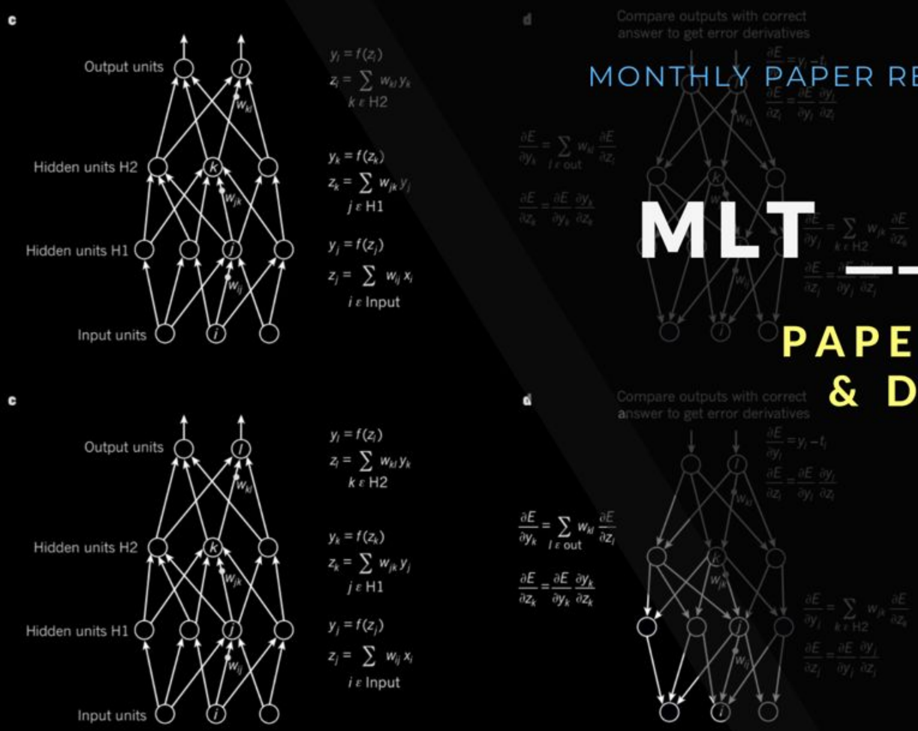
MONTHLY PAPER READING SESSIONS

MLT __init__

PAPER READING & DISCUSSION



MACHINE LEARNING TOKYO

Session # 3:
Squeeze & Excitation Nets

Alisher Abdulkhaev | 2021.03.14

@alisher_ai

Self Introduction

- Name: **Alisher Abdulkhaev**
- Board Director @ **Machine Learning Tokyo (MLT)**
- Computer Vision Engineer @ **Browzzin, Inc**

  (AI powered social fashion App)
- Ph.D. student @ **CVLAB**, University of Tsukuba (supervisor: **Prof. Fukui**)
- Teaching Fellow @ **Tokyo Data Science** (online data science school

  executed by Michal Fabinger)
- Twitter: **@alisher_ai**

Outline

- Universal Approximation Theorem — Neural Networks
- Inductive Biases
- Squeeze-and-Excitation Networks (SENets)
  - Introduction
  - Squeeze-and-Excitation Block
  - Results
  - Conclusions
- Suggested links & PwA
- Free discussion + Q&A

Neural Networks* & Universal Approximation Theorem

- NN aim to find any mathematical function or (series of) transformation which map an input (x) to output (y);

$$y = f(x)$$

- The Universal Approximation Theorem tells us that Neural Networks (with sufficient number of nodes/neurons and layers) can approximate any function f(x), i.e. NN has a universality

* Multi Layer Perceptron | Fully Connected NN | Dense NN

Inductive Bias

> The final meaning of *bias* we will consider here is *inductive bias*; in this meaning, all machine learning relies on some sort of bias. This type of bias is frequently implicit in the technique, and is also referred to as *model bias* or *representation bias*. Rather than a source of statistical error, this type of bias can be thought of as a set of assumptions being made (usually *a priori*) about which possible solutions are worth considering, which should be preferred, and which can be ignored. Without a bias of this type, machine learning not would be possible.

The spatial inductive bias of deep learning, Benjamin R. Mitchell

- Instead of considering huge neural networks for all kind of data and tasks, we would prefer to make some assumptions on the nature of the data.

