Log-Polar Space Convolution Layers

Anonymous Author(s)
Affiliation
Address
email

Abstract

Convolutional neural networks use regular quadrilateral convolution kernels to extract features. Since the number of parameters increases quadratically with the size of the convolution kernel, many popular models use small convolution kernels, resulting in small local receptive fields in lower layers. This paper proposes a novel log-polar space convolution (LPSC) layer, where the convolution kernel is elliptical and adaptively divides its local receptive field into different regions according to the relative directions and logarithmic distances. The local receptive field grows exponentially with the number of distance levels. Therefore, the proposed LPSC not only naturally encodes local spatial structures, but also greatly increases the single-layer receptive field while maintaining the number of parameters. We show that LPSC can be implemented with conventional convolution via log-polar space pooling and can be applied in any network architecture to replace conventional convolutions. Experiments on different tasks and datasets demonstrate the effectiveness of the proposed LPSC.

1 Introduction

Convolutional neural networks [1, 2] have achieved great success in the field of computer vision. The size of the convolution kernel determines the locally weighted range of the image or feature map, which is called the *local receptive field (LRF)*. In many computer vision tasks such as image classification [2, 3, 4] and intensive prediction [5, 6, 7], larger LRF is generally desired to capture the dependencies between long-distance spatial positions and a wide range of context information. Simply increasing the size of the convolution kernel is not plausible because the number of parameters increases quadratically with the size.

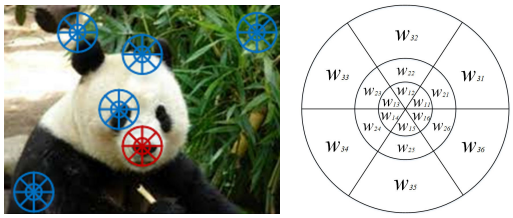
In practice, commonly used techniques to obtain larger receptive fields include adding pooling layers, replacing a single-layer large convolution kernel with multi-layer small convolution kernels, and using dilated convolutions [8, 9]. The pooling process often causes information loss. Increasing the number of convolutional layers may cause vanishing gradients and make training more difficult. Moreover, going deeper with small kernels may not indicate a larger receptive field. A plain CNN with all 3×3 convolution kernels cannot be too deep without residual connections. Some studies [10] have found that ResNets behave like ensembles of shallow networks. Regardless of the actual depth, the effective number of layers for ResNets maybe limited. That is, even if a ResNet with hundreds of layers is stacked, its actual receptive field may be equivalent to that of a shallow network.

According to the effective receptive field (ERF) theory [11], the ERF is proportional to the square root of the depth and directly proportional to the kernel size. Therefore, it is easier to achieve a large ERF by increasing the kernel size than by adding layers. The success of Vision Transformers [12, 13] may also reveal the effectiveness of large local windows, while various sparse attention mechanisms [14, 15, 16] for Transformers are proposed to allow larger LRFs with limited increases of calculations. In this paper, we reconsider lightweight CNNs with large convolution kernels. Dilated convolution kernels are able to increase the LRFs greatly, but they are not continuous since not all pixels in the

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

LRF are involved in convolution calculation. The skipped pixels are regularly selected. With the same number of parameters, the larger the LRF, the more pixels are skipped, which may miss some details and cause discontinuity of information.

In addition, conventional and dilated convolutions use regular square kernels. Each position is assigned a different weight within the LRF. All positions are equally treated regardless of the size of the kernel. However, intuitively, the correlation between neighboring pixels and the center pixel is usually higher, while the farther the pixel, the smaller the impact on the center pixel. The effects of two adjacent pixels that are far away from the center are usually similar, thus they can share the same parameter rather than be assigned different weights separately. As shown in red in Fig. 1(a), according to the configuration of surrounding regions, it can be inferred that the center position is located on the upper edge of the nose. Pixels in the same upper-left outer half-fan-shaped region show that the far upper left of the center point is white fur, but there is little difference in the effects of two specific fur points.



(a) (b)

Figure 1: (a) At different locations of an image, local contextual pixels can be divided into different regions according to their relative distances and directions in the log-polar space. For each location, pixels falling in the same region are generally similar and can share the same weight. (b) The LPSC kernel. For this example, $L_r = 3, L_\theta = 6, g = 2$, thus there are only 18+1 parameters.

In this paper, we propose a novel *log-polar space convolution (LPSC)* method. The shape of the LPSC kernel is not a regular square, but an ellipse. Parameters of the kernel are not evenly distributed in the LRF, but are assigned in the log-polar coordinate space. As shown in Fig. 1(b), the LPSC kernel divides the LRF into different regions, where regions become larger with the increase of the distance to the center. Pixels that fall into the same region share the same weight. In this way, LPSC can increase the LRF exponentially without increasing the number of parameters. Besides, LPSC naturally imposes a contextual structure on the local neighboring distribution.

The main contributions of this paper include: 1. We propose a new convolution method where the kernel lies in the log-polar space to capture the structured context information and greatly expand the LRF without increasing the number of parameters. 2. We propose log-polar space pooling to up-sample the feature map, by which conventional convolution can be conveniently used to achieve LPSC. 3. We apply LPSC to replace the conventional and dilated convolution in different network architectures including AlexNet, VGGNet, ResNet, DeepLabv3+, and CE-Net. We demonstrate the effectiveness of LPSC through empirical evaluations on different tasks and datasets.

2 Related work

Context pooling. Our method is highly motivated by shape context [17, 18]. Centered at a reference point, all other points are divided into bins that are uniformly distributed in the log-polar space. The histogram among these bins is used as the descriptor. Geometric blur [19] sparsely samples and aggregates a blurred signal in the log-polar space. Pyramid context [20] pools log-spaced context points at multiple scales. Different from these methods, we design a kernel in the log-polar space for convolution, each region is assigned a weight to aggregate information from the bins. We incorporate the kernel into deep neural networks.

Methods to increase LRFs. In [21] and [22], it is found that imposing a regularization on large convolution kernels is equivalent to the superposition of multiple convolution layers with smaller kernels. Based on this observation, many state-of-the-art network architectures use multi-layer small kernels. However, deeper layers may cause vanishing gradients, making the network more difficult to train. Moreover, according to [23], the effective receptive field (ERF) is proportional to the square root of the depth and proportional to the kernel size. Thus it is easier to achieve a large ERF by increasing the kernel size than by adding layers. We provide a way to increase the LRF without increasing either the number of layers or the number of parameters. In cases where large input or

LRF is required but very deep networks are not allowed restricted by resources, our method may be applied to construct a lightweight model.

In [8], atrous (or dilated) convolution increases the LRF by inserting holes (zeros) between parameters in the kernel, where the interval is determined by a dilation rate. Dilated convolution has been applied in different tasks [24, 9, 7, 25, 26, 27]. In [28] and [29], scale-adaptive convolution learns adaptive dilation rate with a scale regression layer. Due to the insertion of holes, not all pixels in the LRF are used for calculating the output. In [11] and [30], this problem is alleviated by hybrid dilated convolution and Kronecker convolution that uses the Kronecker product to share parameters.

Other convolution methods. Fractionally strided convolution [31, 32] up-samples the input by padding. In [33], a spatial transformer transforms the regular spatial grid into a sampling grid. Active convolution [34] learns the shape of convolution by introducing the convolution unit with position parameters. Deformable convolution [6] learns additional offsets to augment the sampling locations, thereby adaptively changing the LRF into a polygon. For active and deformable convolutions, the adapted LRF contains holes, the positions and offsets are learned through additional convolutions, which increases the parameters. Deformable kernels [35] resample the original kernel space and adapt it to the deformation of objects. The offsets for kernel positions also need to be learned.

Group convolution [2, 36, 37] and separable convolution [38] do not increase the LRF of kernels. Octave convolution [39] decomposes the feature map into high-frequency and low-frequency features. Multi-scale convolution is performed in [40] and [41]. In [42] and [43], stand-alone self-attention is used to replace convolution. The filter in the attention module lies in a regular and square grid. In [44], the polar transformer network generates a log-polar representation of the input by differentiable sampling and interpolation techniques. The polar transform is applied to a single predicted origin location. In contrast, LPSC performs log-polar pooling via binning and can be applied at any location.

Differences. For dilated and other advanced convolutions, the kernel is still performed in a regular grid and all parameters are treated equally. Regardless of the distance from the center, the interval or the sharing range of a parameter is the same among different positions. In contrast, the proposed LPSC expands the LRF in the log-polar space, where near and far regions are distinguished in parameter sharing. The farther away from the center, the larger the range of parameter sharing.

