Efficient rgb-d semantic segmentation for indoor scene analysis

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- **Problem/Objective**
  - Desire to excel in scene analysis on mobile robots.

- **Contribution/Key Idea**
  - Propose ESANet* for RGB-D semantic segmentation.

*ESANet = Efficient Scene Analysis Network.

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- **Background.**

- Robots need to perform several tasks in parallel.

(Person perception, free space detection, mapping, navigation.)

- Too many constraints exist.

(Real time performance, limited computing and battery capabilities.)

- Efficient and shared initial processing step can facilitate tasks.

- Semantic segmentation is well suited for such as initial step.

- Propose ESANet* for RGB-D semantic segmentation.

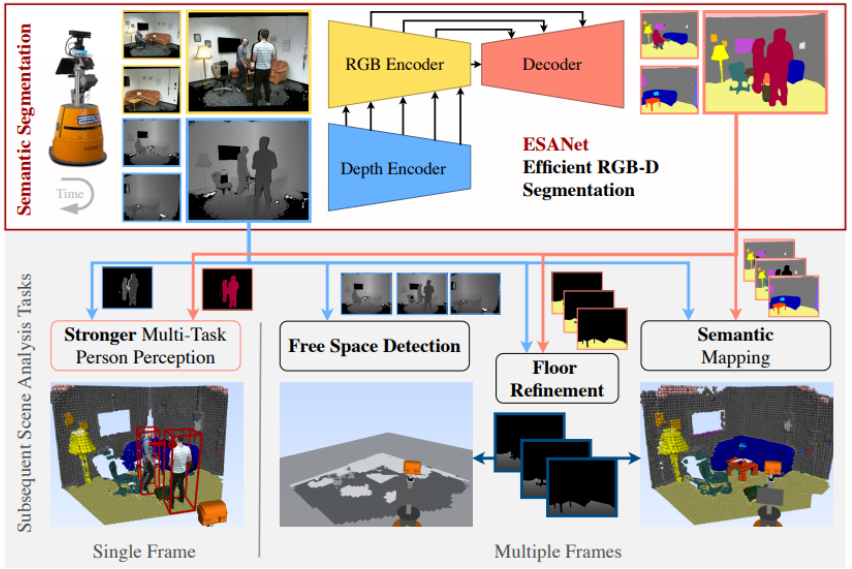

Fig. 1: Our proposed efficient RGB-D segmentation approach can serve as a common preprocessing step for subsequent tasks such as person perception, free space detection to avoid even small obstacles below the laser, or semantic mapping.

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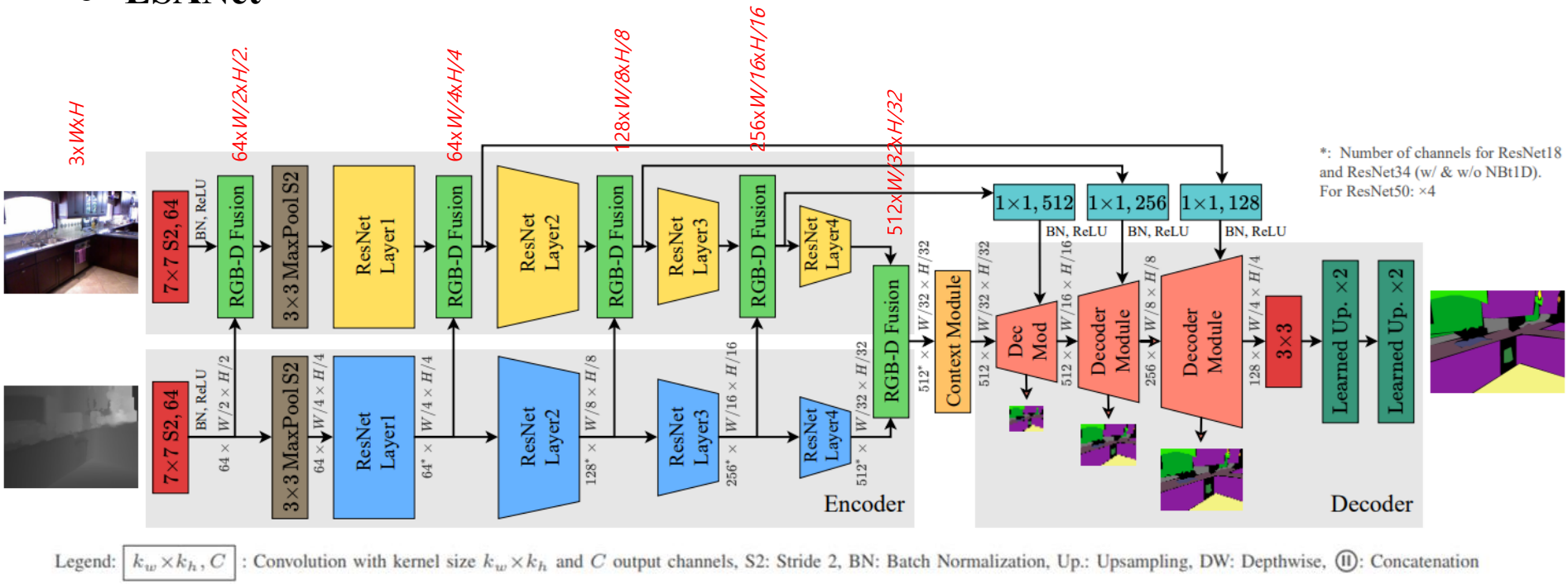
- **ESANet**



- Encoder
- Context module
- Decoder

*ESANet = Efficient Scene Analysis Network.

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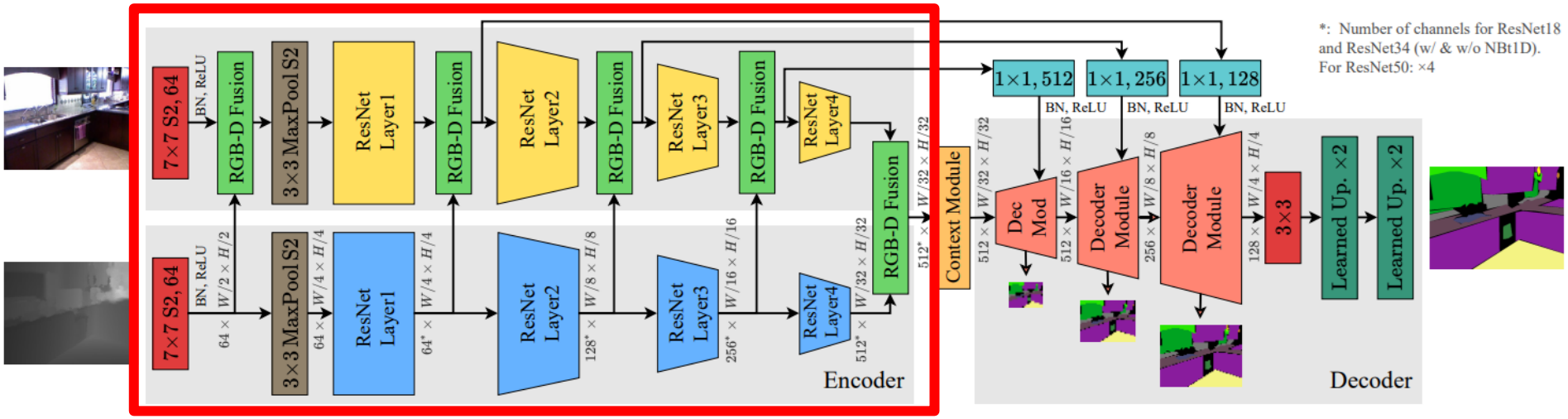
- **Encoder**



1. RGB-D segmentation.
2. RGB-D fusion.
3. NBt1D*.

*NBt1D = Non-Bottleneck-1D-Block.

