CONTEXTUAL CONVOLUTIONAL NETWORKS

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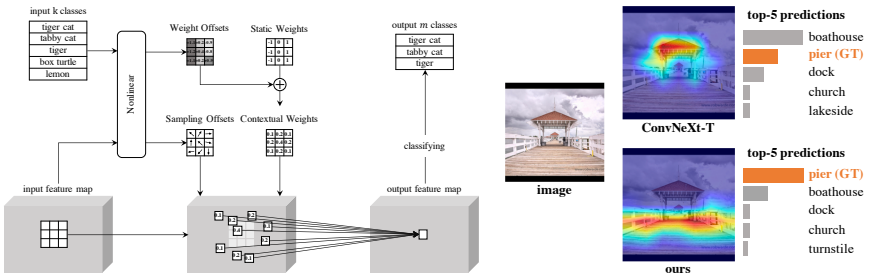
ABSTRACT

This paper presents a new Convolutional Neural Network, named Contextual Convolutional Network, that capably serves as a general-purpose backbone for visual recognition. Most existing convolutional backbones follow the representation-to-classification paradigm, where representations of the input are firstly generated by category-agnostic convolutional operations, and then fed into classifiers for specific perceptual tasks (e.g., classification and segmentation). In this paper, we deviate from this classic paradigm and propose to augment potential category memberships as contextual priors in the convolution for contextualized representation learning. Specifically, top-k likely classes from the preceding stage are encoded as a contextual prior vector. Based on this vector and the preceding features, offsets for spatial sampling locations and kernel weights are generated to modulate the convolution operations. The new convolutions can readily replace their plain counterparts in existing CNNs and can be easily trained end-to-end by standard back-propagation without additional supervision. The qualities of Contextual Convolutional Networks make it compatible with a broad range of vision tasks and boost the state-of-the-art architecture ConvNeXt-Tiny by 1.8% on top-1 accuracy of ImageNet classification. The superiority of the proposed model reveals the potential of contextualized representation learning for vision tasks. Code will be released in the final version.

1 INTRODUCTION

Beginning with the AlexNet (Krizhevsky et al., 2012) and its revolutionary performance on the ImageNet image classification challenge, convolutional neural networks (CNNs) have achieved significant success for visual recognition tasks, such as image classification (Deng et al., 2009), instance segmentation (Zhou et al., 2017) and object detection (Lin et al., 2014). Lots of powerful CNN backbones are proposed to improve the performances, including greater scale (Simonyan & Zisserman, 2014; Szegedy et al., 2015; He et al., 2016), more extensive connections (Huang et al., 2017; Xie et al., 2017; Sun et al., 2019; Yang et al., 2018), and more sophisticated forms of convolution (Dai et al., 2017; Zhu et al., 2019; Yang et al., 2019). Most of these architectures follow the representation-to-classification paradigm, where representations of the input are firstly generated by category-agnostic convolutional operations, and then fed into classifiers for specific perceptual tasks. Consequently, all inputs are processed by consecutive static convolutional operations and expressed as universal representations.

In parallel, in the neuroscience community, evidence accumulates that human visual system integrates both bottom-up processing from the retina and top-down modulation from higher-order cortical areas (Rao & Ballard, 1999; Lee & Mumford, 2003; Friston, 2005). On the one hand, the bottom-up processing is based on feedforward connections along a hierarchy that represents progressively more complex aspects of the visual scenes (Gilbert & Sigman, 2007). This property is shared with the aforementioned representation-to-classification paradigm (Zeiler & Fergus, 2014; Yamins et al., 2014). On the other hand, recent findings suggest that the top-down modulation affects the bottom-up processing in a way that enables the neurons to carry more information about the stimulus being discriminated (Gilbert & Li, 2013). For example, recordings in the prefrontal cortex reveal that the same neuron can be modulated to express different categorical representations as the categorical context changes (e.g., from discriminating animals to discriminating cars) (Cromer et al., 2010; Gilbert & Li, 2013). Moreover, words with categorical labels (e.g., "chair") can set visual priors that alter how visual information is processed from the very beginning, allowing for more effective



(a) 3×3 contextual convolution (b) visualization of learned features

Figure 1: **Left**: Illustration of a 3×3 contextual convolution. Given preceding instance features and top-k likely classes, sampling offsets and weight offsets are generated via non-linear layers. These offsets are added to regular grid sampling locations and static kernel weights of a standard convolution, respectively. **Right**: Grad-CAM visualization (Selvaraju et al., 2017) of the learned features of ConvNeXt-T (Liu et al., 2022) and our model. Grad-CAM is used to interpret the learned features by highlighting corresponding regions that discriminate the predicted class from other classes.

representational separation of category members and nonmembers (Lupyan & Ward, 2013; Boutonnet & Lupyan, 2015). Consequently, the top-down modulation can help to resolve challenging vision tasks with complex scenes or visual distractors. This property is however not considered by recent CNN backbones yet.

Motivated by the top-down modulation with categorical context in the brain, we present a novel architecture, namely Contextual Convolutional Networks (Contextual CNN), which augments potential category memberships as contextual priors in the convolution for representation learning. Specifically, the top-k likely classes by far are encoded as a contextual vector. Based on this vector and preceding features, offsets for spatial sampling locations and kernel weights are generated to modulate the convolutional operations in the current stage (illustrated in Fig. 1a). The sampling offsets enable free form deformation of the local sampling grid considering the likely classes and the input instance, which modulates *where* to locate information about the image being discriminated. The weight offsets allow the adjustment of specific convolutional kernels (e.g. "edges" to "corners"), which modulates *how* to extract discriminative features from the input image. Meanwhile, the considered classes are reduced from k to m ($m < k$) and fed to the following stage for further discrimination.

