Advanced Deep Spatial Models

AI602: Recent Advances in Deep Learning

Lecture 2

Slide made by

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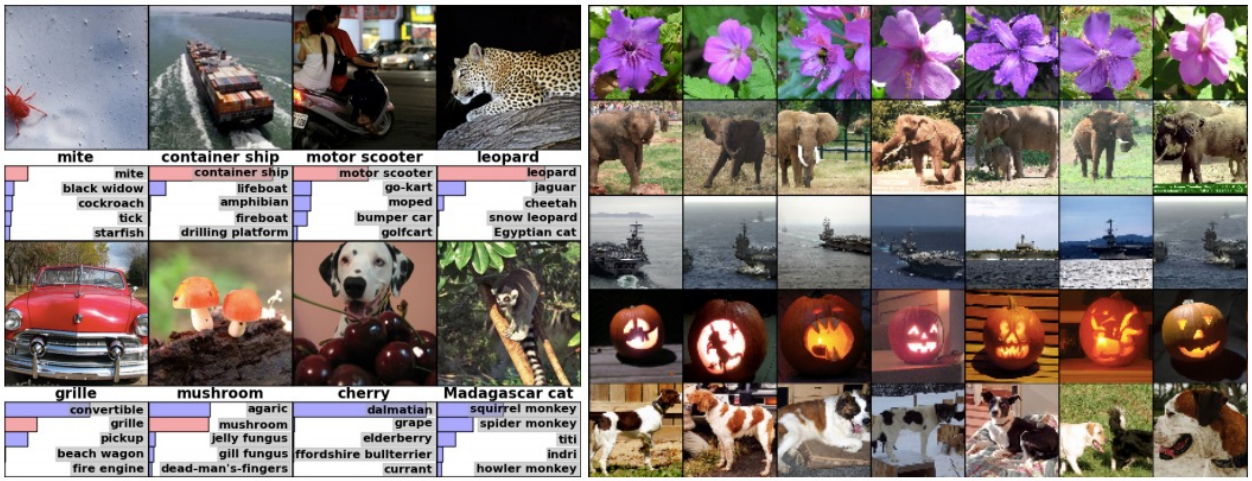
KAIST EE & AI

Convolutional neural networks have been tremendously successful in practical applications;

Classification and retrieval [Krizhevsky et al., 2012]



Detection [Ren et al., 2015]

Segmentation [Farabet et al., 2013]

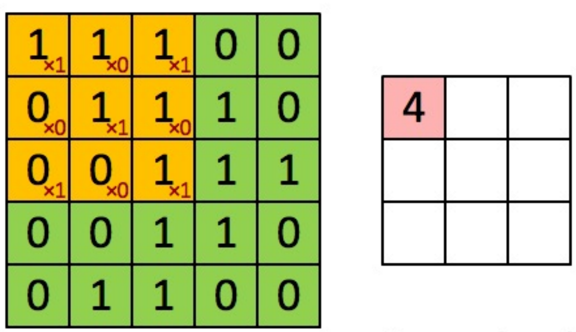
Overview: Convolutional Neural Networks

Neural networks that use convolution in place of general matrix multiplication

- Sharing parameters across **multiple image locations**
- Translation equivariant (invariant with **pooling**) operation

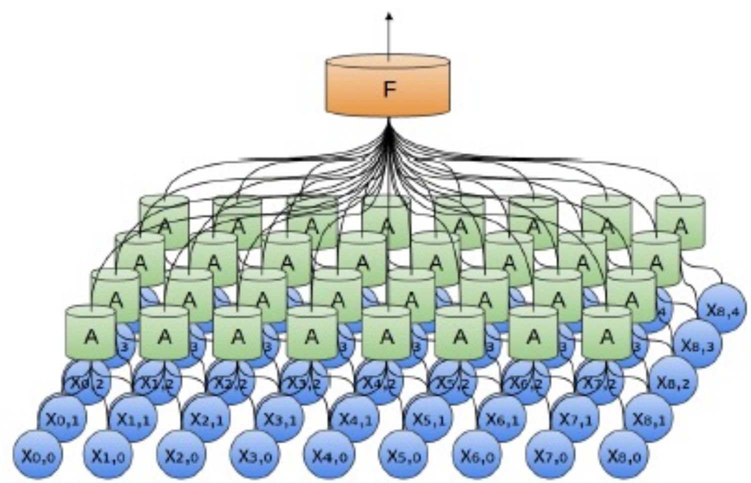
Specialized for processing data that has a known, grid-like topology

- e.g., time-series data (1D grid), image data (2D grid)



Image

Convolved Feature

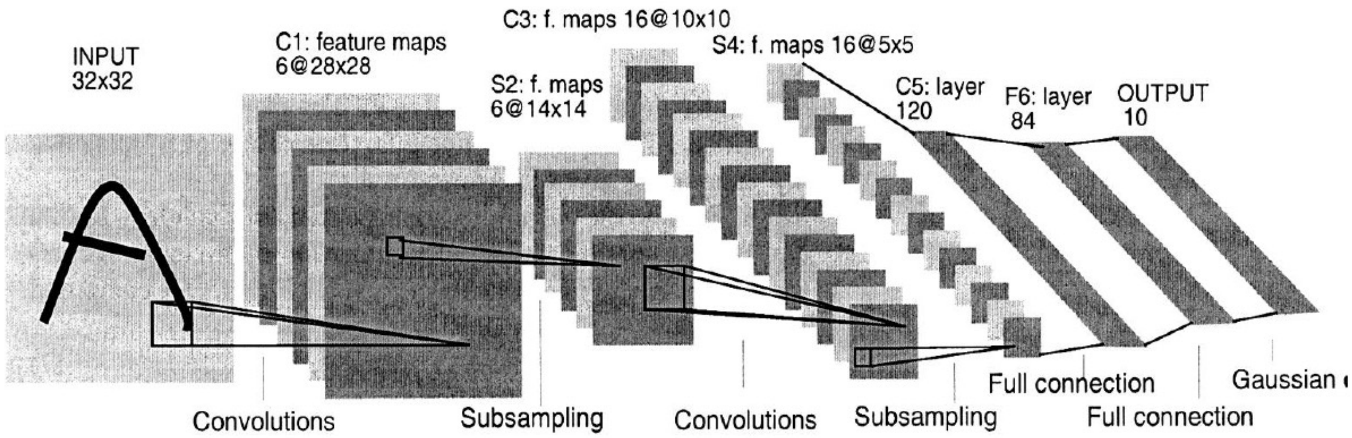


*sources :
- https://www.cc.gatech.edu/~san37/post/dlhc-cnn/
- http://colah.github.io/posts/2014-07-Conv-Nets-Modular/

Typically, designing a CNN model requires some effort

- There are a lot of **design choices**: # layers, # filters, sizes of kernel, pooling, …
- It is **costly** to measure the performance of each model and choose the best one

Example: LeNet for handwritten digits recognition [LeCun et al., 1998]

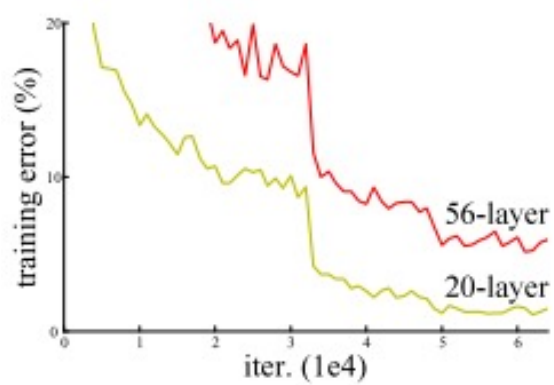


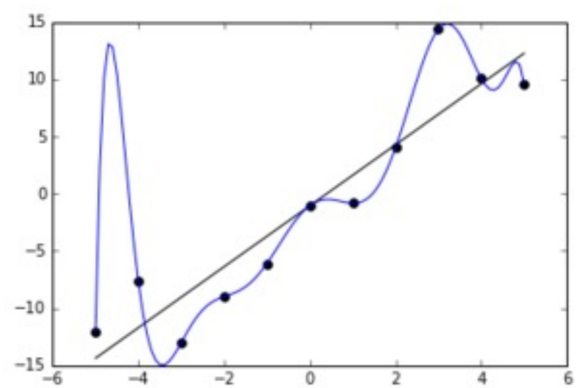
- However, **LeNet** is not enough to solve real-world problems in AI domain
  - CNNs are typically applied to extremely complicated domains, e.g. raw RGB images
  - We need to design **a larger model** to solve them adequately

Problem: The larger the network, the more difficult it is to design

1. **Optimization difficulty**
   - When the training loss is degraded
   - Deeper networks are typically much harder to optimize
   - Related to gradient vanishing and exploding
2. **Generalization difficulty**
   - The training is done well, but the testing error is degraded
   - Larger networks are more likely to over-fit, i.e., regularization is necessary

- Good architectures should be **scalable** that solves both of these problems





*sources :
- He et al. “Deep residual learning for image recognition”. CVPR 2016.
- https://upload.wikimedia.org/wikipedia/commons/thumb/6/68/Overfitted_Data.png/300px-Overfitted_Data.png

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- Transformer architecture for Vision
- MLP architecture for Vision