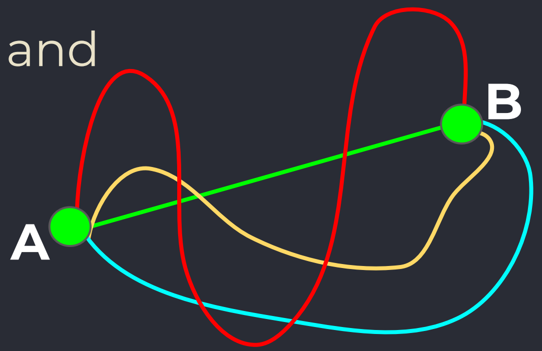
Without an Inductive Bias

- Without some form of inductive bias to restrict the hypothesis space;
  - the basic tasks of machine learning would become impossible: generalization and evaluation,
  - need a dataset representing the true distribution of the data.

The Need for Biases in Learning Generalizations, Tom Mitchell

With Inductive Bias

- Restricts the hypothesis space, i.e. ease the neural network design depending on the data being worked on.
- A number of possible models crossing points A and B is infinitesimal. Inductive bias would help to limit the choices (e.g., linear model)
- Less data and less computation



Examples for Inductive Biases

- Occam's Razor: a bias towards the simplicity.
- Graph NN — relational inductive bias
- Recurrent NN — recurrent inductive bias (sequential input)
    - Transformers process the input in parallel, not sequentially...

  Samira Abnar's Blog Post: https://samiraabnar.github.io/articles/2020-05/recurrence

- Convolutional Neural Networks ...

CNN as an Inductive Bias

- When we work on data with spatial dimensions, we can leverage the prior belief/knowledge of visual data.
- CNNs are special type of NN which have a very powerful inductive bias — spatial structure such as local connectivity.
- I think, all CNN architecture designs try to enhance the inductive bias:
  - Residual connections
  - Attention

Squeeze & Excitation Network

SENet proposes some additional “inductive bias”

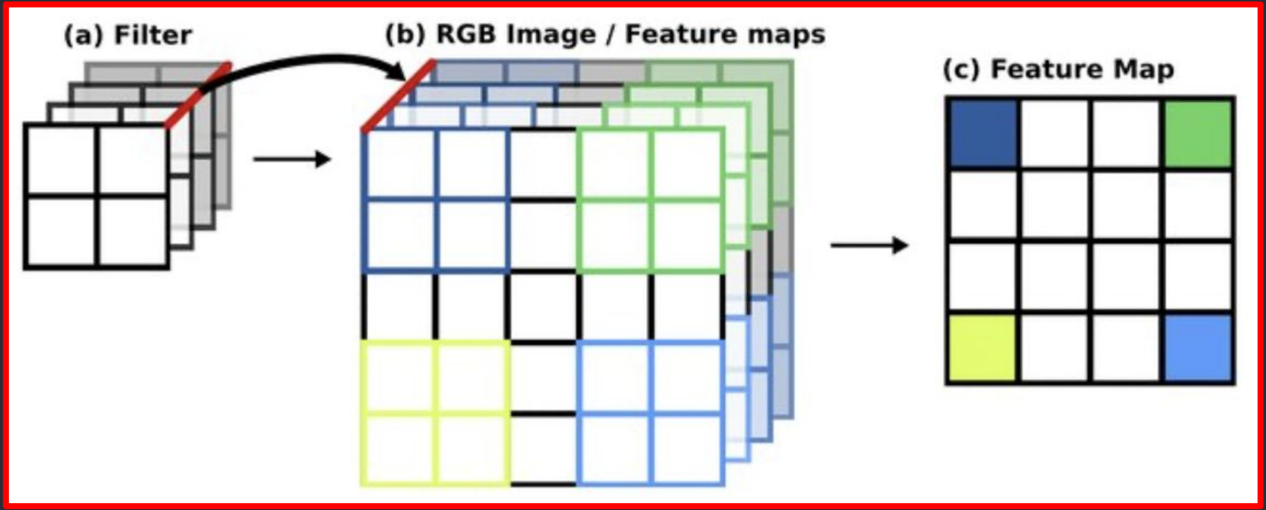
— the relationship between feature map

channels and feature recalibration.

SENet: Introduction

- Central theme in Computer Vision is to search for task and data dependent powerful representation for visual data.
- Deep Learning is about representation learning...
- CNN is a DNN consists of convolutional, non-linear activation and pooling and fully connected layers in principle.