The proposed contextual convolution can be used as a drop-in replacement for existing convolutions in CNNs and trained end-to-end without additional supervision. Serving as a general-purposed backbone, the newly proposed Contextual CNN is compatible with other backbones or methods in a broad range of vision tasks, including image classification, video classification and instance segmentation. Its performance surpasses the counterpart models by a margin of $+1.8\%$ top-1 accuracy (with 3% additional computational cost) on ImageNet-1K (Deng et al., 2009), $+2.3\%$ top-1 accuracy on Kinetics-400 (Kay et al., 2017), $+1.1\%$ box AP and $+1.0\%$ mask AP on COCO (Lin et al., 2014), demonstrating the potential of contextualized representation learning for vision tasks. The qualitative results also reveal that Contextual CNN can take on selectivity for discriminative features according to the categorical context, functionally analogous to the top-down modulation of the human brain. As shown in Figure 1b, the counterpart model presents high but wrong score for "boathouse" w.r.t. the groundtruth class "pier" based on features of the oceanside house, which are shared across images of both classes. In contrast, the proposed model predicts correctly by generating features of the long walkway stretching from the shore to the water, which is a crucial cue to discriminate "pier" from "boathouse". We hope that Contextual CNN's strong performance on various vision problems can promote the research on a new paradigm of convolutional backbone architectures.

2 Related Works

Classic CNNs. The exploration of CNN architectures has been an active research area. VGG nets (Simonyan & Zisserman, 2014) and GoogLeNet (Szegedy et al., 2015) demonstrate the benefits of increasing depth. ResNets (He et al., 2016) verify the effectiveness of learning deeper networks

via residual mapping. Highway Network adopts a gating mechanism to adjust the routing of short connections between layers. More recently, some works include more extensive connections to further improve the capacity of CNNs. For example, DenseNet (Huang et al., 2017) connects each layer to every other layer. ResNeXt (Xie et al., 2017) aggregates a set of transformations via grouped convolutions. SENet recalibrates channel-wise feature response using global information. HRNet (Wang et al., 2020) connects the high-to-low resolution convolution streams in parallel. Other recent works improve the efficiency of CNNs by introducing depthwise separable convolutions (Howard et al., 2017) and shift operation (Wu et al., 2018a).

Dynamic CNNs. Different from the classic CNNs, dynamic CNNs adapt their structures or parameters to the input during inference, showing better accuracy or efficiency for visual recognition. One line of work drops part of an existing model based on the input instance. For example, some works skip convolutional layers on a per-input basis, either based on reinforcement learning (Wang et al., 2018; Wu et al., 2018b) or early-exit mechanism (Huang et al., 2018). The other line of work uses dynamic kernel weights or dynamic sampling offsets for different inputs. Specifically, some works aggregate multiple convolution kernels using attention (Yang et al., 2019; Chen et al., 2020) or channel fusion (Li et al., 2021). Ma et al. (2020) unifies kernel aggregation and channel excitation (Hu et al., 2018) via grouped fully-connected layers. Dai et al. (2017) and Zhu et al. (2019) learn different sampling offsets of convolution for each input image. The proposed Contextual CNN shares some similar high level spirit with these dynamic CNNs. A key difference of our method is that we explicitly adopt potential category memberships as contextual priors to constrain the adaptive inference.

3 Contextual Convolutional Networks

In this section, we describe the proposed Contextual Convolutional Networks. The overall architecture is introduced in Section 3.1. In Section 3.2, we present contextualizing layers, which generates contextual priors for Contextual CNN. In Section 3.3, we present contextual convolution blocks, which modulate the convolutions according to the contextual priors. Without loss of generality, this section is based on the ConvNeXt-T version (Liu et al., 2022), namely Contextual ConvNeXt-T.

3.1 Overall Architecture

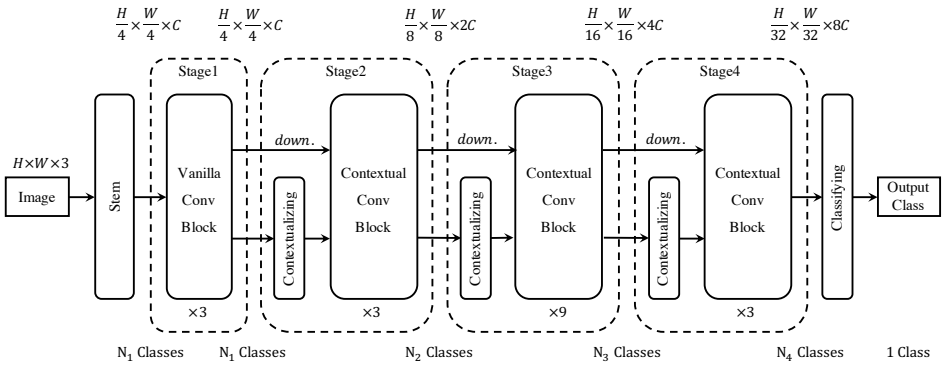


Figure 2: The architecture of a Contextual Convolutional Network (Contextual ConvNext-T). For simplicity, we denote the downsampling layers at "*Stage2-4*" by "*down.*".