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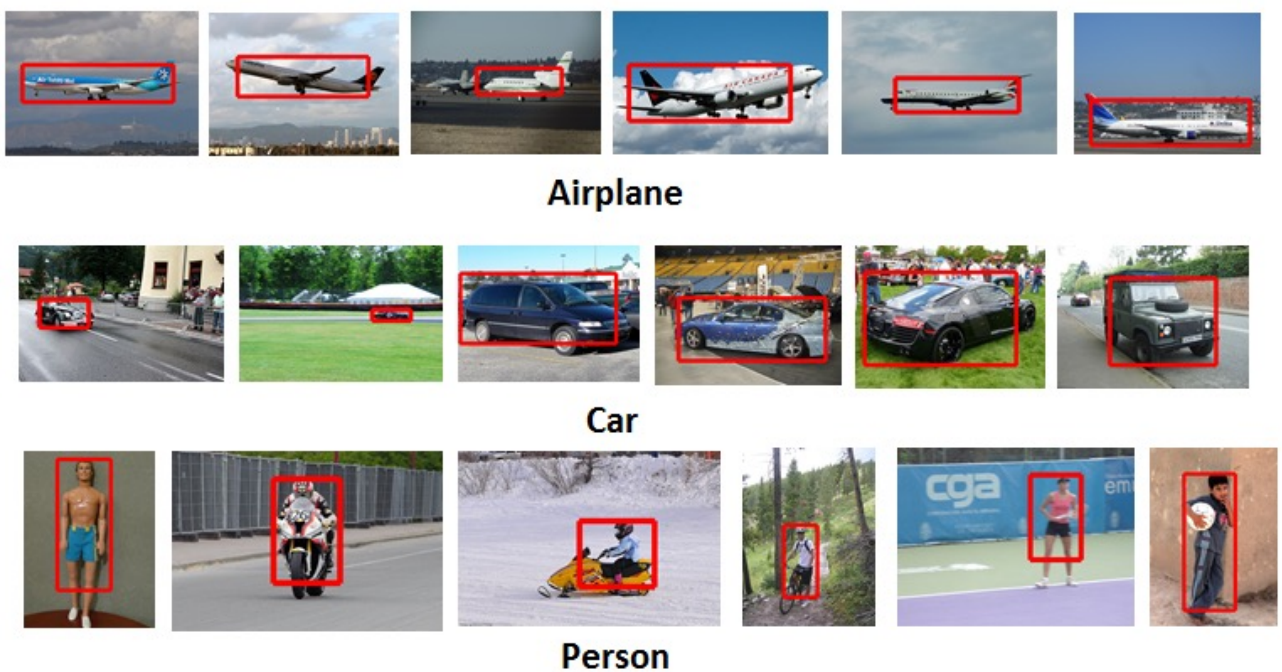
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

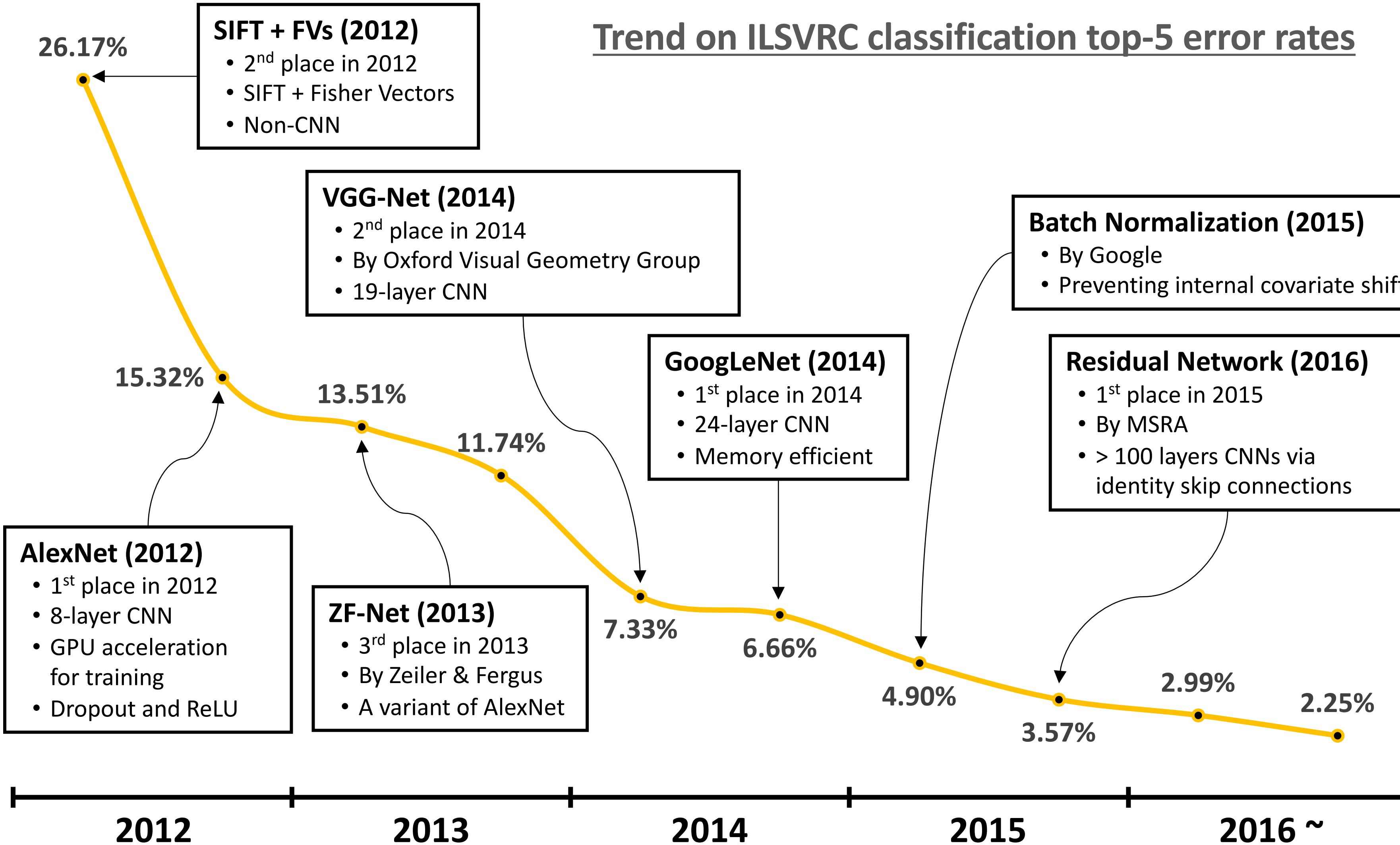
- ImageNet dataset: a large database of visual objects
    - ~14M labeled images, 20K classes
    - Human labels via Amazon MTurk
- Classification: 1,281,167 images for training / 1,000 categories
- Annually ran from 2010 to 2017, and now hosted by Kaggle
- For details, see [Russakovsky et al., 2015]



