InterActive: Inter-layer Activeness Propagation

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ABSTRACT

An increasing number of computer vision tasks can be tackled with deep features, which are the intermediate outputs of a pre-trained Convolutional Neural Network. Despite the astonishing performance, deep features extracted from low-level neurons are still below satisfaction, arguably because they cannot access the spatial context contained in the higher layers. In this paper, we present InterActive, a novel algorithm which computes the activeness of neurons and network connections. Activeness is propagated through a neuron in a top-down manner, carrying highlevel context and improving the descriptive power of lowlevel and mid-level neurons. Visualization indicates that neuron activeness can be interpreted as spatial-weighted neuron responses. We achieve state-of-the-art classification performance on a wide range of image datasets.

CONTRIBUTION

In this paper, we present a novel algorithm named **InterActive**, which is an efficient way of deep feature extraction from a single image.

First of all, we propose *a new baseline* for deep feature extraction. We do not simply resize the input image into the same fixed size (*e.g.*, 224×224 in VGGNet), but resize it into a larger scale (the area is approximately 512^2) while maximally preserving its aspect ratio. Such a simple improvement significantly boosts the classification accuracy with deep features.

In this method, the receptive field of a neuron is relatively small (*e.g.*, in the 19-layer VGGNet, a *pool-5* neuron can see 268^2 pixels) compared to the input image size (approximately 512^2). We argue that two problems occur under this setting, *i.e.*, the *big* problem and the *small* problem, illustrated in the figure to the right.

The main reason of these problems is that conventional deep feature extraction methods involve only forward-propagating visual signals through the network. The useful information contained in the remaining part of the network is discarded. We suggest that back-propagation is needed, which uses high-level visual clues to help mid-level feature extraction.

The proposed **InterActive** algorithm is based on such a motivation. A back-propagation process is performed in deep feature extraction, which uses a *score function* as the loss function. The gradient with respect to network weights can be considered as the *activeness* of each neuron connection, and collecting them obtains the *activeness* or the *weight* of each neuron.

THE PROPOSED ALGORITHM

Improved deep feature extraction

Input: an image with $W \times H$ pixels.
Reference model: a pre-trained VGGNet.
Original deep feature extraction: resizing the image into 224×224, passing it through the network, and extracting the intermediate response on the l-th layer.
Improved deep feature extraction: resizing the image so that:

- The aspect ratio is maximally preserved;
- The area (number of pixels) $\approx 512^2$;
- The width and height are multipliers of 32 (the down-sampling rate of VGGNet)

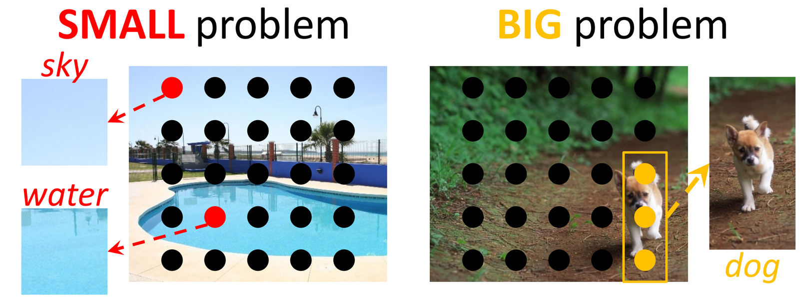
passing the resized image through the network, extracting the intermediate response on the l-th layer, and averaging over all the spatial positions.

Significant accuracy gain

	pool-5		*fc-6*	
	ORIG	IMPR	ORIG	IMPR
Caltech256	77.46	81.40	80.41	83.51
SUN-397	48.19	55.22	53.06	61.30
Flower-102	86.87	94.70	84.89	93.54

Two Problems

SMALL problem　　**BIG** problem



Main reason: conventional deep feature extraction only involves forward-propagation, useful information in high-level layers is discarded.
Solution: introducing a back-propagation process into deep feature extraction!

Inter-layer activeness propagation

Key idea: unsupervised back-propagation in the deep feature extraction process.

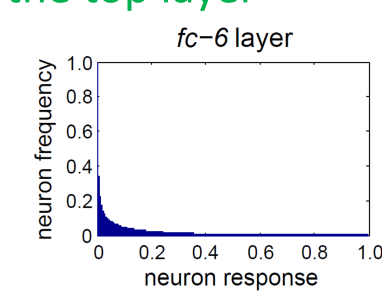
- Defining a *score function* at the top level;
- Back-propagating gradients to obtain the *activeness of neuron connections*;
- Collecting the activeness of neuron connections as the *activeness of neurons*.