3 Log-polar space convolution

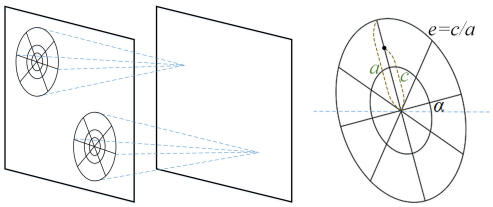
Let $\boldsymbol{X} \in \mathbb{R}^{H \times W \times C}$ be the input image or feature map, where H, W, and C are the height, width, and number of channels of $\boldsymbol{X}$, respectively. $\boldsymbol{W} \in \mathbb{R}^{(2M+1)\times(2N+1)\times C}$ is a conventional convolution kernel with a size of $(2M+1) \times (2N+1)$. The central parameter of $\boldsymbol{W}$ is indexed by $(0, 0)$, parameters of $\boldsymbol{W}$ lie in a regular grid $\{(-M, -N), (-M, -N+1), \cdots, (M-1, N), (M, N)\}$. The convolution operation is performed in the 2D spatial domain across the channels. For a spatial location (i, j), the output of the conventional convolution is calculated as

$$(\boldsymbol{X} * \boldsymbol{W})(i, j) = \sum_{m=-M}^{M} \sum_{n=-N}^{N} (\boldsymbol{X}(i+m, j+n) \cdot \boldsymbol{W}(m, n)) + b, \tag{1}$$

where b is the bias. Strictly, Eq. (1) actually performs cross-correlation. For convolution, $\boldsymbol{W}$ needs to be rotated 180 degrees. However, since we can view the learned $\boldsymbol{W}$ as the rotated kernel, we follow the common practice of CNN to formulate convolution into Eq. (1). Parameters of the kernel are uniformly distributed in the regular grid, thus each pixel of $\boldsymbol{X}$ falling into the field is weighted by a separate parameter, i.e., all positions are equally treated. However, pixels that have different distances and directions from the center may have different impacts, e.g., pixels adjacent to the center should have larger contributions to the output. Pixels in the input image usually change gently, adjacent pixels far away from the center often have similar impacts on the center. Based on these intuitions, we design a convolution kernel with a special structure, namely *Log-Polar Space Convolution (LPSC)* kernel, to express a wide range of contextual configurations.

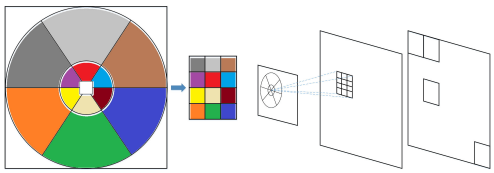
3.1 LPSC kernel

As shown in Fig. 1(b), the proposed LPSC kernel lies in the log-polar space and is shaped by the size $2R+1$, the number of distance levels L_r, the number of direction levels L_θ, and the growth rate g.



(a) (b)

Figure 2: (a) The LPSC kernel is slide through the feature map. (b) The shape and inclination of the LPSC kernel can be changed.



(a) (b)

Figure 3: (a) Log-polar pooling generates a $2L_r \times L_\theta/2$ matrix per position using the pre-computed mask. (b) To perform LPSC on the original input (left), log-polar pooling generates a matrix for each pixel, resulting in an upsampled map (middle), conventional convolution is applied to this map (right).

The LRF of the kernel is the area of the outermost circle whose radius is R. It is uniformly divided into $L_r \times L_\theta$ regions in the log-polar space. Specifically, the log radius is uniformly divided into L_r levels, i.e.,

$$log(R_{l+1}) - log(R_l) = log(R_l) - log(R_{l-1}) = log(g), \tag{2}$$

where $R_l, l = 1, \cdots, L_r$ is the radius of the l-th level and the growth rate g is a hyperparameter controlling the expansion speed. When the center of the kernel is located at position (c_h, c_w), all pixels of $\boldsymbol{X}$ in the range of $\Delta = [c_h - R, c_h + R] \times [c_w - R, c_w + R]$ are divided into L_r levels according to their relative squared distances to the center position. The position $(i, j) \in \Delta$ belongs to the l-th distance level if $R_{l-1} \leq d_{i,j} < R_l$, where $d_{i,j} = (i - c_h)^2 + (j - c_w)^2$. From Eq. (2), we have $R_l = g^{l-1}R_1$. When the innermost radius R_1 is fixed, the LRF grows exponentially with the increase of L_r. The LRF is determined by R which can be set arbitrarily. Given $R_{L_r} = R^2$ and g, we calculate $R_1 = max(2, R^2/g^{L_r-1})$. We use $R = \sqrt{R_{L_r}}$ as a hyperparameter instead of R_1, which is more flexible. Since we use the squared distance, we impose a minimum value of 2 to ensure that all 8-neighborhood pixels fall into the 1-st level.

All positions in the range of Δ are also uniformly divided into L_θ levels according to their relative directions from the center. The position (i, j) belongs to the m-th level if $2\pi(m-1)/L_\theta \leq \theta_{i,j} < 2\pi m/L_\theta$, where $\theta_{i,j}$ is the counterclockwise angle from the vector $(0, 1)$ to the vector $(i - c_h, j - c_w)$. Combining the distance levels and the direction levels, the LRF is divided into $L_r \times L_\theta$ regions.

The LPSC kernel assigns a parameter to each region. All pixels of $\boldsymbol{X}$ falling into the same region share the same parameter. For the region with the l-th distance level and m-th direction level, the assigned parameter is denoted by $w_{l,m}$. The areas of regions increase with l, the farther away from the center, the larger the area, the more pixels sharing parameters. Because the center position of the kernel is important and forms the basis of regions, we assign an additional separate parameter $w_{0,0}$ for the center pixel. A conventional kernel with a size of $(2R+1) \times (2R+1)$ has $(2R+1)^2$ parameters, while a LPSC kernel only has $L_r \times L_\theta + 1$ parameters no matter how large R is. When R ranges from 2 to 9, a single conventional kernel has 25 to 361 parameters. In this range, it is sufficient to set L_r to 2 or 3 and set L_θ to 6 or 8, so an LPSC kernel only has 13 to 25 parameters.

Let $N_{l,m}$ denote the number of pixels falling into the region $bin(l, m)$ with the l-th distance level and the m-th direction level. In faraway regions with large l, $N_{l,m}$, the impacts of pixels in them should be weakened. Therefore, we regularize the weight $w_{l,m}$ of each region by $N_{l,m}$: $w_{l,m}/N_{l,m}$. As a result, the LPSC kernel aggregates finer information from pixels nearing the center and is less sensitive to those of pixels farther away. Similar to conventional convolution, the LPSC kernel is slide along the input feature map X with a pre-defined stride to perform convolution, as shown in Fig. 2(a). When the kernel is located at a spatial location (i, j), the output response is calculated as

$$(\boldsymbol{X} * \boldsymbol{W})(i, j) = \boldsymbol{W}(0, 0) \cdot \boldsymbol{X}(i, j) + \sum_{l=1}^{L_r} \sum_{n=1}^{L_\theta} \boldsymbol{W}(l, m) \cdot (\frac{1}{N_{l,m}} \sum_{u,v \in bin(l,m)} \boldsymbol{X}(u, v)) + b \tag{3}$$

For the LPSC kernel, the shape of its LRF is not necessarily a standard circle, but can be an oblique ellipse. As shown in Fig. 2(b), two additional hyper-parameters are introduced: the initial angle α

and the eccentricity of the ellipse e. When dividing the regions, the distances are calculated according to the squared ellipse distance and the initial angle is added to the calculated directions. In this way, the LPSC kernel can better fit objects with different rotations and scales. In our experiments, we only evaluate the standard circular LRF by setting $\alpha = 0$ and $e = h/w = 1$.

3.2 LPSC via log-polar space pooling

Due to the special structure and parameter sharing, LPSC cannot be directly performed by popular deep learning frameworks. In this subsection, we show that LPSC can be readily implemented by conventional convolutions via log-polar space pooling to utilize efficient convolution modules.

Given the hyper-parameters R, L_r, L_θ, and g of the proposed LPSC, we can pre-compute a mask matrix $\boldsymbol{I}$ to indicate the region indexes of positions. The size of the mask $\boldsymbol{I}$ is $(2R+1) \times (2R+1)$. $1, \cdots, L_\theta \times L_r$ in $\boldsymbol{I}$ indicates the region index of the corresponding position. 0 indicates that the corresponding position does not fall into the LRF, since the region of the mask is the circumscribed rectangle of the LRF. The mask is slide through the input feature map $\boldsymbol{X}$ with the same stride of the LPSC convolution. As shown in Fig. 3(b), when the mask is located at a spatial location (i, j), pixels of $\boldsymbol{X}$ in the range are divided into regions indicated by the mask. All pixels in the same region are encoded into a single pixel by mean pooling. We re-arrange the pooled pixels of different regions into a matrix of $2L_r \times L_\theta/2$ to preserve their relative spatial positions, as shown in Fig. 3(a). In this way, given $H' \times W'$ convolution locations ($H' = H$ and $W' = W$ if the stride is 1 with padding), the spatial size of the output map $\boldsymbol{X}_p$ after log-polar space pooling equals $2H'L_r \times W'L_\theta/2$.