An overview of Contextual CNN is presented in Figure 2. Consider an input RGB image of size $H \times W \times 3$, where H is the height and W is the width. N_1 is the number of all possible classes for the image (for example, N_1 is 1000 for ImageNet-1K (Deng et al., 2009)). A set of class embeddings $\mathcal{E}_1 = \left\{e_1^1, e_1^2, \cdots, e_1^{N_1}\right\}, e_1^i \in \mathbb{R}^d$ is generated from an embedding layer of size $N_1 \times d$. These class embeddings form the basis of categorical context in Contextual CNN.

Following common practice in prior vision backbones (He et al., 2016; Xie et al., 2017; Radosavovic et al., 2020; Liu et al., 2022), Contextual CNN consists of a stem ("*Stem*") that preprocesses the input image, a network body ("*Stage1-4*") that generates the feature maps of various granularities and a final head that predicts the output class. These components are introduced as follows.

The stem. Consistent with the standard design of ConvNeXt-T, the stem of Contexual ConvNeXt-T uses a 4×4, stride 4 convolution. The stem results in a $4\times$ downsampling of the input image, while the output features have $C = 96$ channels.

The body. Several vanilla convolutional blocks are applied on the output features of the stem. Maintaining the resolution of $\frac{H}{4} \times \frac{W}{4}$, these blocks have a output channel size of C and share the same architecture as their ConvNeXt counterparts. These blocks are referred to as "*Stage1*" in this work. A **contextualizing layer** (described in Section 3.2) is used afterwards to extract the contextual prior from the most likely classes. It reduces the number of considered classes from N_1 to N_2 and merges the embeddings of the output N_2 classes as a contextual prior. In parallel, a vanilla convolutional layer is used to $2\times$ downsample the resolution to $\frac{H}{8} \times \frac{W}{8}$ and doubles the channel size to $2C$. Taking the contextual prior and the downsampled feature map as inputs, a few **contextual convolution blocks** (described in Section 3.3) are applied for feature extraction. The contextualizing layer, the downsampling layer and the following blocks are denoted as "*Stage 2*". The procedure is repeated twice, in "*Stage 3*" and "*Stage 4*". Noting that "*Stage 3*" has a feature map resolution of $\frac{H}{16} \times \frac{W}{16}$, maintains $4C$ channels and reduces the number of considered classes to N_3. "*Stage 4*" has a feature map resolution of $\frac{H}{32} \times \frac{W}{32}$, maintains $8C$ channels and reduces the number of considered classes to N_4. As the number of considered classes reduces gradually, the contextual prior conveys more fine-grained categorical information (shown in Fig. 1a), which modulates the higher-level contextual convolutions to extract more discriminative features accordingly. Details of choosing the numbers of considered classes (N_2, N_3 and N_4) are in the supplementary material.

The head. The head of Contextual CNN shares the same procedure of reducing considered classes in the contextualizing layers (i.e., classifying in Section 3.2). And it finally reduces the number of classes from N_4 to 1. The final one class is used as the output class for the input image.

The loss. The number of considered classes are reduced progressively in Contextual CNN ($N_1 \rightarrow N_2 \rightarrow N_3 \rightarrow N_4 \rightarrow 1$). For stage i ($i \in \{1, 2, 3, 4\}$), we adopt a cross entropy loss over the corresponding classification scores s_i (introduced in Section 3.2). Following Radford et al. (2021), given the set of considered classes $\mathcal{N}_i$ ($|\mathcal{N}_i| = N_i$), the loss is calculated by:

$$\mathcal{L}_i = -\mathbb{I}\left(y \in \mathcal{N}_i\right) \cdot \log \frac{exp\left(s_i\left(y\right)/\tau\right)}{\sum_{j=1}^{N_i} \exp\left(s_i\left(\mathcal{N}_i^j\right)/\tau\right)}, \tag{1}$$

where $\mathbb{I}$ is an indicator function, y denotes the ground-truth class and τ is a learnable temperature parameter. The overall loss of Contextual CNN is computed by:

$$\mathcal{L} = \alpha\left(\mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3\right) + \mathcal{L}_4, \tag{2}$$

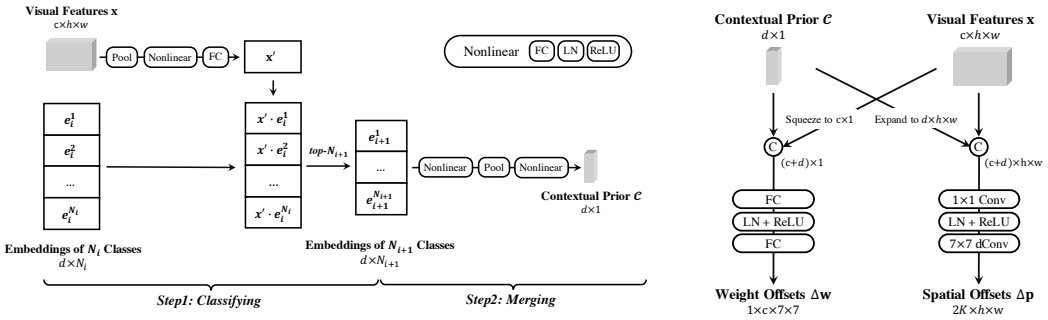
where α is a weight scalar. It is empirically set as 0.15 for all experiments in this paper. Discussions about choosing the value of α are in the supplementary material.

