[Review] DetectoRS: Detecting Objects with Recursive Feature Pyramid and Switchable Atrous Convolution

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Outline

Introduction

Contibution

Exploring a backbone for object detector that looks at the images twice or more.

- Recursive Feature Pyramid (RFP)
- Switchable Atrous Convolution (SAC)
- DetectoRS by combining RFP and SAC

Table: A glimpse of the improvements of the box and mask AP by DetectoRS on COCO test-dev.

Method	Backbone	AP_{box}	AP_{mask}	FPS
HTC [4]	ResNet-50	43.6	38.5	4.3
DetectoRS	ResNet-50	**51.3**	**44.4**	**3.9**

Feature Pyramid Network (FPN) [2]

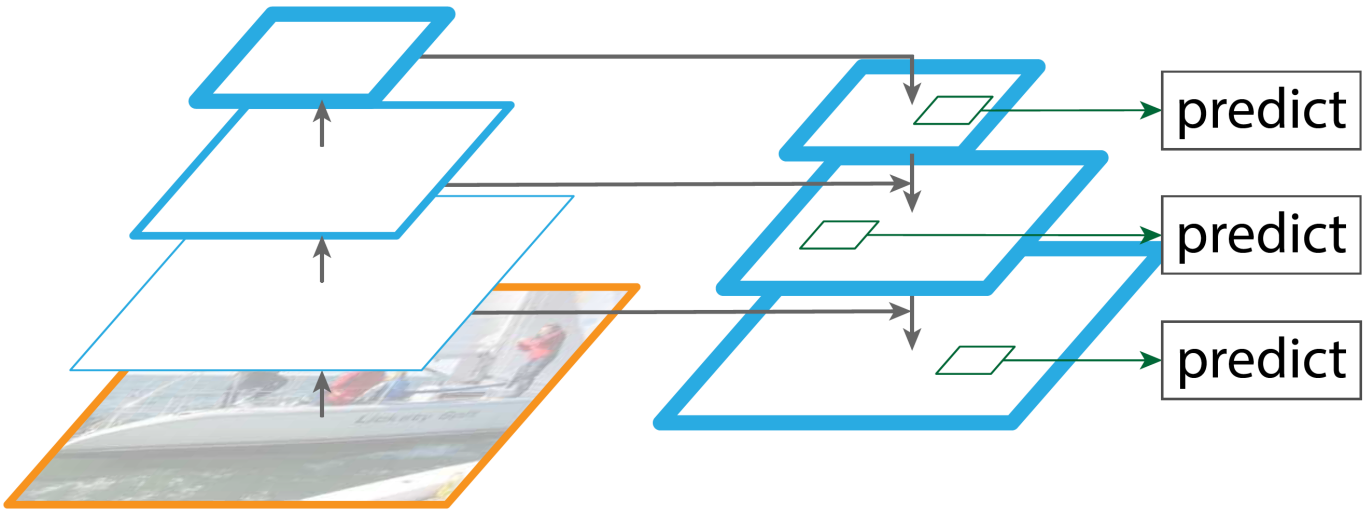

Figure: Feature pyramid network (FPN) [2].

Recursive formula for FPN

Let $\mathbf{B}_i$ denote the i-th stage of the bottom-up backbone, and $\mathbf{F}_i$ denote the i-th top-down FPN operation. The backbone equipped with FPN outputs a set of feature maps $\{\mathbf{f}_i | i = 1, \cdots, S\}$, where S is the number of the stages.

$$\forall i = 1, \cdots, S, \quad \mathbf{f}_i = \mathbf{F}_i(\mathbf{f}_{i+1}, \mathbf{x}_i) \quad \text{and} \quad \mathbf{x}_i = \mathbf{B}_i(\mathbf{x}_{i-1}).$$

Feature Pyramid Network (FPN) [2]