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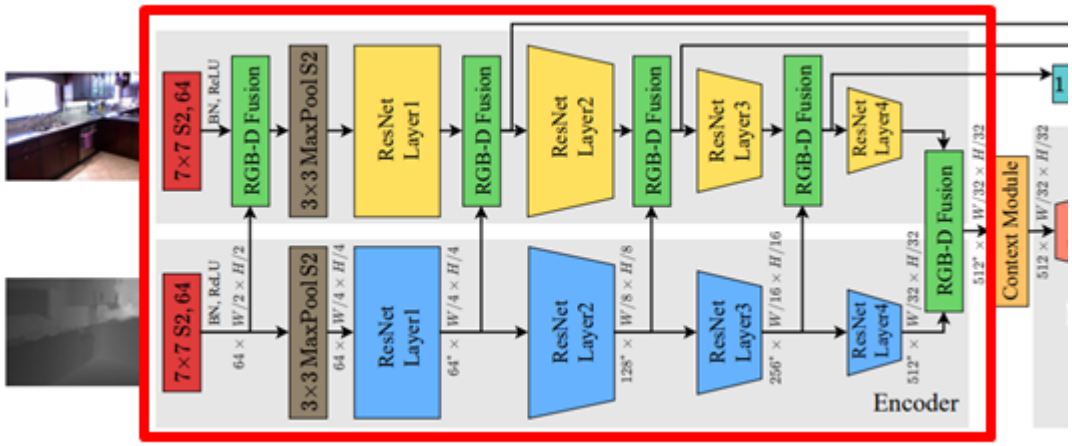
1. RGB-D segmentation.

- Inspired by SwiftNet's RGB segmentation.
- SwiftNet : RGB segmentation

↓ Add Depth encoder.

- ESANet : RGB-D segmentation.
- Depth encoder extracts complementary geometric info that is <u>fused in RGB encoder at five stages using an channel attention mechanism.</u>



2. RGB-D fusion.

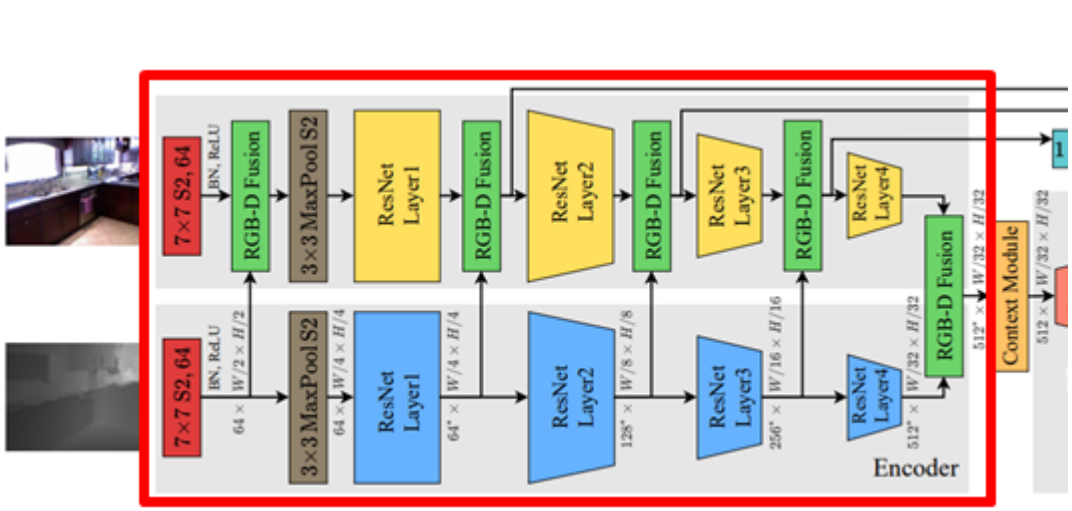
Depth features are fused into the RGB encoder using ‘channel attention mechanism’.

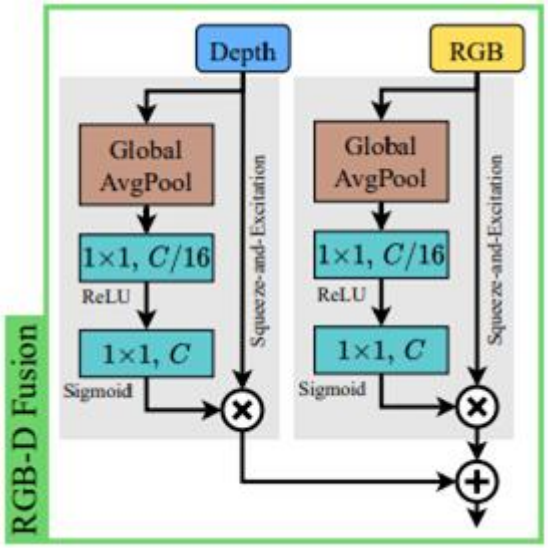
- ‘Channel attention mechanism’

Features from both modalities are reweighted with SE* module
and then summed element-wisely.

- Advantage of using ‘Channel attention mechanism’.

Model can learn which features of which modality to focus on and which to suppress.





*SE module = Squeeze and Excitation module.

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- SE module.

Stack of SE blocks.

- SE block

Recalibrates channel-wise feature responses in two steps, *squeeze* and *excitation* by modelling channel interdependencies.

Squeeze : produce a channel descriptor by aggregating the features maps across HxW dimensions.

Excitation : sample-specific activations govern the excitation of each channel.

- Advantage of SE module.

Be able to increase sensitivity to informative features and suppress less useful ones.

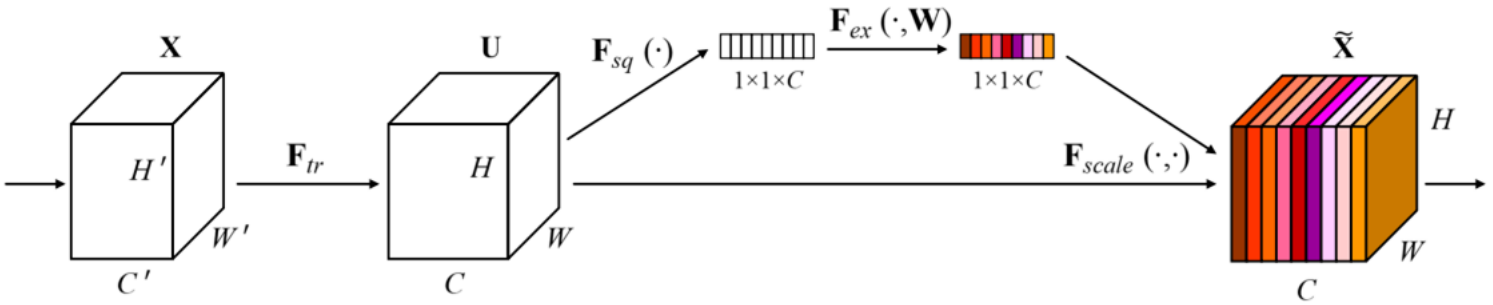
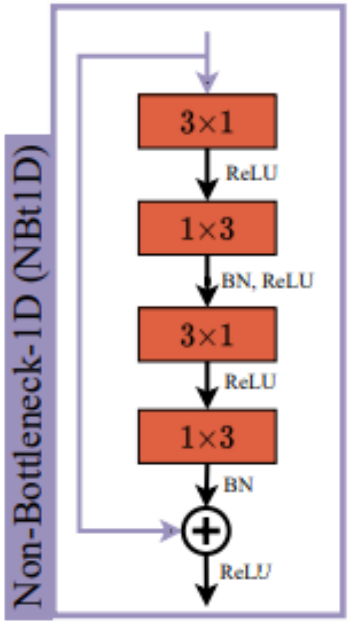


Figure 1: A Squeeze-and-Excitation block.