3.2 Contextualizing Layers

Each contextualizing layer consists of two steps. The first step, dubbed classifying, reduces the number of considered classes from N_i to N_{i+1}, where i is the index of the corresponding stage. The second step, dubbed merging, merges the embeddings of N_{i+1} considered classes into a contextual prior for later contextual convolution blocks.

Classifying. As shown in Figure 3a, given the N_i considered classes, a set of class embeddings $\mathcal{E}_i = \left\{e_i^1, e_i^2, \cdots, e_i^{N_i}\right\}$ is collected from the aforementioned embedding layer. Following Radford et al. (2021), to compare with these embeddings, the visual features $\mathbf{x}$ from the proceding stage are projected to the embedding space. The projection involves a global average pooling and two fully-connected (FC) layers. Layer Normalization (LN) (Ba et al., 2016) and ReLU (Nair & Hinton, 2010) are used between the FC layers. The output of the projection is a visual feature vector with dimension d. Then, cosine similarity is computed between the L2-normalized visual feature vector and the L2-normalized embeddings of the N_i classes. The resulting similarity vector s_i is used as the classification scores of the N_i classes for loss calculation. The top-N_{i+1} highest scoring classes in s_i are collected and propagated to the following merging step as well as the next stage.

Merging. Given the output N_{i+1} classes from the classifying step, we merge their embeddings $\mathcal{E}_{i+1} = \left\{e_{i+1}^1, e_{i+1}^2, \cdots, e_{i+1}^{N_{i+1}}\right\}$ into the contextual prior $\mathcal{C} \in \mathbb{R}^{d \times 1}$. Specifically, the merging



(a) Contextualizing (b) Modulation

Figure 3: Illustration of (a) contextualizing and (b) modulation using contextual prior and features.

operation uses two fully connected layers (followed by LN and ReLU) and a 1D global average pooling layer between them. The context prior $\mathcal{C}$ in this work summarizes the similarities and differences between the considered classes. It acts as task information for the extraction of more discriminative features in the following contextual convolution blocks.

3.3 Contextual Convolution Block

A vanilla ConvNeXt block contains one 7×7 depthwise convolution and two 1×1 pointwise convolutions. A contextual convolution block in Contextual ConvNeXt-T is built by replacing the 7×7 depthwise convolution by a 7×7 contextual convolution with other layers unchanged.

For a vanilla 7×7 depthwise convolution, consider the convolution kernel $\mathbf{w}$ of size $1 \times c \times 7 \times 7$, where c is the input channel size[1]. For each position $\mathbf{p}$ on the output feature map $\mathbf{y}$, the convolution first samples $K = 49$ locations over the input feature map $\mathbf{x}$ using a regular grid $\mathbf{g}$, then sums all sampled values weighted by $\mathbf{w}$:

$$\mathbf{y}(\mathbf{p}) = \sum_{k=1}^{K} \mathbf{w}(k) \cdot \mathbf{x}(\mathbf{p} + \mathbf{g}(k)). \tag{3}$$

In contextual convolutions, we augment the kernel weight $\mathbf{w}$ with weight offsets $\Delta\mathbf{w}$, and augment the grid $\mathbf{g}$ with sampling offsets $\Delta\mathbf{p}$:

$$\mathbf{y}(\mathbf{p}) = \sum_{k=1}^{K} (\mathbf{w}(k) + \Delta\mathbf{w}(k)) \cdot \mathbf{x}(\mathbf{p} + \mathbf{g}(k) + \Delta\mathbf{p}(k)). \tag{4}$$

Weight offsets. The weight offsets $\Delta\mathbf{w}$ allow the adaptive adjustment of the convolution weights according to the contextual priors. As illustrated in Figure 3b, to obtain $\Delta\mathbf{w}$, we squeeze the input map $\mathbf{x}$ via global average pooling (GAP) and then concatenate the resulting feature vector with the contextual prior $\mathcal{C}$. Two FC layers with LN and ReLU between them are applied afterwards to generate $\Delta\mathbf{w}$. Notably, we configure the size of $\Delta\mathbf{w}$ as $1 \times c \times 7 \times 7$, same as the dimensions of w, to allow the summation in equation 4.

Sampling offsets. Following deformable convolutions (Dai et al., 2017; Zhu et al., 2019), the sampling offsets $\Delta\mathbf{p}$ are applied to enable free-form deformation of the sampling grid. In our case, we compute the sampling offsets considering not only the input features but also the contextual priors. As shown in Figure 3b, we first expand the contextual prior $\mathcal{C}$ to the same spatial shape of $\mathbf{x}$, then concatenate them along the channel dimension. The resulting maps are then fed to a nonlinear convolutional block consisting of one 1×1 convolution (followed by LN and ReLU) and one 7×7 depthwise convolution (with the same kernel size and dilation as the replaced vanilla convolution). The output sampling offsets have the same resolution as the input features. The channel size $2K$ corresponds to K 2D offsets.

[1]Depthwise convolutions operate on a per-channel basis and do not change the channel size of features.

To balance accuracy and efficiency, only one of every three blocks is replaced by contextual convolution block in Contextual ConvNeXt-T. More details are in the supplementary material.

4 EXPERIMENTS

In the following, the proposed Contextual CNN is compared with the state-of-the-arts (SOTAs) on three tasks, including image classification, video classification and instance segmentation. Then, we ablate important design elements and analyze the internal properties of Contextual CNN via exemplification and visualizations.

