Squeeze-and-Excitation Networks

UST-ETRI
석사2학기 김형민
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Squeeze-and-Excitation Networks

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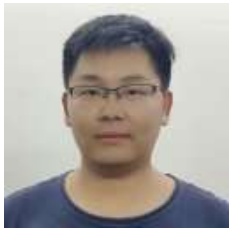


현재 bytedance AI 소속

현재 텐센트 AI 소속

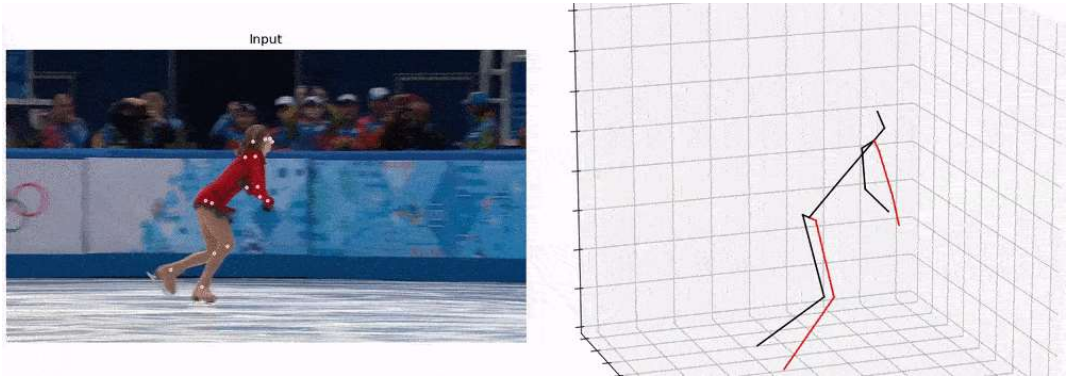
Momenta 소속

기관 : Momenta, Oxford 대학교
인용 : 6436회

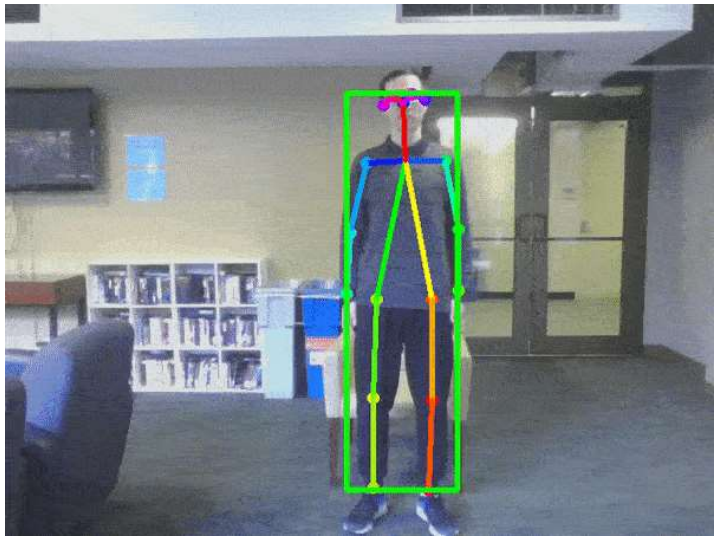
Motivation

CNN

최근 CNN 구조가 여러 Vision task를 효과적으로 풀게 되었다.



Pose estimation



Action recognition and detection

From : https://blog.usejournal.com/3d-human-pose-estimation-ce1259979306

대부분 응용에서 Visual feature extraction을 위해

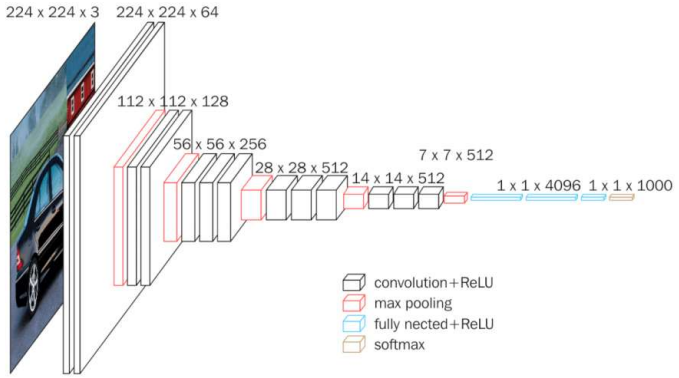
Image Net에서 잘 훈련된 모델을 가져와 backbone으로 사용 했다.

이미지넷 성능을 끌어 올리는 것이 주요 이슈.

때문에 Image Classification Task는 Computer Vision 분야의 core task이다.

Deeper

깊게 해보자.



[39] VGG-19 : 19층

같은 Receptive field 에서 작은 필터를 여러 번 하는 것이
큰 필터를 한번 한 것보다 깊게 구성이 가능하다.
Gradient vanishing 영향을 덜 받는다.

3x3 kernel의 등장

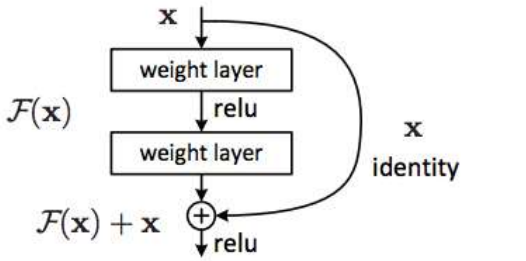


Figure 2. Residual learning: a building block.

[10] ResNet : 152층

Gradient vanishing 문제 해결위해
Skip-Connection 도입.
덧셈 항으로 gradients가 0이 되는 문제 해결.
동시에 Bottleneck 구조와 3x3 conv 적용

Residual Connection 등장.

[39] K. Simonyan et al. "Very Deep Convolutional Networks for Large-Scale Image Recognition", 2015, ICLR
[10] K. He et al. "Deep Residual Learning for Image Recognition", CVPR, 2015

Deeper makes better

method			error (%)
Maxout [10]			9.38
NIN [25]			8.81
DSN [24]			8.22
	# layers	# params	
FitNet [35]	19	2.5M	8.39
Highway [42, 43]	19	2.3M	7.54 (7.72±0.16)
Highway [42, 43]	32	1.25M	8.80
ResNet	20	0.27M	8.75
ResNet	32	0.46M	7.51
ResNet	44	0.66M	7.17
ResNet	56	0.85M	6.97
ResNet	110	1.7M	**6.43** (6.61±0.16)
ResNet	1202	19.4M	7.93

Table 6. Classification error on the **CIFAR-10** test set. All methods are with data augmentation. For ResNet-110, we run it 5 times and show "best (mean±std)" as in [43].

K. He et al. "Deep Residual Learning for Image Recognition", CVPR, 2016

More layers consume more cost

method			error (%)
Maxout [10]			9.38
NIN [25]			8.81
DSN [24]			8.22
	# layers	# params	
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또한, 많은 데이터를 필요로 한다.
하지만 질 좋은 데이터는 제작이 힘들다.

From : https://dataconomy.com/2017/04/history-neural-networks/

층을 많이 쌓는 것은 한계다.

동일한 수준에서 더 자세한 특징 추출이 이루어져야.

또한 Domain specific한 supervision없는
self-learning mechanism이어야 한다.

Capture the more spatial correlation

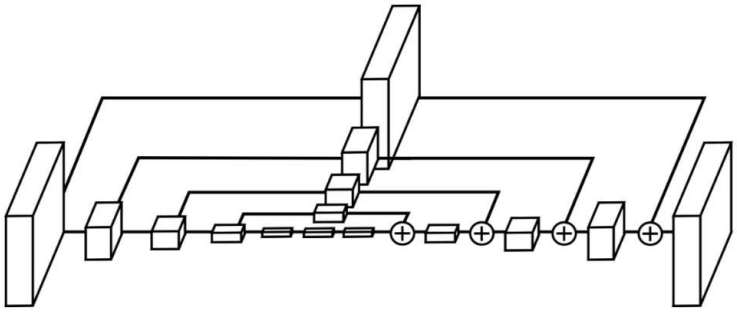
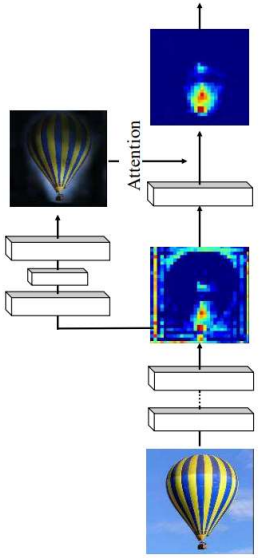


Fig. 3. An illustration of a single "hourglass" module. Each box in the figure corresponds to a residual module as seen in Figure 4. The number of features is consistent across the whole hourglass.

