CARAFE++: Unified Content-Aware ReAssembly of FEatures

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Abstract—Feature reassembly, i.e., feature downsampling and upsampling, is a key operation in a number of modern convolutional network architectures, e.g., residual networks and feature pyramids. Its design is critical for dense prediction tasks such as object detection and semantic/instance segmentation. In this work, we propose unified Content-Aware ReAssembly of FEatures (CARAFE++), a universal, lightweight and highly effective operator to fulfill this goal. CARAFE++ has several appealing properties: (1) Unlike conventional methods such as pooling and interpolation that only exploit sub-pixel neighborhood, CARAFE++ aggregates contextual information within a large receptive field. (2) Instead of using a fixed kernel for all samples (e.g., convolution and deconvolution), CARAFE++ generates adaptive kernels on-the-fly to enable instance-specific content-aware handling. (3) CARAFE++ introduces little computational overhead and can be readily integrated into modern network architectures. We conduct comprehensive evaluations on standard benchmarks in object detection, instance/semantic segmentation and image inpainting. CARAFE++ shows consistent and substantial gains across all the tasks (2.5% AP$_{box}$, 2.1% AP$_{mask}$, 1.94% mIoU, 1.35 dB respectively) with negligible computational overhead. It shows great potential to serve as a strong building block for modern deep networks.

Index Terms—Feature Reassembly, Object Detection, Instance Segmentation, Semantic Segmentation, Image Inpainting.

1 INTRODUCTION

Feature reassembly, i.e., downsampling and upsampling, is one of the most fundamental operations in deep neural networks. On the one hand, in dense prediction tasks (e.g., super resolution [8], [22], inpainting [15], [34] and semantic segmentation [5], [47]), the input image is downsampled in the encoders to enlarge receptive field, gather semantic information, and reduce computational cost. For the decoders, the high-level/low-resolution feature map is upsampled to match the high-resolution supervision. On the other hand, feature reassembly is also involved in fusing a high-level/low-resolution feature map with a low-level/high-resolution feature map, which is widely adopted in many state-of-the-art architectures, e.g., Feature Pyramid Network [23], U-Net [36] and Stacked Hourglass [32]. Therefore, designing an effective feature reassembly operator becomes a critical issue.

Feature reassembly is composed of downsampling and upsampling on feature maps. Pooling and interpolation are the most widely adopted operator families for down-sampling and upsampling, respectively. The max pooling and average pooling are two representative pooling methods, which reassemble features inside a local region with a hand-crafted kernel. The nearest neighbor and bilinear interpolations are the most commonly used upsampling operators, which adopt spatial distance between pixels to guide the upsampling process. However, both pooling and interpolation are rule-based operators, which fail to capture the rich semantic information required by dense prediction tasks.

An alternative method for adaptive feature reassembly is convolution and deconvolution [33]. A convolution layer...
adjusts ‘stride’ to control the spatial distance to apply
convolution kernel. A deconvolution layer works as an
inverse operator of a convolution layer, which learns a set of
instance-agnostic upsampling kernels. However, there exist
two major drawbacks. First, a convolution/deconvolution
operator applies the same kernel across the entire image,
regardless of the underlying content. This restricts its ca-
pability in responding to local variations. Second, it comes
with heavy computational workload when a large kernel
size is used. This makes it difficult to cover a larger region
that goes beyond a small neighborhood, thus limiting its
expressive power and performance.

In this work, we move beyond these limitations, and
seek a feature reassembly operator that is capable of 1)
aggregating information within large receptive field, 2)
adapting to instance-specific contents on-the-fly, and 3)
maintaining computation efficiency. To this end, we propose
a lightweight yet highly effective operator, called unified
Content-Aware ReAssembly of Features (CARAFE++). Specif-
ically, CARAFE++ reassembles the features inside a prede-
fined region via a weighted combination, where the weights
are generated in a content-aware manner. A reassembly
kernel is generated for each target location. And the feature
reassembly is performed on the corresponding location of
the input feature map.

Note that these spatially adaptive weights are not
learned as network parameters. Instead, they are predicted
on-the-fly, using a lightweight fully-convolutional module
with softmax activation. Figure 1 reveals the working mech-
anism of CARAFE++ in an upsampling case. We visualize
the feature maps in the top-down pathway of feature pyra-
mid network (FPN) [23] and compare CARAFE++with the
nearest neighbor interpolation baseline. After upsamped
by CARAFE++, a feature map can represent the shape of
an object more accurately, so that the model can predict
better instance segmentation results. Our CARAFE++ not
only rescales the feature map spatially, but also learns to
enhance its discrimination.

To demonstrate the universal effectiveness of
CARAFE++, we conduct comprehensive evaluations
across a wide range of dense prediction tasks, i.e., object
detection, instance segmentation, semantic segmentation,
image inpainting, with mainstream architectures. With
negligible extra cost, CARAFE++ boosts the performance of
Faster R-CNN [35] by 2.5% AP_{box} in object detection and
Mask R-CNN [12] by 2.1% AP_{mask} in instance segmentation
on MS COCO [25] test-dev. CARAFE++ further improves
UperNet [43] by 1.94% mIoU on ADE20k [51] and
val in semantic segmentation, and improves Global&Local [15]
by 1.35 dB of PSNR on Places [50] val in image inpainting.
The substantial gains on all the tasks demonstrate that
CARAFE++ is an effective and efficient feature reassembly
operator that has great potential to serve as a strong
building block for future research.

In a previous conference version in ICCV 2019, we
proposed CARAFE [40], which is an effective and effi-
cient upsampling operator. CARAFE++ shares a similar
design while it is more universal. CARAFE++ can be
readily integrated to networks for both upsampling and
downsampling. We perform an extensive evaluation of
CARAFE++ when it is applied in a wide range of net-
work architectures. Experimental results show that adopting
CARAFE++ in both upsampling and downsampling can
consistently and substantially outperforms CARAFE [41] on
object detection, instance segmentation, semantic segmen-
tation and image inpainting.

2 RELATED WORK

Downsampling & Upsampling Operators. Downsampling
& upsampling operators are basic building blocks of convo-
lutional neural network architectures. Contemporary con-
volution networks usually downsample the input features
in the first few layers. Feature upsampling operators are
essential for convolutional networks to make high-quality
dense predictions.