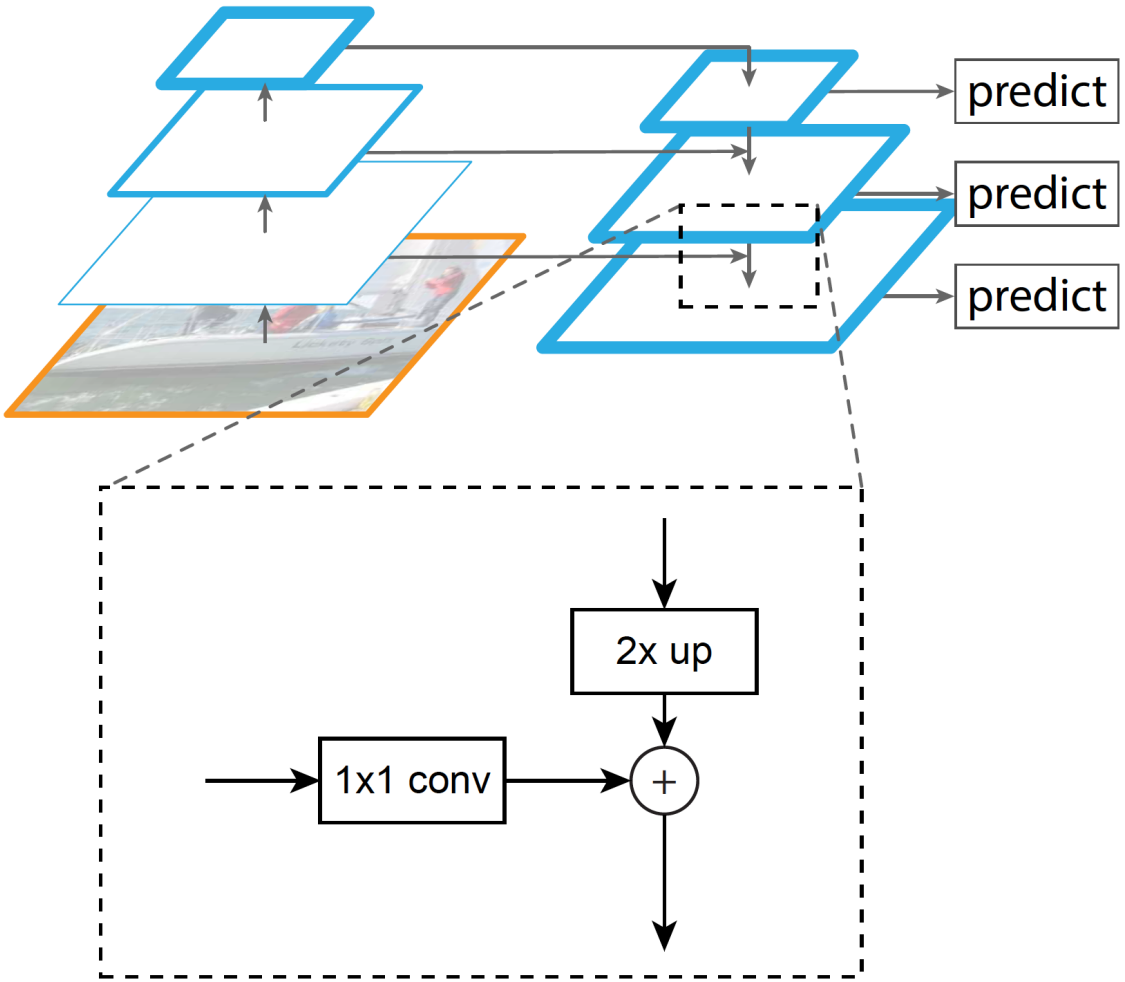

Figure: Feature pyramid network (FPN). A building block illustrating the lateral connection and the top-down pathway, merged by addition [2].

Atrous Convolution

Atrous Convolution

Consider one-dimensional case. The output $\mathbf{y}[i]$ of atrous convolution of a 1-D input $\mathbf{x}[i]$ with a filter $\mathbf{w}[k]$ of length K is defined as:

$$\mathbf{y}[i] = \sum_{k=1}^{K} \mathbf{x}[i + r \cdot k]\mathbf{w}[k],$$

where r is *atrous rate* parameter.

- Note that if the original kernel size is $k \times k$ and with the rate parameter r, the kernel of atrous convolution is $k + (k-1)(r-1)$.

Atrous Convolution

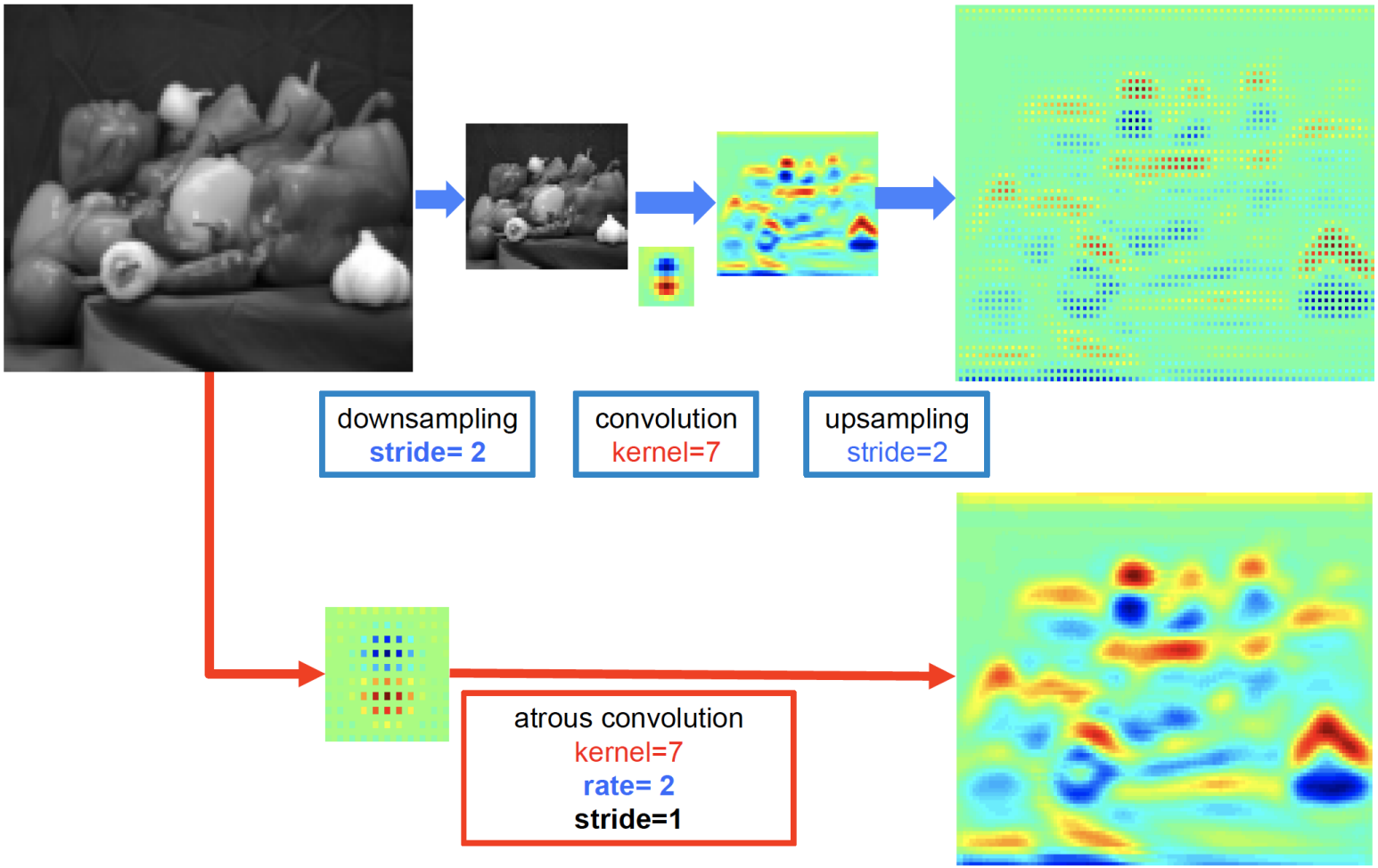

Figure: Illustration of Atrous Convolution in 2-D. The kernel here is the vertical Gaussian derivative [3].