Mathematical notations

A pre-trained CNN: $\mathbf{h}(\mathbf{X}^{(0)};\boldsymbol{\theta})$. $\mathbf{X}^{(0)}$ is the input, and $\boldsymbol{\theta}$ is the weights. $\mathbf{X}^{(t)}$ is the neuron responses on the t-th layer, a $W_t \times H_t \times D_t$ cube. $\mathbf{x}^{(t)}$ (D_t-dimensional) is the average over all spatial positions of $\mathbf{X}^{(t)}$.

Feature distribution on the top layer

We study the PDF of neuron responses on the T-th layer, i.e., the starting point of backprop. We assume the following PDF:



$f(\mathbf{x}^{(T)}) = C_p \times \exp\left\{-\left\|\mathbf{x}^{(T)}\right\|_p^p\right\}$, where p is the norm (1 or 2) and C_p is the normalization coefficient.

Score function and activeness of connections

The *activeness of neuron connection* is computed using the *score function*, *i.e.*, the gradient of log-distribution over $\boldsymbol{\theta}^{(t)}$: $\frac{\partial \ln f^{(T)}}{\partial \boldsymbol{\theta}^{(t)}} = \frac{\partial \ln f^{(T)}}{\partial \mathbf{X}^{(t+1)}} \times \frac{\partial \mathbf{X}^{(t+1)}}{\partial \boldsymbol{\theta}^{(t)}}$. Here, $\frac{\partial \ln f^{(T)}}{\partial \mathbf{X}^{(t+1)}}$ is the *layer score*, and $\frac{\partial \mathbf{X}^{(t+1)}}{\partial \boldsymbol{\theta}^{(t)}}$ is the *inter-layer activeness*.

Activeness (importance, weights) of neurons

Each neuron collects the activeness from the related connections as its activeness, $\tilde{x}_{w,h,d}^{(t)}$. $\tilde{x}_{w,h,d}^{(t)}$ is the improved deep feature, which can be **explicitly** written as $\tilde{x}_{w,h,d}^{(t)} = x_{w,h,d}^{(t)} \times \gamma_{w,h,d}^{(t)}$, where $\gamma_{w,h,d}^{(t)}$ is the weight of $x_{w,h,d}^{(t)}$ obtained with InterActive. We visualize these weights using a 2D heatmap: $\hat{\gamma}_{w,h}^{(t)} = \sum_d \gamma_{w,h,d}^{(t)}$.

Visualization results are shown in the figure to the right.

Visualization of neuron activeness

The ***last*** configuration: $T = L - 1$ (L is the total number of layers), the t-th layer receives the information from the highest level;
The ***next*** configuration: $T = t + 1$, the t-th layer receives the information from the next layer.