[31] stacked hourglass
multi-scale manner

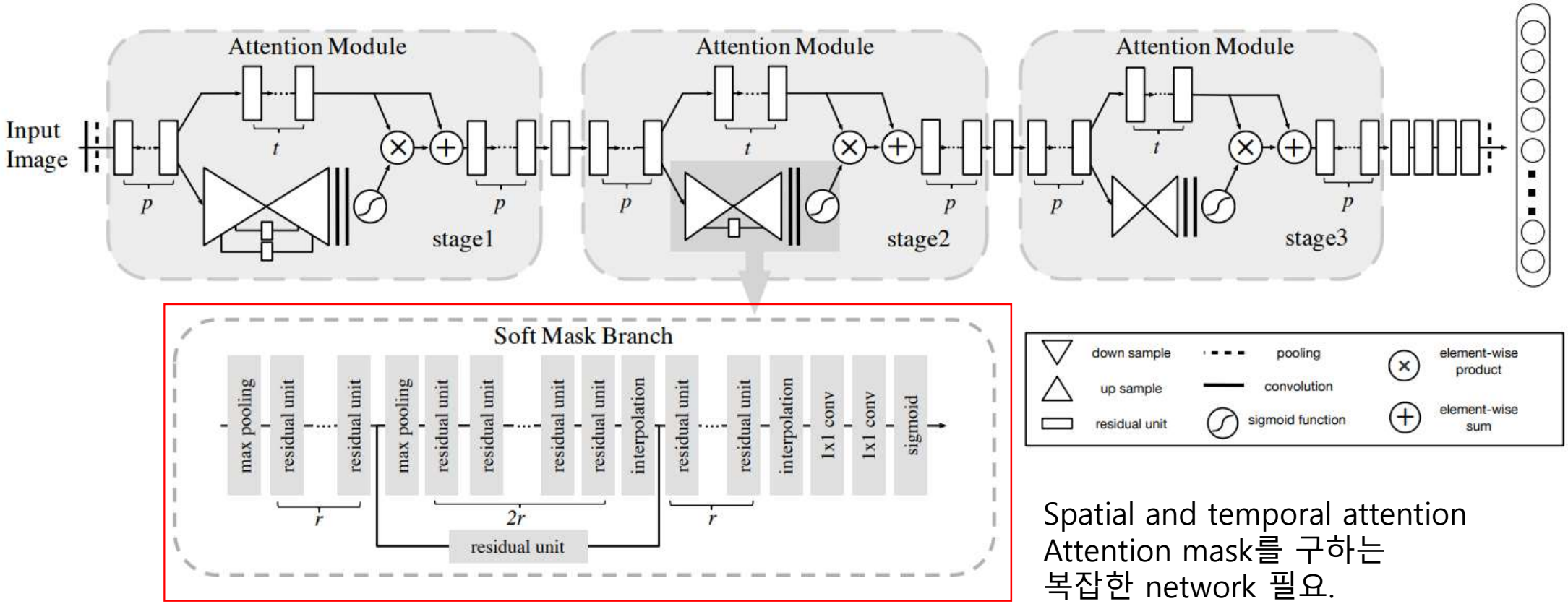


Attention mechanism

Residual attention (2017.04)

[31] A. Newell, et al. "Stacked hourglass networks for human pose estimation, ECCV, 2016
F. Wang et al. "Residual Attention Network for Image Classification", CVPR, 2017

Residual Attention Network (17.04)



Spatial and temporal attention
Attention mask를 구하는
복잡한 network 필요.

F. Wang et al. "Residual Attention Network for Image Classification", CVPR, 2017

Channel 간의 중요도는?

Filter in Computer Vision

Local image feature

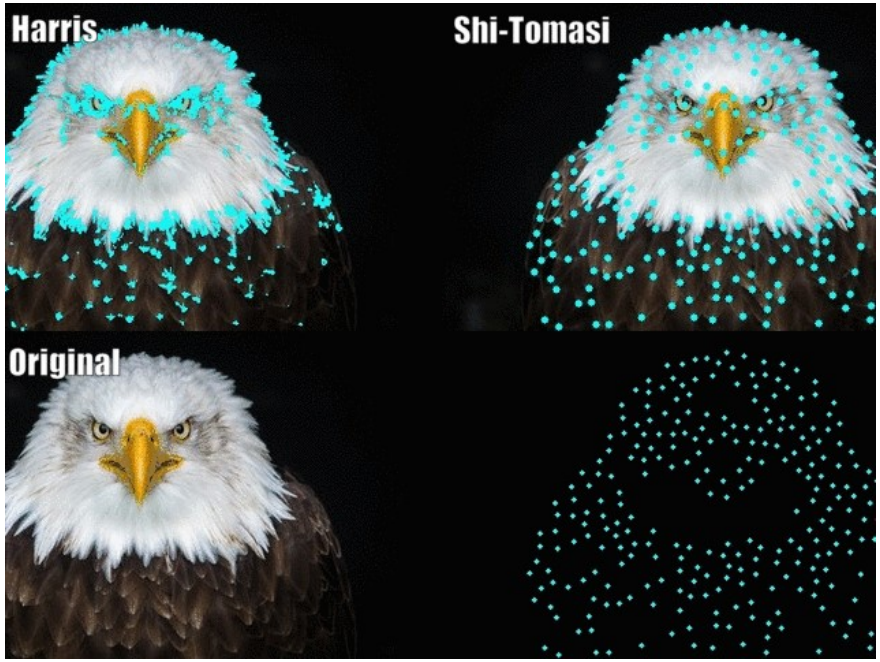
- An interesting part of an image

SIFT → Bag of visual word → Kernel SVM

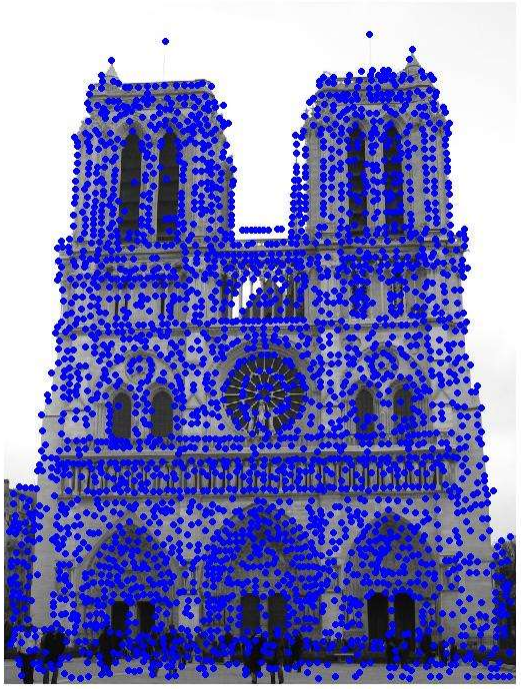
CNN 이전에는 unique하게 검출될 수 있는 부분에 대해서 feature extraction을 진행.

From : CS576 lecture note, Seung-hoon Hong, KAIST

Interest point detection using filters



Corner detection kernel



Blob detection kernel

From : https://medium.com/pixel-wise/detect-those-corners-aba0f034078b

Convolutions can learn the filters

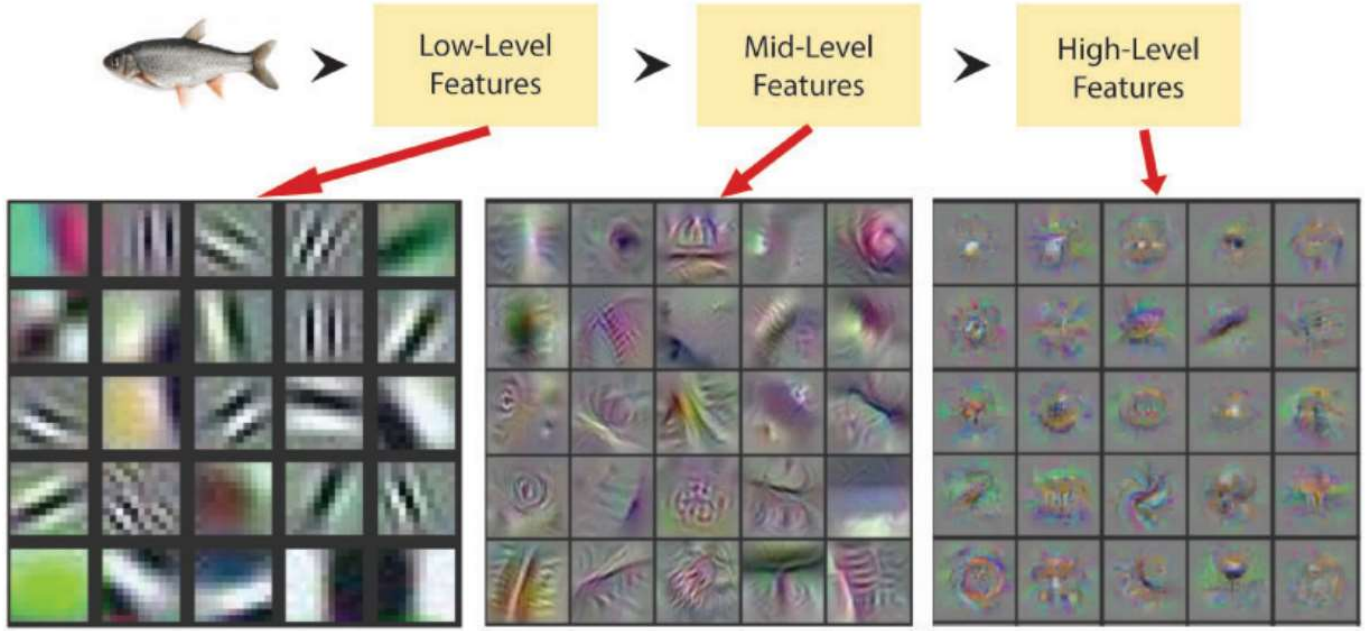


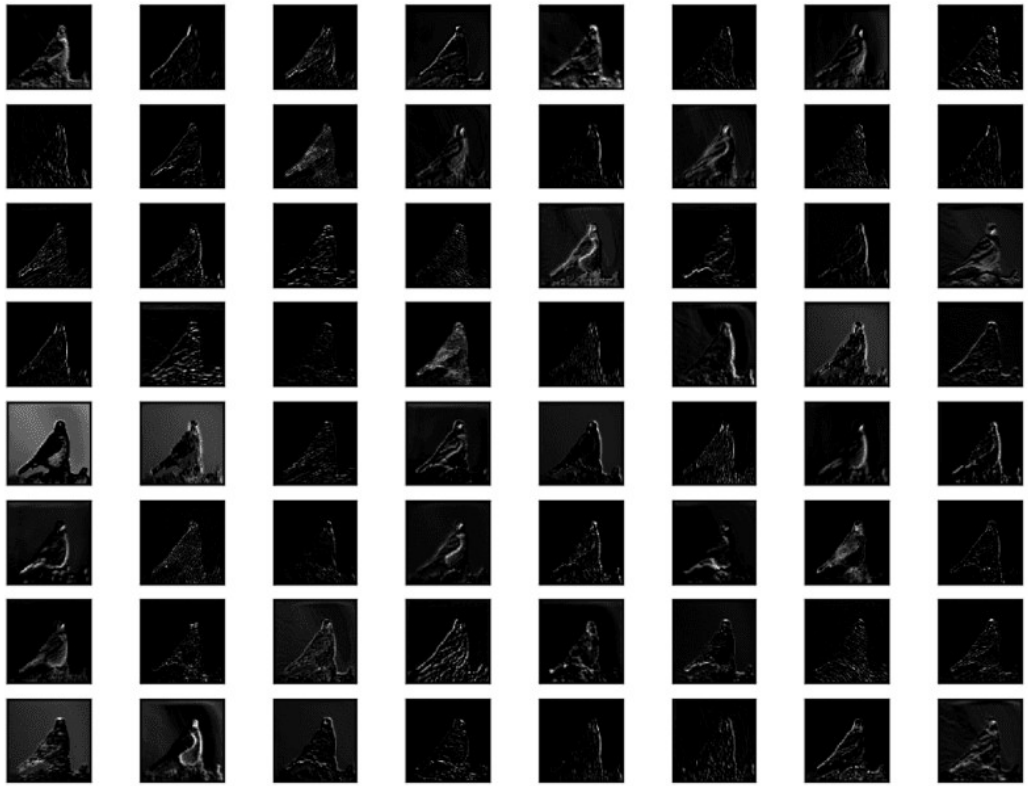
Figure 4. Hierarchical representation learning by a CNN where the initial layer detects simple patterns like edges and gradients while higher layers detect more abstract features (Yosinski *et al.*, 2015).