*SE module = Squeeze and Excitation module.

3. NBt1D*.

Each 3x3 convolution is replaced by a 3x1 and a 1x3 convolution with a ReLU in-between.



*NBt1D = Non-Bottleneck-1D-Block.

- NBt1D : initially proposed in ERFNet for real-time & accurate semantic segmentation.

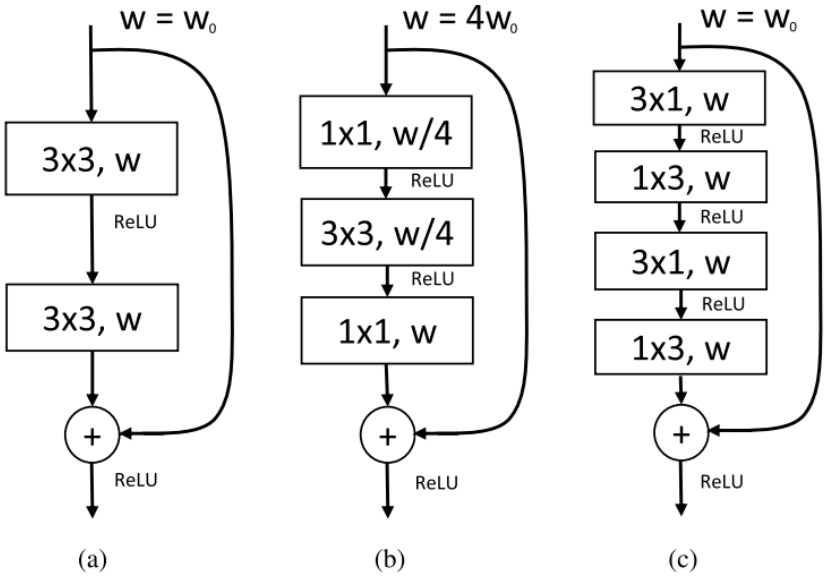


Fig. 2. Depiction of the two residual layers originally proposed in [6] (Non-bottleneck and Bottleneck), and our proposed design (Non-bottleneck-1D). w represents the number of feature maps input to the layer, internally reduced by 4 in the bottleneck design. In the convolutional blocks, "$d_1 \times d_2$, f" indicate their kernel sizes (d_1, d_2) and number of output feature maps (f). (a) Non-bottleneck. (b) Bottleneck. (c) Non-bottleneck-1D.

(a) Non-bottleneck.
Advantage : High accuracy.
Disadvantage : High computational cost.

(a) Bottleneck.
Advantage : Low computational cost.
Disadvantage : Low accuracy.

(a) NBt1D
High accuracy + Low computational cost.

*NBt1D = Non-Bottleneck-1D-Block.

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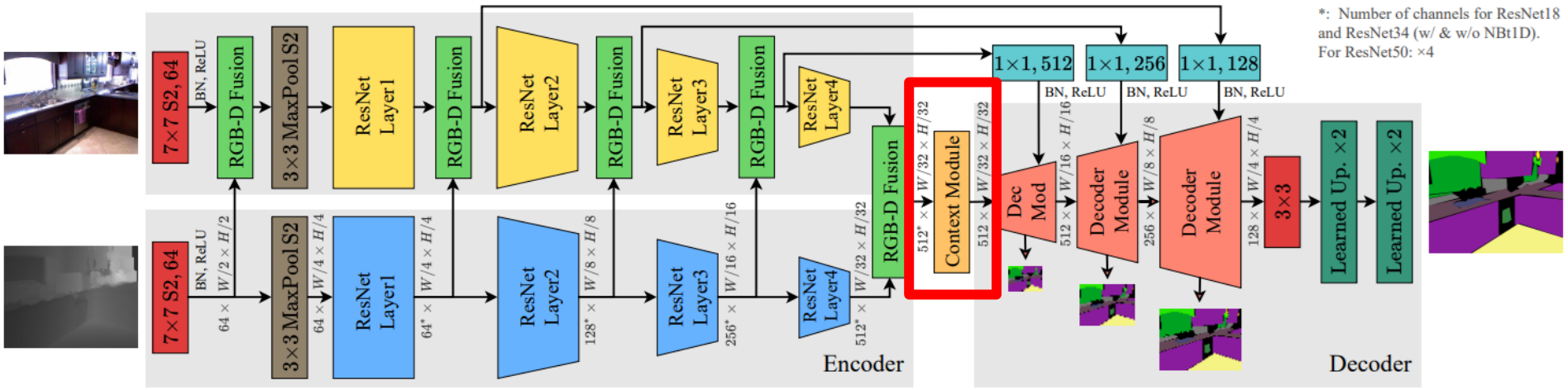
- **Context Module**



1. Use several branches.
2. Pooling sizes are always a factor of the input resolution of the context module.

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1. Use several branches.

- Objective.

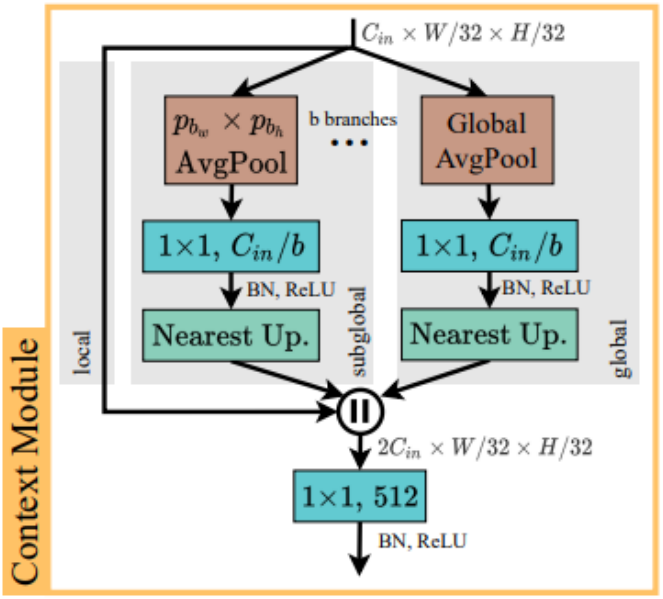
Incorporate context information by aggregating features at different scales.

- Problem.

Limited receptive field of ResNet.

- Solution.

Using several branches in a context module similar to the Pyramid Pooling Module in PSPNet*.



*PSPNet = Pyramid Scene Parsing network.