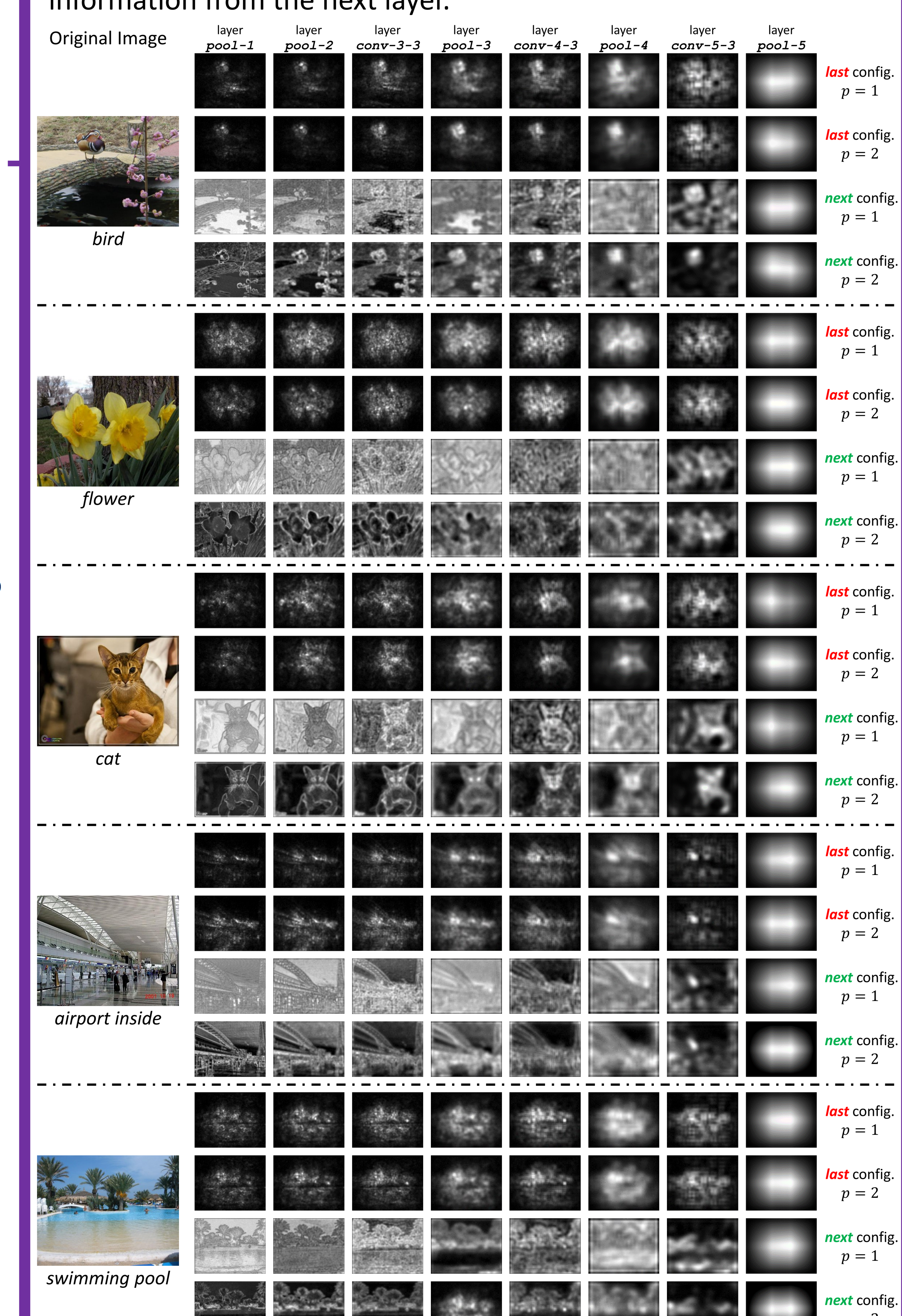


Image classification results with *low-level* (left), *mid-level* (middle) and *high-level* (right) deep features

Layer	Model	Dims	C-256	I-67	S-397	P-37	F-102	B-200
conv-3-3	ORIG, AVG-p	256	26.44	36.42	22.73	27.78	49.70	10.47
conv-3-3	ORIG, MAX-p	256	24.18	33.27	19.71	31.43	48.02	13.85
conv-3-3	***next***, $p=1$	256	27.29	36.97	22.84	28.89	50.62	10.93
conv-3-3	***next***, $p=2$	256	27.62	37.36	23.41	30.38	54.06	12.73
conv-3-3	***last***, $p=1$	256	34.50	39.40	25.84	49.41	60.53	24.21
conv-3-3	***last***, $p=2$	256	**35.29**	**39.68**	**26.02**	**50.57**	**61.06**	**25.27**
pool-3	ORIG, AVG-p	256	29.17	37.98	23.59	29.88	52.44	11.00
pool-3	ORIG, MAX-p	256	26.53	34.65	20.83	33.68	50.93	13.66
pool-3	***next***, $p=1$	256	29.09	38.12	24.05	30.08	52.26	10.89
pool-3	***next***, $p=2$	256	29.55	38.61	24.31	31.98	55.06	12.65
pool-3	***last***, $p=1$	256	36.96	41.02	26.73	50.91	62.41	24.58
pool-3	***last***, $p=2$	256	**37.40**	**41.45**	**27.22**	**51.96**	**63.06**	**25.47**