S. Ahmed Siddiui et al. "Automatic fish species classification in underwater videos: Exploiting pertrained deep neural network models to compensate for limited labelled data, ICES Journal of Marine Science, 2017

Block 1 in VGG

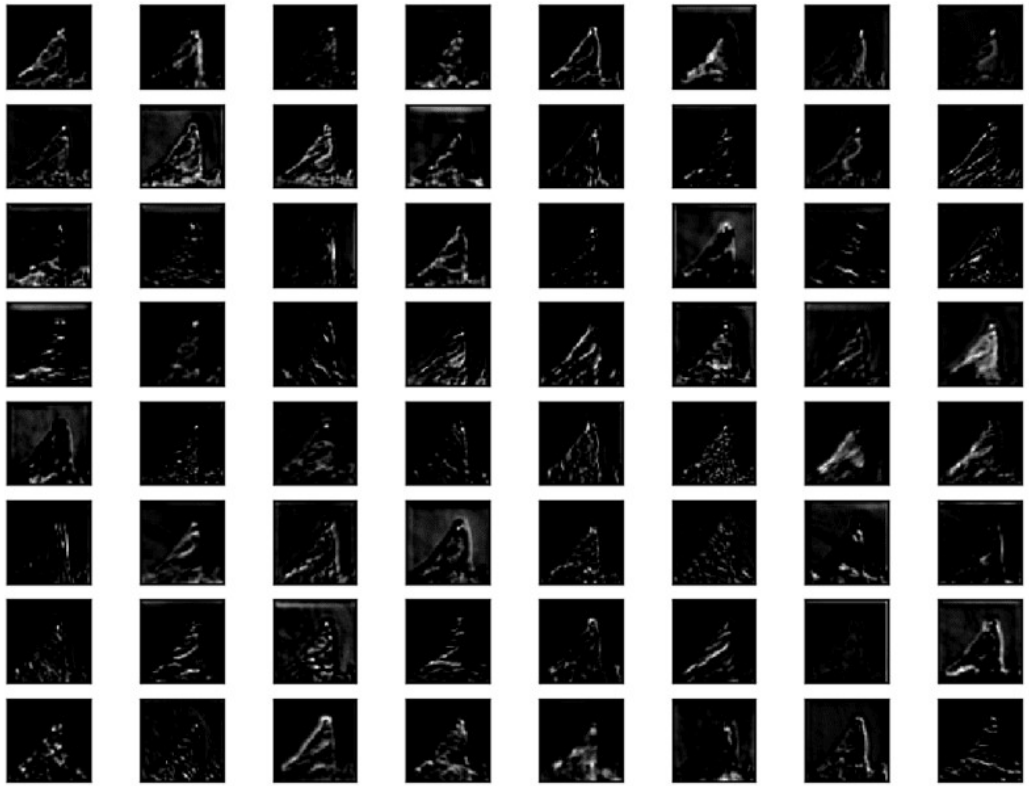
From : https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

Block 2 in VGG



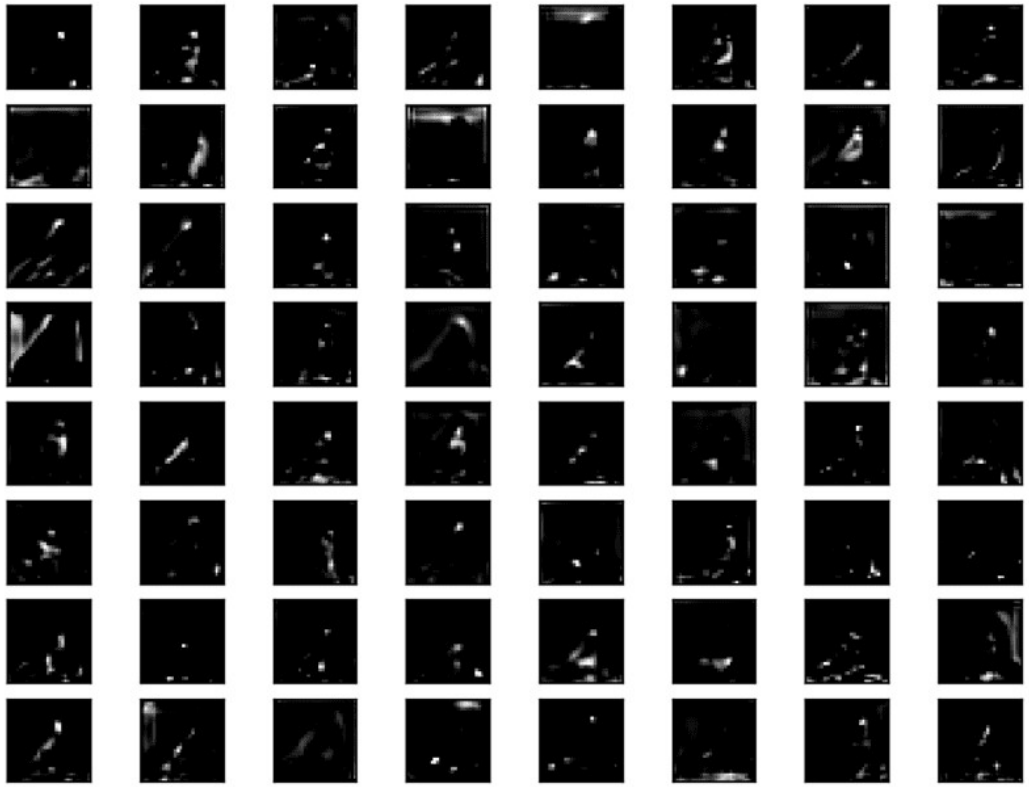
From : https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

Block 3 in VGG



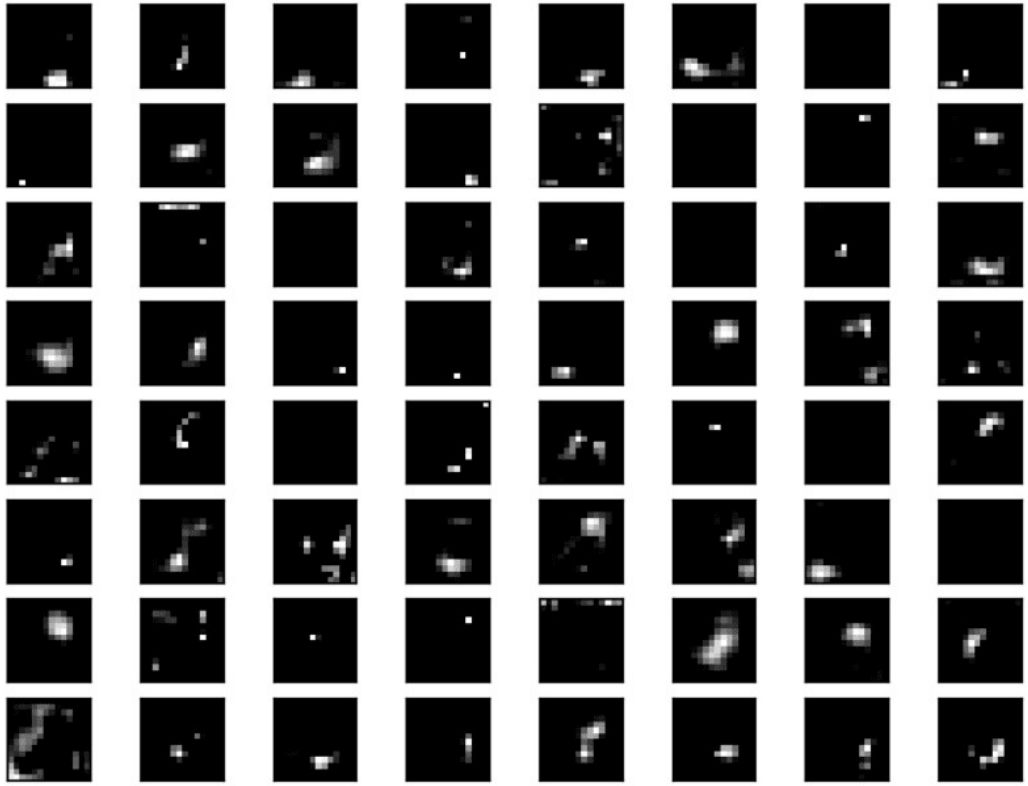
From : https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