SENet: Introduction

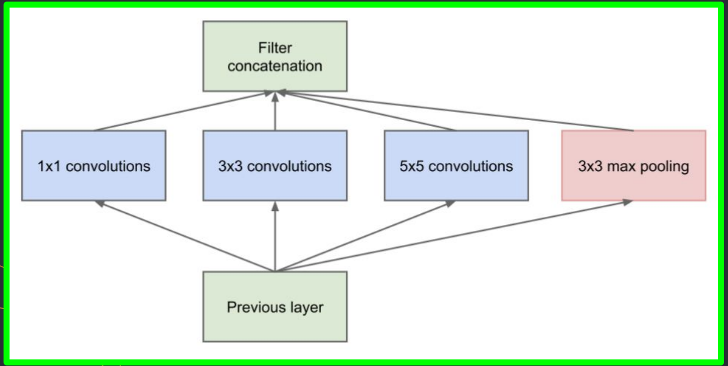


- Convolutional layers fuse spatial and channel-wise information together.

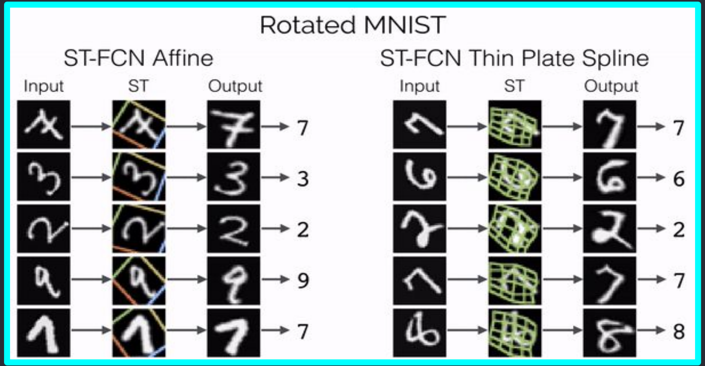
SENet: Introduction

- Representations produced by CNN can strengthened by integrating learning mechanisms to capture spatial correlations between features.

- Inception family: multi-scale processing



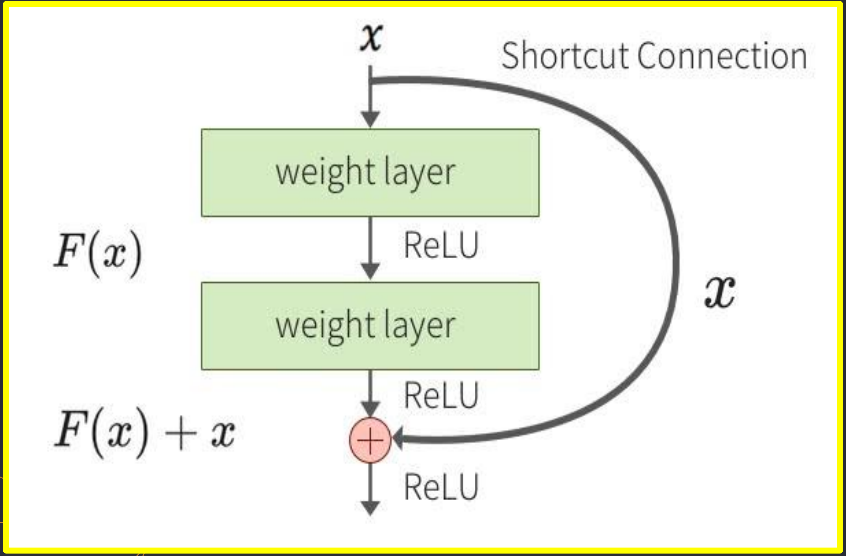
- Spatial Transformer Nets: spatially transform feature maps