Atrous Spatial Pyramid Pooling (ASPP) [3]

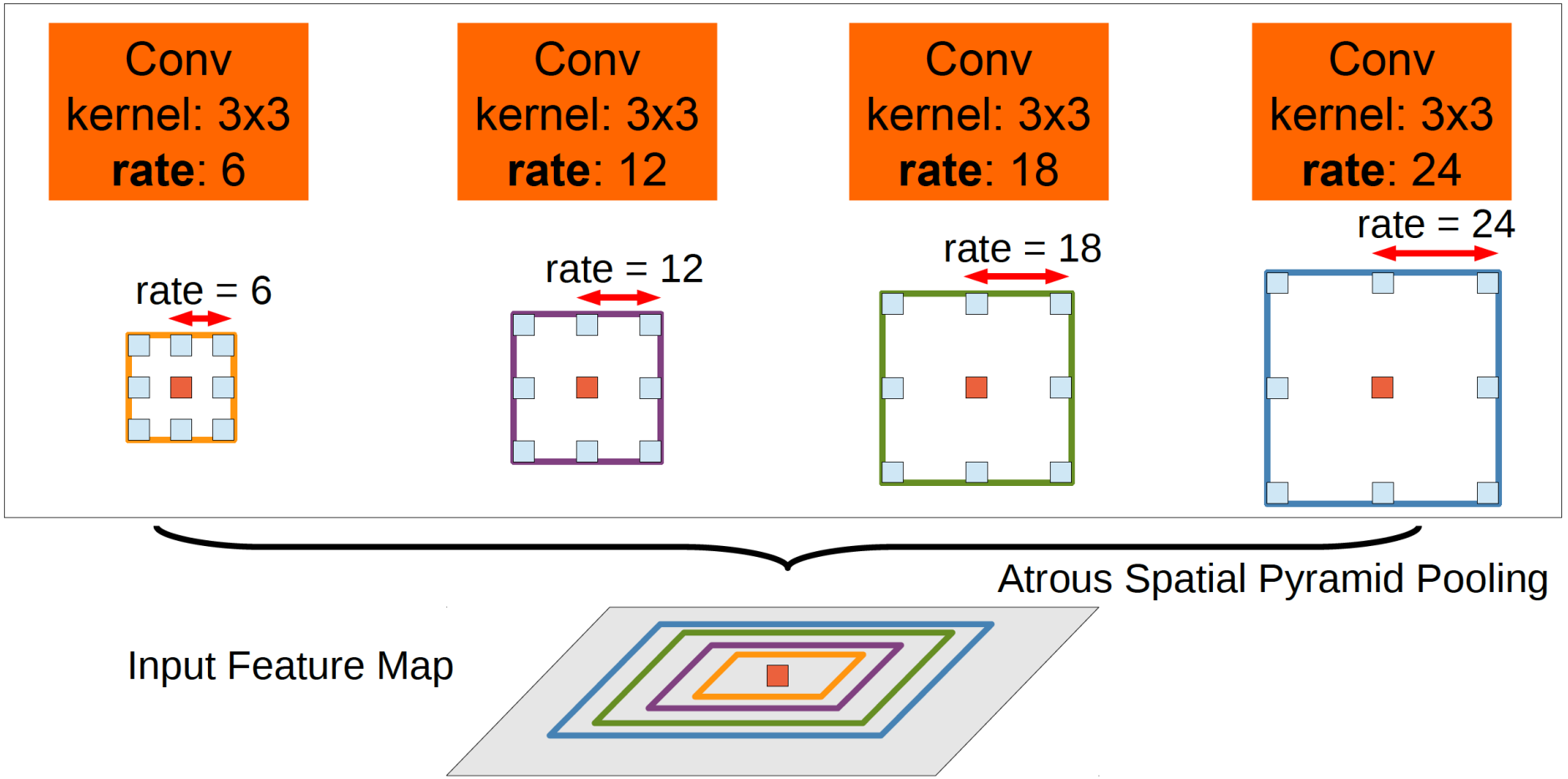

Figure: Illustration of ASPP in 2-D [3].

Recursive Feature Pyramid (RFP)