Table 1: Comparison with the state-of-the-arts on ImageNet-1K. "FLOPs" denotes multiply-add operations. Following Liu et al. (2021), inference throughput is measured on a V100 GPU.

model	image size	#param.	FLOPs	throughput (images/s)	top-1 acc.
RegNetY-4G (Radosavovic et al., 2020)	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G (Radosavovic et al., 2020)	224^2	39M	8.0G	591.7	81.7
RegNetY-16G (Radosavovic et al., 2020)	224^2	84M	16.0G	334.7	82.9
Swin-T (Liu et al., 2021)	224^2	28M	4.5G	757.9	81.3
Swin-S (Liu et al., 2021)	224^2	50M	8.7G	436.7	83.0
Swin-B (Liu et al., 2021)	224^2	88M	15.4G	286.6	83.5
ConvNeXt-T (Liu et al., 2022)	224^2	29M	4.5G	774.7	82.1
ConvNeXt-S (Liu et al., 2022)	224^2	50M	8.7G	447.1	83.1
ConvNeXt-B (Liu et al., 2022)	224^2	89M	15.4G	292.1	83.8
Contextual ConvNeXt-T (ours)	224^2	32M	4.6G	770.6	**83.9**
Contextual ConvNeXt-S (ours)	224^2	53M	8.9G	445.2	**84.6**
Contextual ConvNeXt-B (ours)	224^2	93M	15.8G	291.0	**85.2**

4.1 IMAGE CLASSIFICATION ON IMAGENET-1K

Settings. For image classification, we benchmark Contextual CNN on ImageNet-1K (Deng et al., 2009). It contains 1.28M training images and 50K validation images from $1,000$ classes. The top-1 accuracy on a single crop of size 224×224 is reported. To compare with the SOTAs, we instantiate Contextual CNN using the recent method ConvNeXt (Liu et al., 2022), dubbed Contextual ConvNeXt. Following (Touvron et al., 2021; Liu et al., 2021; 2022), we train the model for 300 epochs using an AdamW optimizer (Loshchilov & Hutter, 2017) with a learning rate of 0.001. There is a 20-epoch linear warmup and a cosine learning rate decaying schedule afterward. The batch size we use is 4096 and the weight decay is 0.05. We adopt the same augmentation and regularization strategies as Liu et al. (2022) in training. Unless otherwise specified, the channel size of class embeddings d is set as 256. The numbers of considered classes for the four stages on ImageNet-1K are empirically set as: $N_1 = 1000$, $N_2 = 500$, $N_3 = 200$ and $N_4 = 50$. Discussions about these parameters are in Section 4.3 and the supplementary material, respectively.

Results Table 1 presents the ImageNet-1K results of various SOTA architectures, including RegNet (Radosavovic et al., 2020), Swin Transformer (Liu et al., 2021) and ConvNeXt (Liu et al., 2022). Contextual ConvNeXt outperforms all these architectures with similar complexities, e.g., $+1.8\%$ vs. ConvNeXt-T, $+1.5\%$ vs. ConvNeXt-S and $+1.4\%$ vs. ConvNeXt-S. In addition to the substantially better performances, Contextual ConvNeXt enjoys high inference throughput that is comparable to Swin Transformer and ConvNeXt. The above results verify the effectiveness of Contextual CNN for large-scale image classification, showing the potential of contextualized represention learning.

4.2 EMPIRICAL EVALUATION ON DOWNSTREAM TASKS

Video classification on Kinetics-400. Kinetics-400 (Kay et al., 2017) is a large-scale video action classification dataset with 240K training and 20K validation videos from 400 action classes. We

Table 2: Kinetics-400 video action classifcation results using TSM (Lin et al., 2019). † denotes the reproduced results using the same training recipe.

backbone	image size	#frames	FLOPs	top-1	top-5
ResNet50	224^2	16	65G	74.7	91.4
ResNet101 †	224^2	16	125G	75.9	92.1
Contextual ResNet50 (ours)	224^2	16	68G	**77.0**	**93.1**

Table 3: COCO object detection and segmentation results using Mask-RCNN. Following Liu et al. (2021), FLOPs are calculated with image size 1280×800.

backbone	FLOPs	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}
Swin-T (Liu et al., 2021)	267G	46.0	68.1	50.3	41.6	65.1	44.9
ConvNeXt-T (Liu et al., 2022)	262G	46.2	67.9	50.8	41.7	65.0	44.9
Contextual ConvNeXt-T (ours)	267G	**47.3**	**69.0**	**52.2**	**42.7**	**66.2**	**45.6**

fine-tune TSM (Lin et al., 2019) model with a ResNet50-based Contextual CNN backbone (dubbed Contextual ResNet50) (He et al., 2016). For a fair comparison, the Contextual ResNet50 is firstly pretrained on ImageNet-1K using the same recipe as the original ResNet50, and then fine-tuned on Kinetics-400 using the same recipe as TSM. More details are deferred to the supplementary material.

Table 2 lists the video action classification results of Contextual ResNet50 and ResNet50 / ResNet101. It is observed that Contextual ResNet50 is +2.3%/+1.7% better on top-1/5 accuracy than ResNet50-based TSM with similar computation cost. Moreover, Contextual ResNet50 is even better than the more sophisticated backbone ResNet101. These results verify that the Contextual CNN architecture can be effectively extended to general visual recognition tasks like video classification.