We perform conventional convolution with C' output channels on the output map $\boldsymbol{X}_p$ without padding. The size of the conventional convolution kernel is set to $(2L_r, L_\theta/2)$ and the stride is also $(2L_r, L_\theta/2)$. The output feature map $\boldsymbol{Y}_p$ has a size of $H' \times W' \times C'$. This is equivalent to performing the second term in Eq. (3). To model the first term, we use a separate 1×1 conventional convolution with the same C' channels on the original $\boldsymbol{X}$. The stride is the same as the log-polar space pooling. The output feature map $\boldsymbol{Y}_c$ contains the convolution responses of the center pixels. We add this separate center pixel convolution output $\boldsymbol{Y}_c$ to the contextual convolution output $\boldsymbol{Y}_p$. $\boldsymbol{Y}_c + \boldsymbol{Y}_p$ serves as the output feature map of the proposed LPSC.

3.3 Incorporating LPSC into different CNNs

LPSC can be integrated into different CNN architectures. A straightforward way is to replace all conventional convolution kernels with LPSC kernels in a part of convolution layers. For plain CNN architectures such as AlexNet [2] and VGGNet [21], we simply perform this strategy in lower layers to increase the LRFs. However, some network architectures such as ResNet [22] are constituted of specifically designed blocks. In ResNet, either the bottleneck or the basicblock structure only contains 3×3 and 1×1 convolutions. Due to the difference in the local receptive field, the information captured by these small convolutions and LPSC may be different. In order to better incorporate these two types of information, we propose a cross convolution strategy as an alternative to replacing all convolutions in each layer of the block. Specifically, we set a ratio p. For each of several consecutive layers, we replace $p\%$ of all convolution kernels to LPSC kernels, while the remaining $(100-p)\%$ of conventional kernels remain the same. In this way, each convolution kernel in the next layer, whether it is a conventional or an LPSC kernel, perceives the outputs generated by both the conventional and LPSC kernels of the previous layer. We denote this cross-convolution strategy by LPSC-CC. Details on how to incorporate LPSCs depend on the CNN architecture and will be presented in Section 4.

3.4 Discussions

Complexity. For a $(2M+1) \times (2N+1) \times C$ kernel, conventional convolution involves $(2M+1) \times (2N+1) \times C$ multiplications and $(2M+1) \times (2N+1) \times C$ additions. LPSC with L_r distance levels and L_θ direction levels only involves $2 * L_r \times L_\theta \times C$ multiplications, $(2M+1) \times (2N+1) \times C$ additions, and $(2M+1) \times (2N+1)$ lookups. The complexity of pre-computing the mask for lookup is $O(R^2)$, which only needs to be calculated once when initialing the layer. Typically, if $L_r = 2$, $L_\theta = 6$, LPSC only executes $24C$ multiplications for any size. However, even for a small $(2M+1) \times (2N+1) = 5 \times 5$ kernel, conventional convolution executes $25C$ multiplications; for a 9×9 kernel, multiplications increase to $81C$.

Structural benefits. With the special log-polar structure, the LPSC kernel naturally encodes the local spatial distribution of pixels w.r.t. the center and puts more attention to those adjacent pixels. Pixels with similar relative distances and directions share the same parameter, which not only reduces the number of parameters, but also makes the filter more robust and compact. Due to the logarithm effect, when located at different objects, small objects are relatively enlarged, while large objects are relatively reduced. Therefore, LPSC is less sensitive to the size of objects. Advantages of log-polar space pooling and extensions of LPSC to 1-D and 3-D data are discussed in the appendix.

Relation with effective receptive field [23]. In [23], it is found that the ERF only occupies a fraction of the full theoretical receptive field. Specifically, the ERF size is $O(k\sqrt{n})$, where $k = 2R + 1$ is the kernel size and n is the number of layers. Therefore, increasing the kernel size has a greater effect on expanding the ERF. It is also found that not all pixels in the LRF contribute equally, where the impacts of pixels near the center are much larger. The LPSC kernel follows this spirit to treat pixels near the center finely and increase the LRF exponentially.

Relation with advanced convolution methods. For LPSC, parameters distribute in the log-polar space. Most advanced convolution methods discussed in Section 2 do not change the regular sampling grid and focus on different aspects with LPSC. Therefore, these advances may be propagated to LPSC as well. For example, group and separable convolution [38, 37] separates the channel dimension into groups and hence can be combined with the LPSC kernel in spatial dimensions. Graph convolution can also take advantage of LPSC as long as the relative distance and direction between nodes are defined. The solution in [45] to the coordinate transform problem can also be directly applied to our LPSC by putting Cartesian coordinate into pixel.

Drawbacks. LPSC has two main drawbacks. (1) It introduces three additional hyper-parameters: L_r, L_θ, and g. However, in practice, their selectable ranges are quite limited. Generally, to make the 8-neighborhoods of the center pixel have finer and non-redundant regional resolution, L_r is set to 2 or 3, L_θ is set to 6 or 8, and g is set to 2 or 3. (2) Its implementation via log-polar space pooling incurs large memory overhead. The space complexity of the upsampled feature map $\boldsymbol{X}_p$ is $O(H'W'L_rL_\theta C)$. For a single layer, the space complexity of LPSC is $O(H'W'L_rL_\theta C + L_rL_\theta CC' + H'W'C')$.

4 Experiments

We empirically study the effects and potential of the proposed LPSC on two tasks: image classification and semantic segmentation.

4.1 Image classification experiments

For image classification, we evaluate the behaviors of LPSC integrated with different CNN architectures on three datasets: CIFAR-10, CIFAR-100 [46], and ImageNet [47]. We plug LPSC into three typical CNN architectures, including AlexNet [2], VGGNet-19 [21], and ResNet20 [22], by replacing a part of the conventional convolution layers. We use the Pytorch [48] implementation[1] of these architectures as our baseline. For the AlexNet, there are 5 convolution layers each followed by a ReLU activation layer. The sizes of the convolution kernels are 11×11, 5×5, 3×3, 3×3, and 3×3, respectively. For the VGG19 Net, there are sixteen convolution layers. The kernel size for all convolution layers is 3×3. For the ResNet-20, there are 9 basic blocks. Each block contains two 3×3 convolution layers. A 3×3 convolution layer is applied before all blocks. When the conventional convolutions in a layer or block are replaced by LPSCs, the number of kernels and the size of the output feature map remain the same as the original convolution layer.

To make a fair comparison, all experimental setup and details including the learning rate, batch size, number of filters per layer, hyper-parameters for the optimizer (e.g., γ, momentum, weight decay) remain exactly the same as in the baseline. We did not tune any of these setups for our LPSC. Therefore, the differences in performances only come from the changes in convolution layers. The numbers of parameters are computed on the CIFAR-10 dataset. Top-1 accuracy is used as the performance measure.

Results on the CIFAR10 and CIFAR100 dataset. We train the AlexNet, VGGNet-19, and ResNet-20 with conventional convolution, dilation convolution, and LPSC five times by using different

[1] https://github.com/bearpaw/pytorch-classification

Table 1: Comparison of different convolution methods.

(a) Accuracy (%) with AlexNet and VGGNet-19

Convolution	AlexNet			VGGNet-19		
	Ori	Dilation	LPSC	Ori	Dilation	LPSC
# Params (M)	2.47	2.34	2.31	20.04	20.08	20.08
CIFAR-10	77.43 (0.25)	75.42 (0.06)	**78.44** (0.12)	93.54 (0.06)	93.46 (0.14)	**93.92** (0.06)
CIFAR-100	43.98 (0.43)	44.43 (0.10)	**47.43** (0.20)	72.41 (0.17)	73.03 (0.34)	**73.13** (0.12)

(b) Accuracy (%) with ResNet-20

Convolution	Ori	Dilation	LPSC	LPSC-CC
# Params (M)	0.27	0.27	0.27	0.27
Acc. CIFAR-10 (%)	91.66 (0.13)	91.44 (0.10)	**91.81** (0.21)	**92.01** (0.08)
Acc. CIFAR-100 (%)	67.56 (0.27)	66.90 (0.25)	**67.63** (0.27)	**68.09** (0.27)

Table 2: Results with ResNet-110 on CIFAR-100.

Model	Time	Acc
Conv	0.025 (0.0053)	73.50 (0.24)
LPSC	0.036 (0.0047)	73.54 (0.38)
LPSC-CC	0.135 (0.0035)	**74.13** (0.14)

Table 3: Results with ResNet-18 on ImageNet.