*source : http://visgraph.cse.ust.hk/ilsvrc/files/tesor.png

Evolution of CNN Architectures

ILSVRC contributed greatly to development of CNN architectures



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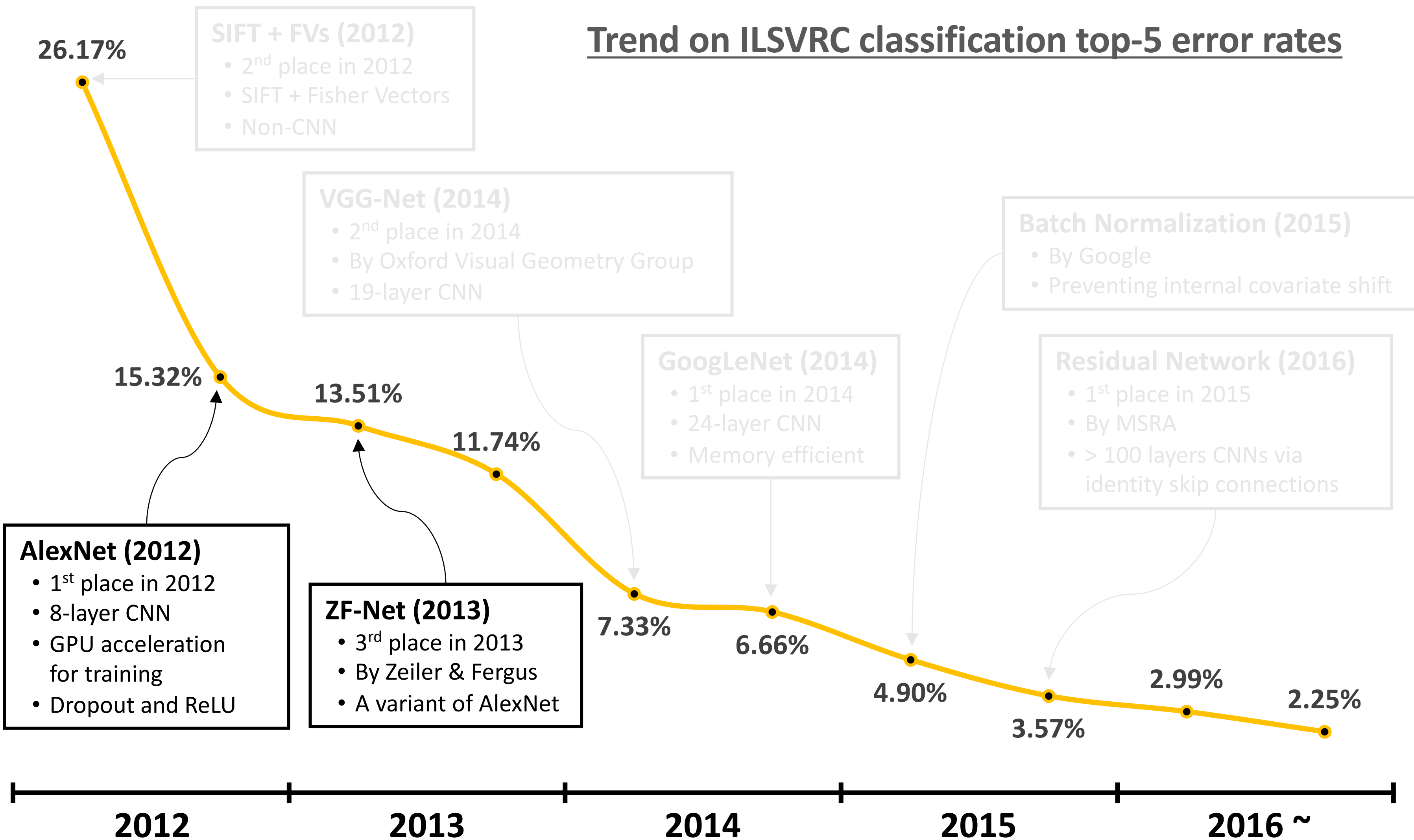
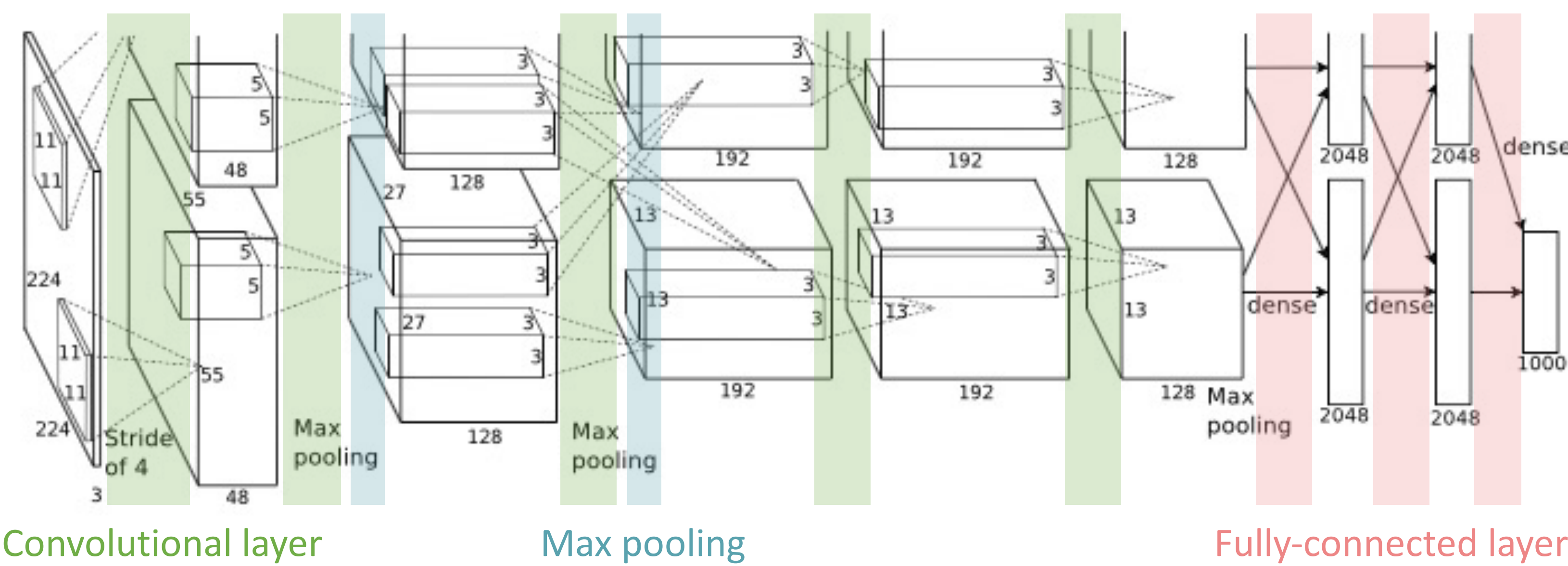


The first winner to use CNN in ILSVRC, with an astounding improvement

- Top-5 error is largely improved: 25.8% → **15.3%**
- The 2nd best entry at that time was **26.2%**

- 8-layer CNN (5 Conv + 3 FC)
- Utilized 2 GPUs (GTX-580 × 2) for training the network
  - Split a single network into 2 parts to distribute them into each GPU



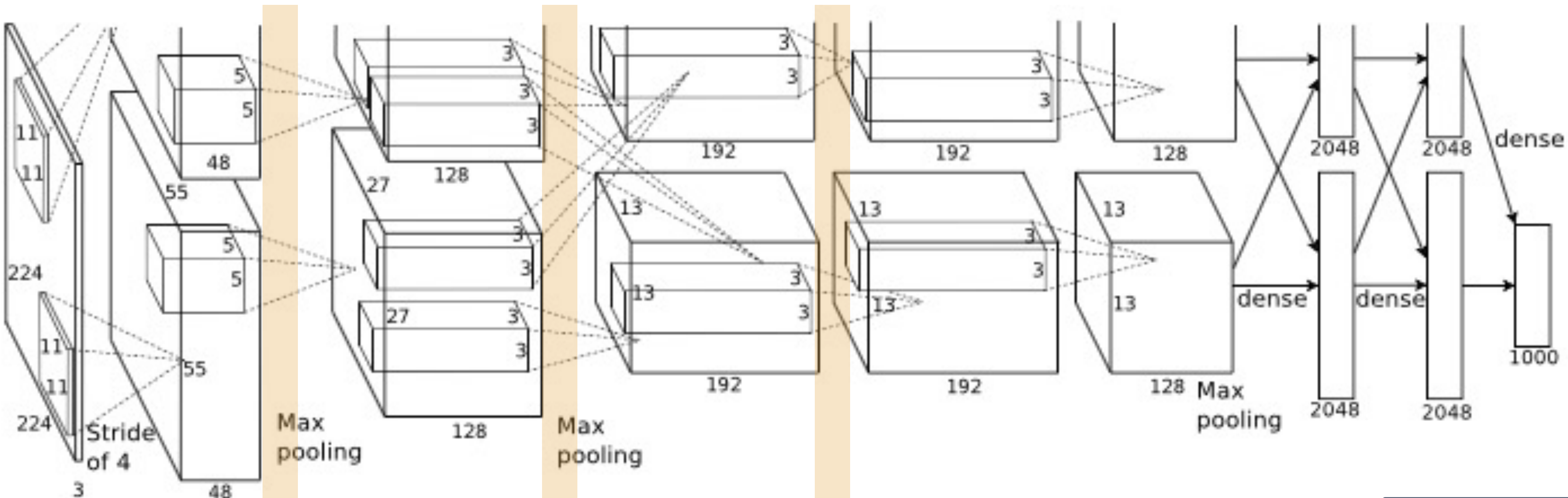
*source : Krizhevsky et al. "Imagenet classification with deep convolutional neural networks". NIPS 2012

Local response normalization layers (LRN)

- Detects high-frequency features with a big neuron response
- Dampens responses that are uniformly large in a local neighborhood

Useful when using neurons with **unbounded** activations (e.g. ReLU)

$$b^i_{x,y} = a^i_{x,y} \Big/ \left(k + \alpha \sum_{j=\max(0, i-\frac{n}{2})}^{\min(N-1, i+\frac{n}{2})} (a^j_{x,y})^2 \right)^\beta$$



Next, ZFNet

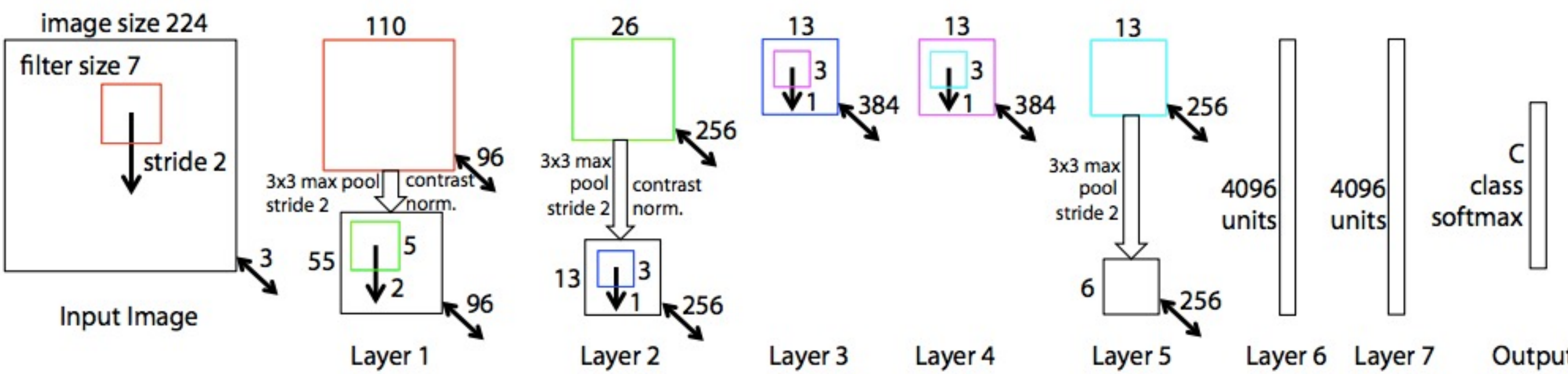
*source : Krizhevsky et al. “Imagenet classification with deep convolutional neural networks”. NIPS 2012