Block 4 in VGG



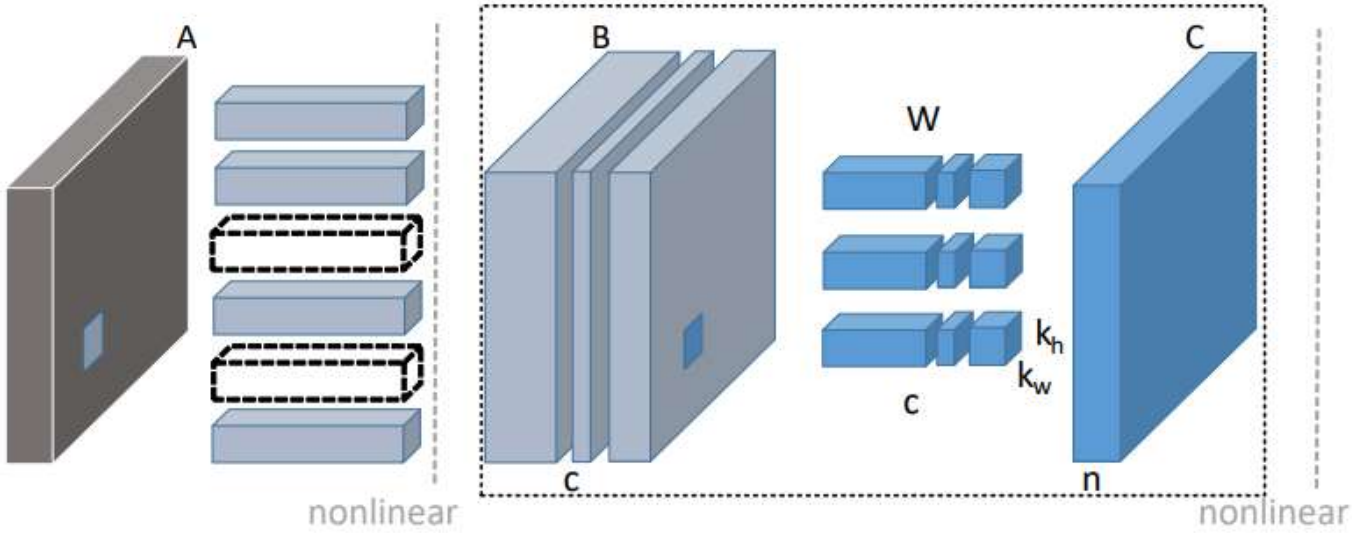
From : https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

Block 1 in VGG



From : https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

Channel pruning



"사실 일부 커널만이 의사결정에 중요한 영향을 미친다."

Y. He et al. "Channel Pruning for Accelerating Very Deep Neural Networks", 2017, ICCV

동적으로 Channel wise attention을 준다면?

Squeeze and Excitation Networks

Squeeze and Excitation Network (17.09)

기존의 대부분의 접근법들은 Spatial Attention 기법.
채널간 correlation만 고려하면 어떨까?

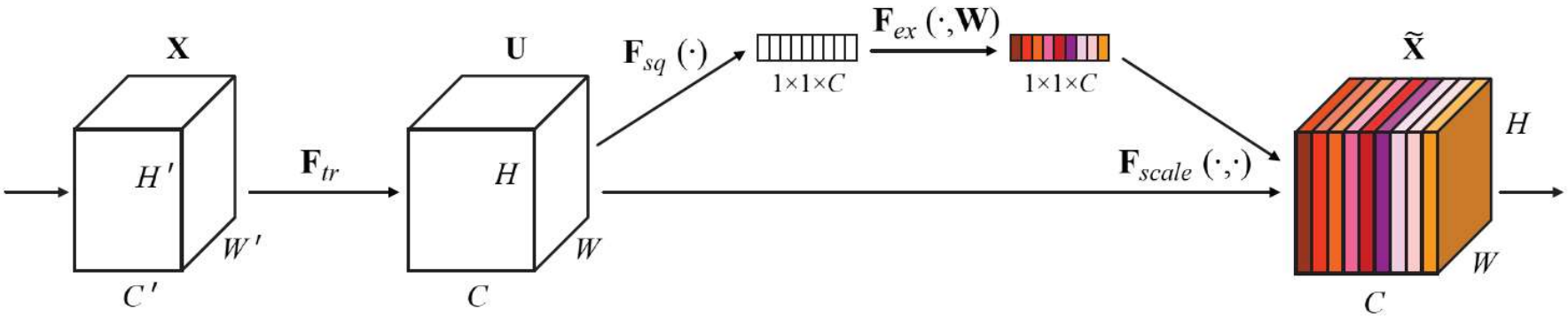


Figure 1: A Squeeze-and-Excitation block.

The Squeeze Operation

Global Average Pooling을 통한, channel-wise feature vector 생성

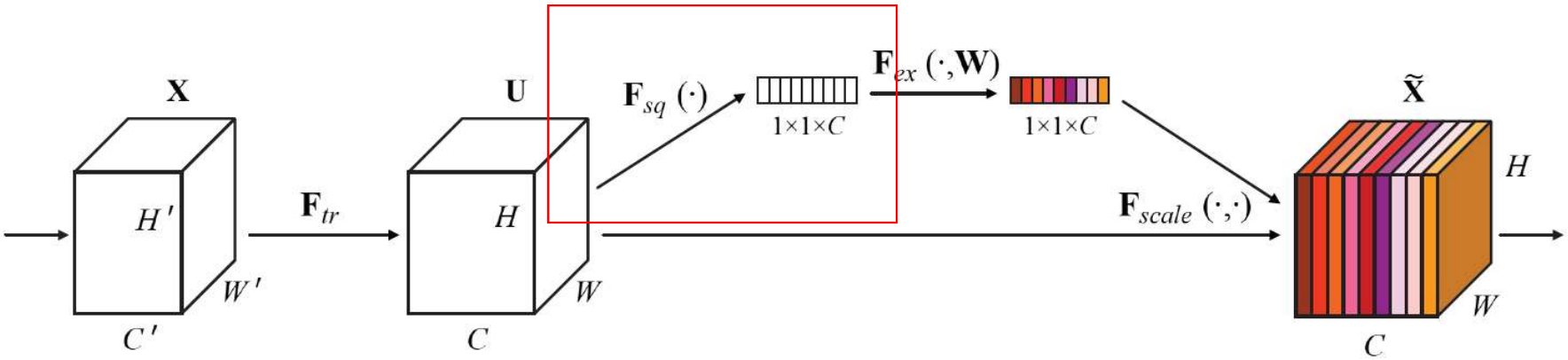


Figure 1: A Squeeze-and-Excitation block.

Global average pooling

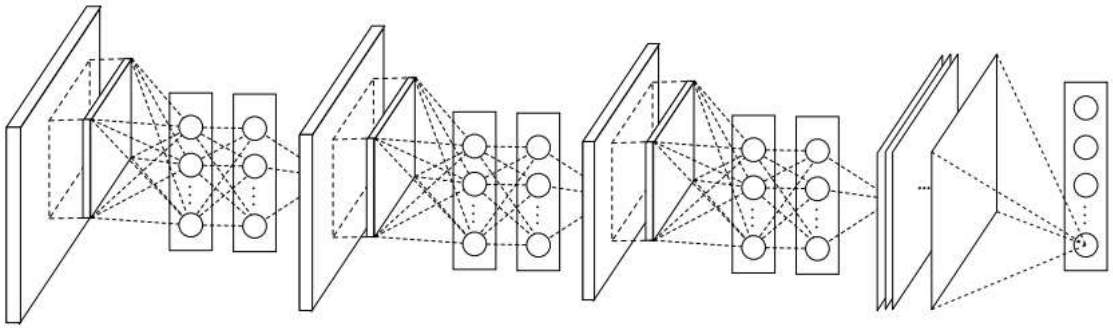
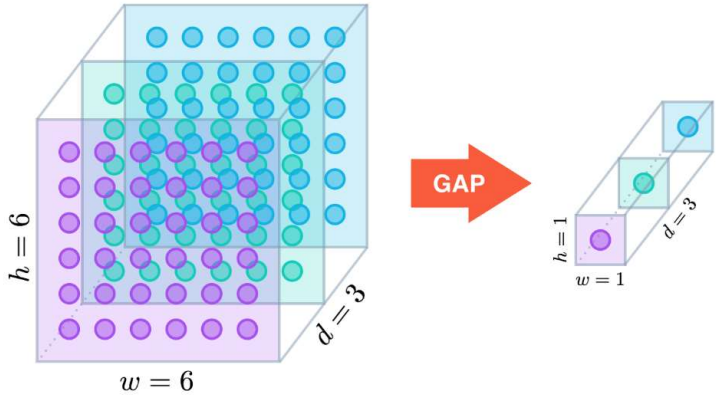


Figure 2: The overall structure of Network In Network. In this paper the NINs include the stacking of three mlpconv layers and one global average pooling layer.



M. Lin et al. "Network in Network", arXiv, 2013

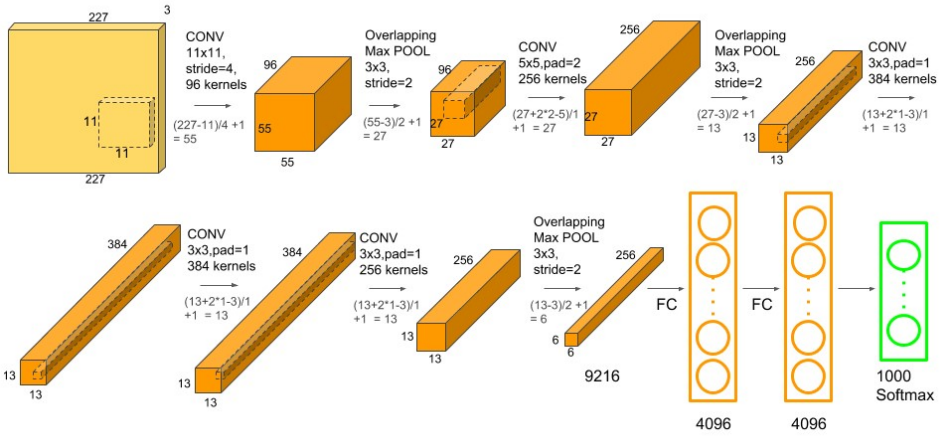
Global average pooling

However, the fully connected layers are prone to overfitting, thus hampering the generalization ability of the overall network. Dropout is proposed by Hinton et al. [5] as a regularizer which randomly sets half of the activations to the fully connected layers to zero during training. It has improved the generalization ability and largely prevents overfitting [4].