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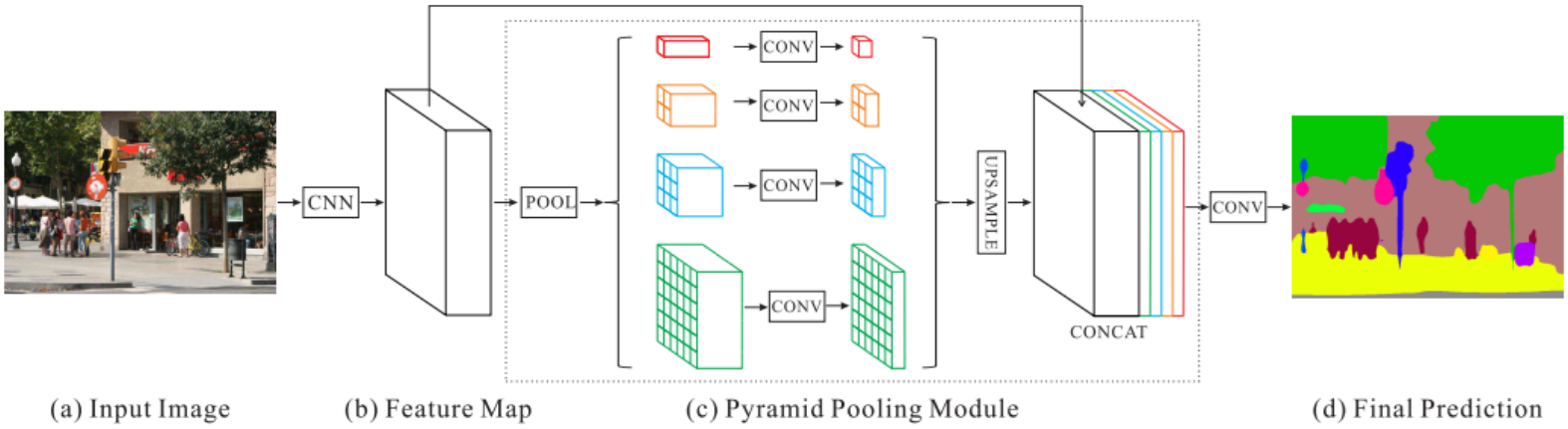

Figure 3. Overview of our proposed PSPNet. Given an input image (a), we first use CNN to get the feature map of the last convolutional layer (b), then a pyramid parsing module is applied to harvest different sub-region representations, followed by upsampling and concatenation layers to form the final feature representation, which carries both local and global context information in (c). Finally, the representation is fed into a convolution layer to get the final per-pixel prediction (d).

2. Design pooling sizes to be always a factor of the input resolution of the context module.

- Reason

NVIDIA TensorRT only supports pooling with fixed sizes.

*PSPNet = Pyramid Scene Parsing network.

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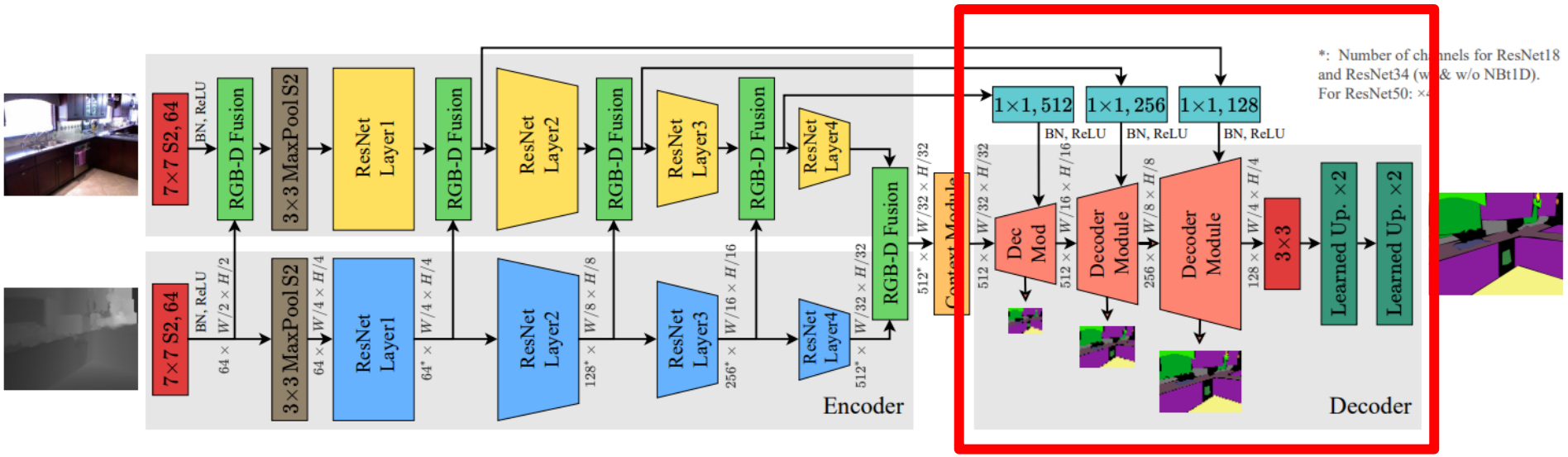
- **Decoder**



1. 512 channels in the first decoder module.
2. Skip connection.
3. 3 additional NBt1D.
4. Light-weight learned upsampling method.
5. Add supervision to each decoder module.

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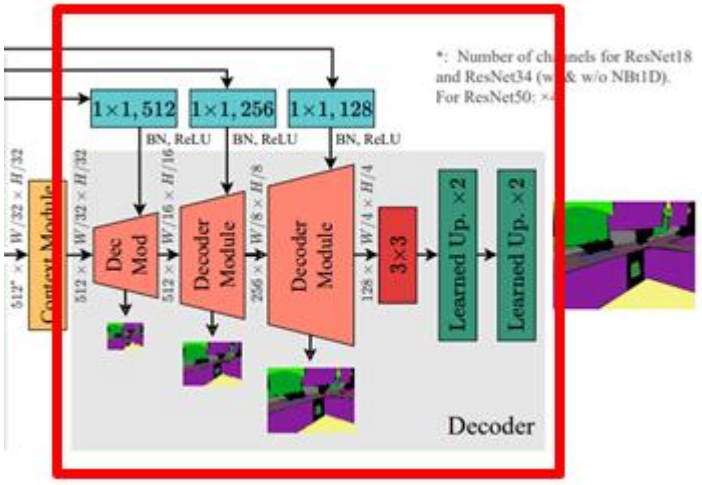

1. 512 channels in the first decoder module.

   - SwiftNet.

   Use a fixed number of 128 channels.

   ↓

   - ESANet.

   Use 512 channels at first decoder module and decrease the number of channels as the resolution increases.

2. Skip connection.

   - Problem.

   Too many details were lost during downsampling in the encoders.

   - Solution.

   Design skip connections from encoder to decoder stages of the same resolution.