Among various downsampling operators, max pooling
and average pooling are the most widely used choices.
They reassemble features in a rule-based manner. For up-
sampling, nearest neighbor and bilinear interpolations are
representative methods. These interpolations leverage dis-
tances to measure the correlations between pixels, and hand-
crafted upsampling kernels are used in them. Several meth-
ods are proposed to downsample and upsample a feature
map using learnable operators. For example, convolution
and deconvolution (transposed convolution) [33] are the
most representative ones among those learnable upsam-
plers. Pixel Shuffle [38] proposes an upsampling operator
that reshapes depth of the channel space into width and
height of the spatial space. Guided Upsampling (GUM) [50]
performs interpolation by sampling pixels with learnable
offsets. In the downsampling pipeline, detail-preserving
pooling (DPP) [37] is proposed to preserve more detail in-
formation by focusing on local spatial changes of pixels in a
sliding window. Local Importance-based Pooling (LIP) [9]
is a recently proposed downsampling operator, which per-
forms a weighted average pooling. However, these methods
either exploit contextual information in a small neighbor-
hood, or require expensive computation to perform adap-
tive downsampling and upsampling. Within the realms of
super-resolution and denoising, some other works [14],
[18], [51] also explore the use of learnable kernels spatially in
low-level vision. In this study, we demonstrate the effectiveness
and working mechanism of unified content-aware feature reas-
sembly for downsampling and upsampling in several visual perception tasks, and provide a lightweight solution.

Dense Prediction Tasks. Object detection [24], [28],
[35], [41], [42] is the task of localizing objects with bounding-
boxes, instance segmentation [12] further requires the pre-
diction of instance-wise masks. Many studies [19], [23],
[27], [49] exploit multi-scale feature pyramids to deal with
objects at different scales. By adding extra mask predic-
tion branches, Mask R-CNN [12] and its variants [1] yield
promising pixel-level results. Semantic segmentation [21],
[29] requires pixel-wise semantic prediction for given im-
ages. PSPNet [47] introduces spatial pooling at multiple
grid scales. UperNet [43] designs a more generalized fram-
ework based on PSPNet. These detection and segmentation
methods usually adopt backbones, e.g., ResNet [13], which
are pretrained on image classification dataset. The input

1. Adopting CARAFE is equivalent to adopting CARAFE++ for up-
sampling.
features are downsampled for several times in such image classification networks. Image or video inpainting [39, 41], [46] is a classical problem that aims at completing missing regions of images. U-net [36], which adopts multiple downsampling and upsampling operators, is popular among recent works [15], [39]. Liu et al. [26] introduce partial convolution layer to alleviate the influence of missing regions on the convolution layers. By replacing the downsampling and upsampling operators in the aforementioned networks, our CARAFE++ demonstrates consistent effectiveness across a wide range of dense prediction tasks.

3 CONTENT-AWARE REASSEMBLY OF FEATURES

Feature reassembly, i.e., downsampling, upsampling, is a key operator in many modern convolutional network architectures developed for tasks including object detection, instance segmentation, and scene parsing. In this work, we propose Content-Aware ReAssembly of Features (CARAFE++) to reassemble a feature map. On each location, CARAFE++ leverages the underlying content information to predict reassembly kernels and reassemble the features inside a predefined nearby region. Thanks to this unique capability, CARAFE++ achieves better performance than the mainstream downsampling and upsampling operators, e.g., pooling or interpolation.

3.1 Formulation

CARAFE++ works as a reassembly operator with content-aware kernels. It consists of two steps. The first step is to predict a reassembly kernel for each target location according to its content, and the second step is to reassemble the features with the predicted kernels.

Given a feature map \( X \) of size \( C \times H \times W \) and a resizing ratio \( \sigma \) (supposing \( \sigma \) is an integer), CARAFE++ will produce a new feature map \( X' \) of size \( C \times \lceil H/\sigma \rceil \times \lceil W/\sigma \rceil \) in the downsampling process and \( C \times \sigma H \times \sigma W \) in the upsampling process. For any target location \( l' = (i', j') \) of the output \( X' \), there is a corresponding source location \( l = (i, j) \) at the input \( X \), where \( i = \sigma i', j = \sigma j' \) for downsampling, and \( i = \lfloor i'/\sigma \rfloor, j = \lfloor j'/\sigma \rfloor \) for upsampling. Here we denote \( N(X_l, k) \) as the \( k \times k \) sub-region of \( X \) centered at the location \( l \), i.e., the neighbor of \( X_l \).

In the first step, the kernel prediction module \( \psi \) predicts a location-wise kernel \( W_l \) for each location \( l' \), based on the neighbor of \( X_l \), as shown in Eqn. (1). The reassembly step is formulated as Eqn. (2), where \( \phi \) is the content-aware reassembly module that reassembles the neighbor of \( X_l \) with the kernel \( W_l \):

\[
W_l = \psi(N(X_l, k_{encoder})).
\]  

\[
X_{l'} = \phi(N(X_l, k_{reassembly}), W_l').
\]

We specify the details of \( \psi \) and \( \phi \) in the following parts.

3.2 Kernel Prediction Module

The kernel prediction module is responsible for generating the reassembly kernels in a content-aware manner. Each target location corresponds to a source location and requires a \( k_{reassembly} \times k_{reassembly} \) reassembly kernel, where \( k_{reassembly} \) is the reassembly kernel size. Therefore, this module will output the reassembly kernels of size \( C_{reassembly} \times \lceil H/\sigma \rceil \times \lceil W/\sigma \rceil \) for downsampling, and \( C_{reassembly} \times \sigma H \times \sigma W \) for upsampling, where \( C_{reassembly} = k_{reassembly}^2 \).

The kernel prediction module is composed of three sub-modules, i.e., channel compressor, content encoder and kernel...
The overall framework of CARAFE++ for upsampling. A feature map with size $C \times H \times W$ is upsampled by a factor of $\sigma (= 2)$ in this figure.

normalizer, as shown in Figure 2 and Figure 3. The channel compressor reduces the channel of the input feature map. The content encoder then takes the compressed feature map as input and encodes the content to generate reassembly kernels. Lastly, the kernel normalizer applies a softmax function to each reassembly kernel. The three submodules are explained in detail as follows.