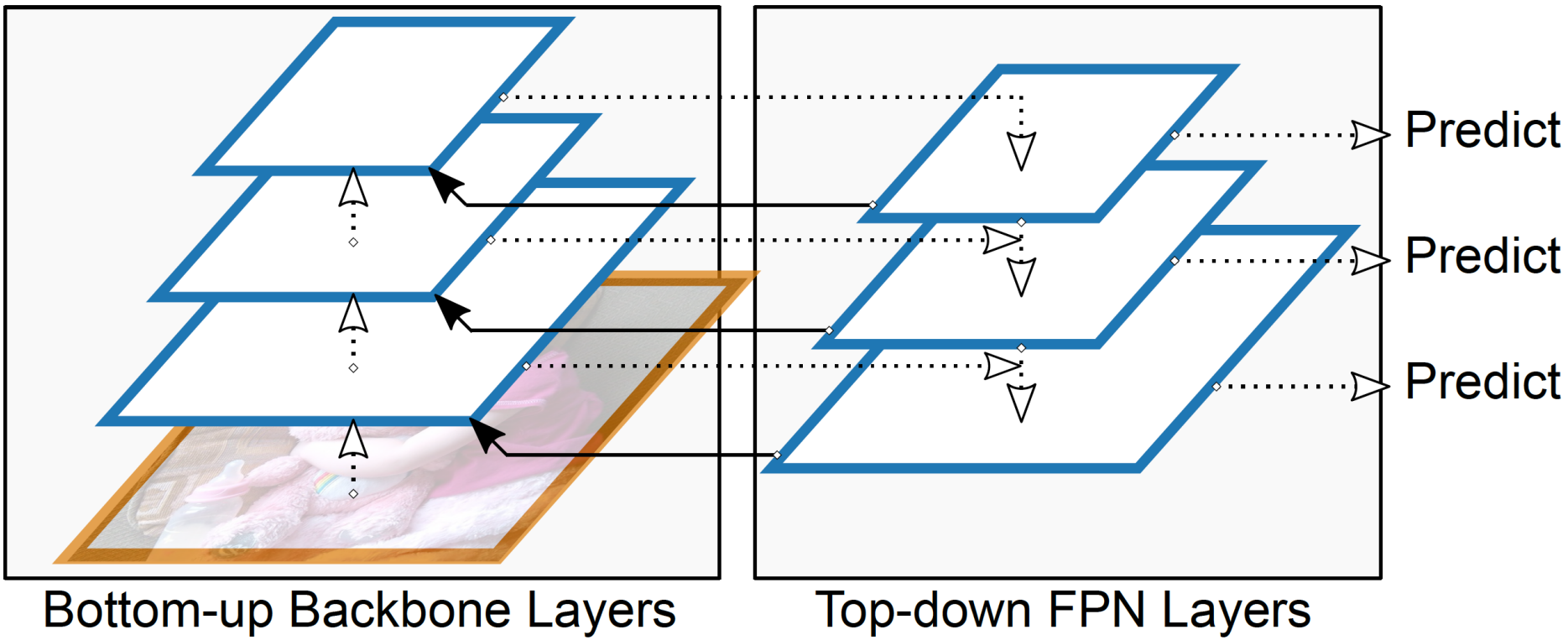

Figure: Recursive feature pyramid (RFP) which incorporates feedback connections into FPN.

Recursive Feature Pyramid (RFP)

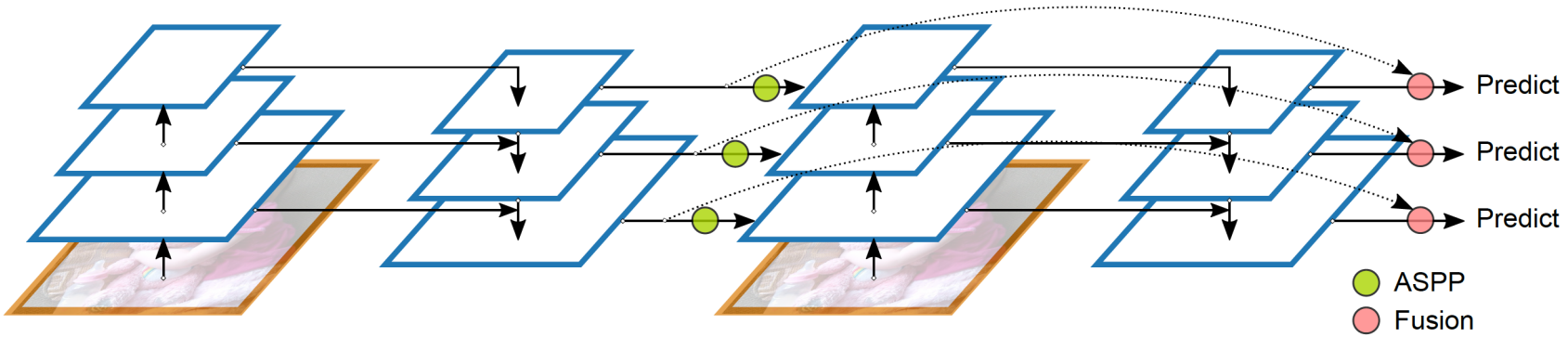

Figure: Recursive feature pyramid unrolled to a 2-step sequential network.

Recursive Formula for RFP

Let $\mathbf{R}_i$ denote the feature transformers before connecting them back to the bottom-up backbone. Then $\forall i = 1, \cdots, S$, $\forall t = 1, \cdots, T$,

$$\mathbf{f}_i^t = \mathbf{F}_i^t(\mathbf{f}_{i+1}^t, \mathbf{x}_i^t), \quad \mathbf{x}_i^t = \mathbf{B}_i^t(\mathbf{x}_{i-1}^t, \mathbf{R}_i^t(\mathbf{f}_i^{t-1})),$$

where T is the number of unrolled iterations, and we use superscript t to denote operations and features at the step t.

Recursive Feature Pyramid (RFP)