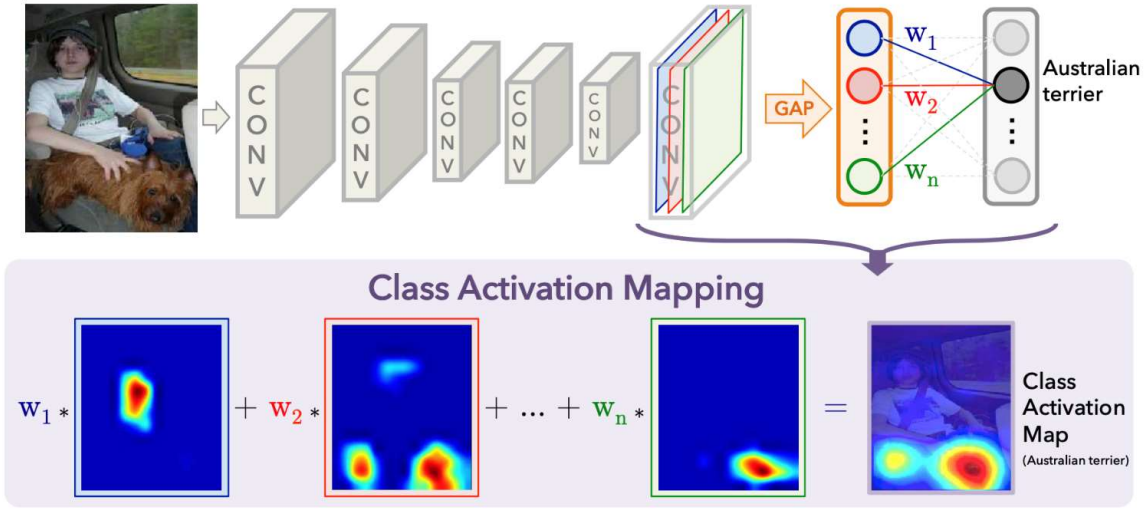
In this paper, we propose another strategy called global average pooling to replace the traditional fully connected layers in CNN. The idea is to generate one feature map for each corresponding category of the classification task in the last mlpconv layer. Instead of adding fully connected layers on top of the feature maps, we take the average of each feature map, and the resulting vector is fed directly into the softmax layer. One advantage of global average pooling over the fully connected layers is that it is more native to the convolution structure by enforcing correspondences between feature maps and categories. Thus the feature maps can be easily interpreted as categories confidence maps. Another advantage is that there is no parameter to optimize in the global average pooling thus overfitting is avoided at this layer. Futhermore, global average pooling sums out the spatial information, thus it is more robust to spatial translations of the input.

M. Lin et al. "Network in Network", arXiv, 2013

Global average pooling



[AlexNet]
Flatten -> conv 채널과 예측 class와의 관계 해석 불가능



[CAM]
GAP 적용시 어느 피처맵이 의사결정에 얼마나 영향을 미치는지 유추 가능.

B. Zhou, et al. "Learning Deep Features for Discriminative Localization", CVPR, 2016

The Squeeze Operation

Global Average Pooling을 통한, channel-wise feature vector 생성

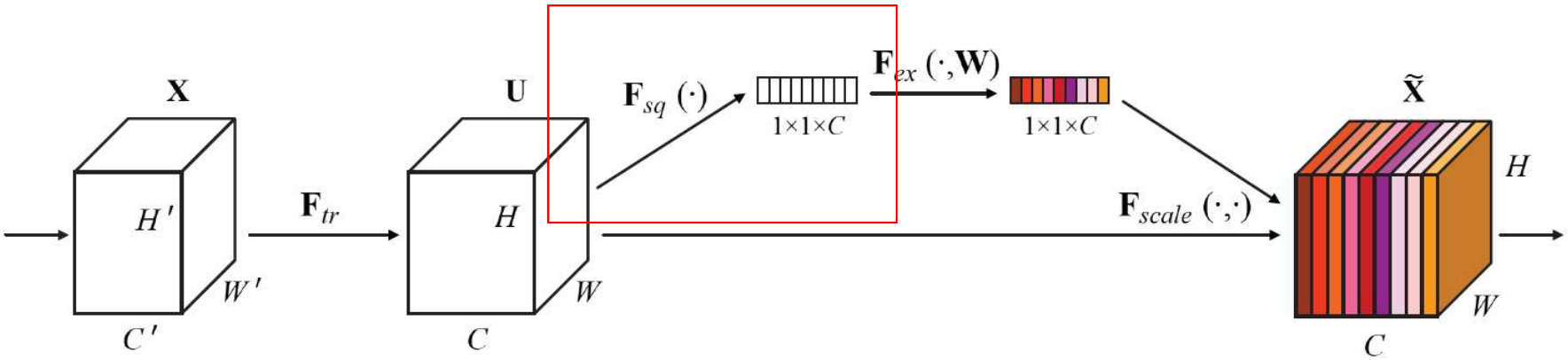
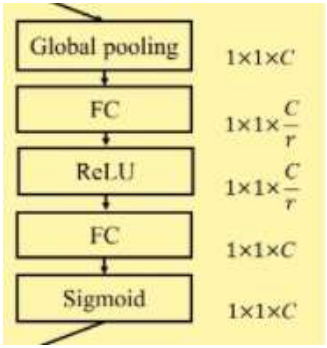


Figure 1: A Squeeze-and-Excitation block.

The Squeeze Operation

Channel-wise importance vector 생성.

Weights를 곱하여 중요도 모델링
Activation으로 sigmoid 사용해 0~1 사이 중요도값 출력



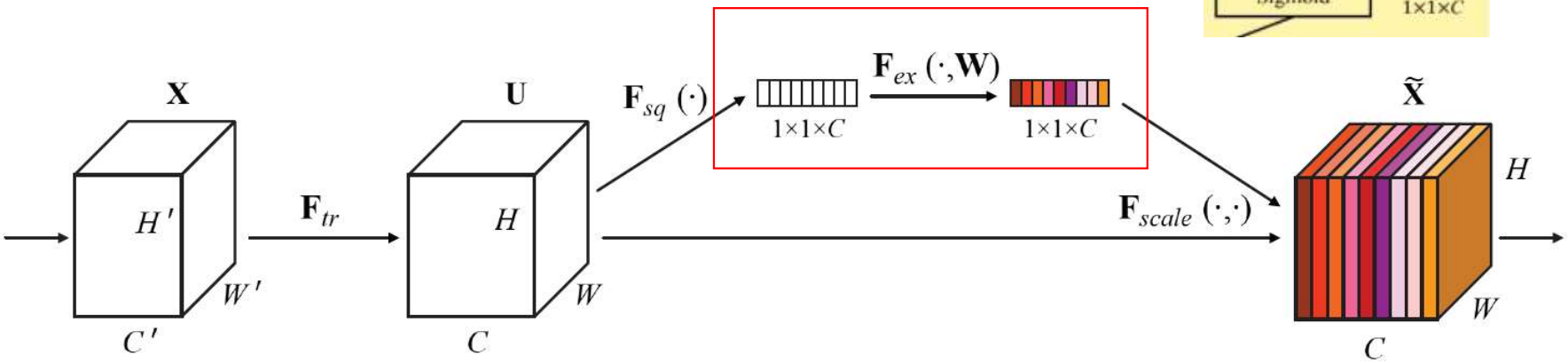
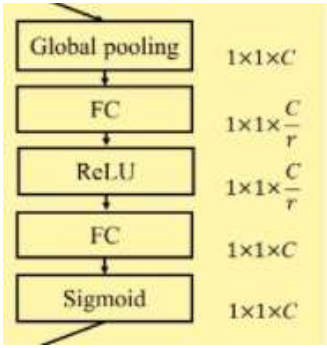


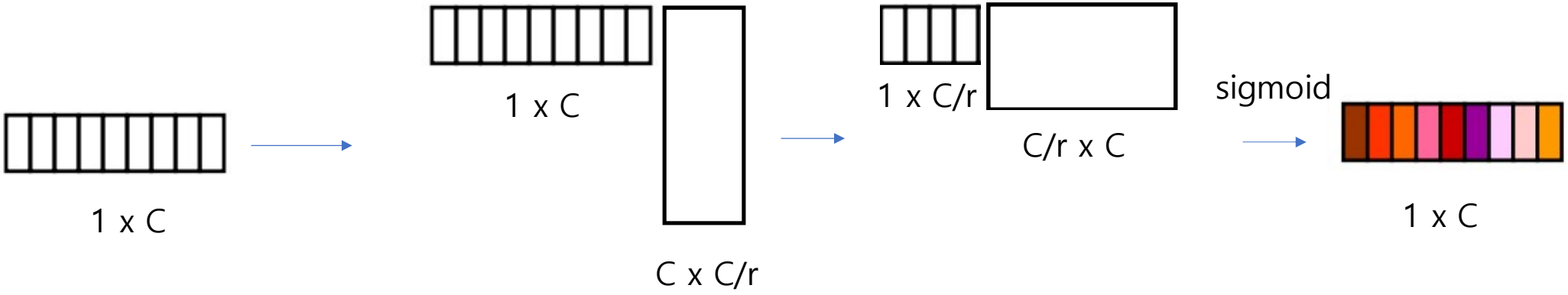
Figure 1: A Squeeze-and-Excitation block.

The Squeeze Operation



Bottleneck in squeeze operation

Efficiency를 위해 중간 weights matrix의 크기를 1/r로 감소



The Excitation Operation

Channel-wise Attention

앞서 모델링된 채널 중요도와 입력 피처맵 간 Hadamard product
입력 피처맵이 recalibration 되었다.