**Channel Compressor.** We adopt a $1 \times 1$ convolution layer to compress the input feature channel from $C$ to $C_m$. Specifically, we adopt $C_m = 16$ for downsampling and $C_m = 64$ for upsampling in experiments. Reducing the channel of input feature map leads to less computational cost in the following steps, making CARAFE++ much more efficient. It is also possible to use larger kernel sizes for the content encoder under the same budget. Experimental results show that reducing the feature channel in an acceptable range will not harm the performance.

**Content Encoder.** We use a convolution layer of kernel size $k_{encoder}$ to generate reassembly kernels based on the content of input features. The input channel of this convolution layer is $C_m$. Certain settings are different for downsampling and upsampling.

For downsampling, the stride of this convolution layer is $\sigma$. Thus, the predicted reassembly kernel has a size of $C_{reassembly} \times \lfloor H/\sigma \rfloor \times \lfloor W/\sigma \rfloor$. For upsampling, the output channels of this convolution layer is $\sigma^2 C_{reassembly}$. It is then reorganized from depth of the channel space into width and height of the spatial space. Finally, the predicted reassembly kernel has a size of $C_{reassembly} \times \sigma H \times \sigma W$.

Intuitively, increasing $k_{encoder}$ enlarges the receptive field of the encoder, and this allows one to exploit contextual information within a larger region, which is important for predicting the reassembly kernels. However, the computational complexity grows quadratically with the kernel size, while the benefits from a larger kernel size may not match equally. An empirical formula, $k_{encoder} = k_{reassembly} - 2$, is a good trade-off between performance and efficiency through our study in Section 5.3.

**Kernel Normalizer.** Before being applied to the input feature map, each reassembly kernel with size of $k_{reassembly} \times k_{reassembly}$ is normalized with a softmax function spatially. The normalization step forces the sum of kernel values to 1. The normalized values result a soft selection across a local region. Due to the kernel normalizer, CARAFE++ does not perform any rescaling and change to the mean values of the feature map, but reassembles features spatially.

### 3.3 Content-aware Reassembly Module

With each reassembly kernel $W_l$, the content-aware reassembly module reassembles the features within a local region via the function $\phi$. We adopt a simple form of $\phi$, which is just a weighted sum operator. For a target location $l'$ and the corresponding square region $N(X_l, k_{reassembly})$ centered at $l = (i, j)$, the reassembly is shown in Eqn. 3, where $r = \lfloor k_{reassembly}/2 \rfloor$:

$$X'_l = \sum_{n=-r}^{r} \sum_{m=-r}^{r} W_l(n, m) \cdot X_l(i+n,j+m).$$

With the reassembly kernel, each pixel in the region of $N(X_l, k_{reassembly})$ contributes to the target pixel $l'$ differently, based on the content of features. The semantics of the reassembled feature map can be stronger than the original one, since the information from relevant points in a local region can be more attended.

### 3.4 Relation to Previous Operators

Here we discuss the relations between CARAFE++ and dynamic filter [17], spatial attention [3], local importance-based pooling [9], spatial transformer [16] and deformable convolution [1], which share similar design philosophy but with different focuses.

**Dynamic Filter.** Dynamic filter generates instance-specific convolutional filters conditioned on the input of the network, and then applies the predicted filter on the input. Both
dynamic filter and CARAFE++ are content-aware operators, but a fundamental difference between them lies at their kernel generation process. Specifically, dynamic filter works as a two-step convolution, where the additional dynamic filter prediction step requires heavy computation. On the contrary, CARAFE++ is simply a reassembly of features in local regions, without learning the feature transformation across channels. Supposing the channels of input feature map is $C$ and kernel size of the filter is $K$, then the predicted kernel weights for each location is $C \times C \times K \times K$ in dynamic filter. For CARAFE++, the kernel weights is only $K \times K$. Thus, it is more efficient in memory and speed.

**Spatial Attention.** Spatial attention predicts an attention map with the same spatial size as the input feature, and then rescales the feature map on each location. Our CARAFE++ reassembles the features in a local region by weighted summation. In summary, spatial attention is a rescaling operator with point-wise guidance while CARAFE++ is a reassembly operator with region-wise local guidance. Spatial attention can be seen as a special case of CARAFE++ where the reassembly kernel size is 1, regardless of the kernel normalizer.

**Local Importance-Based Pooling (LIP).** Local Importance-Based Pooling (LIP) is a recently proposed pooling method, which combines the self-attention and average pooling. In LIP, an attention map with the same shape (i.e., spatial size and channels) as the input feature map is predicted by a series of convolution layers. The predicted attention map is normalized by a sigmoid function, and then directly multiplied by the original feature map. A standard average pooling downsamples the feature map after self-attention. The self-attention in LIP is a combination of spatial attention and channel attention. Similar to spatial attention, it fails to adaptively reassemble information from a large receptive field. To predict the attention map with the same shape as the input, LIP requires a series of convolution layers with deep output channels and brings heavy computational cost. Moreover, LIP is not available for upsampling.

**Spatial Transformer Networks (STN).** STN predicts a global parametric transformation conditioned on the input feature map and warps the feature via the transformation. However, this global parametric transformation assumption is too strong to represent complex spatial variance; and STN is known to be unstable to train. Here, CARAFE++ uses the location-specific reassembly to handle the spatial relations, which enables more flexible local geometry modeling.

**Deformable Convolutional Networks (DCN).** DCN also adopts the idea of learning geometric transformation and combines it with the regular convolution layers. It predicts kernel offsets other than using grid convolution kernels. Similar to dynamic filter, it is also a heavy parametric operator with much more computational cost than CARAFE++.

### 4 Applications of CARAFE++

CARAFE++ can be seamlessly integrated into existing frameworks where downsampling & upsampling operators are needed. Here we present some applications in mainstream dense prediction tasks. With negligible additional computational cost, CARAFE++ benefits mainstream methods in both high-level and low-level tasks, such as object detection, instance segmentation, semantic segmentation and image inpainting.

![Fig. 4: Bottleneck architecture with CARAFE++ in ResNet.](image)

CARAFE++ can be readily integrated into Bottleneck with strided convolution. CARAFE++ downsamples the input feature map by 2x. And convolution layers with the same kernel size but no stride are applied afterwards.