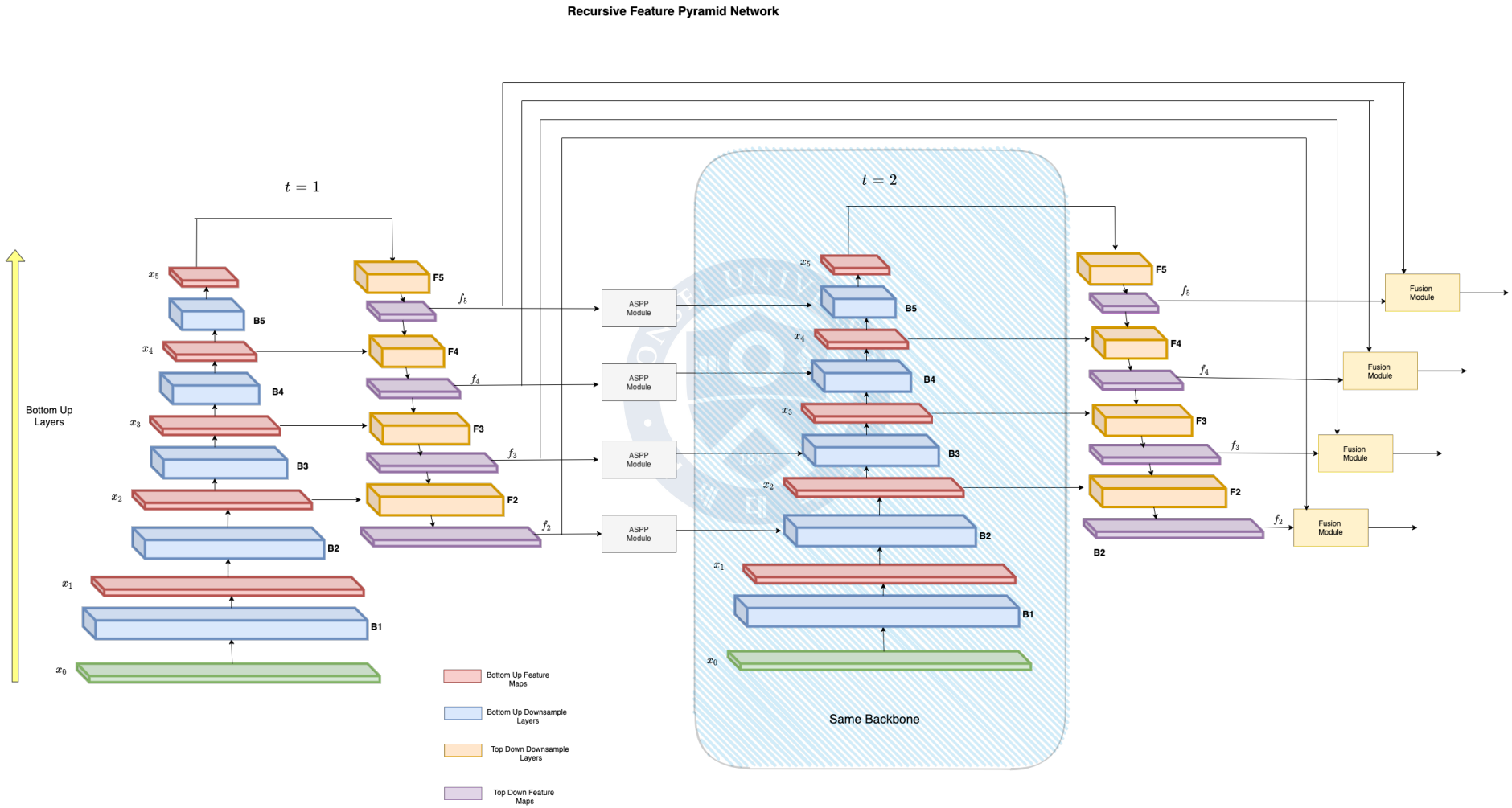

Figure: Recursive feature pyramid unrolled to a 2-step sequential network (detail).

ASPP as the Connecting Module

Connecting Module

- Authors make changes to the ResNet backbone **B** to allow it to take both **x** and **R**(**f**) as its input.
- They only make changes to the first block of each ResNet stage by combining RFP features.

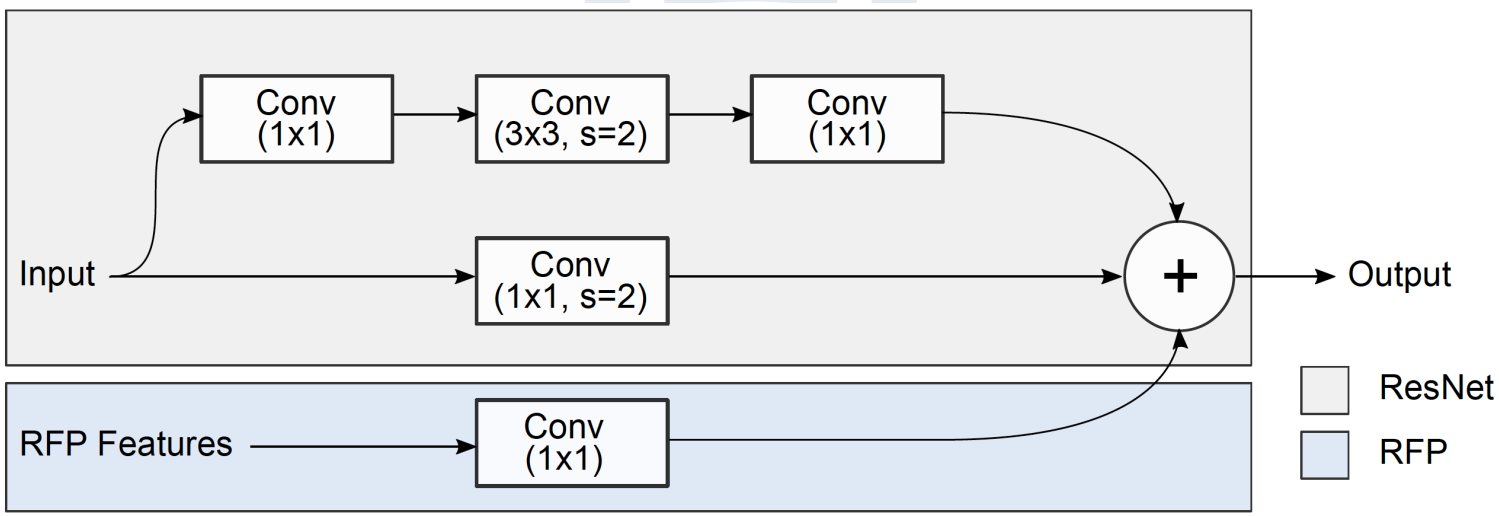

Figure: ASPP as the connecting module.