A simple variant of AlexNet, placing the 3rd in ILSVRC'13 (15.3% → 13.5%)

- Smaller kernel at input: 11 × 11 → 7 × 7
- Smaller stride at input: 4 → 2
- The # of hidden filters are doubled

Lessons

1. Design principle: Use smaller kernel, and smaller stride
2. CNN architectures can be very sensitive on hyperparameters



*source : Zeiler et al., "Visualizing and understanding convolutional networks". ECCV 2014

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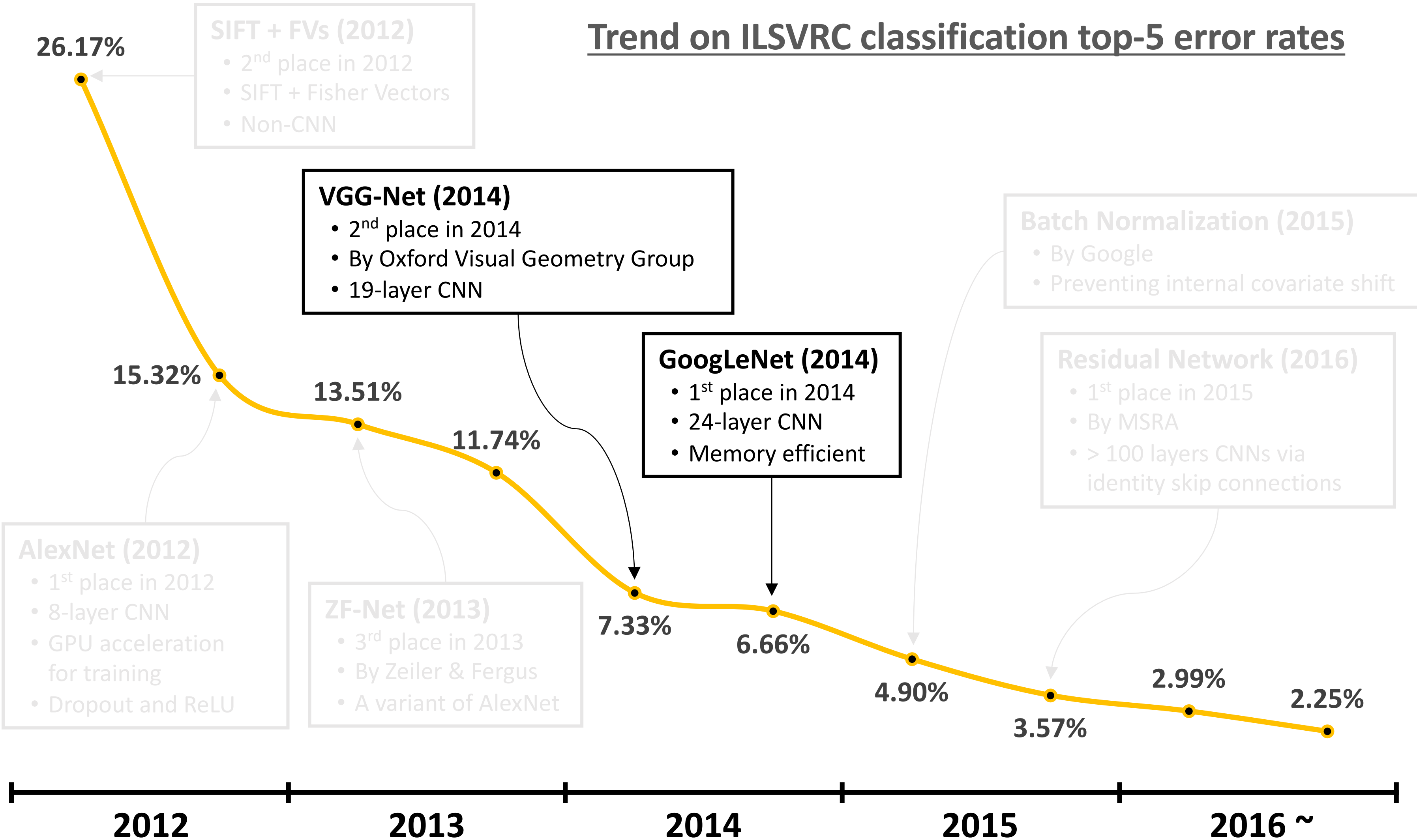


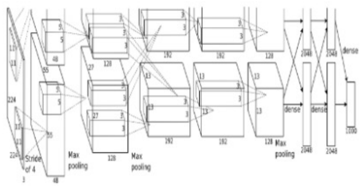
Networks were getting deeper

- AlexNet: 8 layers
- VGGNet: **19** layers
- GoogleNet: **24** layers

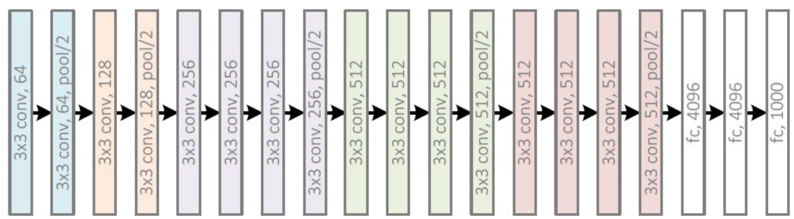
Both focused on parameter efficiency of each block

- Mainly to allow larger networks computable at that time

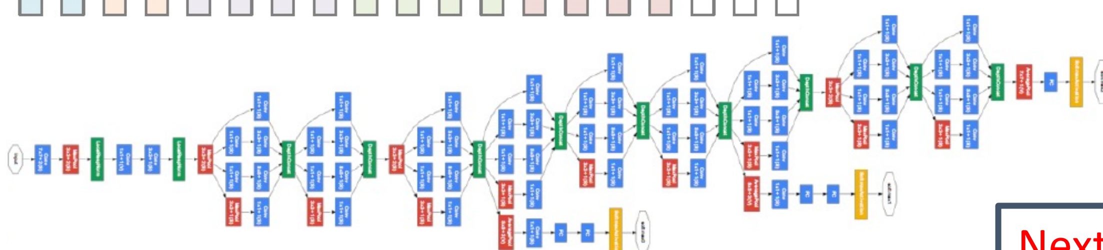
AlexNet



VGGNet



GoogLeNet



Next, VGGNet

*sources :
- Krizhevsky et al. “Imagenet classification with deep convolutional neural networks”. NIPS 2012
- Simonyan et al., “Very deep convolutional networks for large-scale image recognition”. arXiv 2014.
- Szegedy et al., “Going deeper with convolutions”. CVPR 2015

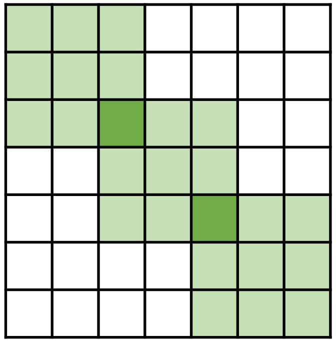
The 2nd place in ILSVRC'14 (11.7% → 7.33%)

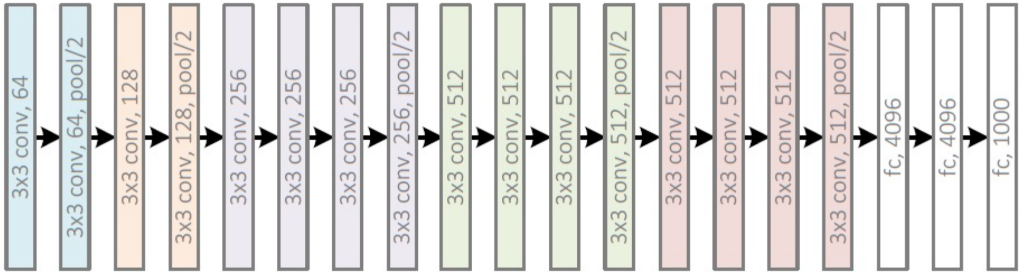
- Designed using only 3×3 kernels for convolutions

Lesson: **Stacking multiple 3×3** is advantageous than using other kernels

Example: $((3\times3)\times3)$ v.s. (7×7)

- Essentially, they get the same receptive field
- $((3\times3)\times3)$ have less # parameters
  - $3\times\left(C\times\left((3\times3)\times C\right)\right) = \mathbf{27C^2}$
  - $C\times\left((7\times7)\times C\right) = \mathbf{49C^2}$
- $((3\times3)\times3)$ gives more non-linearities



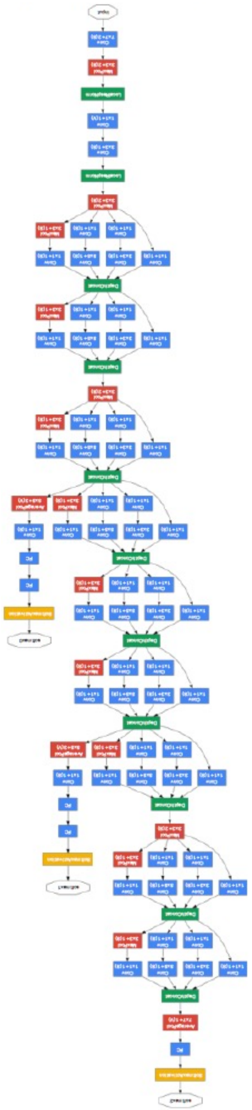


Next, GoogLeNet

*source : Simonyan et al., "Very deep convolutional networks for large-scale image recognition". arXiv 2014.

