# **CONCATENATED FEATURE PYRAMID NETWORK FOR INSTANCE SEGMENTATION**

Yongqing Sun \*

Pranav Shenoy K P \*†

P \*† Jun Shimamura \*

Atsushi Sagata\*

\* Media Intelligence Lab, NTT Corporation, Japan † Georgia Institute of Technology, USA

{yongqing.sun.fb, jun.shimamura.ec, atsushi.sagata.hw}@hco.ntt.co.jp pskp3@gatech.edu

# ABSTRACT

Low level features like edges and textures play an important role in accurately localizing instances in neural networks. In this paper, we propose an architecture which improves feature pyramid networks commonly used instance segmentation networks by incorporating low level features in all layers of the pyramid in an optimal and efficient way. Specifically, we introduce a new layer which learns new correlations from feature maps of multiple feature pyramid levels holistically and enhances the semantic information of the feature pyramid to improve accuracy. Our architecture is simple to implement in instance segmentation or object detection frameworks to boost accuracy. Using this method in Mask RCNN, our model achieves consistent improvement in precision on COCO Dataset with the computational overhead compared to the original feature pyramid network.

*Index Terms*— Instance Segmentation, Concatenation, Feature Pyramids, Inception

## 1. INTRODUCTION

Instance segmentation is one of the most important developments in computer vision. It combines object detection and semantic segmentation and finds its application in a wide variety of applications ranging from autonomous driving to medical imaging to video surveillance. One of challenges faced by instance segmentation is detecting and segmenting objects at vastly different scales. An efficient way to overcome this challenge would be to create feature pyramids from multiple layers of the CNN [1, 2, 3, 4]. This type of framework combines low resolution but semantically strong features with high resolution but semantically weak features in a top-down pathway with lateral connections from lower layers.

Mask RCNN[5] and Path Aggregation Networks or PANet[6] are popular state-of-the-art frameworks used for instance segmentation[7]. Mask RCNN extends Faster RCNN[8] by adding a Fully Cconvolutional Network[9] branch for predicting an object mask in parallel with the existing branch for bounding box recognition and utilizes feature pyramids[1] to achieve high accuracy. PANet enhances this architecture by adding a bottom-up pathway with lateral connections after the top-down pathway along with other improvements to Mask RCNN. By adding a bottomup pathway, the features in low levels which are helpful for identifying large objects take a shorter path to reach higher levels and improve localization. However, in both of these frameworks, the features are added to subsequent layers one after the other and by using element-wise addition. Also due to this process of addition, there are no layers which contain the correlation between high-level and low-level features. Experiments have shown that utilizing correlations between different levels of features can potentially further improve the performance of the network[10]. Experiments and papers such as [11, 12] have shown that concatenation is more flexible compared to element-wise addition and can improve the performance of the network. DenseNet[12] uses concatenations or dense connections to achieve parameter efficiency and feature reuse which can give better performance with lesser or similar computational resources.

The motivation behind this paper is to improve the performance and mask quality of the network by overcoming the drawbacks of existing frameworks. To achieve this, we propose the following:

- A new convolutional layer to learn correlations between different levels of features.
- 2. A bottom-up pathway to infuse low-level features from the lower pyramid levels to the higher levels in a computationally efficient way.

#### 1.1. Feature Pyramids

Analysis by M. D. Zeiler and R. Fergus[13] on feature maps have shown that neurons in the higher layers of the network are activated by entire objects or large regions of objects while neurons in lower layers are more likely to be activated by edges, local texture, patterns and other lower level features. The localization accuracy of a framework can be further enhanced by propagating strong activations of low-level featuress to higher layers since strong activations to edges or object parts are good indicators to accurately localize objects; particularly small objects. Hence by adding low-level features



Fig. 1: Illustration of our network. (a) FPN backbone. (b) Bottom-up pathway. (c) Inception module. (d) ROI Align.

to higher levels of the feature pyramid, we can achieve better performance for mask generation.