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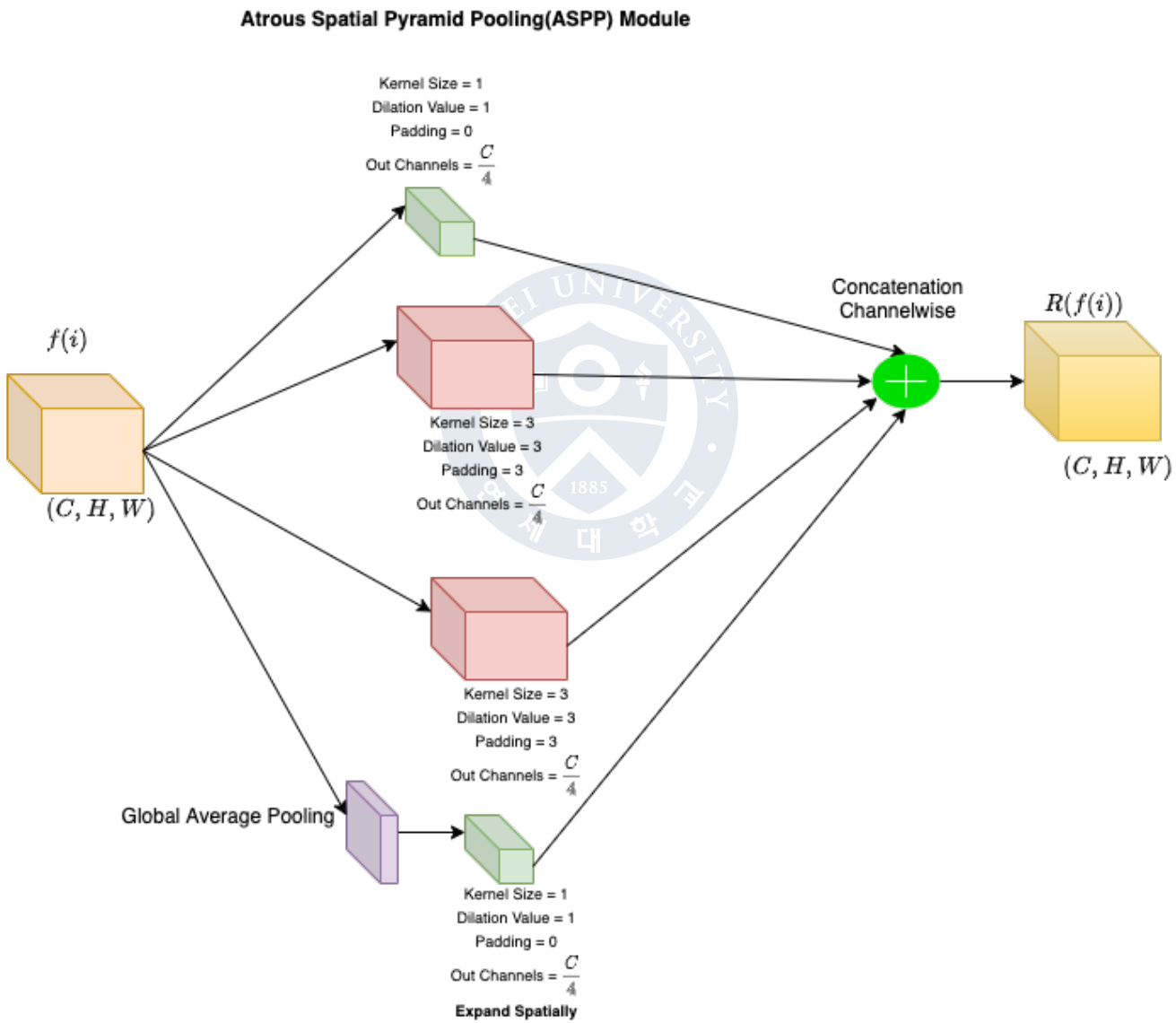
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
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

Figure: Structure summary of ResNet [5].

ASPP as the Connecting Module [6]



Fusion Module

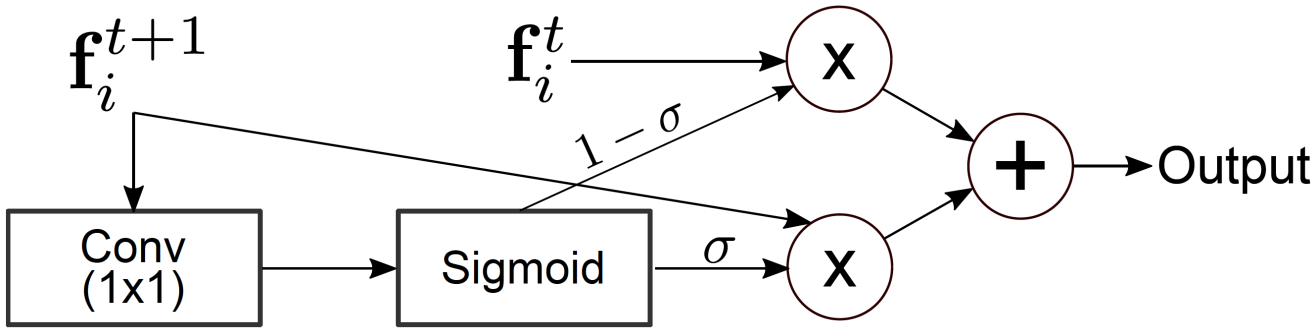
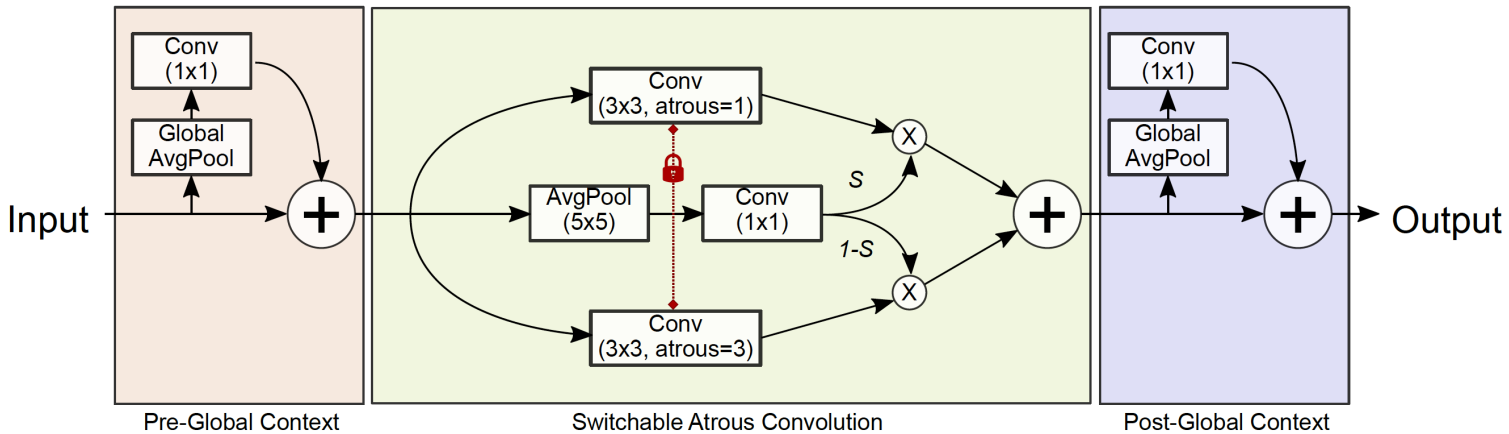