Instance segmentation on COCO. The instance segmentation experiments are conducted on COCO (Lin et al., 2014), which contains 118K training and 5K validation images. We fine-tune Mask R-CNN (He et al., 2017) on the COCO dataset with the aforementioned Contextual ConvNeXt backbones. Following Swin Transformer (Liu et al., 2021), we use multi-scale training, AdamW optimizer, and a $3\times$ schedule. More details are presented in the supplementary material.

Table 3 shows the instance segmentation results of the proposed Contextual ConvNeXt, ConvNeXt and Swin Transformer. With similar model complexity, Contextual ConvNeXt achieves better performance than ConvNeXt and Swin-Transformer, in terms of both box and mask AP. This demonstrate that the superiority of Contextual CNN's contextualized representations still hold for downstream dense vision tasks (i.e., detection and segmentation), indicating that Contextual CNN is able to serve as a general-purpose backbone for computer vision.

4.3 Ablation Study

In this section, we ablate major design elements in the proposed Contextual Convolutional Networks, using ImageNet-1K image classification dataset. All instantiations in this subsection are based on ResNet50 (He et al., 2016). Details of the architecture are deferred to the supplementary material.

Table 4: Ablations on the proposed components. "Ctx" denotes contextualizing layers and "CtxConv" denotes contextual convolutions. "DeformV2" denotes deformable convolutions V2 (Zhu et al., 2019). The **bold** row denotes the final settings of Contextual CNN.

	model	#param.	FLOPs	top-1 acc.
a1	R50	25.5M	4.1G	76.58
a2	+ Ctx	25.7M	4.1G	77.18
a3	+ CtxConv	27.2M	4.2G	77.59
a4	+ DeformV2	25.7M	4.2G	77.24
a5	**+ Ctx + CtxConv**	**27.9M**	**4.3G**	**79.35**

Block design (Table 4). We empirically analyze the effect of the proposed components in our work: contextualizing layers and contextual convolutions. First, compared with vanilla ResNet50 (*a1*), simply using contextual prior $\mathcal{C}$ as an extra input to conventional residual blocks[2] (*a2*) shows a slightly better result ($+0.60\%$). This phenomenon reveals that feeding the contextual prior without modulation provides limited gains for representation learning. Second, applying contextual convolutions alone (*a3*) leads to a $+1.01\%$ gain on top-1 accuracy while a deformable counterpart alone (Zhu et al., 2019) shows a $+0.66\%$ gain (*a4*). These results imply that modulating convolutions according only to input features improves the expressive power of learned representations. This *spirit* is shared between contextual convolutions, deformable convolutions and other forms of dynamic convolutions (refer to Section 2). Third, combining the two proposed components, we observe a significant improvement of $+2.77\%$ compared to the vanilla model (*a5* vs. *a1*) and an improvement of $+1.76\%$ compared to the model with similar complexity (*a5* vs. *a3*). These results verify that the categorical context provides important cues about the more discriminative directions to modulate the convolutions, highlighting the advantage of using potential category memberships as contextual priors.

Table 5: Ablations on modulation. The **bold** row denotes the final settings of Contextual CNN.

	weight offset	sampling offset	#param.	FLOPs	top-1 acc.
b1			25.5M	4.1G	77.18
b2	✓		27.5M	4.2G	78.30
b3		✓	25.9M	4.3G	78.44
b4	✓	✓	**27.9M**	**4.3G**	**79.35**

Modulation design (Table 5). We investigate how the two forms of contextual modulations (weight offsets and sampling offsets) in convolutions affect the performance. Using weight/sampling offsets alone brings in a $+1.12\%$/$+1.26\%$ improvement (*b2*/*b3* vs. *b1*), which indicates that either form of the modulation leverages the contextual information to some degree. The combination of the two forms leads to a more significant gain of $+2.17\%$ (*b4* vs. *b1*). This result implies that the two forms of modulations complete each other.

Table 6: Ablations on contextualizing. The "✓" means the adoption of the contextual stages. d is the dimension of class embeddings. The **bold** row denotes the final settings of Contextual CNN.

	Stage1	*Stage2*	*Stage3*	*Stage4*	d	#param.	FLOPs	top-1 acc.
c1					256	25.5M	4.1G	76.58
c2				✓	256	26.7M	4.1G	77.86
c3			✓	✓	256	27.7M	4.2G	78.63
c4		✓	✓	✓	**256**	**27.9M**	**4.3G**	**79.35**
c5	✓	✓	✓	✓	256	28.0M	4.3G	77.99
c6		✓	✓	✓	64	27.3M	4.2G	77.59
c7		✓	✓	✓	128	27.5M	4.3G	78.44
c8		✓	✓	✓	512	28.3M	4.3G	78.89

Contextualizing design (Table 6). We investigate the influence of two hyperparameters: the number of contextualizing stages and the dimension of class embeddings d. The Contextual ResNet50 model with 3 contextual stages ("*Stage2-4*") yields the best top-1 accuracy compared to those with more or less contextual stages (*c3* vs. *c0*/*c1*/*c2*/*c4*). This suggests that the contextual modulation is more effective on middle-level and high-level features. Then, by increasing the dimension of class embeddings d, the top-1 accuracy of the model improves steadily and saturates at 256 (*c4* vs. *c6*/*c7*/*c8*), which reveals the strategy of choosing d in practice.