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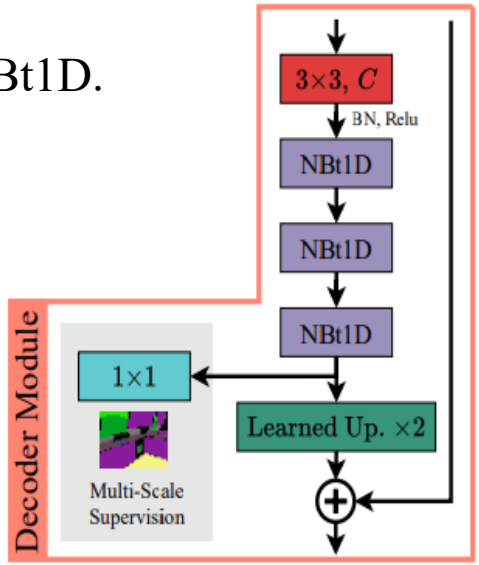
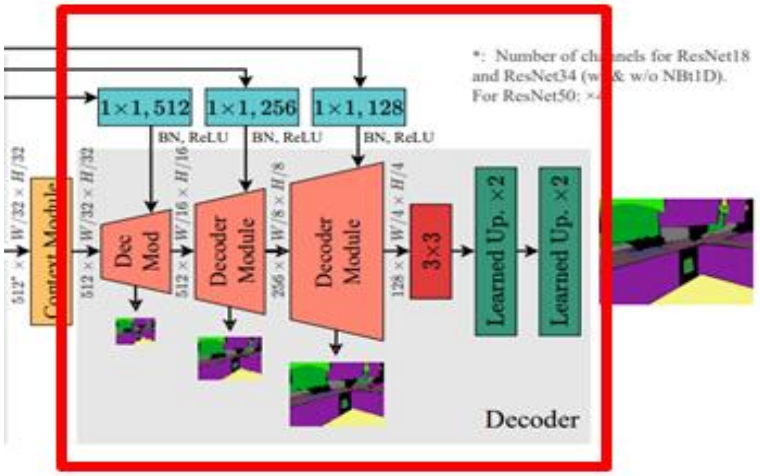
3. 3 additional NBt1D.





4. Light-weight learned upsampling method.

- Problem.

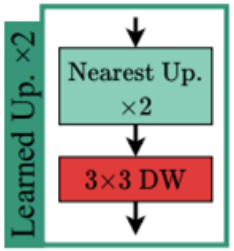
Transposed convolutions for upsampling : expensive, undesired artifacts.

- Solution.

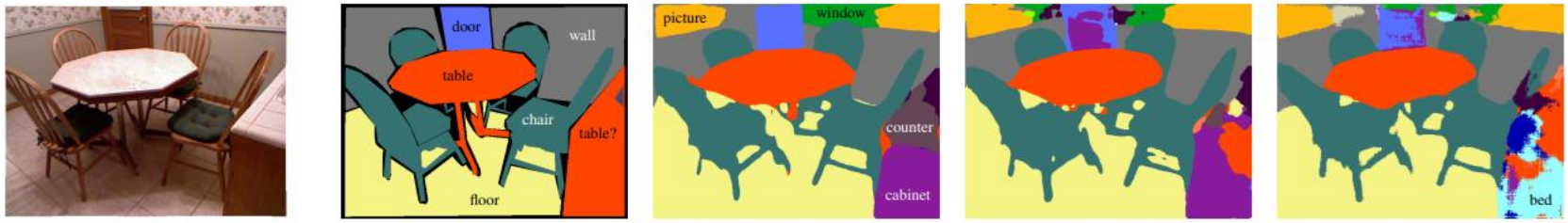
Use light-weight learned upsampling method.

- Method.

1. Use nearest neighbor upsampling to enlarge the resolution.
2. 3x3 depthwise convolution is applied to combine adjacent features.



*NBt1D = Non-Bottleneck-1D-Block.



RGB image | Ground Truth | **Learned Up. (ours)** | Bilinear Up. | Transp. Conv. (ACNet [11])

Fig. 3: Qualitative comparison of upsampling methods on NYUv2 test set (same colors as in Fig. 1 and Fig. 6).

5. Add supervision to each decoder module.

At each scale, a 1x1 convolution computes a segmentation of a smaller scale, which is supervised by the down-scaled ground truth segmentation.

- **Experiments**

Train networks using PyTorch.
500 epochs.
Batch size = 8.
Best models were chosen based on the mIoU.

- Indoor dataset.

NYUv2 : 795 training images, 654 testing images, 40 classes.
SUNRGB-D : 5285 training images, 5050 testing images, 37 classes.

- Outdoor dataset.

Cityscapes : 2975 training images, 500 validation images, 1525 testing images, 19 classes.

- **Results**

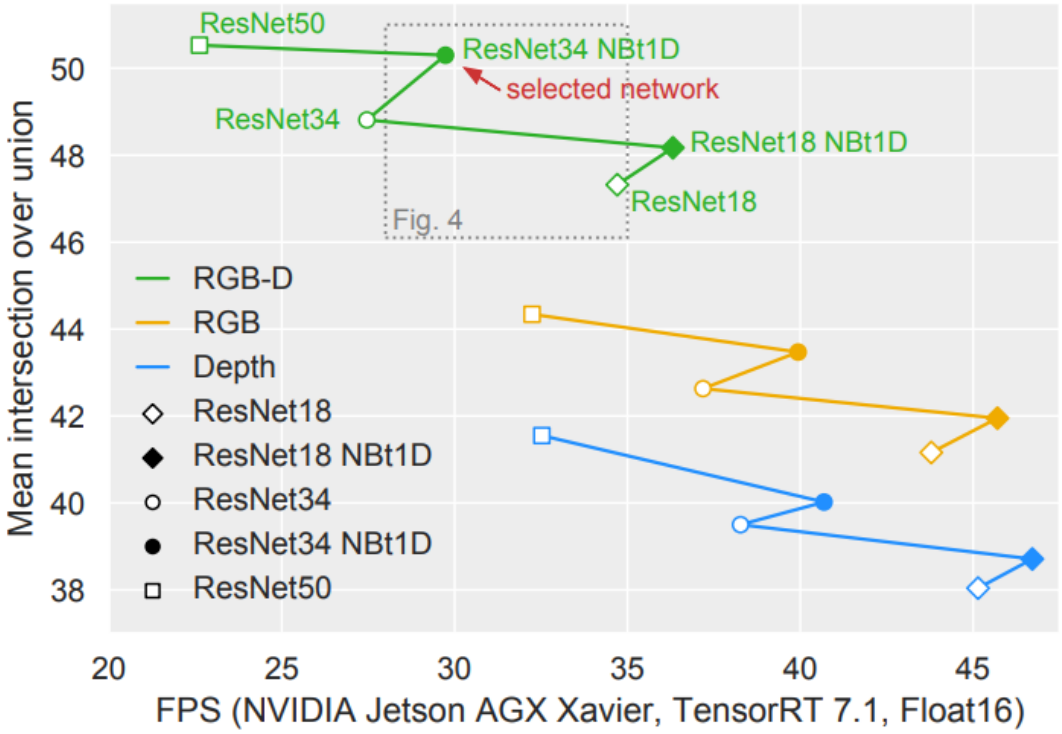


Fig. 4: Comparison of RGB-D to RGB and depth networks (single encoder) and different backbones on NYUv2 test set.