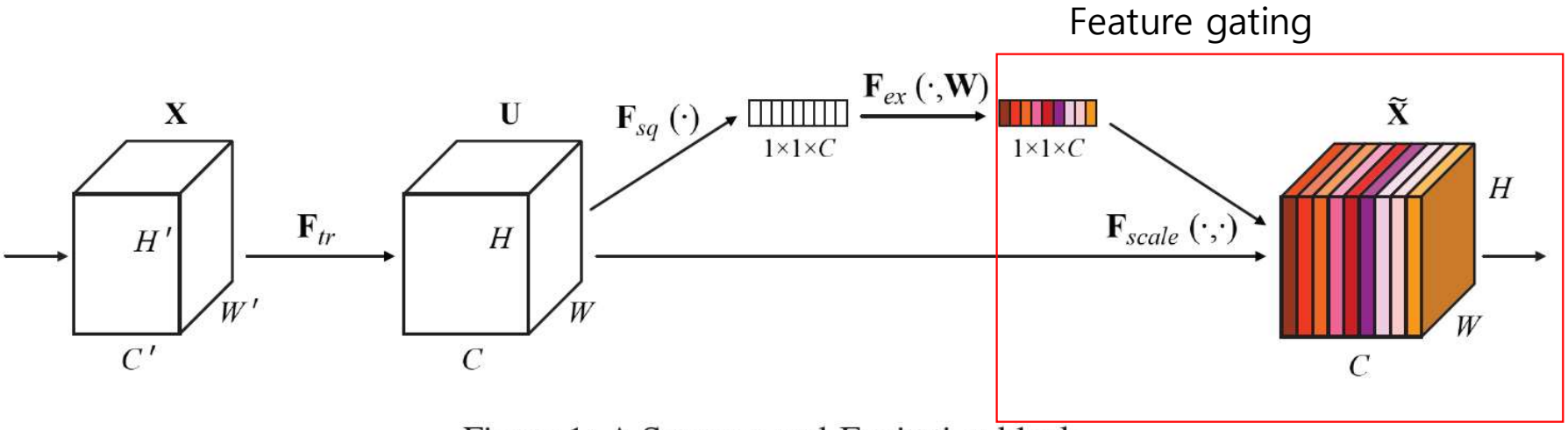


Figure 1: A Squeeze-and-Excitation block.

Contributions

1. 새로운 CNN backbone network를 설계 하는 것은 어렵다. (hyper parameters searching 등)

   > SE Block은 간단한 구조로 설계되어 구현이 쉽고 현재 SOTA 모델에 바로 적용 가능하다.

2. SE Block은 적은 cost로 동작한다.

   > 추가적인 parameter 연산이 원본 CNN 모델에 비해 매우 적기 때문에 efficient 하다.

3. 성능이 좋다.

   > 간단하여 이해하기 쉽고, 구현도 쉬우며, 적용성이 넓고, 높은 성능 향상효과가 있다.
   > ILSVRC 2017 classification competition에서 top5 error 2.251%를 기록하며 당해 1위 등극.

Experiments

Experiment : 다른 모델에 적용

	original		re-implementation			SENet		
	top-1 err.	top-5 err.	top-1err.	top-5 err.	GFLOPs	top-1 err.	top-5 err.	GFLOPs
ResNet-50 [10]	24.7	7.8	24.80	7.48	3.86	$23.29_{(1.51)}$	$6.62_{(0.86)}$	3.87
ResNet-101 [10]	23.6	7.1	23.17	6.52	7.58	$22.38_{(0.79)}$	$6.07_{(0.45)}$	7.60
ResNet-152 [10]	23.0	6.7	22.42	6.34	11.30	$21.57_{(0.85)}$	$5.73_{(0.61)}$	11.32
ResNeXt-50 [47]	22.2	-	22.11	5.90	4.24	$21.10_{(1.01)}$	$5.49_{(0.41)}$	4.25
ResNeXt-101 [47]	21.2	5.6	21.18	5.57	7.99	$20.70_{(0.48)}$	$5.01_{(0.56)}$	8.00
VGG-16 [39]	-	-	27.02	8.81	15.47	$25.22_{(1.80)}$	$7.70_{(1.11)}$	15.48
BN-Inception [16]	25.2	7.82	25.38	7.89	2.03	$24.23_{(1.15)}$	$7.14_{(0.75)}$	2.04
Inception-ResNet-v2 [42]	$19.9^{\dagger}$	$4.9^{\dagger}$	20.37	5.21	11.75	$19.80_{(0.57)}$	$4.79_{(0.42)}$	11.76

Table 2: Single-crop error rates (%) on the ImageNet validation set and complexity comparisons. The *original* column refers to the results reported in the original papers. To enable a fair comparison, we re-train the baseline models and report the scores in the *re-implementation* column. The *SENet* column refers to the corresponding architectures in which SE blocks have been added. The numbers in brackets denote the performance improvement over the re-implemented baselines. † indicates that the model has been evaluated on the non-blacklisted subset of the validation set (this is discussed in more detail in [42]), which may slightly improve results. VGG-16 and SE-VGG-16 are trained with batch normalization.

SE block 적용시 모든 modern architecture에서 error 감소 효과 보임
또한 ResNet구조로 살펴볼 때 모든 depth에서 동일하게 성능 향상 효과를 보임

Experiment : 다른 모델에 적용

	original		re-implementation			SENet		
	top-1 err.	top-5 err.	top-1err.	top-5 err.	GFLOPs	top-1 err.	top-5 err.	GFLOPs
ResNet-50 [10]	24.7	7.8	24.80	7.48	3.86	$23.29_{(1.51)}$	$6.62_{(0.86)}$	3.87
ResNet-101 [10]	23.6	7.1	23.17	6.52	7.58	$22.38_{(0.79)}$	$6.07_{(0.45)}$	7.60
ResNet-152 [10]	23.0	6.7	22.42	6.34	11.30	$21.57_{(0.85)}$	$5.73_{(0.61)}$	11.32
ResNeXt-50 [47]	22.2	-	22.11	5.90	4.24	$21.10_{(1.01)}$	$5.49_{(0.41)}$	4.25
ResNeXt-101 [47]	21.2	5.6	21.18	5.57	7.99	$20.70_{(0.48)}$	$5.01_{(0.56)}$	8.00
VGG-16 [39]	-	-	27.02	8.81	15.47	$25.22_{(1.80)}$	$7.70_{(1.11)}$	15.48
BN-Inception [16]	25.2	7.82	25.38	7.89	2.03	$24.23_{(1.15)}$	$7.14_{(0.75)}$	2.04
Inception-ResNet-v2 [42]	$19.9^{\dagger}$	$4.9^{\dagger}$	20.37	5.21	11.75	$19.80_{(0.57)}$	$4.79_{(0.42)}$	11.76

Table 2: Single-crop error rates (%) on the ImageNet validation set and complexity comparisons. The *original* column refers to the results reported in the original papers. To enable a fair comparison, we re-train the baseline models and report the scores in the *re-implementation* column. The *SENet* column refers to the corresponding architectures in which SE blocks have been added. The numbers in brackets denote the performance improvement over the re-implemented baselines. † indicates that the model has been evaluated on the non-blacklisted subset of the validation set (this is discussed in more detail in [42]), which may slightly improve results. VGG-16 and SE-VGG-16 are trained with batch normalization.

거의 없다시피한 GFLOPs 상승만으로 엄청난 성능 향상 달성.

Experiment : 다른 모델에 적용

	original		re-implementation				SENet			
	top-1 err.	top-5 err.	top-1 err.	top-5 err.	MFLOPs	Million Parameters	top-1 err.	top-5 err.	MFLOPs	Million Parameters
MobileNet [13]	29.4	-	29.1	10.1	569	4.2	$25.3_{(3.8)}$	$7.9_{(2.2)}$	572	4.7
ShuffleNet [52]	34.1	-	33.9	13.6	140	1.8	$31.7_{(2.2)}$	$11.7_{(1.9)}$	142	2.4

Table 3: Single-crop error rates (%) on the ImageNet validation set and complexity comparisons. Here, MobileNet refers to "1.0 MobileNet-224" in [13] and ShuffleNet refers to "ShuffleNet $1 \times (g = 3)$" in [52].

경량 구조에서도 상당한 error 감소 효과를 보임.

ImageNet2017 Competition

	224 × 224		320 × 320 / 299 × 299	
	top-1 err.	top-5 err.	top-1 err.	top-5 err.
ResNet-152 [10]	23.0	6.7	21.3	5.5
ResNet-200 [11]	21.7	5.8	20.1	4.8
Inception-v3 [44]	-	-	21.2	5.6
Inception-v4 [42]	-	-	20.0	5.0
Inception-ResNet-v2 [42]	-	-	19.9	4.9
ResNeXt-101 (64 × 4d) [47]	20.4	5.3	19.1	4.4
DenseNet-264 [14]	22.15	6.12	-	-
Attention-92 [46]	-	-	19.5	4.8
Very Deep PolyNet [51] †	-	-	18.71	4.25
PyramidNet-200 [8]	20.1	5.4	19.2	4.7
DPN-131 [5]	19.93	5.12	18.55	4.16
SENet-154	**18.68**	**4.47**	**17.28**	**3.79**
NASNet-A (6@4032) [55] †	-	-	17.3‡	3.8‡
SENet-154 (post-challenge)	-	-	**16.88‡**	**3.58‡**

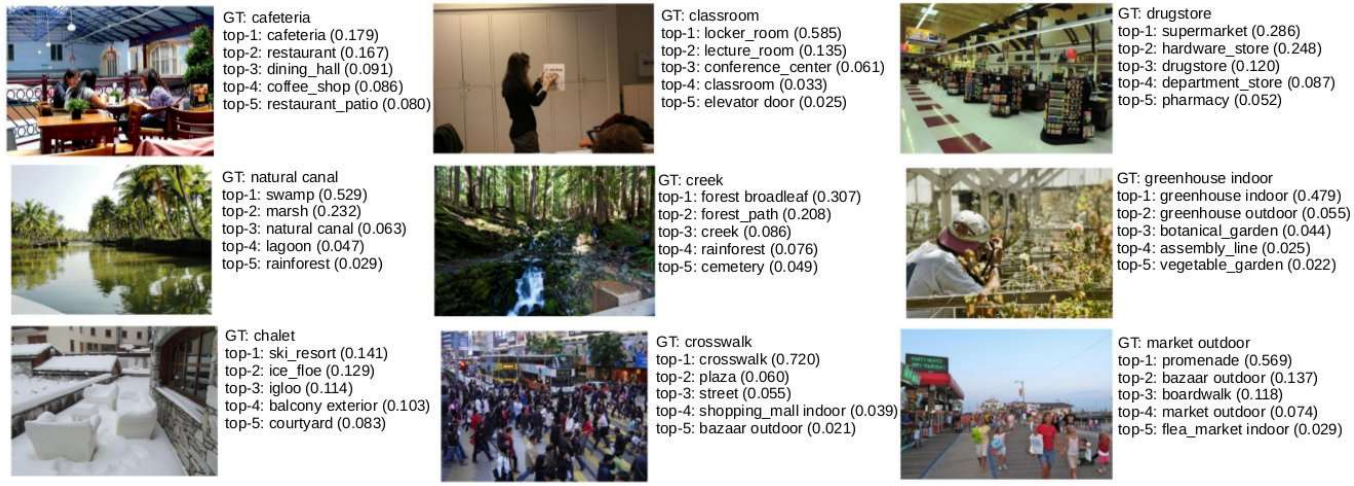
Table 4: Single-crop error rates of state-of-the-art CNNs on ImageNet validation set. The size of test crop is 224 × 224 and 320 × 320 / 299 × 299 as in [11]. † denotes the model with a larger crop 331 × 331. ‡ denotes the post-challenge result. SENet-154 (post-challenge) is trained with a larger input size 320 × 320 compared to the original one with the input size 224 × 224.