4.4 More Analysis

Analysis of generated features. We adopt Grad-CAM (Selvaraju et al., 2017) to interpret the learned features by highlighting the corresponding regions that discriminate different classes (shown in

[2]by expanding $\mathcal{C}$ to the shape of input features, then concatenating them along the channel dimension.

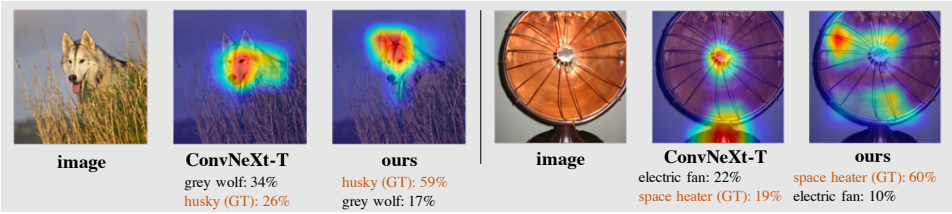
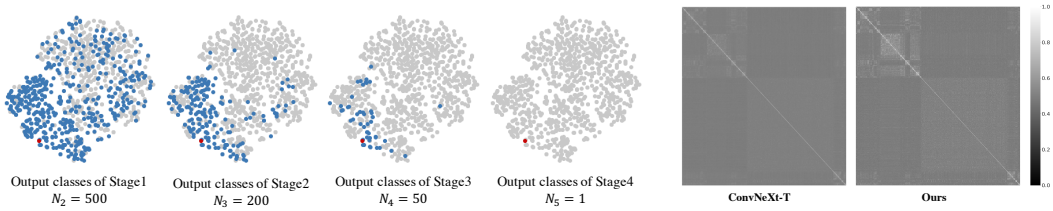


Figure 4: Comparison of Grad-CAM visualization results. The Grad-CAM visualization is calculated for the last convolutional outputs. "GT" denotes the ground truth class of the image.



(a) Selected classes from "*Stage1*" to "*Stage4*"

(b) Confusion matrix

Figure 5: **Left**: The t-SNE distributions of the class embeddings on ImageNet-1K. The points in blue denote the selected classes of the corresponding stage and the point in red denotes the groud-truth class. **Right**: Comparison of class embeddings between ConvNeXt-T and our Contextual ConvNext-T on ImageNet-1K. For ConvNeXt-T, we normalize the weights of the classifier as its class embeddings (1000×768). The confusion matrix denotes the similarity matrix of class embeddings (1000×1000).

Figure 4). Specifically, in the first case, the counterpart model (ConvNeXt-T) generates features w.r.t. the face of the animal, which shares similar appearances between the "husky" and the "wolf". Our model predicts by generating features of the ears that are long and stand upright on top, which are the key factor to differentiate "husky" from "wolf" (offset and triangular). In the second case, the counterpart model generates features corresponding to base and the center hub of the object, both are shared between the "space heater" and the "electric fan". In contrast, our model generates features w.r.t. the fan region, which is very different between the two categories in color and local parts (filaments vs. vanes). In summary, the counterpart model generates shared patterns of the most likely classes, which help select these classes out of 1000 classes but fail to further differentiate them. This behavior is reasonable since the convolutions in counterpart model are category-agnostic. Contextual CNN, in contrast, takes a few most likely classes as contextual priors and learns to generate more discriminative features with regard to these classes. As a result, our model is superior in resolving the above challenging cases that confuse the counterpart model.

Analysis of class embeddings. Figure 5a visualizes the stage-wise classifying of Contextual CNN. Specifically, we first adopt t-SNE (Van der Maaten & Hinton, 2008) to visualize the class embeddings of the model. We then highlight the selected classes from *"Stage1"* to *"Stage4"*. The results suggest that the contextual prior progressively converges to semantic neighbors of the groundtruth class. Figure 5b compares the confusion matrix of class embeddings between ConvNext-T and Contextual ConvNeXt-T. Following Chen et al. (2019), we uses the weights of the last fully-connected layer of ConvNext-T as its class embeddings. One can observe that the class embeddings learned by our model exhibit more effective separation of category memberships.

5 Conclusion

This paper presents Contextual Convolutional Network, a new CNN backbone which leverages a few most likely classes as contextual information for representation learning. Contextual CNN surpasses the performance of the counterpart models on various vision tasks including image classification, video classification and object segmentation, revealing the potential of contextualized representation learning for computer vision. We hope that Contextual CNN's strong performance on various vision problems can promote the research on a new paradigm of convolutional backbone architectures.

A ETHICS STATEMENT

First, most modern visual models, including Swin Trasnformer, ConvNeXt and the proposed Contextual CNN, perform best with their huge model variants as well as with large-scale training. The accuracy-driven practice consumes a great amount of energy and leads to an increase in carbon emissions. One important direction is to encourage efficient methods in the field and introduce more appropriate metrics considering energy costs. Then, many of the large-scale datasets have shown biases in various ways, raising the concern of model fairness for real-world applications. While our method enjoys the merits of large-scale training, a reasonable approach to data selection is needed to avoid the potential biases of visual inference.

B REPRODUCIBILITY STATEMENT

We make the following efforts to ensure the reproducibility of this work. First, we present detailed architecture specifications of Contextual ConvNeXt and Contextual ResNet50 in §1 of the supplementary material. Second, we provide detailed experimental settings (e.g., the training recipes) of Contextual CNN for all involved tasks in §2 of the supplementary material. Third, code of Contextual CNN (including the CUDA operator of contextual convolutions) will be released in our final version.