#### 4.1 Object Detection and Instance Segmentation

**ResNet Backbone.** Backbone is the cornerstone of object detection. The backbone with strided convolution layers is adopted to downsample input images and produce pyramid features. The backbone applied in object detection and instance segmentation is generally pretrained on image classification dataset, e.g., ImageNet.

ResNet backbone \[13\] is one of the most widely used backbones in object detection. ResNet has five blocks, named as Res-1, Res-2, Res-3, Res-4 and Res-5, respectively. Res-1 contains one 3x3 convolution layer and one max pooling layer, it is also called as the stem layer. Res-2, Res-3, Res-4 and Res-5 are stacked building blocks. A feature map is downsampled in Res-3, Res-4 and Res-5 at their first building block with strided convolution layers. CARAFE++ can be readily integrated into ResNet. As shown in Figure 4, CARAFE++ is applied to the building block (named as Bottleneck) with strided convolution layers. In the original design of bottleneck, convolution layers with stride downsamples the feature map by 2x directly. In the bottleneck w/ CARAFE++, CARAFE++ downsamples the feature map before convolution layers. Furthermore, CARAFE++ replaces the max pooling which downsamples the feature map by 2x in Res-1 as well. In summary, there are seven CARAFE++ are applied in a ResNet backbone, i.e., one in Res-1, two in each of Res-3, Res-4 and Res-5.

**Feature Pyramid Network (FPN).** FPN is an important and effective architecture in the field of object detection and instance segmentation. It significantly improves the performance of popular frameworks like Faster R-CNN and Mask R-CNN. FPN constructs feature pyramids of strong semantics with the top-down pathway and lateral connections. In the top-down pathway, a low-resolution feature map is firstly upsampled by 2x with the nearest neighbor interpolation and then fused with a high-resolution one, as shown in Figure 5. We propose to substitute the nearest neighbor interpolation in all the feature levels with CARAFE++. This modification is smooth and no extra change is required.
Mask Head. In addition, Mask R-CNN adopts a deconvolution layer at the end of mask head. It is used to upsample the predicted digits from $14 \times 14$ to $28 \times 28$, to obtain finer mask predictions. We can also use CARAFE++ to replace the deconvolution layer, resulting in even less computational cost.

4.2 Semantic Segmentation

Semantic segmentation requires the model to output per-pixel level predictions on the whole image, so that high-resolution feature maps are usually preferred. In a common pipeline of semantic segmentation model, the pretrained backbone, e.g., ResNet, with downsampling layers are first applied to downsample the feature maps. And then upsampling is widely adopted to enlarge feature maps from the backbone and fuse the semantic information of different levels in this task. UperNet is a strong baseline for semantic segmentation. It uses downsampling in ResNet backbone and upsampling in the following three components, i.e., PPM, FPN, FUSE. We adopt CARAFE++ instead of their original downsamplers and upsamplers.

ResNet Backbone. CARAFE++ is adopted as in Section 4.1, i.e., Res-1 and first building block of Res-3, Res-4, Res-5.

Pyramid Pooling Module (PPM). PPM is the key component in PSPNet that hierarchically down-samples an input feature map into multiple scales $\{1 \times 1, 2 \times 2, 3 \times 3, 6 \times 6\}$, and then upsamples them back to the original sizes with bilinear interpolation. The features are finally fused with the original feature by concatenation. Since the upsampling ratio is very large, we adopt a two-step strategy with CARAFE++ as a trade-off between performance and efficiency. Firstly we upsample the $\{1 \times 1, 2 \times 2, 3 \times 3, 6 \times 6\}$ features to half the size of the original feature map with bilinear interpolation, and then use CARAFE++ to further upsample them by 2x.

Feature Pyramid Network (FPN). Similar to detection models, UperNet also adopts FPN to enrich the feature semantics. It only has four different feature levels $\{P2, P3, P4, P5\}$ with strides $\{4, 8, 16, 32\}$. We replace the upsampling operators in the same way as Section 4.1.

Multi-level Feature Fusion (FUSE). UperNet introduces a multi-level feature fusion module after the FPN. It upsamples P3, P4, P5 to the same size as P2 by bilinear interpolation and then fuses these features from different levels by concatenation. The process is equivalent to a sequential upsampling-concatenation that first upsamples P5 to P4 and concatenates them, and then upsamples the concatenated feature map to P3 and so on. We replace the sequential bilinear upsampling here with CARAFE++.

4.3 Image Inpainting

The U-net architecture is popular among recently proposed image inpainting methods, such as Global&Local [15] and Partial Conv [26]. We simply replace the strided convolution layers with CARAFE++ followed by convolution layer without stride, and also substitute upsampling layers with CARAFE++ . As for Partial Conv, we can conveniently keep the mask propagation in CARAFE++ by updating the mask with our content-aware reassembly kernels.

5 EXPERIMENTS

5.1 Experimental Settings

Datasets & Evaluation Metrics. We evaluate CARAFE++ on several important dense prediction benchmarks. We use the train split for training and evaluate the performance on the val split for all these datasets if it is not further specified. The inference speed is reported on a single TiTan XP GPU.

Image Classification. To evaluate CARAFE++ on the backbone of dense prediction tasks, we pretrain backbones on ImageNet-1k [7] train split and evaluate the Top-1 and Top-5 accuracy on val split with the single-crop testing.

Object Detection and Instance Segmentation. We perform experiments on the challenging MS COCO 2017 [25] dataset. Results are evaluated with the standard COCO metric, i.e. AP of IoUs from 0.5 to 0.95.

Semantic Segmentation. We adopt the ADE20k [51], [52] benchmark to evaluate our method in the semantic segmentation task. Results are measured with mean IoU (mIoU) and Pixel Accuracy (P.A.), which respectively indicates the average IoU between predictions and ground truth masks and per-pixel classification accuracy.

Image Inpainting. Places [50] dataset is adopted for image inpainting. We use L1 error (lower is better) and PSNR (higher is better) as evaluation metrics.

Implementation Details. If not otherwise specified, CARAFE++ adopts a fixed set of hyper-parameters in experiments, where $C_m$ is 16 and 64 for the channel compressor in downsampling and upsampling, respectively. And $k_{encoder} = 3$, $k_{reassembly} = 5$ for the content encoder.