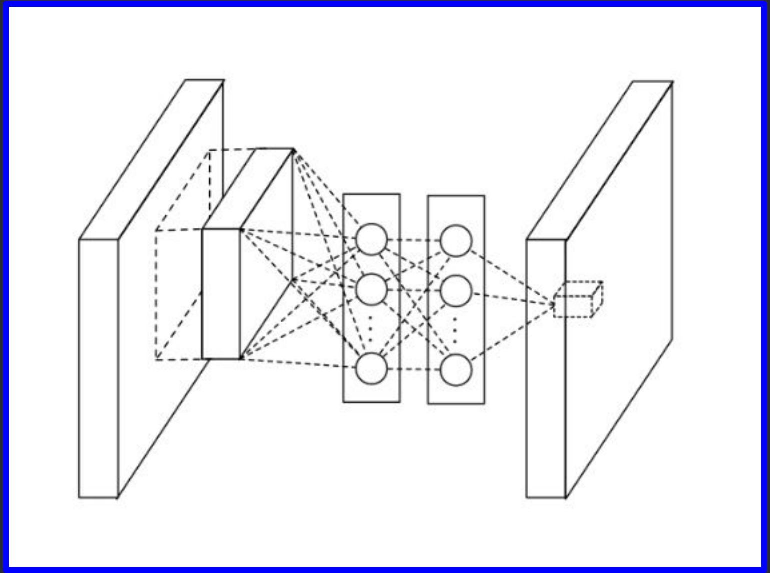


SENet: Introduction

- ResNet: deep and identity based skip connections

- Network in Network: cross-channel correlations



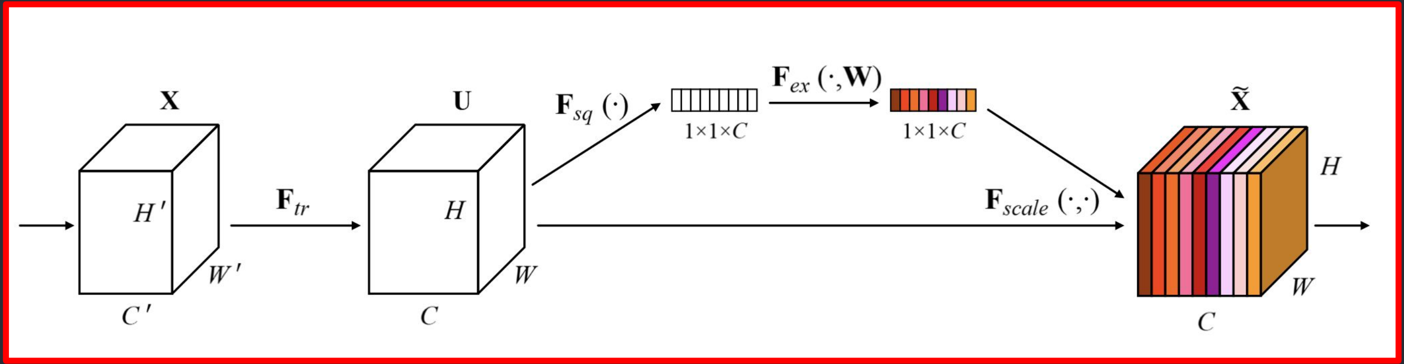


SENet: Introduction

- Each learned filters operates with a local receptive field — unable to exploit contextual information outside if the region.
- SENet investigates the relationship between feature map channels.
- Explicitly models the interdependencies between the channels.
- Feature recalibration: helps the network to learn global information to selectively emphasise informative features while suppressing the less useful ones which ease the learning process.

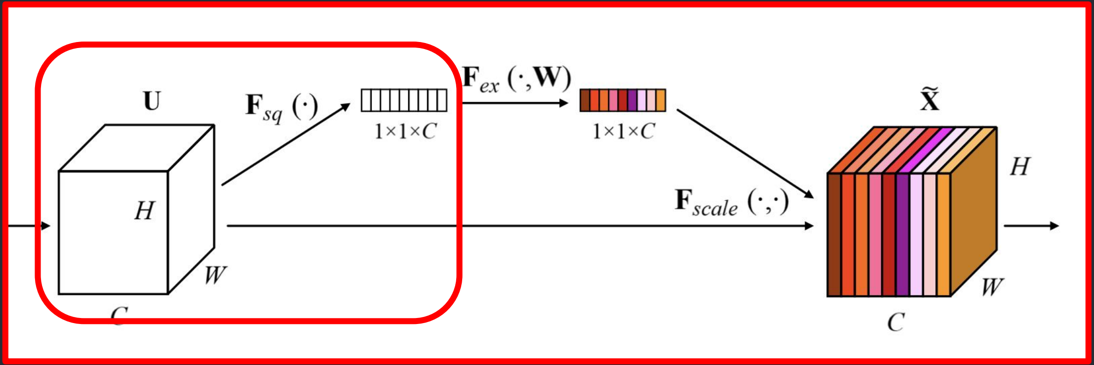
Squeeze-and-Excitation Block

- SE Block intrinsically introduce dynamics conditioned on input — self-attention function.
- SE Block excites:
  - class-agnostic informative features at earlier layers,
  - class-specific informative features at later layers.