Networks like FPN[1], U-Net[14] and TDM[2] improve the accuracy by infusing features from lower layers. FPN augments a top-down path with lateral connections creating a feature pyramid for building high-level semantic feature maps at all scales. The top-down pathway hallucinates higher resolution features by upsampling feature maps from higher pyramid levels and adding them features from lower levels with lateral connections. Through this, the features from higher features reach the lower layers of the pyramid. However, lower level features do not reach the upper levels since the layers are added in a single direction. In figure 1, section (a) is the framework of the original feature pyramid network.

#### 1.2. DenseNet

Densely connected convolutional [12] networks or DenseNet connects all layers in the network directly with each other using concatenation to ensure improved flow of information and gradients between layers. Each layer in the network obtains additional inputs from all preceding layers and passes on its own feature-map to all subsequent layers. This network has direct access to the gradients from loss function and the original input signal leading to an implicit deep supervision[11]. These dense connections also condense the model and make it easy to train and highly parameter-efficient. Concatenating feature-maps learned by different layers increases variation in input of subsequent layers and improves efficiency. Since the bottom layers have a shorter path to the top layers, the gradients reach the bottom layers more efficiently and reduce training error.

### 2. FRAMEWORK

### 2.1. Concatenated Feature Pyramid Network

Concatenated Feature Pyramid Network(CFPN) is an enhanced version of Feature Pyramid Network designed to

overcome the drawbacks of FPN by adding an addition feature pyramid. In this additional pyramid, the features are added in the reverse direction, i.e., from bottom to top. To reduce computation and to further enhance the performance, we have used a combination of concatenation and downsampling to propagate features. The advantage of using concatenation over addition (which is used in bottom-up path augmentation [7]) is that the features are added more flexibly, i.e., the network learns the optimal ratio to infuse the features which boosts performance. However, we use element-wise addition in the original top-down pyramid, since using concatenation did not impact the performance and also required more computation. Finally, we append a 3x3 post-hoc convolution on each concatenated map ( $[I_i, P_i]$ ) to generate the final feature map. This is done to reduce the aliasing effect of upsampling in top-down layers.

To solve the issue of finding correlation between highlevel and low-level features, we introduce a convolutional layer between the top-down pyramid and the new bottom-up pyramid structure as shown in figure 1(c). Here we upsample the top two layers of the top-down pyramid and concatenate them with the third layer. We chose not to include the bottommost layer because this layer is concatenated and processed just after the Inception module. Adding this layer increases cost and also did not affect the final performance. Instead of using a 3x3 convolutional layer, we chose to use an Inception module [15]. The Inception module [16] learns from cross-channel correlations and spatial correlations of the feature map by using multiple kernel sizes for learning features with different field of views[13]. This is particularly useful since the feature of the concatenated layer contain features of different spacial dimensions due to upsampling and also due to their hierarchy in the backbone ResNet. The output of the Inception module is then concatenated to the bottom-most layer of the top-down module as shown in figure 1(b).

We take ResNet backbone as the basic structure and use  $P_2$ ,  $P_3$ ,  $P_4$ ,  $P_5$  to denote the layers of the top-down pathway generated by the FPN. The top most layer of the top-down

pyramid can be represented as

$$P_5 = H_5(B_5)$$
 (1)

Where  $H_5$  denotes the 1x1 convolution function followed by Relu activation. The other lower layers are added with the higher layers using addition. Hence these layers can be represented as

$$P_{l} = H_{l}(B_{l}) + U_{l}(P_{l-1})$$
(2)

Where  $U_l$  is the nearest neighbor upsampling function. We use  $I_2$ ,  $I_3$ ,  $I_4$ ,  $I_5$  to denote the layers of the newly generated Inception pyramid from the output of the Inception module. A detailed illustration of the bottom-up pathway is given in figure 3. The output of the Inception module forms the bottommost layer of the Inception pyramid. It can be written as a function of concatenation of  $P_5$  to  $P_3$ .