Image Classification. We evaluate CARAFE++ on ResNet-50 and ResNet-101 backbones. As described in Section 4.1 CARAFE++ is applied in Bottleneck with strided convolution layers in Res-3, Res-4, Res-5, and replaces the max pooling in Res-1. Furthermore, a BatchNorm (BN) and a Relu layer are adopted after the channel compressor, which is a 1x1 Conv that compresses input channels. The experimental settings mostly follow [11]. We use 16 GPUs with batch size of 1024, i.e., 64 images per GPU. We train backbones for 90 epochs in total on ImageNet-1k classification dataset.

Object Detection and Instance Segmentation. We evaluate CARAFE++ on Faster R-CNN [35] and Mask R-CNN [12]
We use the official implementation and adopt Global&Local [15] as the baseline for Semantic Segmentation. Detectron [10] and MMDetection [2]. Following the 1x and 2x training schedule as 0.0001. We use a batchsize of 16 over 8 GPUs (2 images per GPU). During the training, Adam solver with learning rate 0.0001 is adopted. And we train the model for 20 epochs. We further compare CARAFE++ with Partial Conv [26], we substitute the convolution layers with Partial Conv [26] as the binary mask $M$. Training batch size is 32. The $\beta = 1 - \gamma M$. The maximum length of the longer edge of an image is set to 1200 in both training and inference. For a fair comparison, we use the single scale testing method to evaluate CARAFE++. We employ the generator and discriminator networks from Global&Local [15]. Our generator takes a $256 \times 256$ image $x$ with masked region $M$ as input and produces a $256 \times 256$ prediction of the missing region $\hat{y}$ as output. Then we combine the predicted image with the input by $y = (1 - M) \odot x + M \odot \hat{y}$. Finally, the combined output $y$ is fed into the discriminator. We apply a simple modification to the baseline model to achieve better generation quality. Compared to the original model that employs two discriminators, we employ only one PatchGAN-style discriminator [20] on the inpainted region. For a fair comparison, we use the free-form masks introduced by [15] as the binary mask $M$. We further compare CARAFE++ with Partial Conv [26], we substitute the convolution layers with the official Partial Conv module in our generator. During training, Adam solver with learning rate 0.0001 is adopted where $\beta_1 = 0.5$ and $\beta_2 = 0.9$. Training batch size is 32. The input and output are linearly scaled within range $[-1, 1]$. 

TABLE 1: Detection and Instance Segmentation results on MS COCO 2017 test-dev with 2x training schedule.

| Method               | Backbone       | Task | AP  | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ | Inference speed |
|----------------------|----------------|------|-----|-----------|-----------|--------|--------|--------|-----------------|
| Faster R-CNN         | ResNet-101     | BBox | 39.7 | 61.3      | 43.2      | 22.0   | 43.1   | 50.2   | 10.3 fps        |
| Faster R-CNN w/ CARAFE++ | ResNet-101 | BBox | 42.2 | 64.2      | 46.2      | 24.8   | 45.5   | 53.0   | 9.9 fps         |
| Mask R-CNN           | ResNet-101     | BBox | 40.8 | 62.3      | 44.6      | 22.9   | 43.9   | 52.0   | 7.6 fps         |
| Mask R-CNN w/ CARAFE++ | ResNet-101 | BBox | 37.0 | 59.1      | 39.6      | 16.9   | 39.4   | 53.1   | 7.3 fps         |
| Faster R-CNN         | ResNet-101-DCCnV2 | BBox | 43.2 | 65.1      | 47.4      | 25.8   | 46.4   | 54.4   | 8.5 fps         |
| Faster R-CNN w/ CARAFE++ | ResNet-101-DCCnV2 | BBox | 39.1 | 62.1      | 42.1      | 19.3   | 41.6   | 55.4   | 8.3 fps         |
| Mask R-CNN           | ResNet-101-DCCnV2 | BBox | 45.3 | 66.7      | 49.7      | 26.8   | 48.7   | 58.0   | 6.5 fps         |
| Mask R-CNN w/ CARAFE++ | ResNet-101-DCCnV2 | BBox | 40.6 | 63.8      | 43.9      | 19.9   | 43.1   | 57.8   | 6.5 fps         |

TABLE 2: Image classification results on ImageNet-1k val.

| Model                  | Top-1 | Top-5 |
|------------------------|-------|-------|
| ResNet-50              | 76.43 | 93.21 |
| ResNet-50 w/ CARAFE++  | 77.46 | 93.63 |
| ResNet-101             | 78.10 | 93.92 |
| ResNet-101 w/ CARAFE++ | 78.70 | 94.31 |

TABLE 3: Detection results with Faster R-CNN. Various downsampling methods are used in ResNet-50 backbone. ‘Conv’, ‘MPool’, ‘APool’, ‘DPP’, ‘LIP’ indicates convolution layer with stride, Max Pooling, Average Pooling, Detail Preserved Pooling [37], and Local Importance-based Pooling [9], respectively. The 1x training schedule is applied in experiments.

| Method                     | AP$_{bbox}$ | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ | FPS   |
|----------------------------|-------------|-----------|-----------|--------|--------|--------|-------|
| Conv                       | 36.5        | 58.4      | 39.3      | 21.3   | 40.3   | 47.2   | 12.5 fps |
| Max Pool                   | 37.8        | 59.6      | 40.9      | 22.3   | 42.1   | 48.4   | 12.5 fps |
| Avg Pool                   | 37.9        | 59.8      | 40.9      | 22.1   | 42.1   | 47.9   | 12.3 fps |
| DPP [37]                   | 37.7        | 59.7      | 40.6      | 22.3   | 41.9   | 48.1   | 10.9 fps |
| LIP [9]                    | 38.0        | 60.3      | 41.2      | 23.1   | 41.9   | 48.2   | 10.8 fps |
| CARAFE++                   | 38.8        | 60.8      | 42.2      | 23.3   | 43.1   | 49.2   | 12.1 fps |

TABLE 4: Detection results with Faster R-CNN. Various upsampling methods are used in FPN, N.C., B.C., PS. and S.A. indicate Nearest + Conv, Bilinear + Conv, Pixel Shuffle and Spatial Attention, respectively.