Model	#params(M)	Top-1 Acc (%)
Conv	11.69	69.86 (0.082)
LPSC	11.69	**69.96** (0.081)
LPSC-CC	11.70	69.95 (0.079)

random seeds for initialization, respectively, and compare the average accuracies and standard deviations. "Mean accuracy (standard deviation)" results are reported in Table 1. We use LPSC in the first two convolution layers for AlexNet, in the added first convolution before all blocks for VGGNet-19, and in the first convolution layer before all residual blocks for ResNet-20. Hyper-parameters of the LPSC kernels in different layers and networks are the same as the first three columns in Table 8(d), respectively. These choices are based on the ablation study as described in the appendix A.1 and A.2. For dilation convolution, we replace the conventional convolutions with dilation convolution in the same layers in the three architectures, respectively, where the kernel size and dilation rates are set so that the LRF and number of parameters are comparable with LPSC. Specifically, for AlexNet, the kernel size and dilation rate are set to 5 and 2 in the first convolution layer, respectively, and 4 and 2 in the second convolution layer, respectively. For VGGNet-19, the kernel size and dilation rate are set to 4 and 2 in the added first convolution layer before all blocks, respectively. For ResNet-20, the kernel size and dilation rate are set to 4 and 3 in the first convolution layer before all residual blocks, respectively. These choices are based on the evaluations in Table 8 of the appendix A.2. From Table 1, we observe that LPSC outperforms dilation convolutions with comparable LRF and parameters. The standard deviations for LPSC are limited, which shows that LPSC is not particularly sensitive to initializations. In some cases, the worst results also exceed those of the original networks with conventional convolutions and dilation convolutions by a margin.

We also evaluate the cross convolution strategy for ResNet-20. We apply LPSC-CC to the layer before all blocks and all 3×3 layers of the first block with a fixed p of 50. From Table 1(b), we observe that the cross convolution strategy further improves the performances.

Results with ResNet-110. We train ResNet-110 with different convolutions on CIFAR-100 in Tab. 2. We follow the same setting for evaluating ResNet20, where 5×5 LPSC kernels ($L_r, L_\theta, g = 2, 6, 3$) are used to replace 3×3 convolutions in the first layer before all blocks in LPSC and in the first three layers with a fixed p of 50 in LPSC-CC. For the deeper model, the advantage of LPSC is weakened, but LPSC-CC still improves ResNet110 significantly.

Comparison of FLOPs. Comparisons of the average runtime per batch for using different convolutions in ResNet110 are shown in Tab 2. LPSC runs slower than conventional convolution, but this is because we use of-the-shell conventional convolution modules in Pytorch to implement LPSC, which are highly optimized and very efficient for conventional convolution. LPSC can be greatly accelerated if it can be directly implemented with CUDA or by directly adapting the underlying code of convolutions in the integrated framework. On CIFAR10 with AlexNet, the FLOPs (recorded by the fvcore toolbox[2]) of conventional convolution, dilated convolution, and LPSC are 14.95M, 24.71M, and 11.42M, respectively. LPSC has much lower FLOPs than other convolution methods.

[2]https://github.com/facebookresearch/fvcore

Table 4: Results on the VOC 2012 dataset. "-" means that the results are not reported. "*" indicates our reproduced results.

Method	oAcc	mAcc	fAcc	mIoU
DeepLabv3	-	-	-	0.701
DeepLabv3+	-	-	-	0.711
DeepLabv3+*	0.9230	0.8332	0.8652	0.7144
DeepLabv3+LPSC	**0.9273**	**0.8388**	**0.8714**	**0.7260**

Table 5: Results on the DRIVE dataset [49]. "*" indicates our reproduced results.

Method	Sen	Acc	AUC
HED [50]	0.7364	0.9434	0.9723
Azzopardi et al. [51]	0.7655	0.9442	0.9614
Zhao et al. [52]	0.7420	0.9540	0.8620
U-Net [53]	0.7537	0.9531	0.9601
Deep Vessel [54]	0.7603	0.9523	0.9752
CE-Net [55]	0.8309	0.9545	0.9779
CE-Net* [55]	0.8266 (0.0106)	0.9550 (0.0009)	0.9782 (0.0008)
CE-Net-LPSC-1	0.8300 (0.0079)	**0.9552** (0.0011)	0.9782 (0.0008)
CE-Net-LPSC-2	**0.8312** (0.0075)	0.9548 (0.0011)	**0.9784** (0.0007)

Results on the ImageNet dataset. ImageNet [47] contains 1.28 million training images and 50k validation images from 1000 classes. We again use the Pytorch implementation[3] of ResNet-18 as the baseline. For LPSC, we replace conventional convolution with LPSC in the first convolution layer before all blocks of ResNet-18, where the size $2R + 1$, L_r, L_θ, and g for LPSC kernels are 9, 3, 8, and 2, respectively. For LPSC-CC, in addition to reduce p from 100 to 25 in the first layer, we also replace a quarter of 3×3 kernels with LPSC kernels in the first residual block (i.e., $p = 25$), where the size $2R + 1$, L_r, L_θ, and g for LPSC kernels in the block are 5, 2, 6, and 3, respectively. The setting of these hyper-parameters for LPSC follows the suggestions in the ablation study in the appendix A.1. Due to the limitation of computing resources, we reduced the batch size and learning rate by 4 times. Other hyper-parameters remain the same. We compare the mean top-1 accuracy and the standard deviation of the last ten epoches in Tab. 3. Both LPSC and LPSC-CC slightly improve the top-1 accuracy and the standard deviation of ResNet-18.

4.2 Semantic segmentation experiments

LPSC can also be applied to other vision tasks. On the PASCAL VOC 2012 dataset [56, 57] for general image semantic segmentation, we adopt the Pytorch implementation[4] of DeepLabv3+ [58] with the MobileNet [59] backbone as the baseline. The training set is augmented by extra annotations provided in [60]. Overall accuracy (oAcc), mean accuracy (mAcc), freqw accuracy (fAcc), and mean IoU (mIoU) on the validation set are evaluated. In DeepLabv3+, the atrous spatial pyramid pooling (ASPP) module probes multi-scale features by applying atrous/dilated convolutions with three different rates. For DeepLabv3+LPSC, we replace the dilated convolution with the largest rate by LPSC in ASPP. The kernel size, L_r, L_θ, and g of LPSC are set to 9, 2, 8, 2, respectively. Comparisons with the reported and reproduced results are shown in Tab. 4. LPSC improves DeepLabv3+ by a margin of 1.1% on mIoU. All hyper-parameters and setups such as the learning rate, batch size, etc, remain the same, so the performance gains are only attributed to the proposed LPSC.

On the DRIVE dataset [49] for retinal vessel detection, we adopt CE-Net [55] as the baseline. Sensitivity (Sen), accuracy (Acc), and AUC are evaluated on the test set. The dense atrous convolution (DAC) block of CE-Net uses four cascade branches with increasing numbers of dilated convolutions. For CE-Net-LPSC-1, we replace the dilated convolutions with rates of 3 and 5 by LPSCs with sizes of 5 and 11 in DAC, respectively, so that LPSCs have the same LRFs with dilated convolutions. L_r, L_θ, and g of LPSCs are set to 2, 6, 3, respectively. For CE-Net-LPSC-2, we increase the kernel sizes of LPSCs to 9 and 15, respectively, to further increase LRFs. We accordingly use more parameters by setting L_r, L_θ, and g to 3, 8, 1.5, respectively. Other hyper-parameters remain the same[5]. We run our models ten times and report the average performances. Comparisons with the reported

[3] https://github.com/bearpaw/pytorch-classification

[4] https://github.com/VainF/DeepLabV3Plus-Pytorch

[5] https://github.com/Guzaiwang/CE-Net

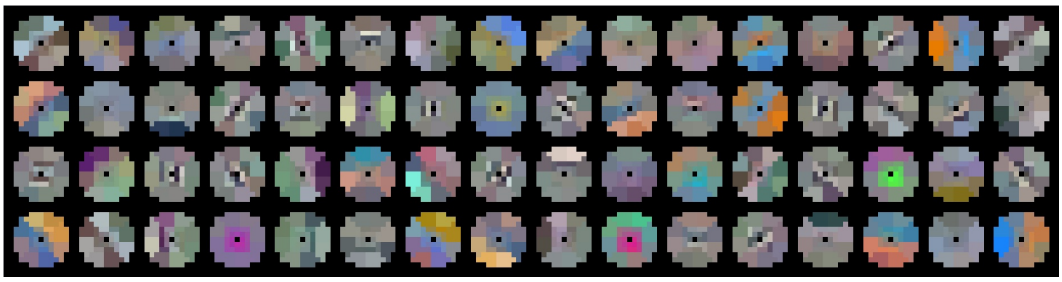
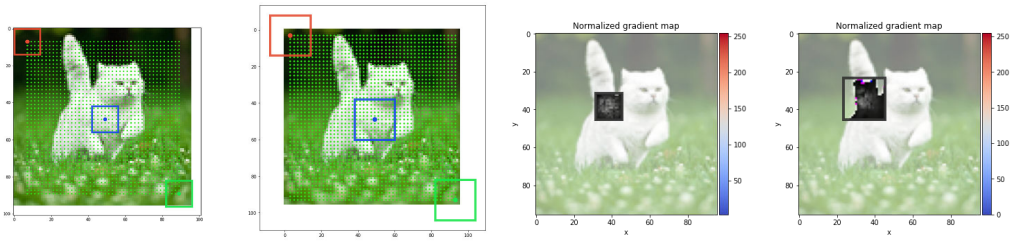


Figure 4: Visualization of the learned circular LPSC kernels without center convolution in the first convolution layer of Alexnet on the CIFAR-10 dataset.