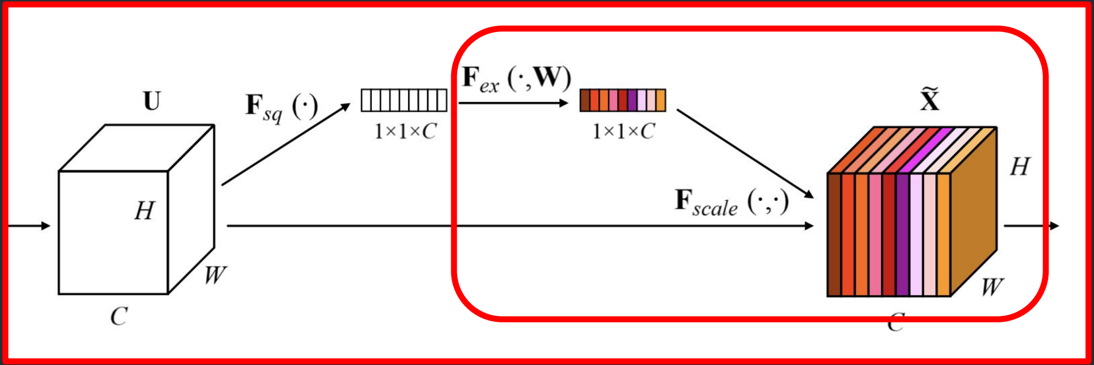
Squeeze-and-Excitation Block

- **Squeeze: global information embedding**
  - Global average pooling: generates channel-wise statistics.
  - Local descriptors with expressive statistics of the whole feature map.



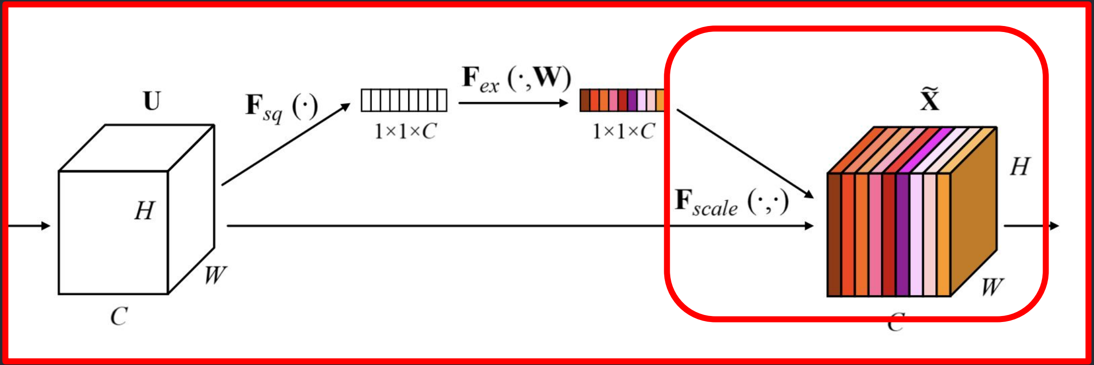
Squeeze-and-Excitation Block

- **Excitation: adaptive re-calibration**
  - Captures the channel-wise dependencies
  - Maps input specific descriptor to a set of channel weights