| Method                     | AP$_{bbox}$ | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ | FPS   |
|----------------------------|-------------|-----------|-----------|--------|--------|--------|-------|
| Nearest                    | 36.5        | 58.4      | 39.3      | 21.3   | 40.3   | 47.2   | 12.5 fps |
| Bilinear                   | 36.7        | 58.7      | 39.7      | 21.0   | 40.5   | 47.5   | 12.5 fps |
| N.C.                       | 36.6        | 58.6      | 39.5      | 21.4   | 40.3   | 46.4   | 11.8 fps |
| B.C.                       | 36.6        | 58.7      | 39.4      | 21.6   | 40.6   | 46.8   | 11.7 fps |
| Deconv [33]                | 36.4        | 58.2      | 39.2      | 21.3   | 39.9   | 46.5   | 11.5 fps |
| PS. [35]                   | 36.5        | 58.8      | 39.1      | 20.9   | 40.4   | 46.7   | 11.7 fps |
| GUM [30]                   | 36.9        | 58.9      | 39.7      | 21.5   | 40.6   | 48.1   | 11.8 fps |
| S.A. [3]                   | 36.9        | 58.8      | 39.8      | 21.7   | 40.8   | 47.0   | 12.3 fps |
| CARAFE++                   | 37.8        | 60.1      | 40.8      | 23.2   | 41.2   | 48.2   | 12.2 fps |

Fig. 6: Comparison of instance segmentation results between baseline (top row) and CARAFE++ (bottom row) on COCO 2017 val.
5.2 Benchmarking Results

Object Detection & Instance Segmentation. We first evaluate CARAFE++ in Faster R-CNN and Mask R-CNN to show its effectiveness in object detection and instance segmentation. We first replace the downsampling layers in ResNet-101 backbone with CARAFE++ and pretrain the modified backbone in ImageNet-1k classification dataset as in Section 4.1. We then substitute the nearest neighbor interpolation in FPN with CARAFE++ for both Faster R-CNN and Mask R-CNN, and the deconvolution layer in the mask head for Mask R-CNN. As shown in Table 1 with ResNet-101 backbone and 2x training schedule, CARAFE++ improves Faster R-CNN by 2.5% (i.e., from 39.7% to 42.2%) on AP$_{box}$ and Mask R-CNN by 2.1% (i.e., from 37.0% to 39.1%) on AP$_{mask}$ with minor extra inference time (i.e., 10.3 fps v.s. 9.9 fps and 7.6 fps v.s. 7.3 fps). The results show the effectiveness and efficiency of CARAFE++. In Figure 6, we show some examples of instance segmentation results comparing the baseline and CARAFE++.

We further apply CARAFE++ in ResNet-101 backbone with powerful Deformable Convolution layers v2 (DCNv2) [53]. In the ResNet-101 with DCNv2 baseline, the 3x3 Convolution layers in Res-2, Res-3, Res-4 are replaced with 3x3 DCNs v2. To investigate the effectiveness of CARAFE++, DCNv2 layers with stride of 2 are replaced with CARAFE++ and a following 3x3 convolution layers without stride. As shown in Table 1, CARAFE++ still achieves substantial gains on such a strong baseline. Specifically, CARAFE++ improves ~1% AP for both Faster R-CNN and Mask R-CNN with similar inference speed.

**CARAFE++ for Downsampling.** Here we investigate the effectiveness of CARAFE++ for downsampling. As illustrated in Table 2, after integrated into ResNet backbone, CARAFE++ improves the Top-1 accuracy of image classification on ResNet-50 and ResNet-100 by 1% and 0.6% respectively. Therefore, apart from dense prediction tasks, CARAFE++ also brings benefits to the classification task.

We further explore different downsampling methods in object detection. To be specific, we adopt different downsampling methods in the ResNet-50 backbone, and then pretrain the backbone on ImageNet-1k classification dataset. The pretrained backbones are used to train Faster R-CNN with FPN on COCO dataset. As summarized in Table 3, we extensively compare convolution layer with stride, Max Pooling, Average Pooling, Detail Preserved Pooling [37], Local Importance-based Pooling [2] and CARAFE++. The strided convolution layer is the baseline. For Max Pooling, Average Pooling, Detail Preserved Pooling, we apply these pooling methods in the same manner with CARAFE++ as described in Section 4.1. LIP [9] is adopted following its original paper. We observe that by simply replacing the baseline (i.e., strided convolution layers) with Max/Average/Detail-Preserved pooling, the performance can be improved by ~1.3%. The recent proposed LIP achieves a slightly better results than these pooling operators. CARAFE++ significantly improves the baseline by 2.3% (i.e., from 36.5% to 38.8% AP) with minor extra cost (i.e., from 12.5 fps to 12.1 fps).

**CARAFE++ for Upsampling.** To investigate the effectiveness of different upsampling operators, we perform extensive experiments on Faster R-CNN by using different operators to perform upsampling in FPN. Results are illustrated in Table 4. For ‘N.C.’ and ‘B.C.’, which respectively indicate ‘Nearest + Conv’ and ‘Bilinear + Conv’, we add an extra 3 x 3 convolution layer after the corresponding upsampling. ‘Deconv’, ‘Pixel Shuffle’ (indicated as ‘P.S.’), ‘GUM’ are three representative learning-based upsampling methods. We also compare ‘Spatial Attention’ here, indicated as ‘S.A.’. CARAFE++ achieves the best AP$_{box}$ among all these upsampling operators with minor extra computation cost, which illustrates it is both effective and efficient. The results of ‘Nearest + Conv’ and ‘Bilinear + Conv’ show that simply adding more convolution layers does not lead to a significant gain. However, it slows down the inference speed from 12.5 fps to 11.8 fps. ‘Deconv’, ‘Pixel Shuffle’, ‘GUM’ and ‘Spatial Attention’ obtain inferior performance to CARAFE++, indicating that the design of effective upsampling operators is critical.

In Table 5, we report the object detection performance of adopting CARAFE++ in Backbone and FPN, respectively. Adopting CARAFE++ both in Backbone and FPN further improves the object detection performance to 39.6%.