(a) (b) (c) (d)

Figure 5: Estimated RFs with (a) conventional convolution and (b) LPSC. The normalized gradient map with (c) conventional convolution and (d) LPSC a sampled location.

results are shown in Tab. 5. Our LPSC achieves good generalization performances on medical image segmentation with limited training samples.

4.3 Visualization

Visualization of the learned LPSC kernels. In Fig. 4, we visualize the learned LPSC kernels in the first convolution layer of AlexNet on the CIFAR-10 dataset. The 11×11 LPSC kernels have 3 distance levels and 8 direction levels. In LPSC kernels, the closer to the center, the higher the regional resolution; the more outward, the larger the range for parameter sharing. We observe that the learned LPSC kernels capture some special local structures and contextual configuration. In some kernels, the weights for adjacent regions are continuous; some kernels are sensitive to specific directions, edges, colors, or local changes; in some other kernels, specific combinations of regions are highlighted. More visualizations are shown in the appendix A.3.

Comparison of effective receptive field (ERF): Fig. 5(a) and (b) show the estimated RFs of SimpleVGGNet on the default example using conventional convolutions and LPSCs in the first two layers by the gradient-based RF estimation[6], respectively. LPSC enlarges the estimated RFs from 14×14 to 22×22. The normalized gradient maps w.r.t. a position of the output for estimating the RF using conventional convolutions and LPSCs are shown in Fig. 5(c) and (d). With LPSC, gradients can be back-propagated to more pixels of the input image.

5 Conclusion

In this paper, we have presented LPSC that naturally encodes the local contextual structures. LPSC distinguishes regions with different distance levels and direction levels, reduces the resolution of remote regions, and reduces the number of parameters by weight sharing for pixels in the same region. The LRF of LPSC increases exponentially with the number of distance levels. We impose a regularization on the parameters and implement LPSC with conventional convolutions by log-polar space pooling and separable center pixel convolution. We analyze the interests and drawbacks of LPSC from different aspects. We empirically show the effectiveness of the proposed LPSC on five datasets for classification and segmentation tasks.

[6]https://github.com/fornaxai/receptivefield

References

[1] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[3] Yongming Rao, Wenliang Zhao, Zheng Zhu, Jiwen Lu, and Jie Zhou. Global filter networks for image classification. *Advances in Neural Information Processing Systems*, 34, 2021.

[4] Xiaohan Ding, Xiangyu Zhang, Ningning Ma, Jungong Han, Guiguang Ding, and Jian Sun. Repvgg: Making vgg-style convnets great again. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13733–13742, 2021.

[5] Chao Peng, Xiangyu Zhang, Gang Yu, Guiming Luo, and Jian Sun. Large kernel matters–improve semantic segmentation by global convolutional network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4353–4361, 2017.

[6] Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, and Yichen Wei. Deformable convolutional networks. In *Proceedings of the IEEE international conference on computer vision*, pages 764–773, 2017.

[7] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, 40(4):834–848, 2017.

[8] Matthias Holschneider, Richard Kronland-Martinet, Jean Morlet, and Ph Tchamitchian. A real-time algorithm for signal analysis with the help of the wavelet transform. In *Wavelets*, pages 286–297. Springer, 1990.

[9] Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. *arXiv preprint arXiv:1511.07122*, 2015.

[10] Andreas Veit, Michael J Wilber, and Serge Belongie. Residual networks behave like ensembles of relatively shallow networks. *Advances in neural information processing systems*, 29:550–558, 2016.

[11] Panqu Wang, Pengfei Chen, Ye Yuan, Ding Liu, Zehua Huang, Xiaodi Hou, and Garrison Cottrell. Understanding convolution for semantic segmentation. In *2018 IEEE winter conference on applications of computer vision (WACV)*, pages 1451–1460. IEEE, 2018.

[12] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *International Conference on Learning Representations*, 2021.

[13] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021.

[14] Juho Lee, Yoonho Lee, Jungtaek Kim, Adam Kosiorek, Seungjin Choi, and Yee Whye Teh. Set transformer: A framework for attention-based permutation-invariant neural networks. In *International Conference on Machine Learning*, pages 3744–3753. PMLR, 2019.

[15] Hongyu Ren, Hanjun Dai, Zihang Dai, Mengjiao Yang, Jure Leskovec, Dale Schuurmans, and Bo Dai. Combiner: Full attention transformer with sparse computation cost. *Advances in Neural Information Processing Systems*, 34, 2021.

[16] Qi Han, Zejia Fan, Qi Dai, Lei Sun, Ming-Ming Cheng, Jiaying Liu, and Jingdong Wang. Demystifying local vision transformer: Sparse connectivity, weight sharing, and dynamic weight. *arXiv preprint arXiv:2106.04263*, 2021.

[17] Serge Belongie, Jitendra Malik, and Jan Puzicha. Shape context: A new descriptor for shape matching and object recognition. In *Advances in neural information processing systems*, pages 831–837, 2001.

[18] Serge Belongie, Jitendra Malik, and Jan Puzicha. Shape matching and object recognition using shape contexts. *IEEE transactions on pattern analysis and machine intelligence*, 24(4):509–522, 2002.

[19] Alexander C Berg and Jitendra Malik. Geometric blur for template matching. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2001.

[20] Jonathan T Barron, Mark D Biggin, Pablo Arbelaez, David W Knowles, Soile VE Keranen, and Jitendra Malik. Volumetric semantic segmentation using pyramid context features. In *Proceedings of the IEEE international conference on computer vision*, pages 3448–3455, 2013.

[21] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[23] Wenjie Luo, Yujia Li, Raquel Urtasun, and Richard Zemel. Understanding the effective receptive field in deep convolutional neural networks. In *Advances in neural information processing systems*, pages 4898–4906, 2016.

[24] Jifeng Dai, Yi Li, Kaiming He, and Jian Sun. R-fcn: Object detection via region-based fully convolutional networks. In *Advances in neural information processing systems*, pages 379–387, 2016.

[25] Laura Sevilla-Lara, Deqing Sun, Varun Jampani, and Michael J Black. Optical flow with semantic segmentation and localized layers. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3889–3898, 2016.

[26] M. Yang, K. Yu, Z. Chi, Z. Li, and K. Yang. Denseaspp for semantic segmentation in street scenes. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018.

[27] Liang-Chieh Chen, Maxwell D. Collins, Yukun Zhu, George Papandreou, Barret Zoph, Florian Schroff, Hartwig Adam, and Jonathon Shlens. Searching for efficient multi-scale architectures for dense image prediction. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, page 8713–8724, 2018.

[28] Rui Zhang, Sheng Tang, Yongdong Zhang, Jintao Li, and Shuicheng Yan. Scale-adaptive convolutions for scene parsing. In *Proceedings of the IEEE international conference on computer vision*, pages 2031–2039, 2017.

[29] Rui Zhang, Sheng Tang, Yongdong Zhang, Jintao Li, and Shuicheng Yan. Perspective-adaptive convolutions for scene parsing. *IEEE transactions on pattern analysis and machine intelligence*, 42(4):909–924, 2019.

[30] Tianyi Wu, Sheng Tang, Rui Zhang, Juan Cao, and Jintao Li. Tree-structured kronecker convolutional network for semantic segmentation. In *IEEE International Conference on Multimedia and Expo*, pages 940–945. IEEE, 2019.

[31] Matthew D Zeiler, Dilip Krishnan, Graham W Taylor, and Rob Fergus. Deconvolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2528–2535. IEEE, 2010.

[32] Matthew D Zeiler, Graham W Taylor, and Rob Fergus. Adaptive deconvolutional networks for mid and high level feature learning. In *Proceedings of the IEEE international conference on computer vision*, pages 2018–2025. IEEE, 2011.

[33] Max Jaderberg, Karen Simonyan, Andrew Zisserman, et al. Spatial transformer networks. In *Advances in neural information processing systems*, pages 2017–2025, 2015.

[34] Yunho Jeon and Junmo Kim. Active convolution: Learning the shape of convolution for image classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4201–4209, 2017.

[35] Hang Gao, Xizhou Zhu, Steve Lin, and Jifeng Dai. Deformable kernels: Adapting effective receptive fields for object deformation. *arXiv preprint arXiv:1910.02940*, 2019.

[36] Ting Zhang, Guo-Jun Qi, Bin Xiao, and Jingdong Wang. Interleaved group convolutions. In *Proceedings of the IEEE international conference on computer vision*, pages 4373–4382, 2017.

[37] Xiangyu Zhang, Xinyu Zhou, Mengxiao Lin, and Jian Sun. Shufflenet: An extremely efficient convolutional neural network for mobile devices. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 6848–6856, 2018.

[38] François Chollet. Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1251–1258, 2017.

[39] Yunpeng Chen, Haoqi Fan, Bing Xu, Zhicheng Yan, Yannis Kalantidis, Marcus Rohrbach, Shuicheng Yan, and Jiashi Feng. Drop an octave: Reducing spatial redundancy in convolutional neural networks with octave convolution. In *Proceedings of the IEEE international conference on computer vision*, pages 3435–3444, 2019.