Figure: Fusion module in RFP.

Fusion Module

- FRP uses a fusion module to combine $\mathbf{f}_i^t$ and $\mathbf{f}_i^{t+1}$ to update the values of $\mathbf{f}_i$ at the unrolled stage $t+1$.
- The fusion module uses the feature $\mathbf{f}_i^{t+1}$ to compute an attention map by a convolutional layer follwed by a Sigmoid operation.
- The resulting attention map is used to compute the weighted sum of $\mathbf{f}_i^t$ and $\mathbf{f}_i^{t+1}$ to form an update $\mathbf{f}_i$.

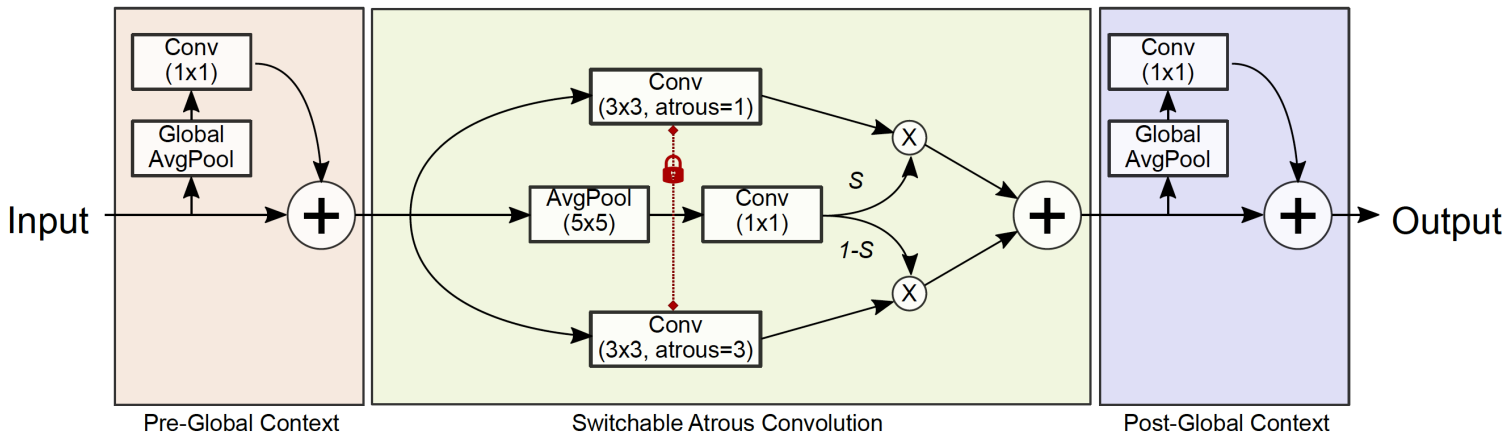
Switchable Atrous Convolution (SAC)



Switchable Atrous Convolution (SAC)

- Authors convert every 3×3 convolutional layer in the backbone to SAC.
- Two global context modules are added before and after the SAC component.

Switchable Atrous Convolution (SAC)

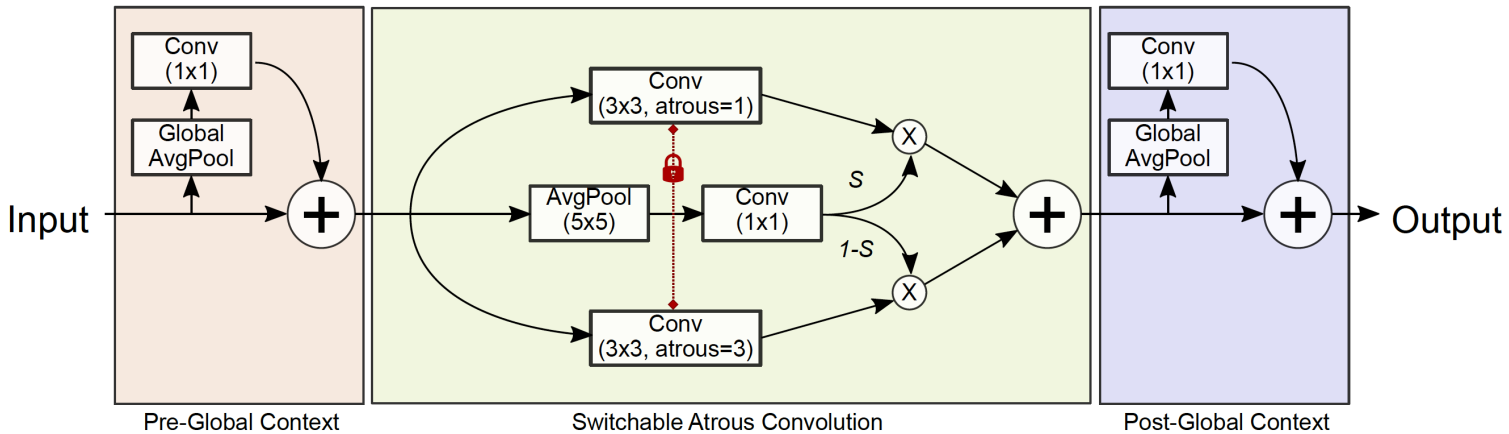


Switchable Atrous Convolution (SAC)