$$I_2 = G_2([P_5, P_4, P_3]) \tag{3}$$

Here [.,.] is the concatenation operation and  $G_2$  denotes the function of the Inception module followed by Relu activation. Each layer in the Inception pyramid  $I_{i+1}$  is created by combining lower layers of the Inception pyramid  $I_i$  and Feature pyramid  $P_i$  and then downsampling it. This process is iterative and terminated after  $I_5$  is generated. This can be represented as

$$I_{l} = F_{l}([D_{l}(I_{l-1}), P_{l}])$$
(4)

Where  $D_l$  represents the downsampling function using strided 3x3 convolution. On the other hand, the Bottom-up path augmentation of PANet uses element-wise addition to combine layers. This is represented as

$$I_l = D_l(I_{l-1}) + P_l$$
 (5)

We can observe that both equations 7 and 8 are recursive. In equation 8 (Bottom-up augmentation), as the layers proceed, more features are added. However in our model (equation 7), in addition to this we notice that the function  $F_l$  has more features to choose from due to concatenation with  $P_l$  compared to bottom-up path augmentation method which doesn't use concatenation. Features from all of the previous layers get reused similar DenseNet. Hence we are able to achieve better performance for the same computational cost of mask RCNN and for lower computational cost of bottom-up path augmentation. In our model, the combined Inception and Feature Pyramid layers form the layers of the feature pyramid. Post hoc 3x3 convolutions are applied to these layers to reduce aliasing caused by upsampling.

### 2.2. Other Feature Pyramid Architectures

In the model discussed previously, we have used concatenation to combine layers in the Bottom-up pathway and at the input to the Inception module. Apart from the model (Model 1) discussed previously, we have experimented on 3 other models to understand the effect of using concatenation to combine layers. The first model (Model 2) uses concatenation to combine layers in the Bottom-up pathway and uses addition to combine layers for the Inception module input. That is, we use the bottom-most layer of the top-down pathway which is the element-wise sum of all other layers as an input to the Inception module.

The next model (Model 3), uses element-wise addition to combine layers in the bottom-up pathway. This method is similar to the layer combining process used in the Top-down pathway except that we downsample the lower layer using strided 3x3 convolution and then add it to the upper layer using element-wise addition. This model can be seen as bottomup augmentation of PANet with our Inception module. The last model (Model 1\*) is similar to the Model 1 except that it does not contain the 3x3 post-hoc convolution which is used to reduce the aliasing effect of upsampling.



Fig. 2: Detailed illustration of Bottom-up pathway.

#### **3. EXPERIMENTS**

#### 3.1. Dataset and Metrics

We have implemented all of the model using Caffe2 and Detectron[18] framework. COCO dataset [19] is one of the most popular dataset for instance segmentation and also one of the most challenging with each image containing multiple instances with complex spatial layout. The dataset consists of 115k labeled images for training, 5k images for validation, 20k images for test dev and 20k images for test-challenge. It has 80 classes with pixel-wise instance annotation. We have trained all the models on train-2017 subset and reported results on val-2017 subset.

### 3.2. Hyper-parameters

We trained all of the models with an image batch size of 4. Based on the image batch size, we have used a learning rate of 0.005 for 300k iterations, 0.0005 for the next 100k iterations and 0.00005 for the last 50k iterations. The learning rate and number of iterations are based on [20]. All models are trained and tested with batch normalized [21] ResNet50