REFERENCES

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv preprint arXiv:1607.06450*, 2016.

Bastien Boutonnet and Gary Lupyan. Words jump-start vision: A label advantage in object recognition. *Journal of Neuroscience*, 2015.

Yinpeng Chen, Xiyang Dai, Mengchen Liu, Dongdong Chen, Lu Yuan, and Zicheng Liu. Dynamic convolution: Attention over convolution kernels. In *CVPR*, 2020.

Zhao-Min Chen, Xiu-Shen Wei, Peng Wang, and Yanwen Guo. Multi-label image recognition with graph convolutional networks. In *CVPR*, 2019.

Jason A Cromer, Jefferson E Roy, and Earl K Miller. Representation of multiple, independent categories in the primate prefrontal cortex. *Neuron*, 2010.

Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, and Yichen Wei. Deformable convolutional networks. In *ICCV*, 2017.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, 2009.

Karl Friston. A theory of cortical responses. *Philosophical transactions of the Royal Society B: Biological sciences*, 2005.

Charles D Gilbert and Wu Li. Top-down influences on visual processing. *Nature Reviews Neuroscience*, 2013.

Charles D Gilbert and Mariano Sigman. Brain states: top-down influences in sensory processing. *Neuron*, 2007.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *ICCV*, 2017.

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.

Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *CVPR*, 2018.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *CVPR*, 2017.

Gao Huang, Danlu Chen, Tianhong Li, Felix Wu, Laurens van der Maaten, and Kilian Q Weinberger. Multi-scale dense networks for resource efficient image classification. In *ICLR*, 2018.

Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, et al. The kinetics human action video dataset. *arXiv preprint arXiv:1705.06950*, 2017.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *NeurIPS*, 2012.

Tai Sing Lee and David Mumford. Hierarchical bayesian inference in the visual cortex. *Journal of the Optical Society of America. A, Optics, image science, and vision*, 2003.

Yunsheng Li, Yinpeng Chen, Xiyang Dai, Mengchen Liu, Dongdong Chen, Ye Yu, Lu Yuan, Zicheng Liu, Mei Chen, and Nuno Vasconcelos. Revisiting dynamic convolution via matrix decomposition. *arXiv preprint arXiv:2103.08756*, 2021.

Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In *ICCV*, 2019.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *ECCV*, 2014.

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. In *ICCV*, 2021.

Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. In *CVPR*, 2022.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.

Gary Lupyan and Emily J Ward. Language can boost otherwise unseen objects into visual awareness. *Proceedings of the National Academy of Sciences*, 2013.

Ningning Ma, Xiangyu Zhang, Jiawei Huang, and Jian Sun. Weightnet: Revisiting the design space of weight networks. In *ECCV*, 2020.

Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *ICML*, 2010.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, 2021.

Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Piotr Dollar. Designing network design spaces. In *CVPR*, 2020.

Rajesh PN Rao and Dana H Ballard. Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. *Nature neuroscience*, 1999.

Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *ICCV*, 2017.

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

Ke Sun, Bin Xiao, Dong Liu, and Jingdong Wang. Deep high-resolution representation learning for human pose estimation. In *CVPR*, 2019.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *CVPR*, 2015.

Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In *ICML*, 2021.

Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 2008.

Jingdong Wang, Ke Sun, Tianheng Cheng, Borui Jiang, Chaorui Deng, Yang Zhao, Dong Liu, Yadong Mu, Mingkui Tan, Xinggang Wang, et al. Deep high-resolution representation learning for visual recognition. *IEEE TPAMI*, 2020.

Xin Wang, Fisher Yu, Zi-Yi Dou, Trevor Darrell, and Joseph E Gonzalez. Skipnet: Learning dynamic routing in convolutional networks. In *ECCV*, 2018.

Bichen Wu, Alvin Wan, Xiangyu Yue, Peter Jin, Sicheng Zhao, Noah Golmant, Amir Gholaminejad, Joseph Gonzalez, and Kurt Keutzer. Shift: A zero flop, zero parameter alternative to spatial convolutions. In *CVPR*, 2018a.

Zuxuan Wu, Tushar Nagarajan, Abhishek Kumar, Steven Rennie, Larry S Davis, Kristen Grauman, and Rogerio Feris. Blockdrop: Dynamic inference paths in residual networks. In *CVPR*, 2018b.

Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In *CVPR*, 2017.

Daniel LK Yamins, Ha Hong, Charles F Cadieu, Ethan A Solomon, Darren Seibert, and James J DiCarlo. Performance-optimized hierarchical models predict neural responses in higher visual cortex. *Proceedings of the national academy of sciences*, 2014.

Brandon Yang, Gabriel Bender, Quoc V Le, and Jiquan Ngiam. Condconv: Conditionally parameterized convolutions for efficient inference. In *NeurIPS*, 2019.

Jiwei Yang, Xu Shen, Xinmei Tian, Houqiang Li, Jianqiang Huang, and Xian-Sheng Hua. Local convolutional neural networks for person re-identification. In *ACM MM*, 2018.

Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In *ECCV*, 2014.

Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In *CVPR*, 2017.

Xizhou Zhu, Han Hu, Stephen Lin, and Jifeng Dai. Deformable convnets v2: More deformable, better results. In *CVPR*, 2019.