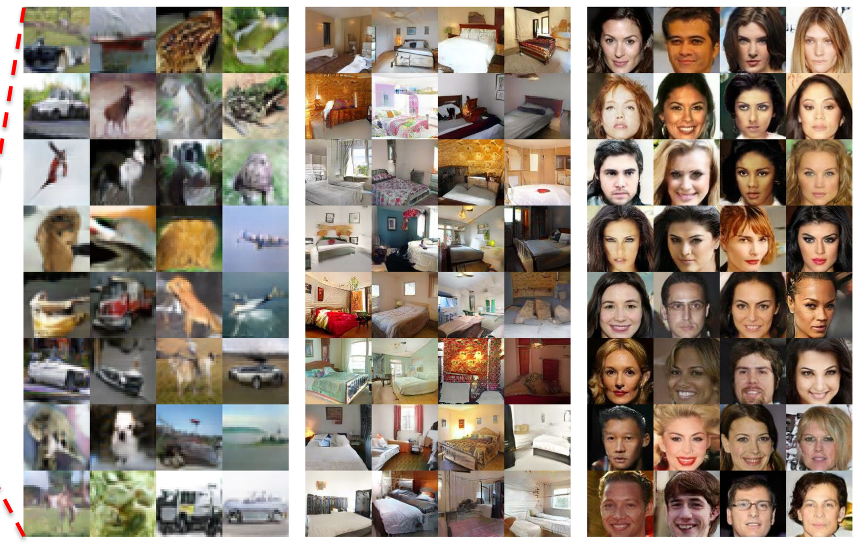
- Classification results:

| Model (ImageNet) | Error (%) | Params (M) | FLOPs (M) |
|---|---|---|---|
| ResNet-50 C3 | **23.8** | 25.5 | 4089 |
| ResNet-50 C2sp | 24.0 | 19.3 | 3062 |
| DenseNet-121 C3 | 24.6 | 8.0 | 2834 |
| DenseNet-121 C2sp | 25.1 | **6.7** | **2143** |
| ResNet-50 0.5x C3 | **26.8** | 6.9 | 1127 |
| ResNet-50 0.5x C2 | 29.8 | 5.3 | 870 |
| ResNet-50 0.5x C2sp | 27.3 | **5.3** | **870** |
| ResNet-50 0.5x C2sp optim | 26.8 | **5.8** | **573** |
| ShuffleNet v2 2.0x | 26.6 | 7.4 | 591 |
| MoibleNet v2 1.4x | **25.8** | 6.1 | 582 |

| Model (CIFAR10) | Error (%) | Params (M) |
|---|---|---|
| NASNet-A | 3.41 | 3.3 |
| PNASNet-5 | 3.41 | 3.2 |
| AmoebaNet-A | **3.34** | 3.2 |
| Wide-DenseNet C3 | 3.81 | 3.4 |
| Wide-DenseNet C2sp | 3.54 | 3.2 |
| NASNet-A + *cutout* | 2.65 | 3.3 |
| Wide-DenseNet C2sp + *cutout* + *mixup* | **2.44** | **3.2** |

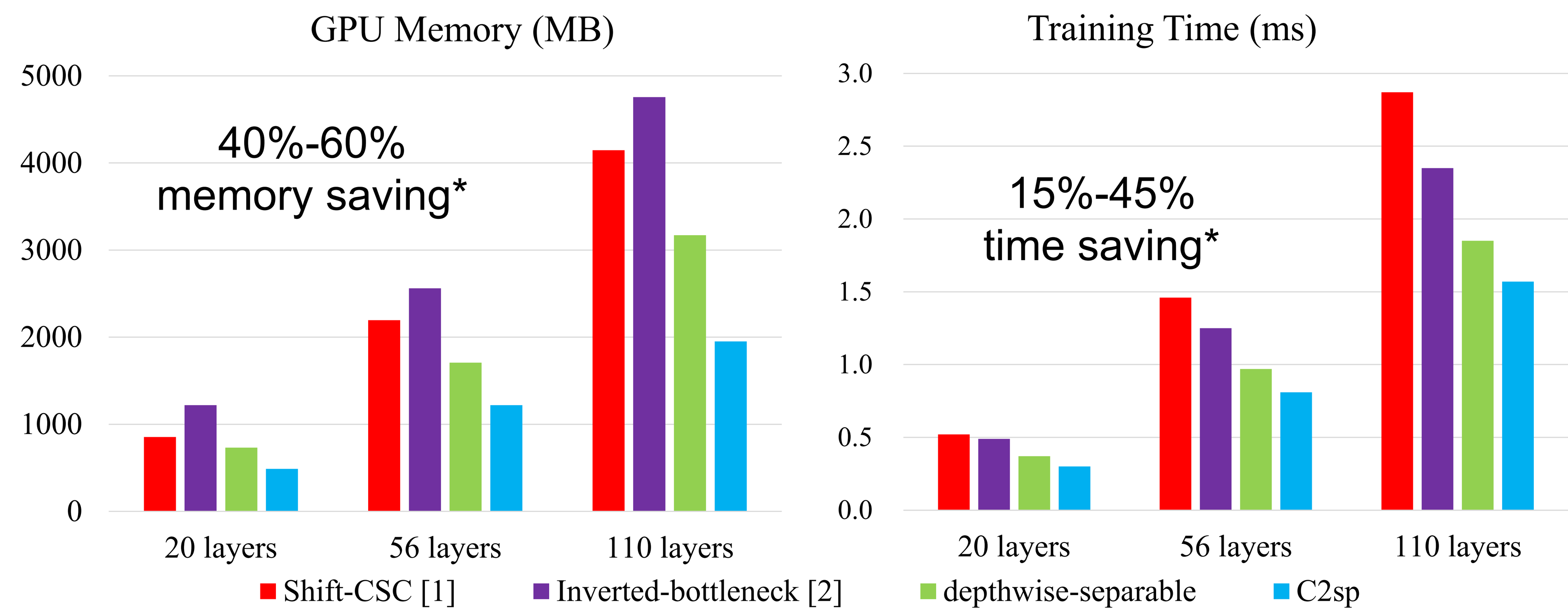
- Image generation tasks (GAN):

| Model | CIFAR10 | LSUN | CelebA |
|---|---|---|---|
| C5 | 26.54±1.38 | 30.84±1.13 | 33.90±3.77 |
| C3 | 24.12±0.47 | 36.04±7.10 | 43.39±5.78 |
| C4 | 26.45±1.50 | 39.17±5.52 | 37.93±7.54 |
| C4sp | 24.86±0.41 | **24.61±2.45** | **30.22±3.02** |
| C2 | | Non-convergence | |
| C2sp | **23.35±0.26** | 27.73±6.76 | 31.25±4.86 |




## Training Overheads

- C2sp vs other compact CNN building blocks




*Naïve Tensorflow high-level implementation, can be further optimized

[1] Wu, B., et al. Shift: A zero flop, zero parameter alternative to spatial convolutions. *ICCV*'18.
[2] Sandler, M., et al. Mobilenetv2: Inverted residuals and linear bottlenecks. *CVPR*'18.
[3] He, K., Sun, J. Convolutional neural networks at constrained time cost. *CVPR*'15.