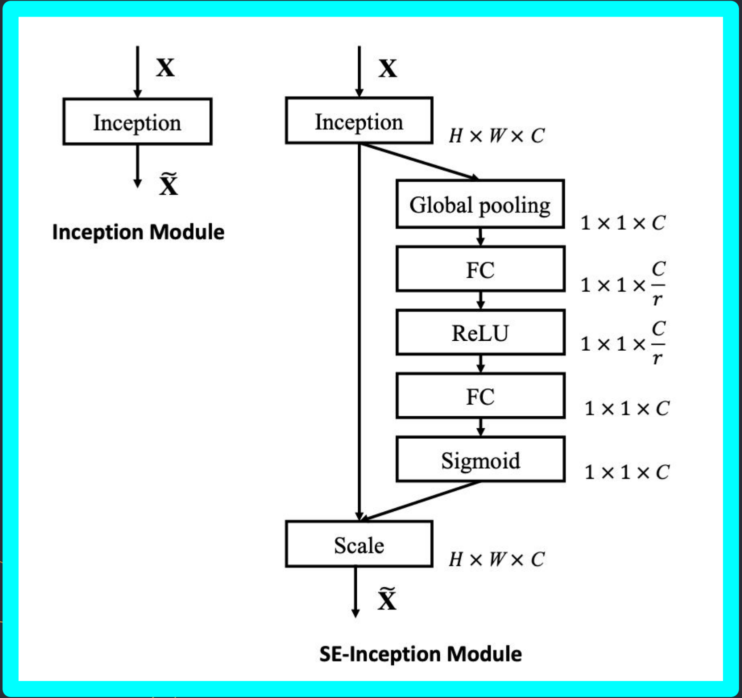
Squeeze-and-Excitation Block

- **Re-scaling:**
  - Channel-wise multiplication between the scalar and the input feature map
  - Constructs the new tensor with spatial dimension



Squeeze-and-Excitation Block

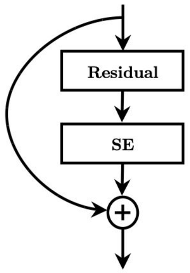
- SE Block can be used as add-on block for various CNN architectures.



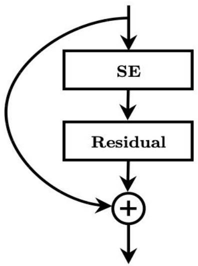
- Input → GAP → $\boxed{\text{FC → ReLU → FC}}$ → sigmoid → output
- r: reduction ratio
- Sigmoid: gives the (importance) weights for each channel
  - Network-in-network design

Squeeze-and-Excitation Block

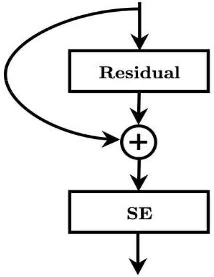
- SE Block can be used as add-on block for various CNN architectures



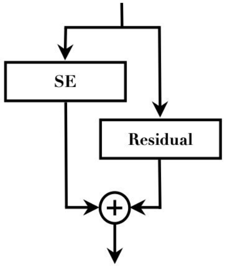
(b) Standard SE block



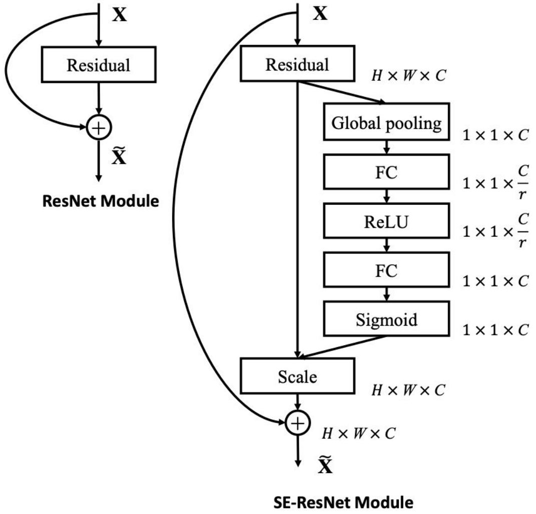
(c) SE-PRE block



(d) SE-POST block



(e) SE-Identity block



Results: ImageNet

- The validation set error-rates of CNN architectures and their SE counterparts:

	original		re-implementation			SENet		
	top-1 err.	top-5 err.	top-1 err.	top-5 err.	GFLOPs	top-1 err.	top-5 err.	GFLOPs
ResNet-50 [13]	24.7	7.8	24.80	7.48	3.86	23.29 $_{(1.51)}$	6.62 $_{(0.86)}$	3.87
ResNet-101 [13]	23.6	7.1	23.17	6.52	7.58	22.38 $_{(0.79)}$	6.07 $_{(0.45)}$	7.60
ResNet-152 [13]	23.0	6.7	22.42	6.34	11.30	21.57 $_{(0.85)}$	5.73 $_{(0.61)}$	11.32
ResNeXt-50 [19]	22.2	-	22.11	5.90	4.24	21.10 $_{(1.01)}$	5.49 $_{(0.41)}$	4.25
ResNeXt-101 [19]	21.2	5.6	21.18	5.57	7.99	20.70 $_{(0.48)}$	5.01 $_{(0.56)}$	8.00
VGG-16 [11]	-	-	27.02	8.81	15.47	25.22 $_{(1.80)}$	7.70 $_{(1.11)}$	15.48
BN-Inception [6]	25.2	7.82	25.38	7.89	2.03	24.23 $_{(1.15)}$	7.14 $_{(0.75)}$	2.04
Inception-ResNet-v2 [21]	19.9†	4.9†	20.37	5.21	11.75	19.80 $_{(0.57)}$	4.79 $_{(0.42)}$	11.76

Results: Places365

- Places 365 is a scene classification challenge/dataset.
- Scene understanding assesses the generalization and abstraction ability.