	Mask						Bounding Box					
Model	AP	$AP_{50}$	AP <sub>75</sub>	$AP_S$	$AP_M$	$AP_L$	AP	AP <sub>50</sub>	AP <sub>75</sub>	$AP_S$	$AP_M$	$AP_L$
Ours:Model 1	34.8	56.3	37.1	15.4	37.5	52.4	38.3	59.7	41.7	22.1	41.2	50.9
Ours:Model 2	34.7	56.4	36.9	15.5	37.2	52.2	38.3	59.6	41.6	21.9	41.3	50.9
Ours:Model 3	34.5	56.0	37.1	15.3	36.8	52.5	38.1	59.1	41.7	21.5	40.9	51.0
Ours:Model 1*	34.6	56.8	36.7	15.0	37.3	52.1	38.1	60.0	41.3	21.6	41.4	50.3
MRCNN + BPA	34.4	56.1	36.4	15.1	36.9	50.8	38.0	59.2	41.2	21.5	41.0	50.1
FCIS ++ [17]	33.6	54.5	-	-	-	-	-	-	-	-	-	-
Baseline:MRCNN	33.9	56.0	35.6	15.1	36.4	51.2	37.8	59.4	40.9	21.6	40.7	49.9

**Table 1**: Comparison of our models with Mask RCNN and Mask RCNN with bottom-up path augmentation(BPA) on COCO dataset. Model 1\* is Model 1 without post hoc convolutions.

Model	MAC Computa-	FPN Parameters
	tions in FPN	
Ours:Model 1	56.7x10 <sup>9</sup>	3.5x10 <sup>6</sup>
Ours:Model 2	58.2x10 <sup>9</sup>	$3.4 \times 10^{6}$
Ours:Model 3	70.2x10 <sup>9</sup>	$4.5 \times 10^{6}$
Ours:Model 1*	<b>9.6x10</b> <sup>9</sup>	<b>1.1x10</b> <sup>6</sup>
Mask RCNN	52.2x10 <sup>9</sup>	$2.6 \times 10^{6}$
MRCNN + BPA	63.9x10 <sup>9</sup>	$4.4 \times 10^{6}$

 Table 2: Comparison of number of Multiply-Accumulate computations assuming 1200x800 image size and parameters.

as backbone. For faster and more efficient training, we have initialized our ResNet backbone with pretrained weights from ImageNet 1k[22].

#### 3.3. Experimental Results

Our first model (Model 1) gave the best precision overall and is closely followed by second and third models. The first model improves mask AP and bounding box AP[23] by 0.9 and 0.5 respectively over Mask RCNN, and by 0.4 and 0.3 over Mask RCNN with bottom-up path augmentation. In figure 3, we can observe that the boundaries of the masks are more likely to bound to the edges of the objects since low-level features are used optimally for all sizes of object proposal in contrast to only small object proposals in Mask RCNN. This performance boost can be observed in AP<sub>L</sub> column of table 1, where it is the highest increase in AP.

Model 2 gives a slightly lower performance than Model 1. This shows that the layer combination method for the Inception module is not critical. However both Model 1 and Model 2 give better performance compared to Model 3. Model 3 is equivalent to the bottom-up augmentation of PANet with our Inception module added. This proves that concatenation indeed gives better performance compared to element-wise addition if used to combine layers in a feature pyramid network.

We can observe that adding a post hoc convolution to reduce aliasing boosts precision, especially of small objects, but comes at the cost of increased computational overhead. The



(a) Mask RCNN



(b) Ours:Model 1



(a) Mask RCNN



(b) Ours:Model 1

**Fig. 3**: Comparison of masks generated by Mask RCNN our model. Our model consistently gives better mask quality within the bounding boxes. Best viewed electronically. Zoom in to see in more detail.

first model without post hoc convolution has better performance over Mask RCNN and Mask RCNN with BPA. Most importantly, it has fewer parameters and a very small computational overhead - much smaller than the original FPN itself!

## 4. CONCLUSION

In this paper, we propose a new framework to optimally infuse low-level features into higher pyramid levels and generate better quality masks. Our experiment results demonstrate that our model can improve the performance compared to Mask RCNN and Bottom-up path Augmentation technique of PANet because our framework takes advantage of optimal combination of different levels of features of all layers of the feature pyramid. All of these improvements are done without any additional computational cost.

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