[40] Junran Peng, Ming Sun, Zhaoxiang Zhang, Tieniu Tan, and Junjie Yan. Pod: Practical object detection with scale-sensitive network. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9607–9616, 2019.

[41] Duo Li, Anbang Yao, and Qifeng Chen. Psconv: Squeezing feature pyramid into one compact poly-scale convolutional layer. *arXiv preprint arXiv:2007.06191*, 2020.

[42] Prajit Ramachandran, Niki Parmar, Ashish Vaswani, Irwan Bello, Anselm Levskaya, and Jonathon Shlens. Stand-alone self-attention in vision models. *arXiv preprint arXiv:1906.05909*, 2019.

[43] Jean-Baptiste Cordonnier, Andreas Loukas, and Martin Jaggi. On the relationship between self-attention and convolutional layers. *arXiv preprint arXiv:1911.03584*, 2019.

[44] Carlos Esteves, Christine Allen-Blanchette, Xiaowei Zhou, and Kostas Daniilidis. Polar transformer networks. *International Conference on Learning Representations*, 2018.

[45] Rosanne Liu, Joel Lehman, Piero Molino, Felipe Petroski Such, Eric Frank, Alex Sergeev, and Jason Yosinski. An intriguing failing of convolutional neural networks and the coordconv solution. In *Advances in Neural Information Processing Systems*, volume 31, 2018.

[46] Alex Krizhevsky. Learning multiple layers of features from tiny images. *Technical Report*, 2009.

[47] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

[48] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems*, pages 8024–8035, 2019.

[49] Joes Staal, Michael D Abràmoff, Meindert Niemeijer, Max A Viergever, and Bram Van Ginneken. Ridge-based vessel segmentation in color images of the retina. *IEEE transactions on medical imaging*, 23(4):501–509, 2004.

[50] Saining Xie and Zhuowen Tu. Holistically-nested edge detection. In *Proceedings of the IEEE international conference on computer vision*, pages 1395–1403, 2015.

[51] George Azzopardi, Nicola Strisciuglio, Mario Vento, and Nicolai Petkov. Trainable cosfire filters for vessel delineation with application to retinal images. *Medical image analysis*, 19(1):46–57, 2015.

[52] Yitian Zhao, Lavdie Rada, Ke Chen, Simon P Harding, and Yalin Zheng. Automated vessel segmentation using infinite perimeter active contour model with hybrid region information with application to retinal images. *IEEE transactions on medical imaging*, 34(9):1797–1807, 2015.

[53] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[54] Huazhu Fu, Yanwu Xu, Stephen Lin, Damon Wing Kee Wong, and Jiang Liu. Deepvessel: Retinal vessel segmentation via deep learning and conditional random field. In *International conference on medical image computing and computer-assisted intervention*, pages 132–139. Springer, 2016.

[55] Zaiwang Gu, Jun Cheng, Huazhu Fu, Kang Zhou, Huaying Hao, Yitian Zhao, Tianyang Zhang, Shenghua Gao, and Jiang Liu. Ce-net: Context encoder network for 2d medical image segmentation. *IEEE transactions on medical imaging*, 38(10):2281–2292, 2019.

[56] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88(2):303–338, 2010.

[57] Mark Everingham, SM Ali Eslami, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes challenge: A retrospective. *International journal of computer vision*, 111(1):98–136, 2015.

[58] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European Conference on Computer Vision*, pages 801–818, 2018.

[59] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.

[60] Bharath Hariharan, Pablo Arbeláez, Lubomir Bourdev, Subhransu Maji, and Jitendra Malik. Semantic contours from inverse detectors. In *Proceedings of the IEEE international conference on computer vision*, pages 991–998. IEEE, 2011.

[61] Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation. *arXiv preprint arXiv:1706.05587*, 2017.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 3.4.
   (c) Did you discuss any potential negative societal impacts of your work? [No] Because this work presents a general convolution module, we did not see any particular foreseeable ethics consequence.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]

(b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See the supplementary files.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Section 4.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Section 4.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See Section 4.
   (b) Did you mention the license of the assets? [No] The assets we adopted are totally public for research purposes.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] See the supplementary files.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No] All datasets used in this work are public for research purposes.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] All used datasets do not contain personally identifiable information or offensive content
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Appendix

A.1 Ablation study

Influence of hyper-parameters. The proposed LPSC kernel has four hyper-parameters: the kernel size $2R+1$, the number of distance levels L_r, the number of direction levels L_θ, and the growth rate g. For small kernels, since we set a minimum value 2 for the smallest distance level, the largest L_r can be determined by R^2 and g. If L_r is too large, no pixels will fall into regions of large distance levels. L_θ can be set to 6 or 8, since in most cases there are only about 8 pixels in the smallest circle in Fig. 1(b). We evaluate the influences of L_r, L_θ, and g by replacing the large 11×11 convolution kernels with the LPSC kernels in the first layer of AlexNet in Tab. 6(a) and by applying LPSC kernels with different sizes in the first convolution layer before all blocks of VGGNet and ResNet in Tab. 6(c) and (d), respectively. We run all models for only one time. Increasing the values of L_r and L_θ results in finer regions and improves the performances, but the number of parameters also increases.

VGGNet and ResNet use small 3×3 kernels. To make the number of parameters comparable, we fix (L_r, L_θ) to $(2, 6)$ and evaluate the influence of the kernel size $2R+1$ in Tab. 6(c)(d). When $2R+1$ is too small, the LRF is limited. When $2R+1$ is too large, the regions with large distance levels may be coarse, i.e., a large amount of positions share the same weight, which may decrease the resolutions of parameters. Overall, for large kernels (11×11), we can set (L_r, L_θ, g) to $(3, 8, 2)$. For small kernels (5×5), we may fix (L_r, L_θ, g) to $(2, 6, 3)$[7].

Influence of the plugged layer. Tab. 6(b) and (d) show the results of using LPSC in different layers or blocks for AlexNet and ResNet-20, respectively. It seems that performing LPSC in low layers is

[7] In this case, since we set a lower bound of the first level distance, $g = 2$ and 3 will result in the same LPSC kernel.

Table 6: Ablation study based on (a)(b) AlexNet (c) VGGNet-19 and (d) ResNet-20.

(a) 11×11 LPSC kernels with different hyper-parameters are used in the first convolution layer of AlexNet.

(L_r, L_θ, g)	(3,8,2)	(3,6,2)	(2,8,3)	(2,8,2)
# Params (M)	2.45	2.45	2.45	2.45
Acc. CIFAR-10 (%)	77.27	76.83	76.23	75.95
Acc. CIFAR-100 (%)	46.35	45.86	45.07	44.61

(b) Effects of using LPSCs in different convolution layers of AlexNet. Kernel size remains the same as in the corresponding layer. (L_r, L_θ, g) is fixed to $3, 8, 2$ and $2, 6, 3$ when applied to the 1st and 2nd layer, respectively.

LPSC layer	1	2	1 + 2
# Params (M)	2.45	2.33	2.31
Acc. CIFAR-10 (%)	77.27	**78.31**	78.28
Acc. CIFAR-100 (%)	46.35	44.81	**47.31**

(c) LPSCs with different sizes and hyper-parameters are used in an additionally added convolution layer before all blocks in VGGNet-19.

$2R+1$	5	9	13	17
(L_r, L_θ, g)	(2,6,3)	(2,6,3)	(2,6,3)	(3,8,4)
# Params (M)	20.08	20.08	20.08	20.08
Acc. CIFAR-10(%)	93.66	**94.01**	93.86	93.73
Acc. CIFAR-100(%)	72.95	73.13	73.08	**73.37**

(d) Effects of using LPSCs in different layers and blocks of ResNet-20. The first two rows denote the sizes and hyper-parameters of LPSCs in the first convolution layer before all blocks. The third row denotes the sizes of LPSCs with fixed hyper-parameters (2,6,2) in all blocks. "-" means that no LPSCs are used in blocks. "B" means that two successive 3×3 convolution layers are replaced with a single LPSC layer in the BasicBlock.

$2R+1$	5	9	13	5	13
(L_r, L_θ, g)	(2,6,2)	(2,6,3)	(2,6,3)	(2,6,2)	(2,6,2)
$2R+1$ for Blocks	-	-	-	5	9(B)
# Params (M)	0.27	0.27	0.27	0.39	0.18
Acc. CIFAR-10 (%)	91.55	91.67	**92.11**	91.82	89.78
Acc. CIFAR-100 (%)	67.23	67.19	66.97	**67.98**	65.10

more beneficial. This may be because pixels in high layers have merged information from large LRFs so that even adjacent pixels may have different influences on the center pixel and the weights for different positions are not suitable for sharing. Applying LPSC in low layers is conducive to increase the LRFs, filter redundant details, and back-propagate the gradients to more bottom pixels. In the last column of Tab. 6(d), the two successive convolution layers in each block are replaced with a single LPSC layer, so the number of convolution layers is reduced by half and the number of parameters is reduced by one third, but the performances are only reduced by 2% using half the layers with LPSC in ResNet.