**CARAFE++ for Mask Prediction.** Besides FPN, which is a pyramid feature fusion structure, we also explore different upsampling operators in the mask head. In typical Mask R-CNN, a deconvolution layer is adopted to upsample the RoI features by 2x. For a fair comparison, we do not make

### Table 5: Object detection results of Faster R-CNN with CARAFE++ in FPN and backbone.

| FPN | Backbone | AP  | AP$_{50}$ | AP$_{75}$ | AP$_{S}$ | AP$_{M}$ | AP$_{L}$ | FPS    |
|-----|----------|-----|----------|----------|---------|---------|---------|--------|
| ✓   |          | 37.8| 60.1     | 40.8     | 23.2    | 41.2    | 48.2    | 12.2 fps|
| ✓   | ✓        | 38.8| 60.8     | 42.2     | 23.3    | 43.1    | 49.2    | 12.1 fps|
| ✓   | ✓        | 39.6| 62.0     | 43.2     | 24.7    | 43.7    | 50.9    | 11.7 fps|

### Table 6: Instance Segmentation results with Mask R-CNN. Various upsampling methods are used in mask head.

| Method  | AP  | AP$_{50}$ | AP$_{75}$ | AP$_{S}$ | AP$_{M}$ | AP$_{L}$ | FPS    |
|---------|-----|----------|----------|---------|---------|---------|--------|
| Nearest | 32.7| 55.0     | 34.8     | 17.7    | 35.9    | 44.4    |        |
| Bilinear| 34.2| 55.9     | 36.4     | 18.5    | 37.5    | 46.2    |        |
| Deconv  | 34.2| 55.5     | 36.3     | 17.6    | 37.8    | 46.7    |        |
| Pixel Shuffle | 34.4| 56.0 | 36.6     | 18.5    | 37.6    | 47.5    |        |
| GUM     | 34.3| 55.7     | 36.5     | 17.6    | 37.6    | 46.9    |        |
| S.A.    | 34.1| 55.6     | 36.5     | 17.6    | 37.4    | 46.6    |        |
| CARAFE++| 34.7| 56.2     | 37.1     | 18.2    | 37.9    | 47.5    |        |

### Table 7: Detection and Instance Segmentation results of Mask R-CNN with CARAFE++ in Backbone, FPN and mask head, respectively. M.H. indicates using CARAFE++ in mask head.

| FPN | M.H. | B.K. | Task | AP  | AP$_{50}$ | AP$_{75}$ | AP$_{S}$ | AP$_{M}$ | AP$_{L}$ | FPS    |
|-----|------|------|------|-----|----------|----------|---------|---------|---------|--------|
| ✓   |      |      | Bbox| 37.4| 59.1     | 40.3     | 21.2    | 41.2    | 48.5    |        |
| ✓   |      |      | Segm| 34.2| 55.5     | 36.3     | 17.6    | 37.8    | 46.7    |        |
| ✓   |      |      |     | 38.6| 60.7     | 42.2     | 23.2    | 42.1    | 49.5    |        |
| ✓   |      |      |     | 35.2| 57.2     | 37.5     | 19.3    | 38.3    | 47.6    |        |
| ✓   |      |      |     | 37.3| 59.0     | 40.2     | 21.8    | 40.8    | 45.6    |        |
| ✓   |      |      |     | 34.7| 56.2     | 37.1     | 18.2    | 37.9    | 47.5    |        |
| ✓   |      |      |     | 35.6| 57.5     | 37.8     | 16.9    | 38.1    | 52.4    |        |
| ✓   |      |      |     | 39.5| 61.3     | 43.2     | 23.9    | 43.4    | 50.7    |        |
| ✓   |      |      |     | 35.9| 57.9     | 38.0     | 17.5    | 38.9    | 51.8    |        |
| ✓   | ✓    |      |     | 40.3| 62.5     | 43.9     | 24.8    | 44.4    | 51.5    |        |
| ✓   | ✓    |      |     | 36.8| 59.2     | 39.2     | 18.0    | 39.9    | 53.6    |        |

any changes to FPN, and only replace the deconvolution layer with various operators. Since we only modify the mask prediction branch, performance is reported in terms of AP\text{mask}, as shown in Table 6. CARAFE++ achieves the best performance in instance segmentation among these methods.

In Table 7, we report the object detection and instance segmentation performance of adopting CARAFE++ in Backbone, FPN and mask head on Mask R-CNN, respectively. Consistent improvements are achieved in these experiments.

Semantic Segmentation. We replace the downsamplers and upsamplers in UperNet with CARAFE++ and evaluate the results on ADE20k benchmark. As shown in Table 8 adopting single scale testing, CARAFE++ improves the mIoU by a large margin from 40.44% to 43.05% on ResNet-50 Backbone and from 42.0% to 43.94% with ResNet-101 backbone. Note that UperNet with CARAFE++ also achieves better performance than other strong baselines such as PSPNet [47] and PSANet [48].

We perform a step-by-step study to inspect the effectiveness of modifying different components in UperNet, as described in Section 4.2. Results in Table 9 show that CARAFE++ is helpful for all the four components and the combination of them results in further gains. Visualization comparisons of UperNet with and without CARAFE++ are shown in Figure 7.

5.3 Ablation Study & Further Analysis

Model Design & Hyper-parameters. We investigate the influence of hyper-parameters in the model design, i.e., the compressed channels $C_m$, encoder kernel size $k_{encoder}$ and reassembly kernel size $k_{reassembly}$. We also test different normalization methods in the kernel normalizer. Faster R-CNN with a ResNet-50 backbone and 1x schedule is adopted for ablation study if not further specified.

We explore different values of $C_m$ in the channel compressor. The experiments are conducted on object detection for upsampling and image classification for downsampling. For the upsampling version of CARAFE++, the influences of $C_m$ is evaluated on Faster R-CNN with ResNet-50 backbone. Experimental results in Table 11 show that compress $C_m$ down to 64 leads to no performance decline, while being more efficient. A further smaller $C_m$ will result in a slight drop of the performance. In addition, we also try removing the channel compressor module, which means the content encoder directly uses input features to predict reassembly kernels. With no channel compressor, it can achieve the same performance, suggesting the capability of the channel compressor in speeding up the kernel prediction without
Fig. 9: CARAFE++ performs content-aware reassembly when rescaling a feature map. Red units are reassembled into the green center unit by CARAFE++.