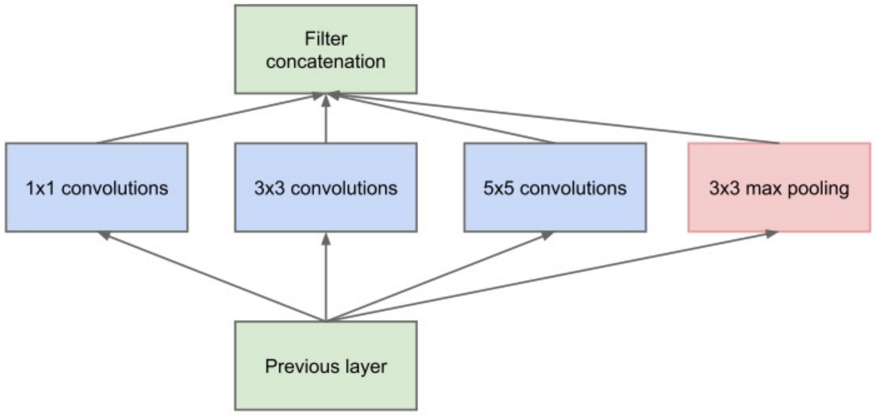
The winner of ILSVRC’14 (11.7% → 6.66%)

- Achieved 12× fewer parameters than AlexNet



Inception module

- Multiple operation paths with different receptive fields
- Each of the outputs are **concatenated** in filter-wise
- Capturing sparse patterns in a stack of features



(a) Inception module, naïve version

*source : Szegedy et al., “Going deeper with convolutions”. CVPR 2015

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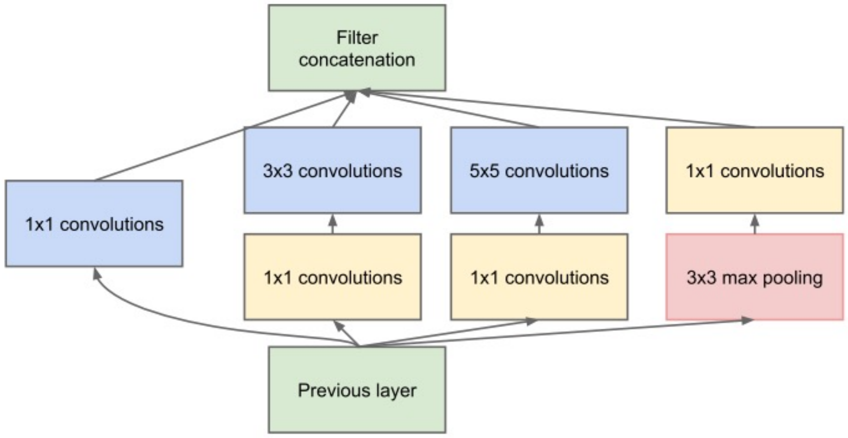
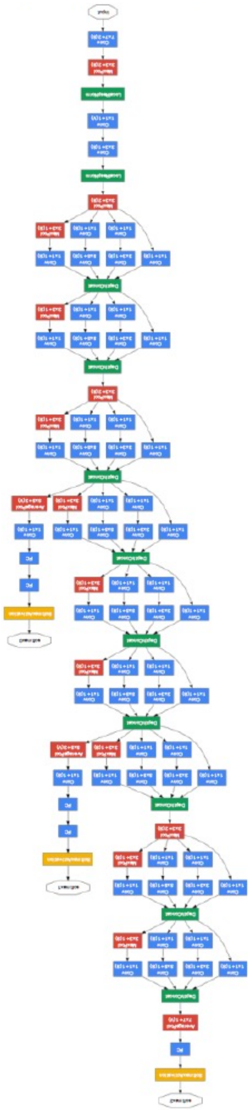
Use of 1 × 1 convolutions

- Naïve inceptions can be too expensive to scale up
- **Dimension reduction** before expensive convolutions
- They also gives more non-linearities



(b) Inception module with dimensionality reduction



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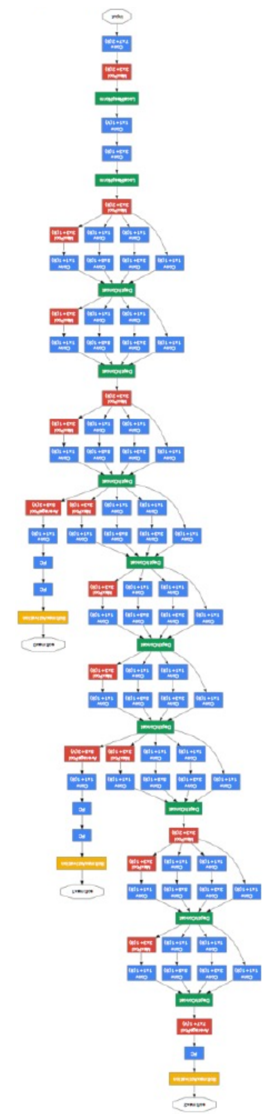
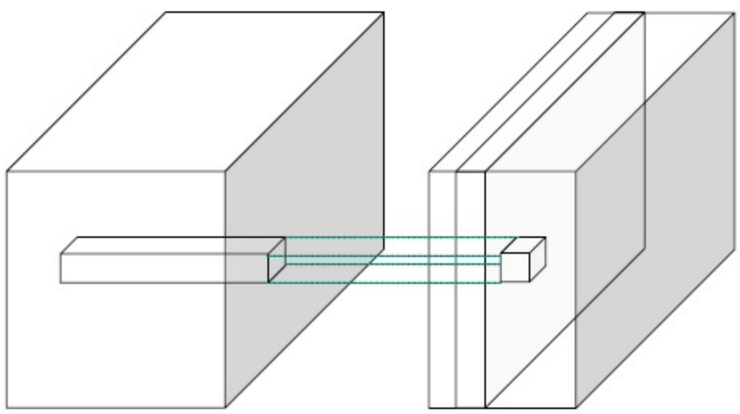


cf. 1 × 1 convolutions

- Linear transformation done in pixel-wise
- Can be represented by a matrix
- Useful for changing # channels efficiently



*sources :

- Szegedy et al., "Going deeper with convolutions". CVPR 2015
- Lana Lazebnik, "Convolutional Neural Network Architectures: from LeNet to ResNet".

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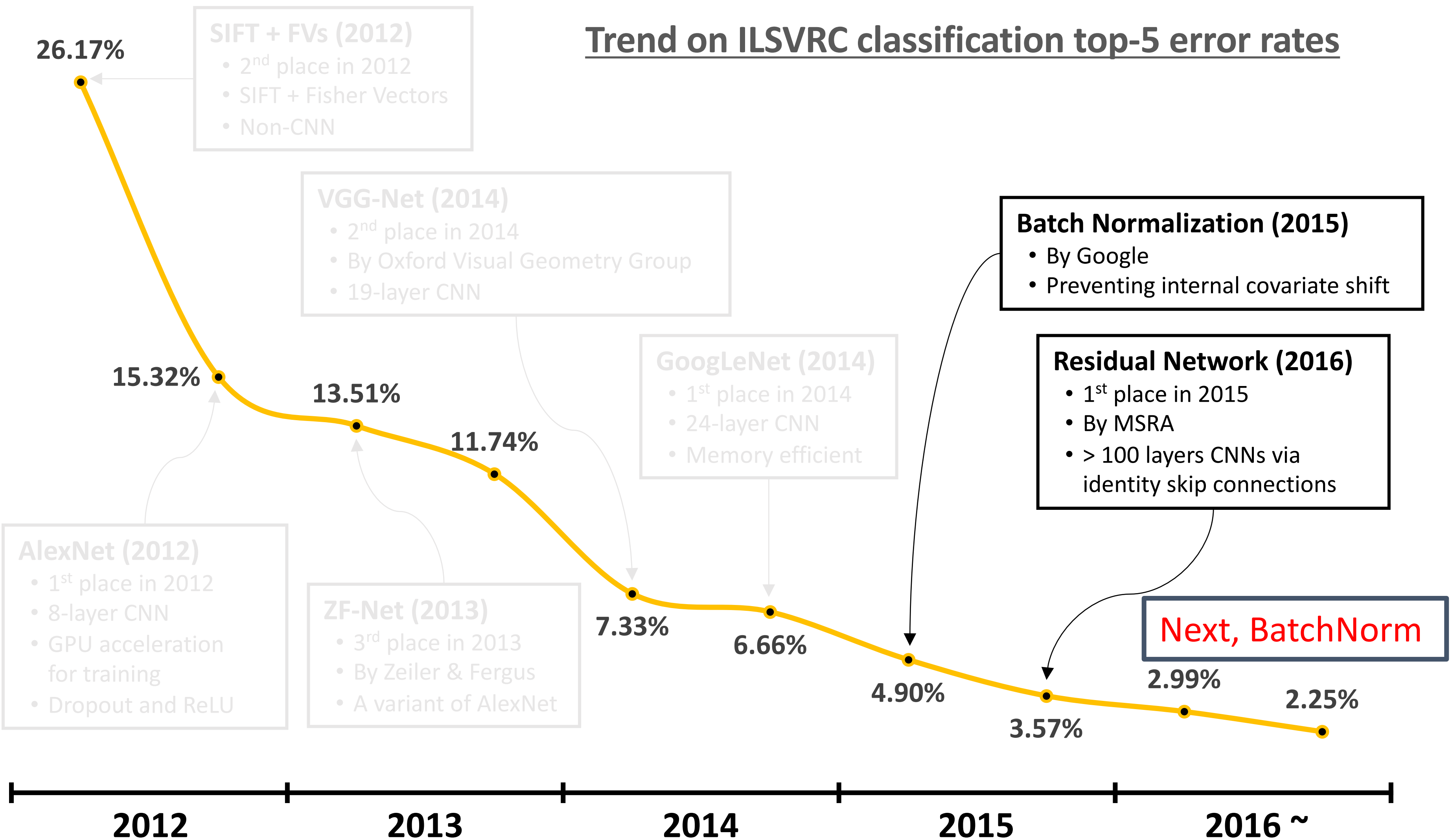