Effects of weight regularization. In Tab. 7, we evaluate the effects of the weight regularization in Eq. (3) based on AlexNet. "Sum" shows the results by using sum pooling instead of mean pooling in log-polar space pooling in the first two LPSC layers. This is equivalent to remove the regularization and the performances are severely degraded. This is because far regions are exponentially larger than nearer regions. If positions in all regions are treated equally, even the weight for a far region is not too large, the accumulation of less relevant distant pixels will still produce an overwhelming response. We also try max pooling. It also performs worse than mean pooling. Due to the large LRF, regions with large distance levels for many adjacent center locations will have large overlaps. Some large

Table 7: Effects of the weight regularization and center pixel convolution based on AlexNet.

Method	Sum	Max	No CenterConv	Mean
Acc. CIFAR-10(%)	21.61	76.65	**78.51**	78.28
Acc. CIFAR-100(%)	5.53	44.63	47.13	**47.31**

Table 8: Comparison with different convolution methods based on different architectures.

(a) AlexNet

Conv Type	Ori	Dilation (size, dilation rate)					Deformable				Square (size, pool size)		
hy.-para. L-1	-	5,3	7,2	-	-	7,2					11,5	-	11,5
hy.-para. oth.		-	-	3,2	3,3	3,3					-	9,3	9,3
Layer	-	1	1	2	2	1,2	1	2	1,2	all	1	2	1,2
#params(M)	2.47	2.45	2.46	2.28	2.28	2.26	2.47	2.55	3.21	7.04	2.45	2.28	2.26
CIFAR10	77.22	73.43	75.7	74.94	78.11	75.95	75.98	55.34	32.96	55.22	76.10	75.17	73.26
CIFAR100	43.87	44.86	45.98	41.08	44.21	44.26	41.96	30.30	30.36	30.82	44.50	42.43	41.89

(b) VGGNet-19

Conv Type	Ori	Dilation (size, dilation rate)				Deformable				Square (size, pool size)		
hy.-para. L-1+	-	-	-	-	-					13,4	9,3	9,3
hy.-para. oth.		3,2	3,2	3,2	3,2					-	-	5,3
Block	-	1	2	1,2	1,2,3	1+	1+,1	1+,1,2	1+,all	1+	1+	1+,1
#params(M)	20.04	20.04	20.04	20.04	20.04	20.04	20.11	20.48	58.53	20.04	20.04	20.04
CIFAR10	93.34	91.53	91.97	89.61	89.56	92.53	70.37	90.64	90.02	87.42	90.01	89.4
CIFAR100	71.95	68.46	69.30	63.75	63.83	69.32	37.50	64.37	61.26	62.51	66.64	65.79

(c) ResNet-20

Conv Type	Ori	Dilation (size, dilation rate)				Deformable		Square (size, pool size)			
hy.-para. L-1+	-	3,2	3,3	5,2	3,2			13,4	9,3	9,3	9,3
hy.-para. oth.		-	-	-	3,2			-	-	5,3	5,3
Block	Ori	1+	1+	1+	1+,1,2,3	1+	1,2,3	1+	1+	1+,1	1+,1,2
#params(M)	0.27	0.27	0.27	0.27	0.27	0.27	0.78	0.27	0.27	0.27	0.28
CIFAR-10	91.96	91.39	91.77	91.33	86.09	90.27	46.57	88.09	89.84	88.43	87.19
CIFAR-100	67.83	66.95	67.58	67.08	59.26	65.44	13.45	61.43	63.54	62.05	60.37

(d) Results of LPSC with different architectures

Architecture	AlexNet	VGGNet	ResNet $(size, L_r, L_\theta, g)$	
hy.-para. L-1+	11,3,8,2	9,2,6,3	13,2,6,3	5,2,6,2
hy.-para. oth.	9,2,6,3	-	-	5,2,6,2
Layer/Block	1,2	1+	1+	1+,all
#params(M)	2.31	20.08	0.27	0.39
CIFAR-10	**78.28**	**94.01**	**92.11**	91.82
CIFAR-100	**47.31**	**73.13**	66.97	**67.98**

responses may dominant repeatedly in many regions for different center locations, which suppress other useful local information.

Effects of center pixel convolution. In the fourth column of Tab. 7, we remove the center pixel convolution, i.e., the first term in Eq. (3). Center pixel convolution enlarges the importance of the center pixel. Contextual information itself may be sufficient for classification when there are few classes. For more complex tasks with more classes, center pixel convolution may provide complementary information.

Running times. On the CIFAR10 dataset, the training time for one epoch and the testing time for AlexNet are 3.4808 and 0.9083, respectively; after replacing conventional convolutions with LPSCs in the first two layers, the training time for one epoch and the testing time are 23.3981 and 3.7476, respectively. In our implementation, LPSC runs much slower than conventional convolution, but

this is because we use of-the-shell conventional convolution modules to implement LPSC. To this end, we must first apply log-polar space pooling with the fold and unfold operations in Pytorch, which consume much time and space complexity. LPSC can be greatly accelerated if it is directly implemented with CUDA or by directly adapting the underlying code of convolutions in the integrated framework.

A.2 Comparison with other convolution methods

Dilated convolution [61] can also exponentially increase the LRF without increasing the number of parameters. Deformable convolution [6] adaptively adjusts the LRF by using additional parameters to infer the offsets for each position. We use the Pytorch implementation of deformable convolution[8] in our experiments. Different from LPSC where regions are divided in the log-polar space, we can also averagely divide the kernel into different square regions, e.g., a 9×9 kernel can be divided into 3×3 regions with a size of 3×3. All positions in the same square region share the same parameter. We denote this alternative convolution method by *square convolution*, which also increases LRF with fewer parameters. Similarly, they can also be used to replace conventional convolution at different layers in different architectures.

In Tab. 8, we compare LPSC with conventional convolution, dilation convolution, deformable convolution, and square convolution in the three architectures, respectively. For dilation convolution, square convolution, and LPSC, the second and third rows show the hyper-parameters of the corresponding kernels in the first convolution layer and in other layers or blocks, respectively. We run all models for only one time. "Size" indicates the kernel size. For VGGNet and ResNet, "1+" indicates the first convolution layer before all blocks. The fourth row indicates the indexes of layers or blocks in which conventional convolution is replaced by the corresponding convolution.

The second columns show the results of the three original architectures. With fewer or comparable parameters, LPSC outperforms conventional convolution in AlexNet and VGGNet, and obtains comparable results in ResNet.

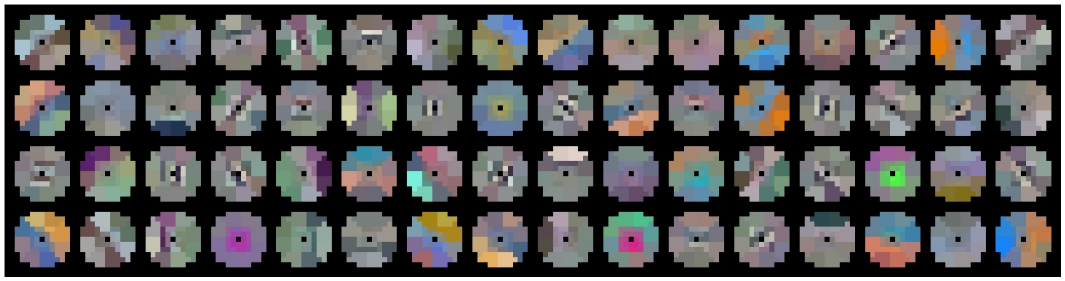
The third column blocks show the results of dilated convolution with different hyper-parameters in different layers. The hyper-parameters, including the kernel size and the dilation rate, are set to keep the total number of parameters and the LRF comparable to conventional convolution and LPSC. In AlexNet and VGGNet, LPSC outperforms dilated convolution with different hyper-parameters significantly. This shows the effectiveness of spatial structure and parameter sharing in LSPC. Applying dilated convolution in higher layers also leads to worse performances, which further verifies our analysis in Sec. A.1, but LPSC outperforms dilated convolution. When only used in the first layer of ResNet, sometimes dilated convolution achieves slightly better results than LPSC. The reason may be that ResNet can stack deeper layers with residual connections and hence achieve large LRF using multi-layer small regular kernels, which eases the need for large LRF in lower layers. Moreover, the non-uniform distribution of parameters in LPSC may cause information dispersion and over-smoothing, therefore it is more difficult to model residuals.

Deformable convolution introduces additional parameters. When applied to all blocks of VGGNet or ResNet, the parameters are more than doubled. Deformable convolution causes performance degradation of different architectures. LPSC also outperforms the average square convolution with different hyper-parameters. This indicates that the spatial structure designed in log-polar space can better capture the contextual information.