Layer	Model	Dims	C-256	I-67	S-397	P-37	F-102	B-200
conv-4-3	ORIG, AVG-p	512	49.62	59.66	42.03	55.57	76.98	21.45
conv-4-3	ORIG, MAX-p	512	47.73	55.83	40.10	59.40	75.72	23.39
conv-4-3	***next***, $p=1$	512	51.83	60.37	43.59	59.29	78.54	25.01
conv-4-3	***next***, $p=2$	512	53.52	60.65	44.17	63.40	80.48	31.07
conv-4-3	***last***, $p=1$	512	61.62	62.45	45.43	75.29	85.91	52.26
conv-4-3	***last***, $p=2$	512	**61.98**	**62.74**	**45.87**	**77.61**	**86.08**	**54.12**
pool-4	ORIG, AVG-p	512	60.39	66.49	49.73	66.76	85.56	28.56
pool-4	ORIG, MAX-p	512	57.92	62.96	47.29	69.23	84.39	30.01
pool-4	***next***, $p=1$	512	60.59	66.48	49.55	66.28	85.68	28.40
pool-4	***next***, $p=2$	512	62.06	66.94	50.10	72.40	87.36	37.49
pool-4	***last***, $p=1$	512	68.20	67.20	51.04	81.04	91.22	57.41
pool-4	***last***, $p=2$	512	**68.60**	**67.40**	**51.30**	**82.56**	**92.00**	**59.25**

Layer	Model	Dims	C-256	I-67	S-397	P-37	F-102	B-200
conv-5-3	ORIG, AVG-p	512	77.40	74.66	59.47	88.36	94.03	55.44
conv-5-3	ORIG, MAX-p	512	75.93	71.38	57.03	87.10	91.30	55.19
conv-5-3	***next***, $p=1$	512	80.31	**74.80**	59.63	90.29	94.84	67.64
conv-5-3	***next***, $p=2$	512	80.73	74.52	**59.74**	**91.56**	95.16	**73.14**
conv-5-3	***last***, $p=1$	512	80.77	73.68	59.10	90.73	95.40	69.32
conv-5-3	***last***, $p=2$	512	**80.84**	73.58	58.96	91.19	**95.70**	69.75
pool-5	ORIG, AVG-p	512	81.40	**74.93**	**55.22**	91.78	94.70	69.72
pool-5	ORIG, MAX-p	512	79.61	71.88	54.04	89.43	90.01	68.52
pool-5	***next***, $p=1$	512	81.50	72.70	53.83	92.01	95.41	71.96
pool-5	***next***, $p=2$	512	81.58	72.63	53.57	**92.30**	95.40	**73.21**
pool-5	***last***, $p=1$	512	81.60	72.58	53.93	92.20	**95.43**	72.47
pool-5	***last***, $p=2$	512	**81.68**	72.68	53.79	92.18	95.41	72.51

RESULTS

Results on some *small* datasets

We use the concatenated deep features from the *pool-1* layer through *fc-6* (9 layers in total)

Model	C-256	I-67	S-397	P-37	F-102	B-200
Murray *et.al.*, CVPR'14	–	–	–	56.8	84.6	33.3
Kobayashi *et.al.*, CVPR'15	58.3	64.8	–	–	–	30.0
Xie *et.al.*, ICCV'15	60.25	64.93	50.12	63.49	86.45	50.81
Ravazian *et.al.*, CVPR'14	–	69.0	–	–	86.8	61.8
Qian *et.al.*, CVPR'15	–	–	–	81.18	89.45	67.86
Xie *et.al.*, ICML'15	–	70.13	54.87	90.03	86.82	62.02
ORIG, AVG-pooling	84.02	78.02	62.30	93.02	95.70	73.35
ORIG, MAX-pooling	84.38	77.32	61.87	93.20	95.98	74.76
next, $p=1$	84.43	78.01	62.26	92.91	96.02	74.37
next, $p=2$	84.64	78.23	62.50	93.22	96.26	74.61
last, $p=1$	84.94	78.40	62.69	93.40	96.35	75.47
last, $p=2$	**85.06**	**78.65**	**62.97**	**93.45**	**96.40**	**75.62**

Please refer to our paper for more results

Results on ImageNet

We use **InterActive** to update the *fc-6* neurons

Model	top-1 error	top-5 error
VGGNet-16, *original*	24.2%	7.1%
VGGNet-16, *InterActive*	23.8%	6.9%
VGGNet-19, *original*	24.0%	7.0%
VGGNet-19, *InterActive*	23.5%	6.7%
VGGNet-combined, *original*	23.6%	6.7%
VGGNet-combined, *InterActive*	23.2%	6.5%

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