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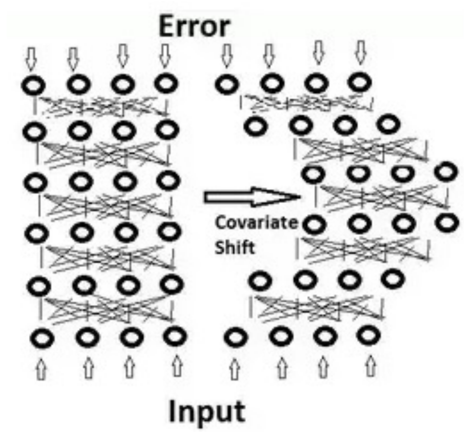
Training a deep network well had been a delicate task

- It requires a careful initialization, with adequately low learning rate
- **Gradient vanishing**: networks containing saturating non-linearity

Ioffe et al. (2015): Such difficulties are come from **internal covariate shift**

Motivation: "The cup game analogy"

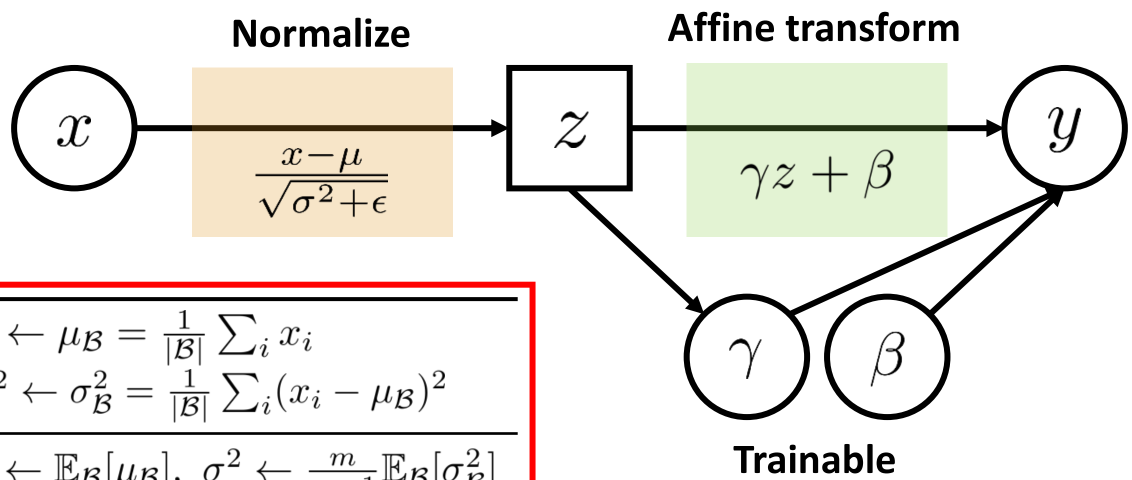


- Similar problem happens during training of deep neural networks
- Updates in early layers may shift the inputs of later layers too much

*sources :
- Ioffe et al., "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". ICML 2015
- http://pages.cs.wisc.edu/~shavlik/cs638/lectureNotes/Batch_Normalization.pptx
- https://www.quora.com/Why-does-batch-normalization-help

Batch normalization (BN) accelerates neural network training by eliminating internal covariate shift inside the network

Idea: A normalization layer that behaves differently in training and testing



Training	$\mu \leftarrow \mu_{\mathcal{B}} = \frac{1}{\lvert\mathcal{B}\rvert}\sum_i x_i$ $\sigma^2 \leftarrow \sigma^2_{\mathcal{B}} = \frac{1}{\lvert\mathcal{B}\rvert}\sum_i (x_i - \mu_{\mathcal{B}})^2$
Testing	$\mu \leftarrow \mathbb{E}_{\mathcal{B}}[\mu_{\mathcal{B}}],\ \sigma^2 \leftarrow \frac{m}{m-1}\mathbb{E}_{\mathcal{B}}[\sigma^2_{\mathcal{B}}]$

1. During training, input distribution of y only depends on γ and β
   - Training mini-batches are always normalized into mean 0, variance 1
2. There is some gap between $\mu_{\mathcal{B}}$ and $\mathbb{E}[\mu_{\mathcal{B}}]$ ($\sigma^2_{\mathcal{B}}$, resp.)
   - Noise injection effect for each mini-batch ⇒ Regularization effect

*source : Ioffe et al., "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". ICML 2015

Batch normalization (BN) accelerates neural network training by eliminating internal covariate shift inside the network

- BN allows much **higher learning rates**, i.e. faster training
- BN **stabilizes** gradient vanishing on saturating non-linearities
- BN also has its own **regularization effect**, so that it allows to reduce weight decay, and to remove dropout layers

- BN makes GoogLeNet much easier to train with great improvements

Model	Resolution	Crops	Models	Top-1 error	Top-5 error
GoogLeNet ensemble	224	144	7	-	6.67%
Deep Image low-res	256	-	1	-	7.96%
Deep Image high-res	512	-	1	24.88	7.42%
Deep Image ensemble	variable	-	-	-	5.98%
BN-Inception single crop	224	1	1	25.2%	7.82%
BN-Inception multicrop	224	144	1	21.99%	5.82%
BN-Inception ensemble	224	144	6	20.1%	**4.9%***

Next, ResNet

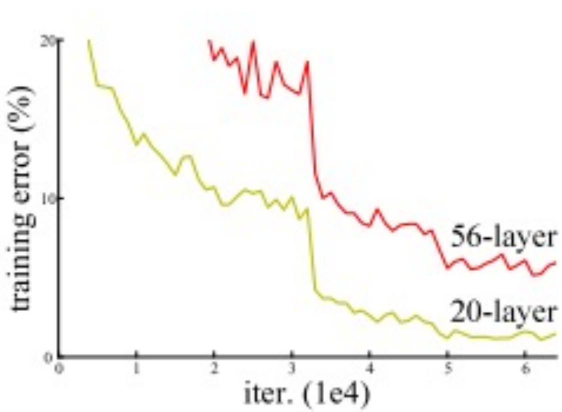
*source : Ioffe et al., “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift”. ICML 2015

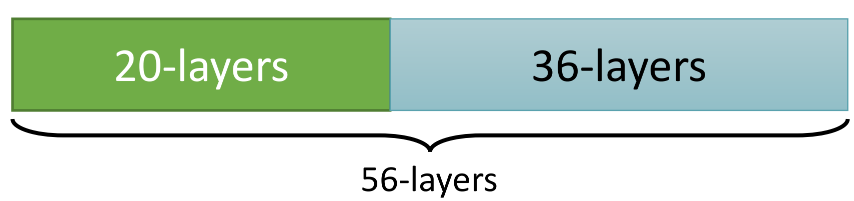
The winner of ILSVRC'15 (6.66% → 3.57%)

- **ResNet** is the first architecture succeeded to train >100-layer networks
  - Prior works could until ~30 layers, but failed for the larger nets

What was the problem?

- 56-layer net gets higher training error than 20-layers network
- Deeper networks are much harder to optimize even if we use BNs
- It's not due to overfitting, but optimization difficulty
- **Quiz**: Why is that?





*source : He et al., "Deep residual learning for image recognition". CVPR 2016

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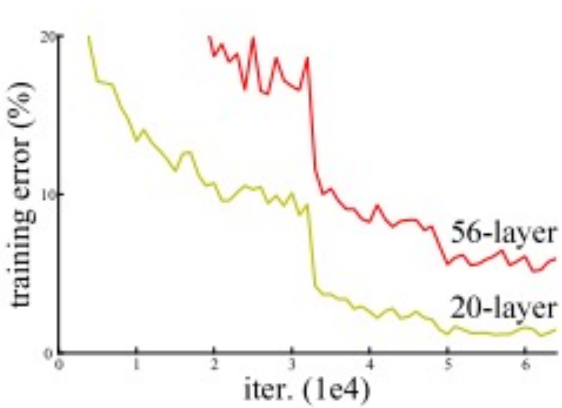
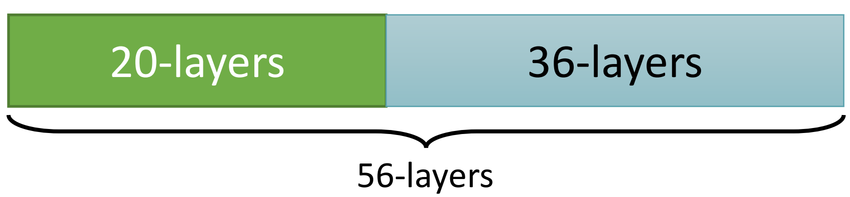
What was the problem?