- **Results**

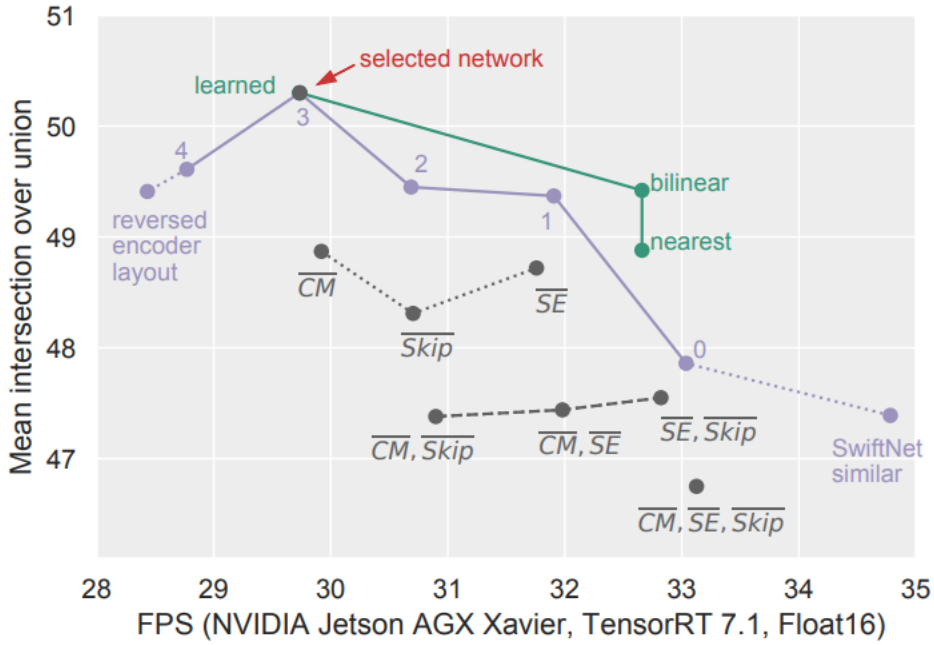


Fig. 5: Ablation Study on NYUv2 test. Each color indicates modifying one aspect: purple: number of NBt1D blocks in decoder module, dark green: upsampling method, and gray: usage of specific network parts with $\overline{CM}$: no context module, $\overline{Skip}$: no encoder-decoder skip connections, and $\overline{SE}$: no Squeeze-and-Excitation before fusing RGB and depth.

추가 공부

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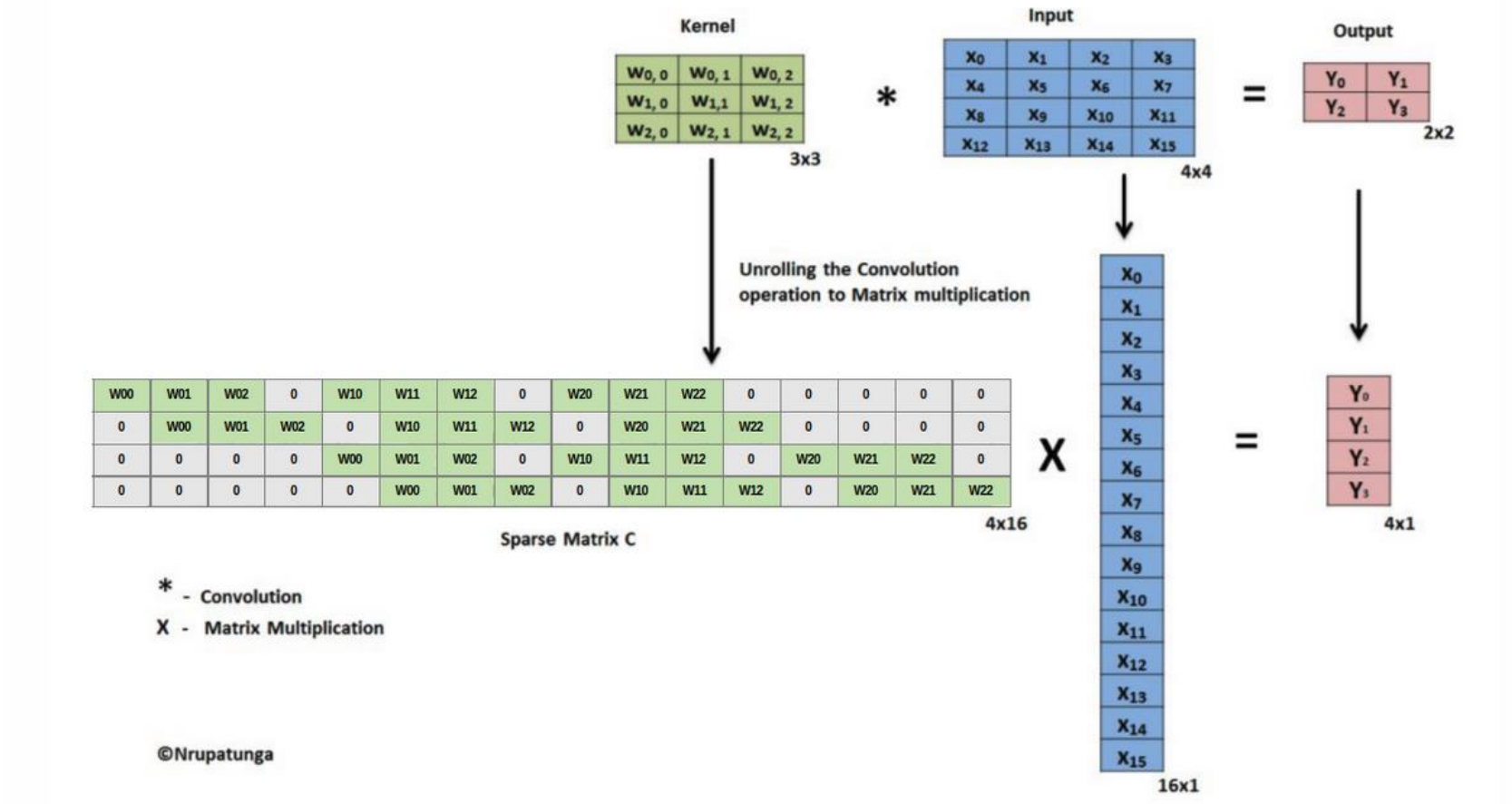
2D Convolution.