TABLE 10: Image inpainting results on Places val.

| Method                | L1(%) | PSNR(dB) |
|-----------------------|-------|----------|
| Global&Local          | 6.69  | 19.58    |
| Global&Local w/ CARAFE++ | 5.82  | 20.93    |
| Partial Conv          | 5.96  | 20.78    |
| Partial Conv w/ CARAFE++ | 5.60  | 21.05    |

TABLE 11: Ablation study of various compressed channels $C_m$ for upsampling. The experiments are performed with Faster R-CNN w/ CARAFE++ in FPN structure on COCO dataset. N/A means channel compressor is removed.

| $C_m$ | AP   | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ |
|-------|------|-----------|-----------|--------|--------|--------|
| 16    | 37.6 | 60.1      | 40.6      | 22.7   | 41.6   | 48.4   |
| 32    | 37.7 | 60.3      | 40.7      | 22.8   | 41.2   | 49.0   |
| 64    | 37.8 | 60.1      | 40.8      | 23.2   | 41.2   | 48.2   |
| 128   | 37.8 | 60.1      | 40.8      | 22.4   | 41.7   | 48.7   |
| 256   | 37.8 | 60.4      | 40.8      | 22.7   | 41.3   | 48.8   |
| N/A   | 37.8 | 60.3      | 40.8      | 22.9   | 41.5   | 48.7   |

TABLE 12: Ablation study of various compressed channels $C_m$ for downsampling. The experiments are performed with ResNet-50 on ImageNet-1k classification dataset.

| $C_m$ | Top-1 | Top-5 |
|-------|-------|-------|
| 4     | 77.31 | 93.59 |
| 8     | 77.43 | 93.63 |
| 16    | 77.46 | 93.63 |
| 32    | 77.40 | 93.60 |
| 64    | 77.46 | 93.67 |

TABLE 13: Detection results with various encoder kernel size $k_{encoder}$ and reassembly kernel size $k_{reassembly}$.

| $k_{encoder}$ | $k_{reassembly}$ | AP   | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ |
|---------------|------------------|------|-----------|-----------|--------|--------|--------|
| 1             | 3                | 37.3 | 59.6      | 40.5      | 22.0   | 40.7   | 48.1   |
| 3             | 5                | 37.3 | 59.9      | 40.0      | 22.3   | 41.1   | 47.3   |
| 5             | 3                | 37.3 | 59.7      | 40.4      | 22.1   | 40.8   | 48.3   |
| 7             | 3                | 37.8 | 60.1      | 40.8      | 23.2   | 41.2   | 48.2   |
| 1             | 5                | 37.8 | 60.0      | 40.9      | 23.0   | 41.5   | 48.4   |
| 5             | 7                | 37.8 | 60.2      | 40.7      | 22.5   | 41.4   | 48.6   |
| 7             | 7                | 38.1 | 60.4      | 41.3      | 23.0   | 41.6   | 48.8   |

harming the performance. Based on the above results, we set $C_m$ to 64 by default as a trade-off between performance and efficiency.

For the downsampling version of CARAFE++, we adopt different settings of $C_m$ in a ResNet-50 for image classification. As shown in Table 12 with different $C_m$, the classification accuracy is relatively stable. We choose $C_m = 16$ that achieves the best performance and involves less computational cost.

We then investigate the influence of $k_{encoder}$ and $k_{reassembly}$. Intuitively, increasing $k_{reassembly}$ also requires a larger $k_{encoder}$, since the content encoder needs a large receptive field to predict a large reassembly kernel. As illustrated in Table 13 increasing $k_{encoder}$ and $k_{reassembly}$ at the same time can boost the performance, while just enlarging one of them will not. We summarize an empirical formula that $k_{encoder} = k_{reassembly} - 2$, which is a good choice in all the settings. Though adopting a larger kernel size is shown helpful, we set $k_{reassembly} = 5$ and $k_{encoder} = 3$ by default as a trade-off between performance and efficiency.

Other than the softmax function, we also test other alternatives in the kernel normalizer, such as sigmoid or sigmoid with normalization. As shown in Table 14 ‘Softmax’ and ‘Sigmoid Normalized’ have the same performance and better than ‘Sigmoid’, which shows that it is crucial to normalize the reassembly kernel to be summed to 1.

How CARAFE++ Works. We conduct a further qualitative study to figure out how CARAFE++ works for upsampling and downsampling. With trained Mask R-CNN models that adopts CARAFE++ as the upsampling and downsampling operator, respectively, we visualize the reassembling process in Figure 9. Specifically, we sample some pixels in the feature map that the upsampling/downsampling process attained, and see which neighbors it is reassembled from. The green circle denotes example locations and red dots indicate highly weighted sources during the reassembly. For upsampling (see Figure 9(a)), in the FPN structure, the low-resolution feature map will be consecutively upsampled several times by CARAFE++. In the process, pixels in a large region of the high-resolution feature map is reassembled to attain a pixel on the low-resolution feature map. As a result, the receptive field of a downsampled feature map increases. For downsampling (see Figure 9(b)), a input high-resolution feature map is downsampled for several times by CARAFE++. In the process, pixels in a large region of the high-resolution feature map is reassembled to a pixel on the low-resolution feature map. As a result, the receptive field of a downsampled feature map increases. From the figure, we can clearly learn that CARAFE++ is content-aware. It tends to reassemble points from the same instance, rather than other objects or nearby background. For locations in the background regions which has weaker semantics, the reassembly is more

Fig. 9: CARAFE++ performs content-aware reassembly when rescaling a feature map. Red units are reassembled into the green center unit by CARAFE++.
uniform or just biased on points with similar low-level texture features.

6 Conclusion

We have presented Unified Content-Aware ReAssembly of EFatures (CARAFE++), a universal, lightweight and highly effective feature reassembly operator. It consistently boosts the performances on standard benchmarks in object detection, instance/semantic segmentation and inpainting by 2.5% $AP_{bbox}$, 2.1% $AP_{mask}$, 1.94% mIoU, 1.35 dB, respectively. More importantly, CARAFE++ introduces little computational overhead and can be readily integrated into modern network architectures. It shows great potential to serve as a strong building block for future research. Moreover, the current version of CARAFE++ supports feature upsampling/downsampling by an integer factor. In our future work, CARAFE++ will support feature reassembly with an arbitrary scalar factor. Then it could be more widely integrated for various network architectures.

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