- It's not due to overfitting, but optimization difficulty
- **Quiz**: Why is that?
- If the 56-layer model optimized well, then it **must be better** than the 20-layer
  - There is a trivial solution for the 36-layer: identity





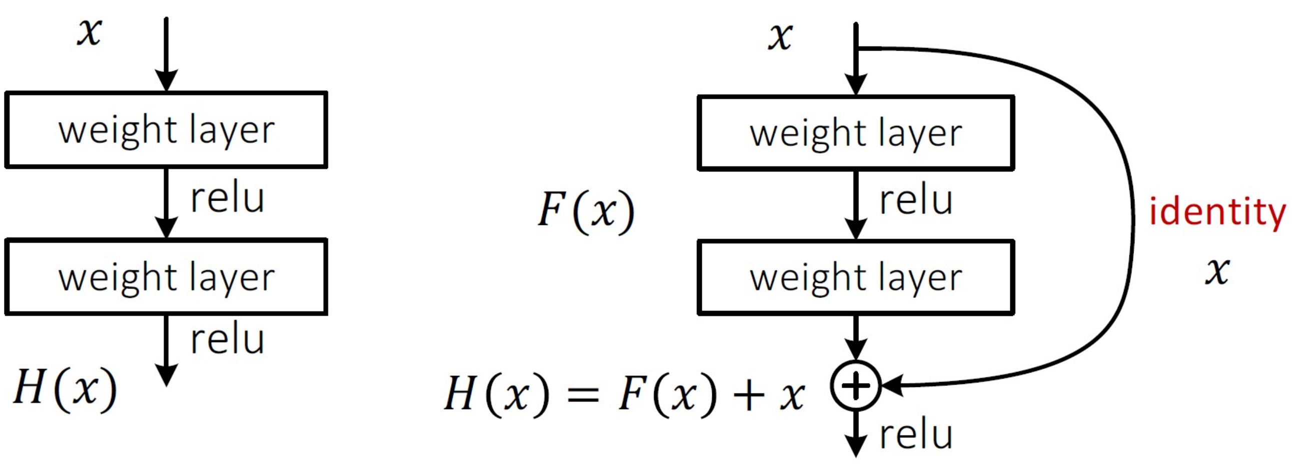
*source : He et al., "Deep residual learning for image recognition". CVPR 2016

Motivation: A non-linear layer may struggle to represent an identity function

- Due to its internal non-linearities, e.g. ReLU
- This may cause the optimization difficulty on large networks

Idea: Reparametrize each layer to make them easy to represent an *identity*

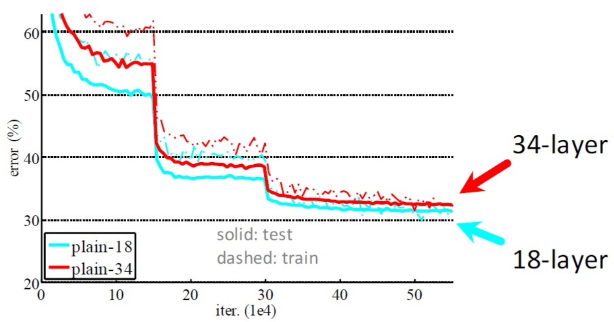
- When all the weights are set to zero, the layer represents an identity



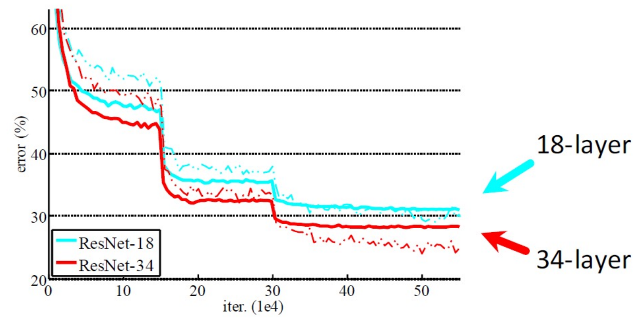
*source : He et al., "Deep residual learning for image recognition". CVPR 2016

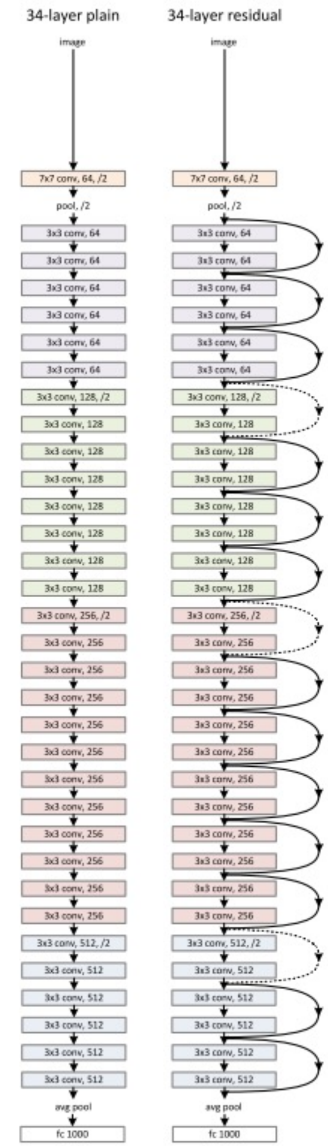
Plain nets v.s. ResNets

ImageNet plain nets

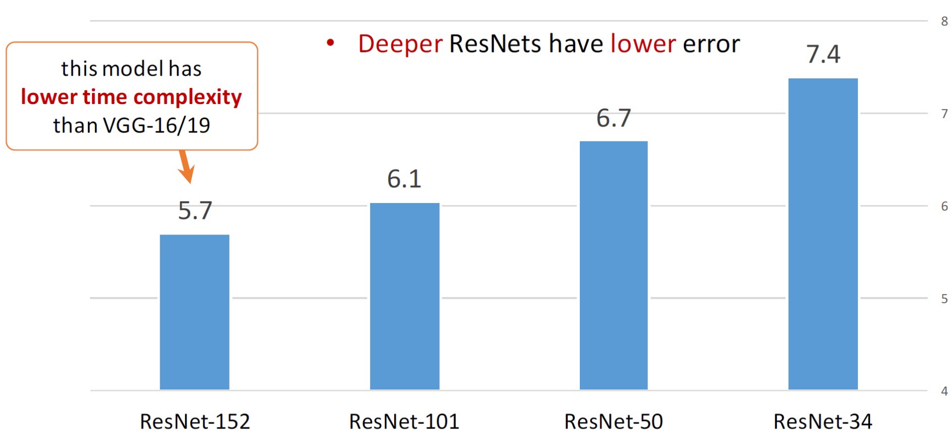


ImageNet ResNets





- Deeper ResNets can be trained without any difficulty



10-crop testing, top-5 val error (%)

*sources :
- He et al., "Deep residual learning for image recognition". CVPR 2016
- He, Kaiming, "Deep Residual Networks: Deep Learning Gets Way Deeper." 2016.

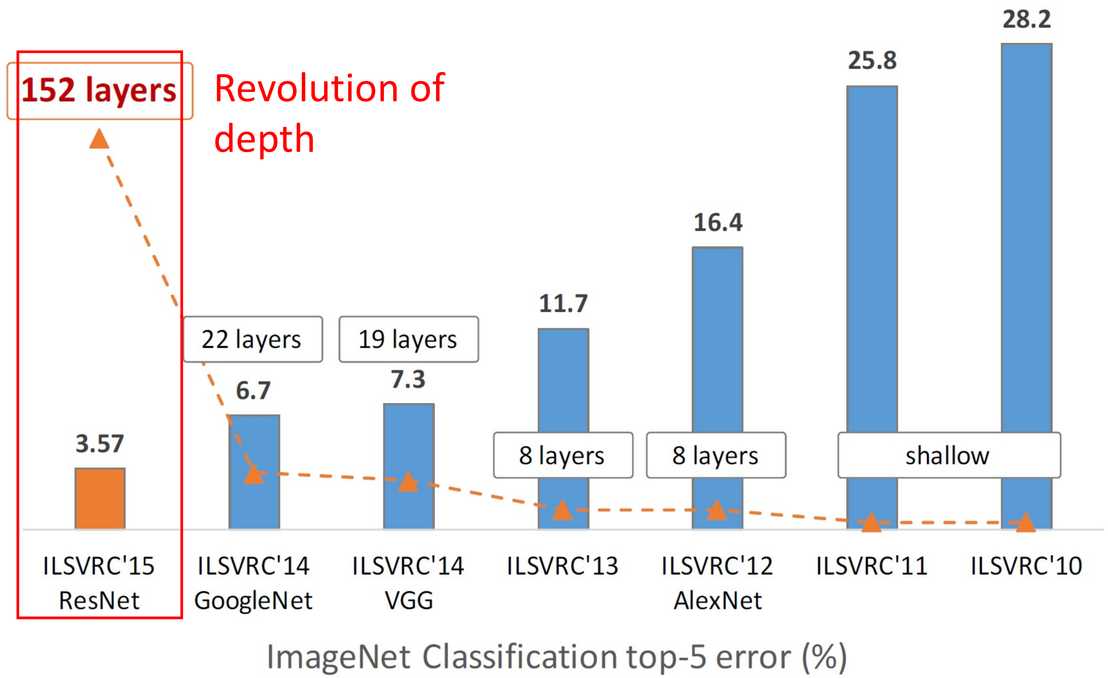
ResNet [He et al., 2016a]