TABLE 6
Single-crop error rates (%) on Places365 validation set.

	top-1 err.	top-5 err.
Places-365-CNN [72]	41.07	11.48
ResNet-152 (ours)	41.15	11.61
SE-ResNet-152	**40.37**	**11.01**

Results: COCO

- MS COCO is an object detection challenge/dataset.
- Object detection is another assessment to measure the model's localization ability.

TABLE 7
Faster R-CNN object detection results (%) on COCO *minival* set.

	AP@IoU=0.5	AP
ResNet-50	57.9	38.0
SE-ResNet-50	61.0	40.4
ResNet-101	60.1	39.9
SE-ResNet-101	62.7	41.9

Conclusion

- SE Block: an architectural unit which improves the representational power of a network.
- Enables to perform dynamic channel-wise feature calibration.
- SE Blocks shed light on the inability of previous CNN architectures to model channel-wise feature dependencies..
- SE Blocks may help to advance the network pruning by selecting the most informative filters and/or feature maps.
- Can SE Blocks be used effectively during the test time — excites the particular channels depending on the input image?

Suggested Links:

- Paper itself: Squeeze-and-Excitation Networks, CVPR-2018
- Squeeze and Excitation Networks Explained with PyTorch Implementation
- Squeeze-and-Excitation Networks by Paul-Louis Prove
- Squeeze-and-Excitation Networks by Rachel Draelos
- SENet Pytorch Implementation: SENet-PyTorch
- The need for biases in learning generalizations
- The spatial inductive bias of deep learning
- Distilling inductive biases

Last words

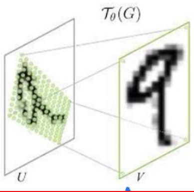
- Papers with Annotations (PwA)
- PwA version of the “Squeeze-and-Excitation Networks” paper is available at: https://github.com/Machine-Learning-Tokyo/papers-with-annotations/blob/master/convolutional-neural-networks/Squeeze-and-Excitation_Networks.pdf

TL;DR:

- Squeeze-and-Excitation Block has been proposed as an add-on to various CNN archs with ease.
- SE Block investigates the relationship between feature map channels
- SE Block emphasise informative features while suppressing the less useful ones.

Squeeze-and-Excitation Networks

Jie Hu[1*] hujie@momenta.ai
Li Shen[2*] lishen@robots.ox.ac.uk
Gang Sun[1] sungang@momenta.ai
[1] Momenta
[2] Department of Engineering Science, University of Oxford



THANK YOU FOR LISTENING!

Q & A

Sessions

Date	Topic	Paper	Presenter	Video
10/Jan/2021	CV: Separable Convolutions	Xception	Jayson Cunanan	
14/Feb/2021	CV: Dilated Convolutions + ASPP	DeepLabv2	J. Miguel Valverde	
14/Mar/2021	CV: Attention in Images	Squeeze and Excitation	Alisher Abdulkhaev	
11/Apr/2021	CV: Attention in GANs	SAGAN	Mayank Bhaskar	
9/May/2021	NLP: Attention	RNN encoder–decoder for SMT	Ana Valeria	
13/Jun/2021	NLP: Attention	Sequence to Sequence Learning with Neural Networks	Charles Melby-Thompson	

Sessions will be held via Zoom starting at 5pm (JST) / 9am (CET). Check at what time is in your region here.

Attendance world-map of the session:

Welcome to MLT __init__ Session #3

- India: 8
- Japan: 7
- Germany: 2
- Czech Republic: 2
- United States: 2
- Finland: 1
- Austria: 1
- Sri Lanka: 1
- Ukraine: 1
- Indonesia: 1
- France: 1
- Norway: 1
- Peru: 1
- Kyrgyzstan: 1
- Nepal: 1
- United Kingdom: 1