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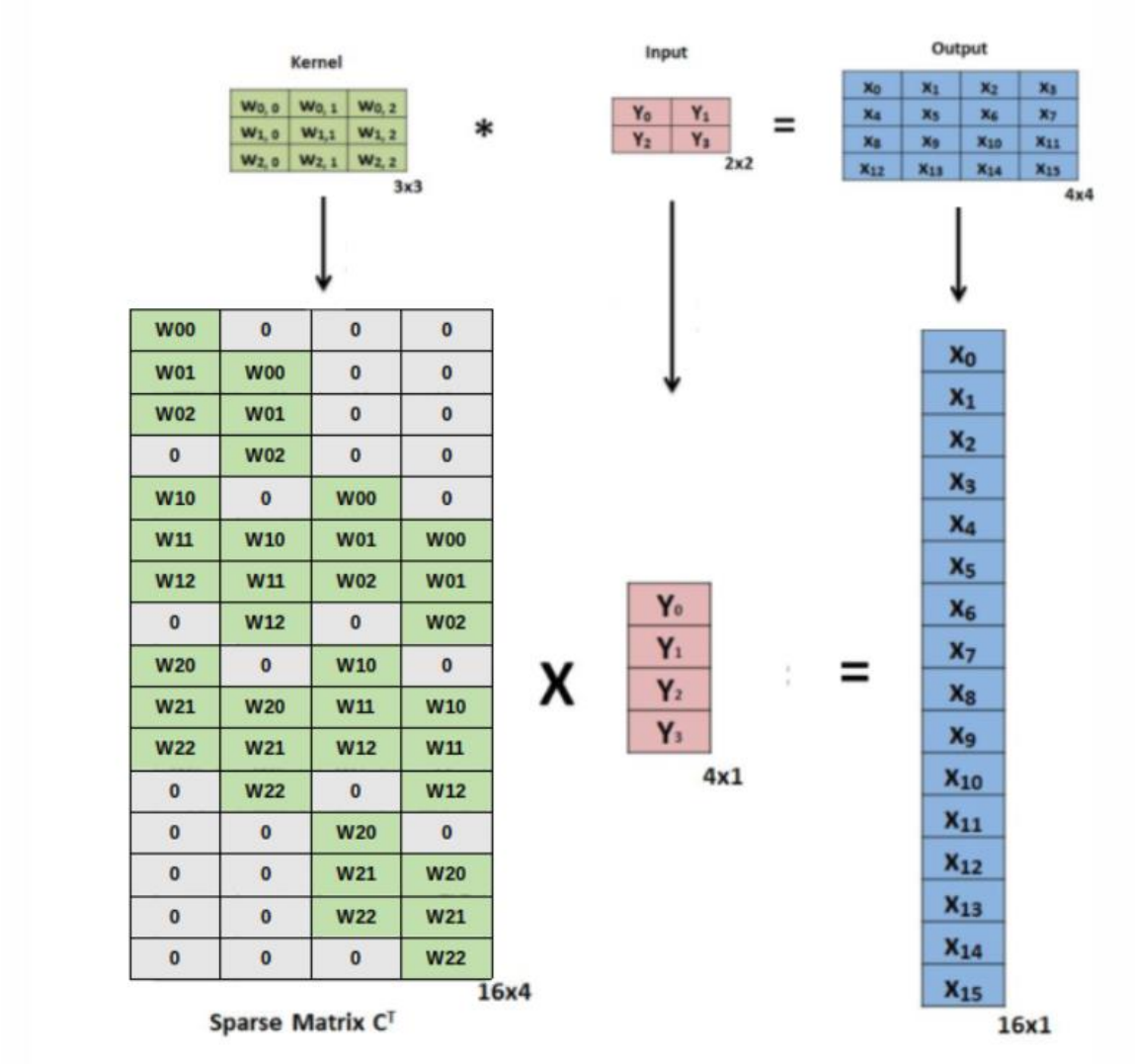
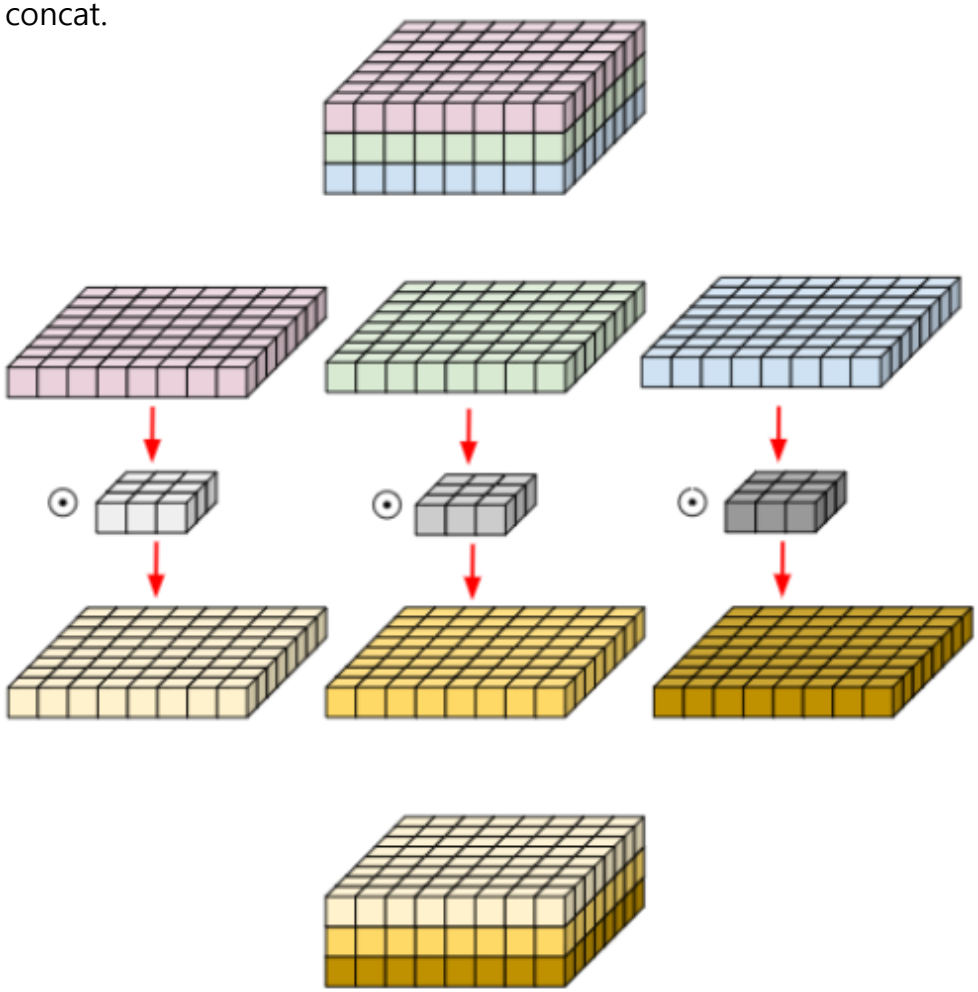
2D Transposed Convolution



https://eehoeskrap.tistory.com/431

Depthwise Convolution

channelwise convolution 후 concat.



https://openaccess.thecvf.com/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

ResNet

RESNet 등장 배경.

깊은 망의 문제점 (1. Vanishing/Exploding Gradient 문제. 2. training 어려움.) 해결 목적.

기존.

목표 : 최적의 H(x) 찾기.

ResNet.

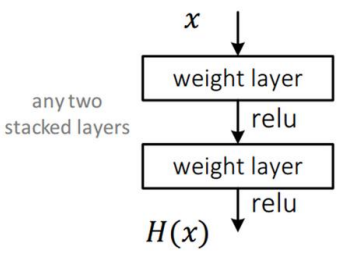
목표 : 최적의 F(x) 찾기.

F(x)=H(x)-x.

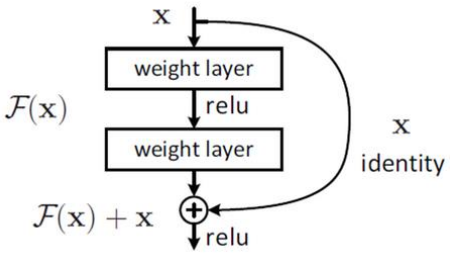
Residual learning의 기본 블락 : 입력에서 출력으로 직행 shortcut 연결 생성 : 연산량 관점에 오직 덧셈만 추가될 뿐.

최적의 경우 F(x) = 0. : 학습 방향 미리 결정되어있음. : pre-conditioning 구실 함.

F(x) = 0 되는 방향으로 학습을 하게 되면, 입력의 작은 움직임(fluctuation)을 쉽게 검출 가능. : F(x)가 작은 움직임을 학습한다. : F(x)가 나머지 (residual)를 학습한다. : residual learning.