Multi-scale/multi-crop fusion strategy(ensemble)

On Validation set

마지막 ImageNet challenge에서 우승.

Experiment : 다양한 task에서도 잘 동작



Scene Recognition

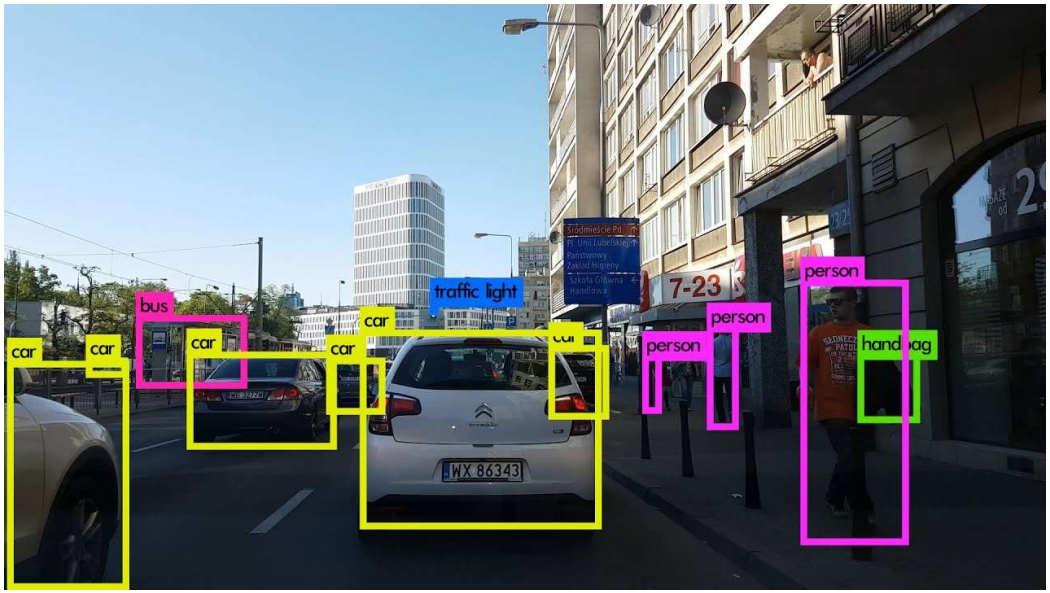
SE block 적용하는 것으로 SOTA 달성.

	top-1 err.	top-5 err.
Places-365-CNN [37]	41.07	11.48
ResNet-152 (ours)	41.15	11.61
SE-ResNet-152	**40.37**	**11.01**

Table 5: Single-crop error rates (%) on Places365 validation set.

Zhou, Bolei and Lapedriza et al. "Places : A 10 million Image Database for Scene Recognition", IEE transactions on Pattern Analysis and Machine Intelligence, 2017

Experiment : 다양한 task에서도 잘 동작



Object Detection (COCO 2014)

	AP@IoU=0.5	AP
ResNet-50	45.2	25.1
SE-ResNet-50	46.8	26.4
ResNet-101	48.4	27.2
SE-ResNet-101	49.2	27.9

Table 6: Object detection results on the COCO 40k validation set by using the basic Faster R-CNN.

SE block 을 trunk network에 적용 하면 Object detection task 에서도 성능향상됨을 보임.

https://www.youtube.com/watch?v=EhcpGpFHCrw

Ablation Study – bottleneck reduction ratio

Ratio r	top-1 err.	top-5 err.	Million Parameters
4	23.21	6.63	35.7
8	23.19	6.64	30.7
16	23.29	6.62	28.1
32	23.40	6.77	26.9
original	24.80	7.48	25.6

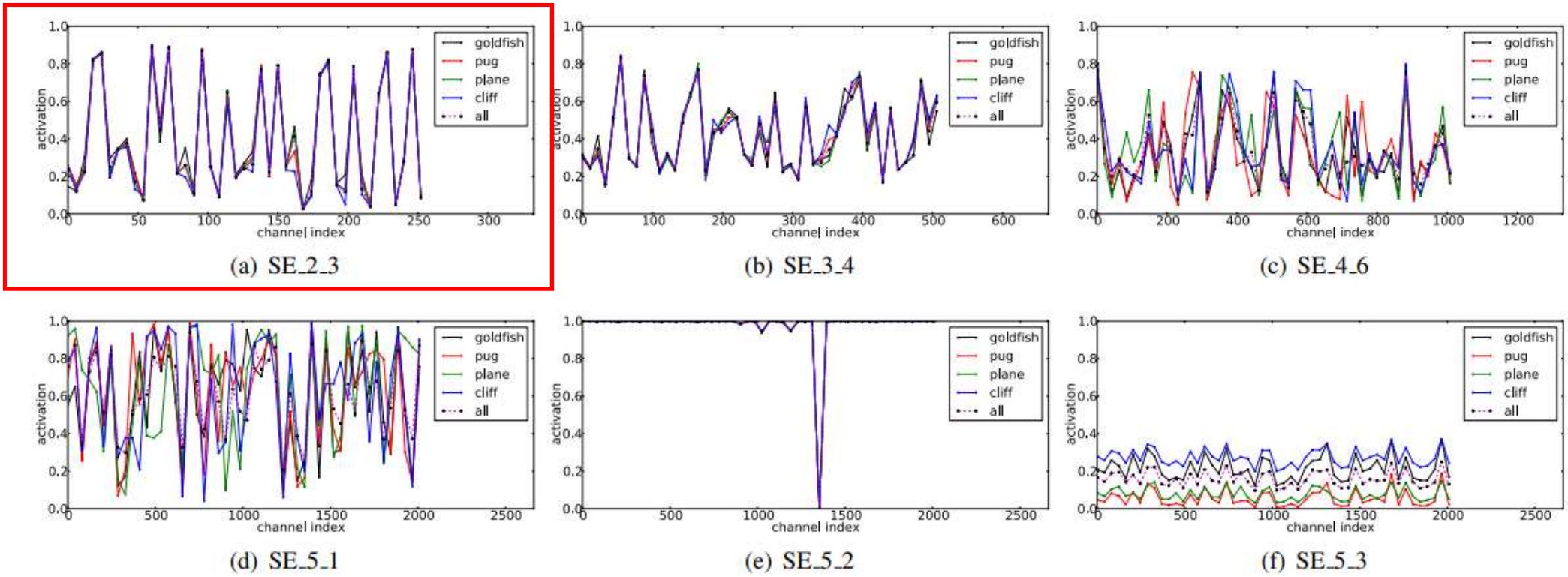
Table 7: Single-crop error rates (%) on ImageNet validation set and parameter sizes for SE-ResNet-50 at different reduction ratios r. Here *original* refers to ResNet-50.

많이 reduction할 경우 파라미터는 감소하나 에러율 증가.
trade-off를 찾아 사용하면 된다.

논문에서는 complexity와 performance간 trade-off로 16선택

초기단계 : distribution이 거의 동일 (아직까지는 매우 저수준의 feature extraction)

Analysis : self-gating이 어떻게 동작?



(a) SE_2_3 (b) SE_3_4 (c) SE_4_6

(d) SE_5_1 (e) SE_5_2 (f) SE_5_3

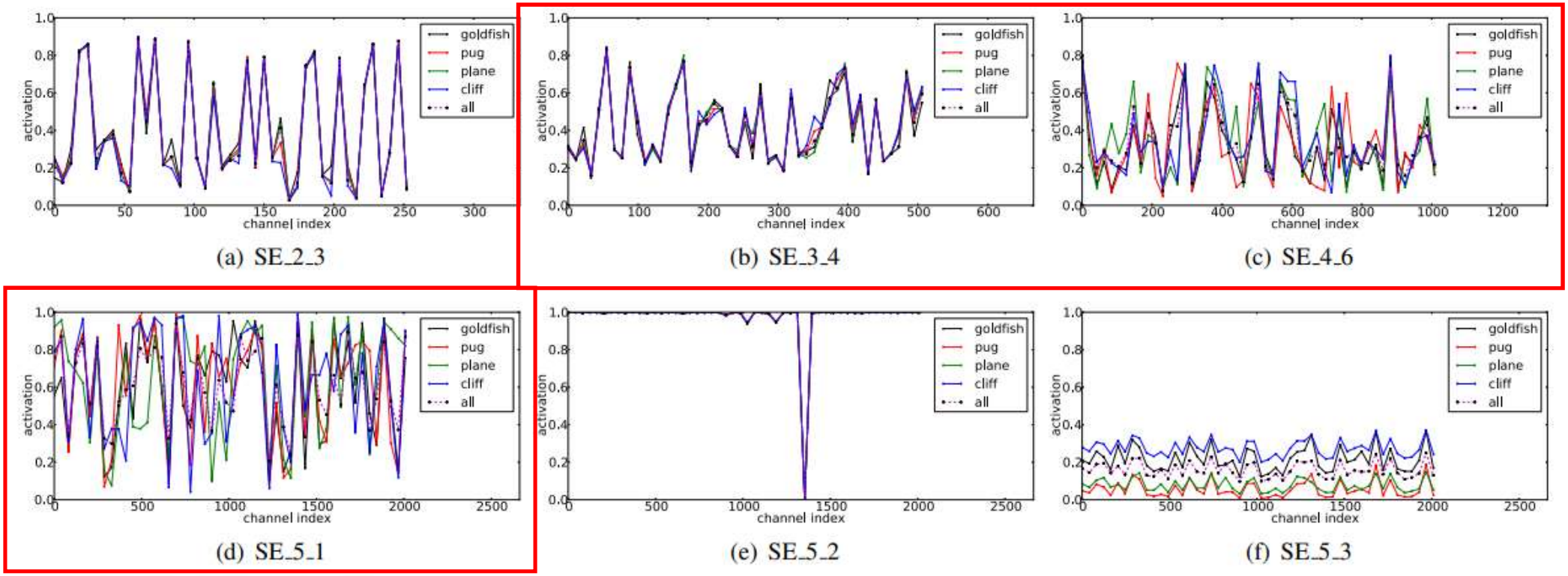
(a) goldfish (b) pug (c) plane (d) cliff

tation in the different modules of SE-ResNet-50 on ImageNet. The module is named as

Fig. 8. Sample images from the four classes of ImageNet used in the experiments described in Sec. 7.2.