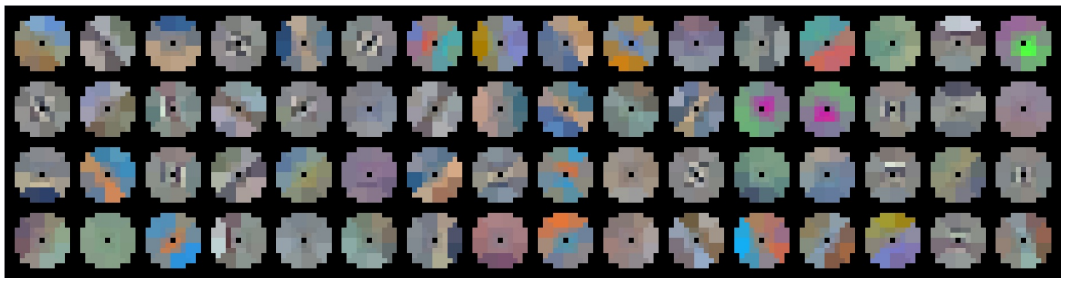
A.3 Visualization

Visualization of the learned LPSC kernels. In Fig. 6, we visualize the learned LPSC kernels in the first convolution layer of AlexNet on the CIFAR-10 and CIFAR-100 datasets. The LPSC kernels have a size of 11×11, 3 distance levels, 8 direction levels, and a growth factor of 2. Since LPSC kernels in the first layer have three channels, we normalize the values of kernels into the range of [0, 255] and view each position of the kernel as an RGB pixel. Different from conventional convolution kernels, in LPSC kernels, the closer to the center, the higher the regional resolution; the more outward, the larger the range for parameter sharing. We observe that the learned LPSC kernels capture some special local structures and contextual configuration. In some kernels, the weights for adjacent regions are

[8] https://github.com/oeway/pytorch-deform-conv



(a)



(b)

Figure 6: Visualization of the learned circular LPSC kernels without center convolution in the first convolution layer of Alexnet on (a) the CIFAR-10 dataset and (b) the CIFAR-100 dataset.

continuous; some kernels are sensitive to simple directions and edges, some others are sensitive to complex boundaries and color combinations, and in some other kernels, specific combinations of regions are highlighted. To fully utilize the space circumscribed by the LRF of the kernel, we fill four corners (positions that do not fall into the LRF) with the weights of corresponding nearest regions in all experiments, respectively, as shown in Fig. 7.

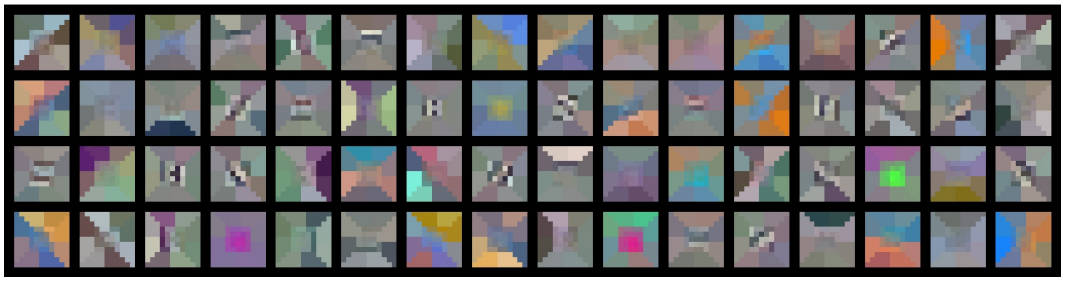
Comparison of effective receptive field (ERF): Fig. 8(a) and (e) show the estimated RFs of SimpleVGGNet on the default example using conventional convolutions and LPSCs in the first two layers by the gradient-based RF estimation[9], respectively. LPSC enlarges the estimated RFs from 14×14 to 22×22. The normalized gradient maps w.r.t. different positions of the output for estimating the RFs using conventional convolutions and LPSCs are shown in Fig. 8(b-d) and Fig. 8(f-h), respectively. With LPSC, gradients can be back-propagated to more pixels of the input image.

A.4 Additional discussions

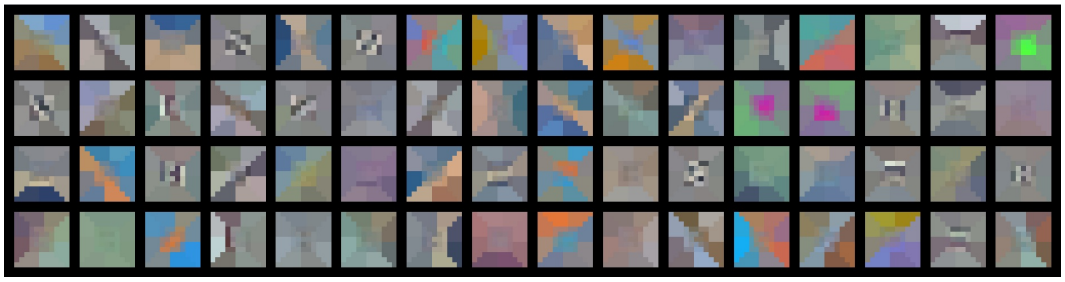
Advantages of log-polar space pooling. In log-polar space pooling, we use mean pooling to achieve the regularization for regions. In this way, LPSC does not increase the effective capacity of the model since only mean pooling within each region is performed w.r.t. the average operation in the innermost parentheses of Eq.(3) and no learnable parameters are involved in log-polar space pooling. If we learn parameters rather than performing pooling in the log-polar space pooling step, much more parameters will be introduced. In this step, other pooling methods are also allowed. For example, if sum pooling is used, it is equivalent to remove the regularization. If max pooling is used, LPSC can be viewed as a special dilated convolution with irregular and data-driven holes.

LPSC cannot be viewed as a special case of separable convolution [37], since after log-polar space pooling we are not performing 1×1 convolutions. On the contrary, LPSC can be combined with separable convolution, i.e., conventional convolutions can be replaced by separable convolutions after log-polar space pooling. When we use LPSC to replace the conventional convolution, after log-polar pooling, kernels with a comparable amount of parameters as the original convolution layer are used. Therefore, log-polar pooling can be approximately viewed as being additionally inserted into the

[9] https://github.com/fornaxai/receptivefield

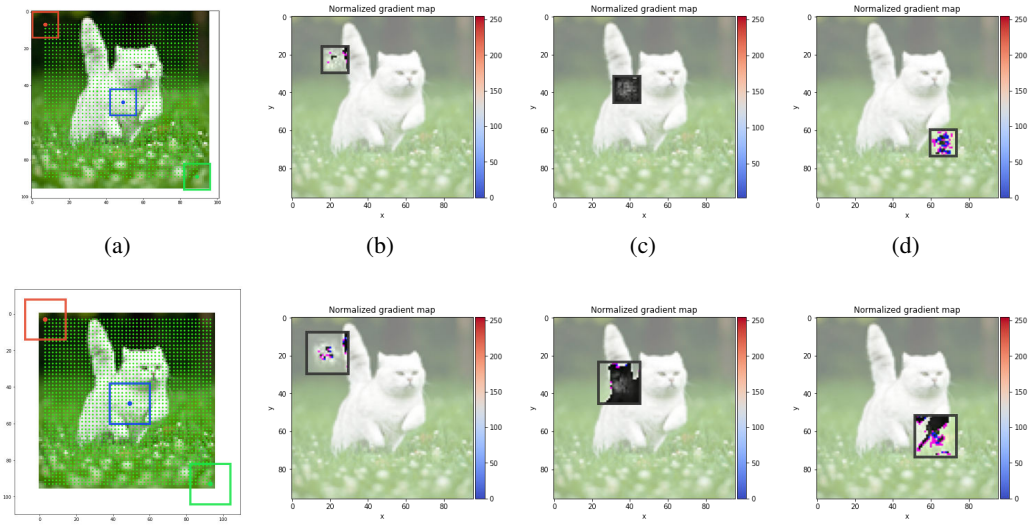


(a)



(b)

Figure 7: Visualization of the filled 11×11 LPSC kernels without center convolution in the first convolution layer of Alexnet on (a) the CIFAR-10 dataset and (b) the CIFAR-100 dataset.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 8: Estimated RFs with (a) conventional convolution and (e) LPSC. The normalized gradient map with (b-d) conventional convolution and (f-h) LPSC at different locations.

original architecture to increase the receptive field and non-linearly aggregate large-range contextual information.

Extending LPSC to tackle 1-D and 3-D data. LPSC kernel can directly degenerate to 1-D kernel, where there are only two directions (forward and backward) with respect to the center point and the kernel is divided into different distance levels along each direction, e.g., regions of the kernel in Fig. 1(b) along the vertical line are extracted to form a 1×7 1D LPSC kernel [w_{32}, w_{32}, w_{12}, w_{00}, w_{15}, w_{25}, w_{35}]. There are two possible ways to extend LPSC to 3-D kernels. (1) Cylindrical kernel: For a $h \times w \times t$ kernel, all t 2-D sub-kernels with a size of $h \times w$ are divided into different regions as in

Fig. 1(b), and regions at the same location in all t sub-kernels share the same weight. (2) Spherical kernel: distance levels can be naturally extended to 3 dimensions (similar to a small ball within a big ball); an additional direction dimension (such as a plane angle) is introduced to divide the direction (similar to cutting a watermelon). We will explore such extensions in our future work.