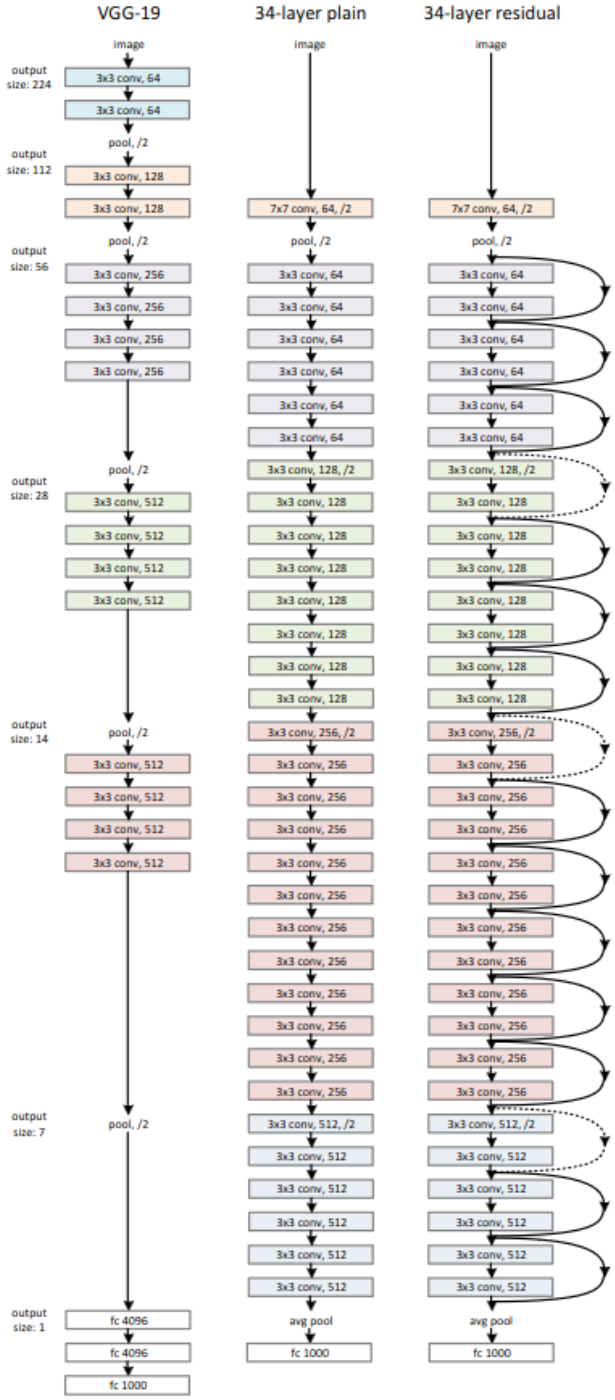
기존.



ResNet block.

https://openaccess. al_Learning_CVPR_2016_paper.pdf

RESNet-34.

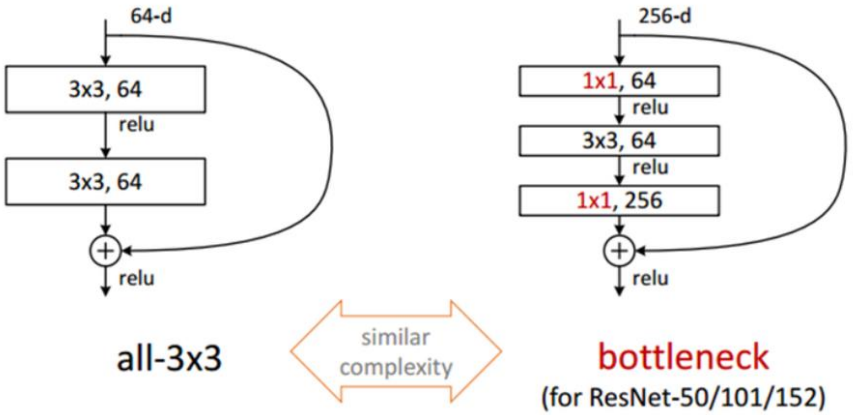


layer name	output size	18-layer	34-layer
conv1	112×112		
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$
	1×1		aver
FLOPs		1.8×10^9	3.6×10^9

Table 1. Architectures for ImageNet. Building blocks are shown in b
sampling is performed by conv3_1, conv4_1, and conv5_1 with a strid

https://openaccess.thecvf.com/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

Bottleneck building block for ResNet-50/101/152.



Bottleneck 구조 명칭 이유 : 차원 감소 후 차원 증가 모습이 병목처럼 보여서.

처음 1x1 conv 효과 : dimension 감소.

마지막 1x1 conv 효과 : dimension 증가.

Bottleneck 구조 사용 이유 : 연산량 절감하여 연산시간 감소.

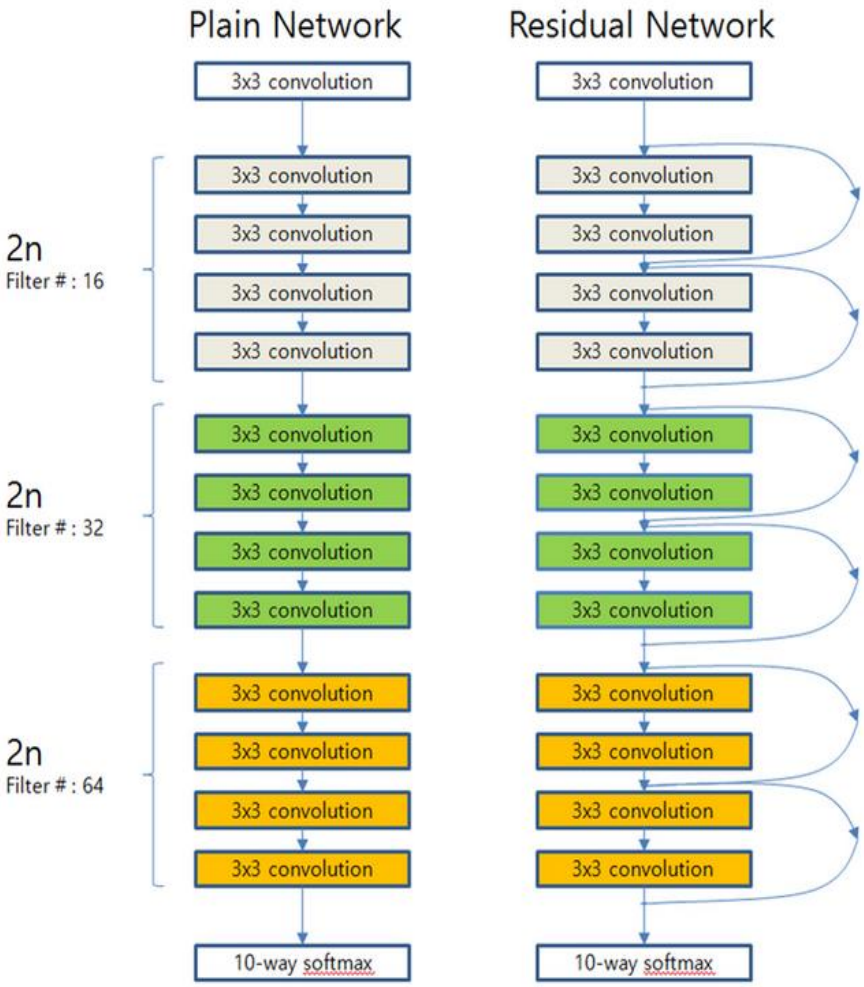
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

https://openaccess.thecvf.com/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

CIFAR-10 dataset에 대한 실험.

CIFAR-10 dataset : 32x32 images. training image 5만개, test image 1만개. 총 10개 class. 즉, class당 6000장 존재함.



-맨 처음 conv layer에 3x3 conv 사용.
이유 :
ImageNet dataset 은 224x224 image로 크기 커서 맨처음 conv layer 에 7x7 conv 사용했지만, CIFAR-10 dataset 은 32x32 image로 크기가 작아서.

-6n개의 3x3 conv layer 그룹 존재.
각 2n에 대해, feature map 크기 {32,16,8}.
filter 개수 {16,32,64}.

-전체 layer 수는 '6n+2' 개.
이유 :
맨 마지막에 global average pooling 과 10-way softmax를 배치해서.