$$\mathbf{Conv}(\mathbf{x}, \mathbf{w}, 1) \xrightarrow[\text{SAC}]{\text{Convert}} \mathbf{S}(\mathbf{x}) \cdot \mathbf{Conv}(\mathbf{x}, \mathbf{w}, 1) + (1 - \mathbf{S}(\mathbf{x})) \cdot \mathbf{Conv}(\mathbf{x}, \mathbf{w} + \triangle\mathbf{w}, r),$$

where $\mathbf{Conv}(\mathbf{x}, \mathbf{w}, 1)$ be the convolutional operation with weight $\mathbf{w}$ and atrous rate r which takes $\mathbf{x}$ as its input and output $\mathbf{y}$.

Switchable Atrous Convolution (SAC)



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where r is a hyper-parameter of SAC, $\triangle\mathbf{w}$ is a trainable weight, and the switch function $\mathbf{S}(\cdot)$ is implemented as an average pooling layer with a 5×5 kernel followed by a 1×1 convolutional layer.

Conclusions

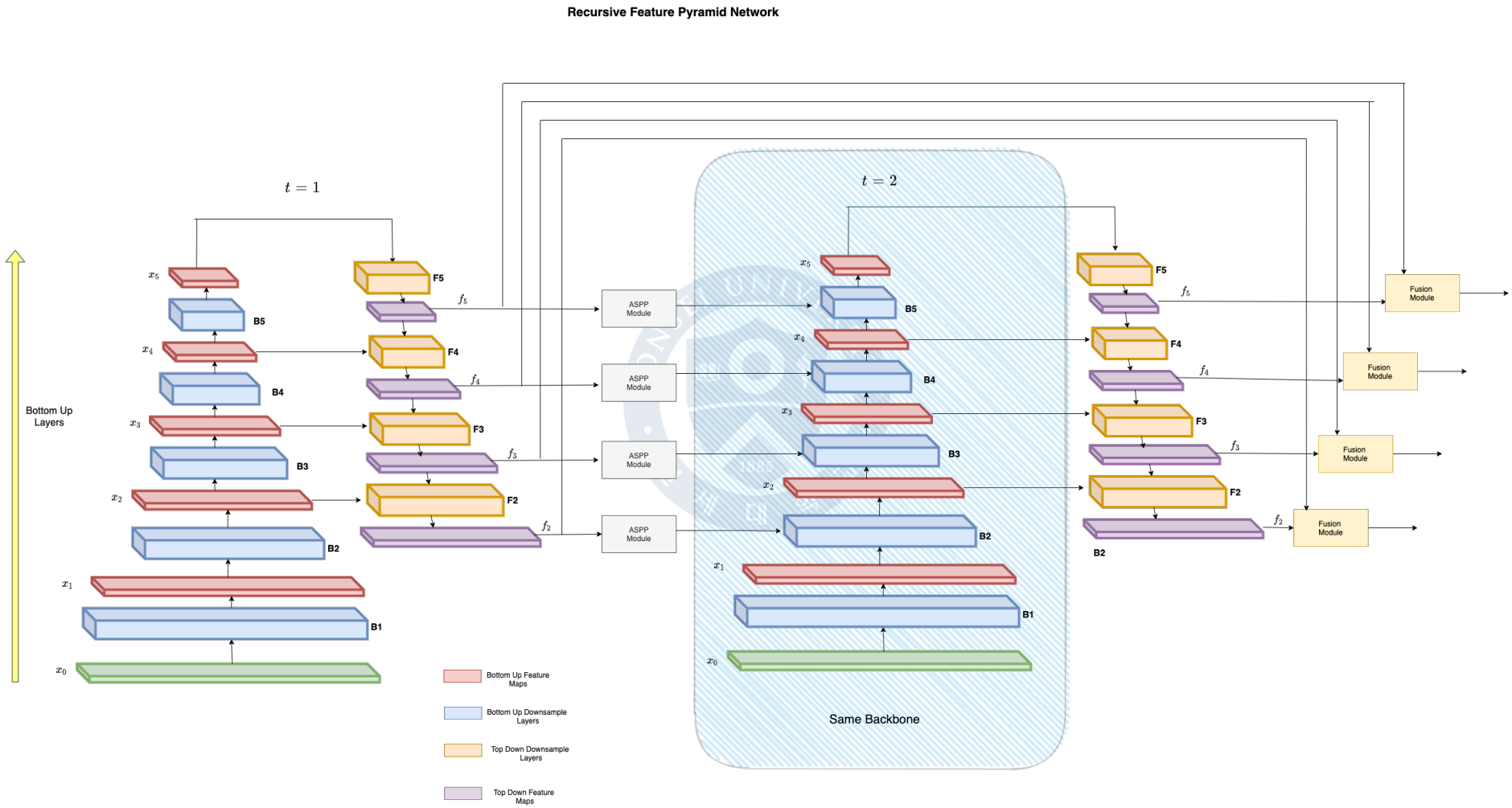

Figure: Recursive feature pyramid unrolled to a 2-step sequential network (detail) [6].

Conclusions

Conclusions

- RFP implements **thinking twice at the macro level**, where the outputs of FPN are brought back to each stage of the bottom-up backbone through feedback connections.
- SAC instantiates **looking twice at the micro level**, where the inputs are convolved with two different atrous rates.

References

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