중간단계 : class wise distribution의 차이가 점점 심해짐 (클래스별로 최적화된 channel selection 과정)

Analysis : self-gating이 어떻게 동작?



(a) SE_2_3 (b) SE_3_4 (c) SE_4_6

(d) SE_5_1 (e) SE_5_2 (f) SE_5_3

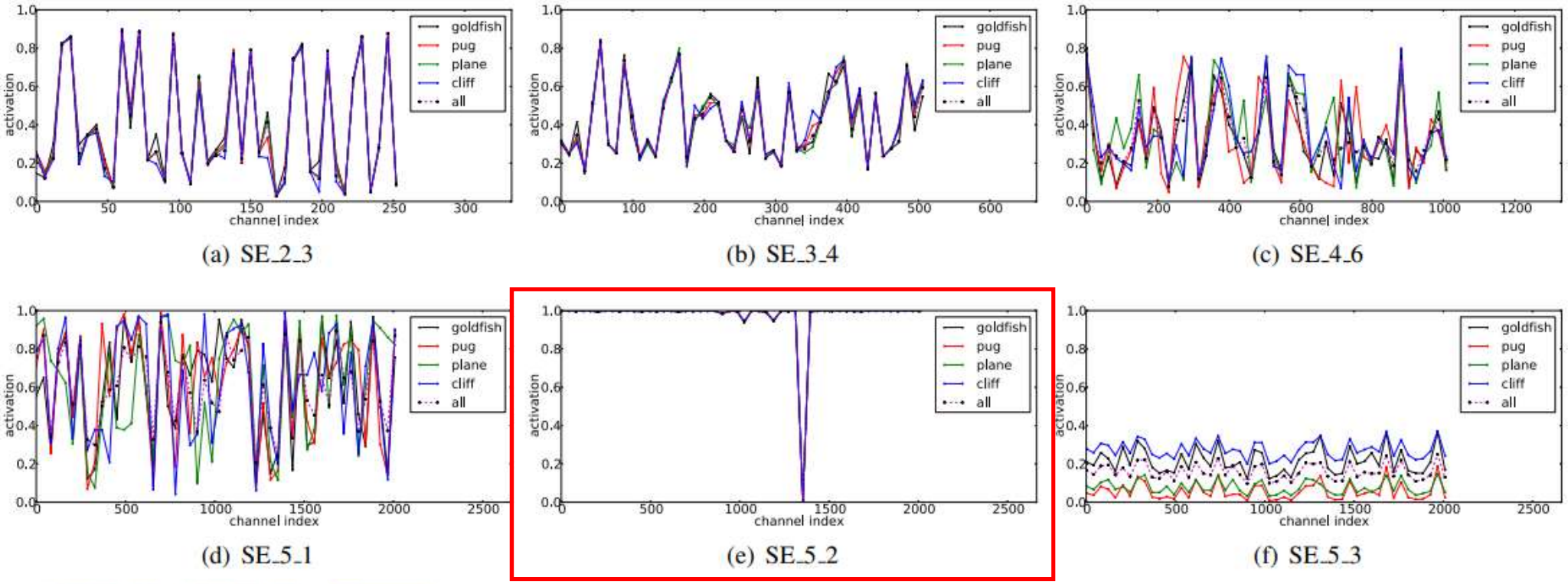
(a) goldfish (b) pug (c) plane (d) cliff

Fig. 8. Sample images from the four classes of ImageNet used in the experiments described in Sec. 7.2.

tation in the different modules of SE-ResNet-50 on ImageNet. The module is named as

SE5_2 : 거의 모든 activation이 1로 수렴 -> 해당 단계에서는 gating 안하는 것이 최적화된 모델

Analysis : self-gating이 어떻게 동작?



(a) SE_2_3 (b) SE_3_4 (c) SE_4_6

(d) SE_5_1 (e) SE_5_2 (f) SE_5_3

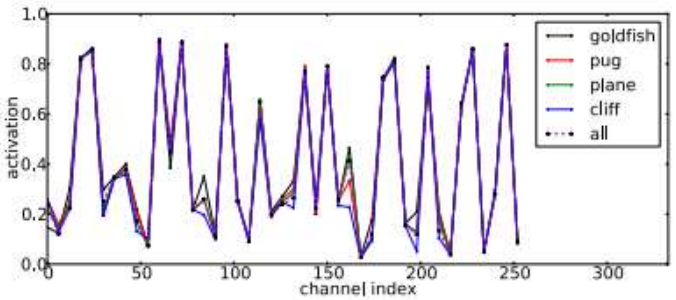
(a) goldfish (b) pug (c) plane (d) cliff

Fig. 8. Sample images from the four classes of ImageNet used in the experiments described in Sec. 7.2.

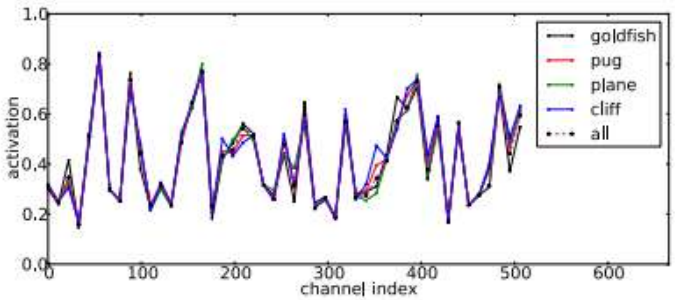
tation in the different modules of SE-ResNet-50 on ImageNet. The module is named as

SE5_3 : 마지막 block (scale만 다르고 모두 동일한 distribution) -> 역시 gating 안 해도 무방

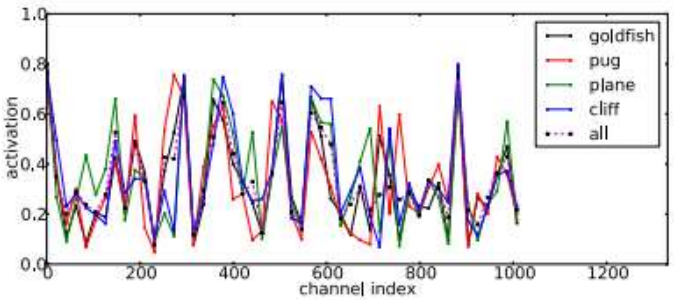
Analysis : self-gating이 어떻게 동작?



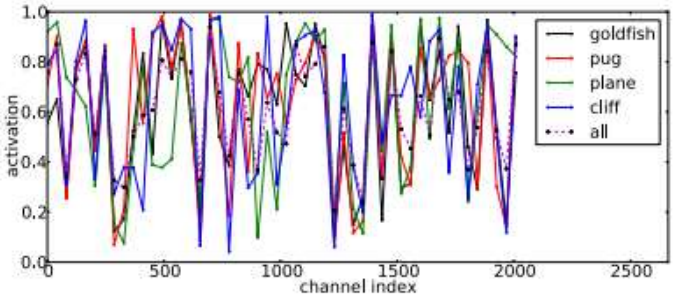
(a) SE_2_3



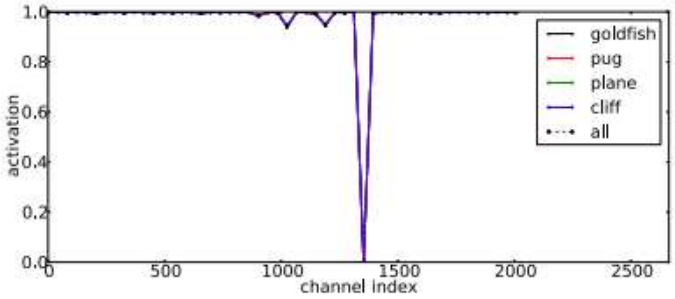
(b) SE_3_4



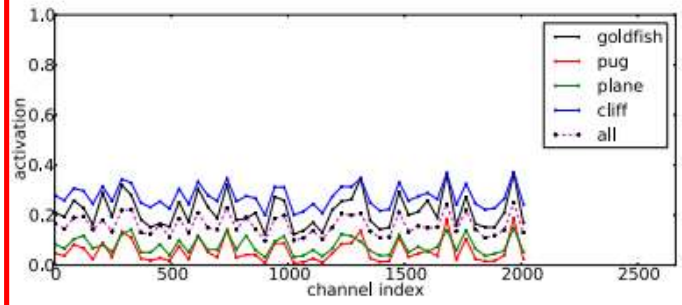
(c) SE_4_6



(d) SE_5_1



(e) SE_5_2



(f) SE_5_3

(a) goldfish (b) pug (c) plane (d) cliff

tation in the different modules of SE-ResNet-50 on ImageNet. The module is named as

Fig. 8. Sample images from the four classes of ImageNet used in the experiments described in Sec. 7.2.

Conclusion

- Automatic Neural Architecture Search를 사람의 인사이트로 능가할 수 있다.

- 그동안 다루어지지 않았던, 피처맵 채널간의 중요도 및 관계에 대해서 알 수 있었다.

- ImageNet 챌린지에서 1위 등극.

- 다양한 테스크에 적용 가능할 것으로 기대됨.

감사합니다.