- Identity connection resolved a major difficulty on optimizing large networks

Revolution of depth: Training >100-layer network without difficulty

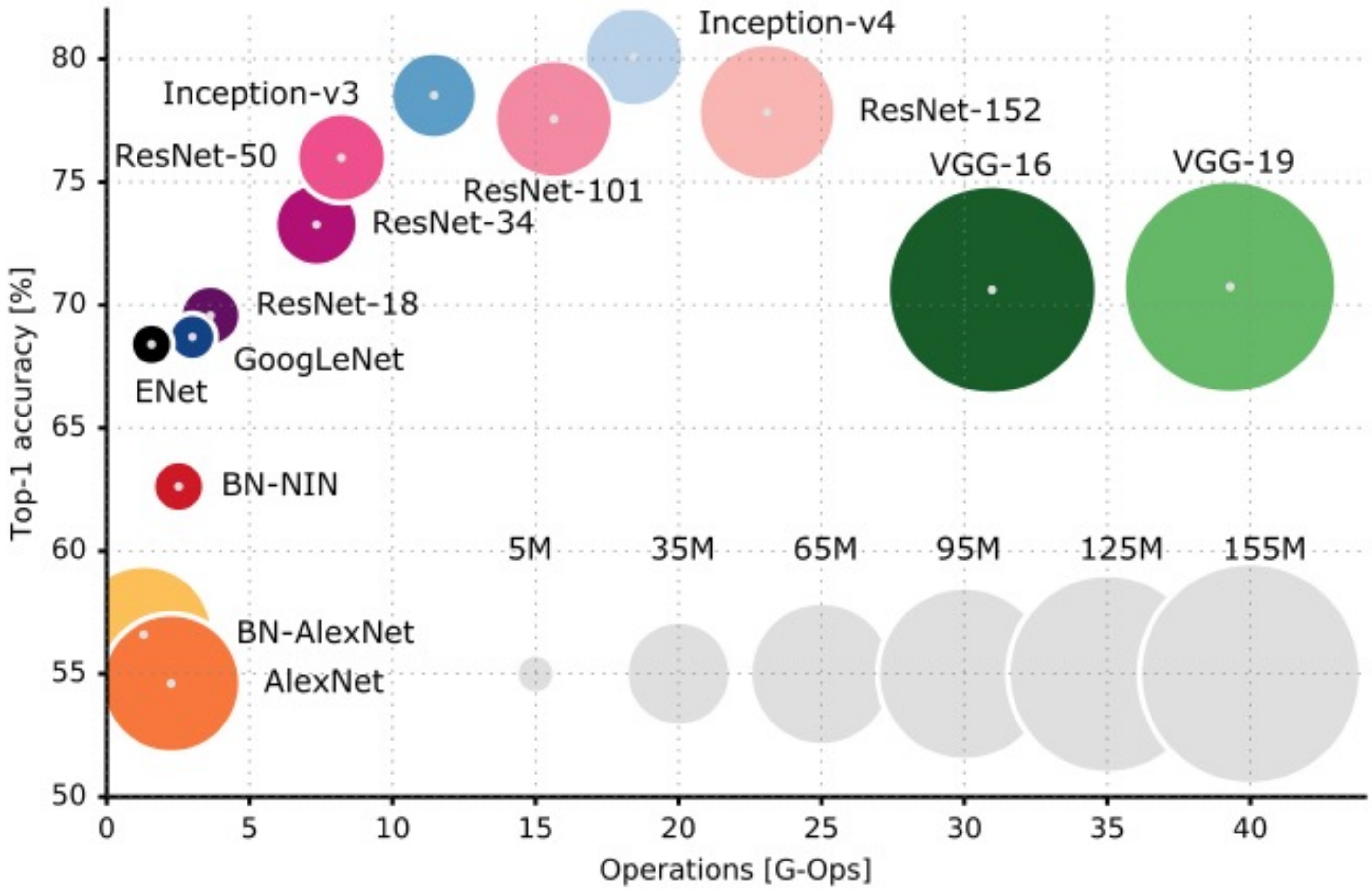
  - Later, ResNet is revised to allow to train up to >1000 layers [He et al., 2016b]

- ResNet also shows good generalization ability as well



*sources :
- He et al., “Deep residual learning for image recognition”. CVPR 2016
- Kaiming He, "Deep Residual Networks: Deep Learning Gets Way Deeper.” 2016.
- He et al. "Identity mappings in deep residual networks.", ECCV 2016

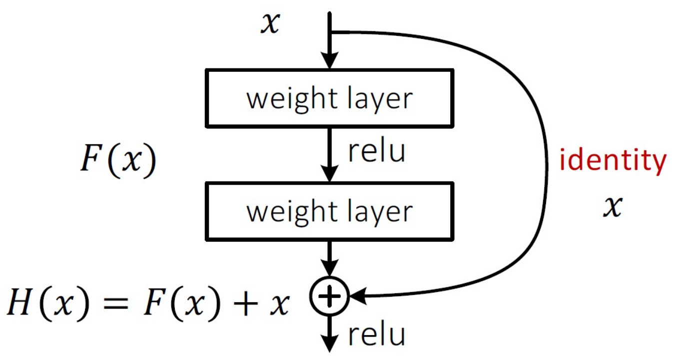
Comparisons on ImageNet for a single model of popular CNNs



*source : https://towardsdatascience.com/neural-network-architectures-156e5bad51ba

Various architectures now are based on ResNet

- ResNet with stochastic depth [Huang et al., 2016]
- Wide ResNet [Zagoruyko et al., 2016]
- ResNet in ResNet [Targ et al., 2016]
- ResNeXt [Xie et al., 2016]
- PyramidNet [Han et al., 2016]
- Inception-v4 [Szegedy et al., 2017]
- DenseNet [Huang et al., 2017]
- Dual Path Network [Chen et al., 2017]



Transition of design paradigm: Optimization ⇒ Generalization

- People are now less concerned about optimization problems in a model
- Instead, they now focus more on its generalization ability
- “How well does an architecture generalize as its scale grows?”

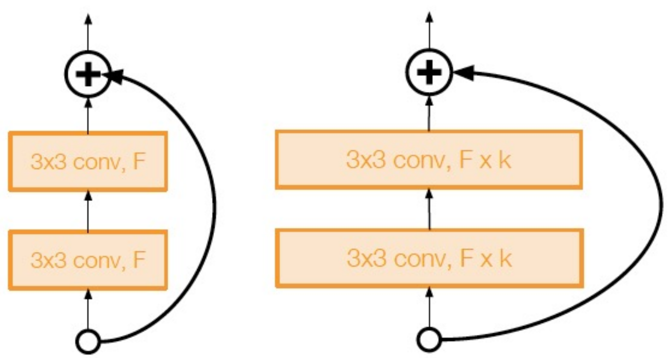
*source : He et al., “Deep residual learning for image recognition”. CVPR 2016

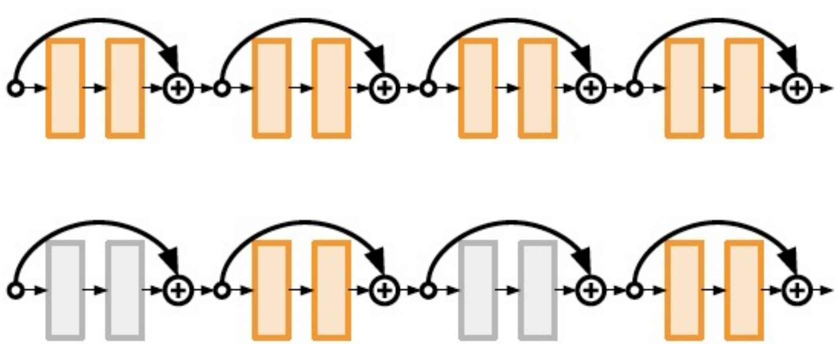
Wide Residual Networks [Zagoruyko et al., 2016]

- Residuals can also work to enlarge the width, not only its depth
- Residual blocks with $\times$k wider filters
- Increasing width instead of depth can be more computationally efficient
  - GPUs are much better on handling "**wide-but-shallow**" than "thin-but-deep“
- WRN-50 outperforms ResNet-152

Deep Networks with Stochastic Depth [Huang et al., 2016]

- Randomly drop a subset of layers during training
- Bypassing via identity connections
- Reduces gradient vanishing, and training time as well

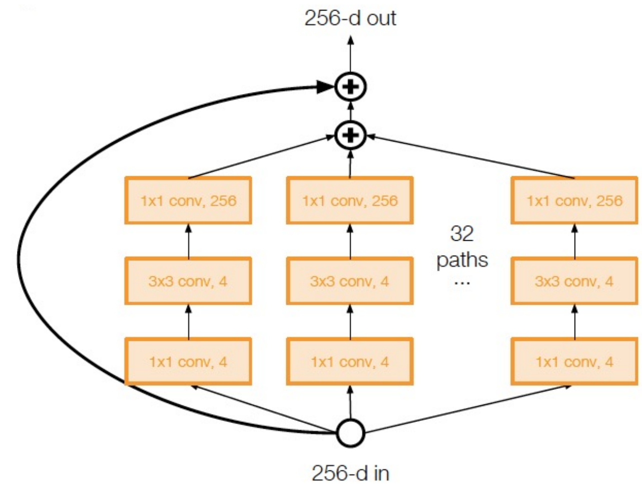




*source : Fei-Fei Li et al. (2018), CS231n Lecture 9, Stanford University

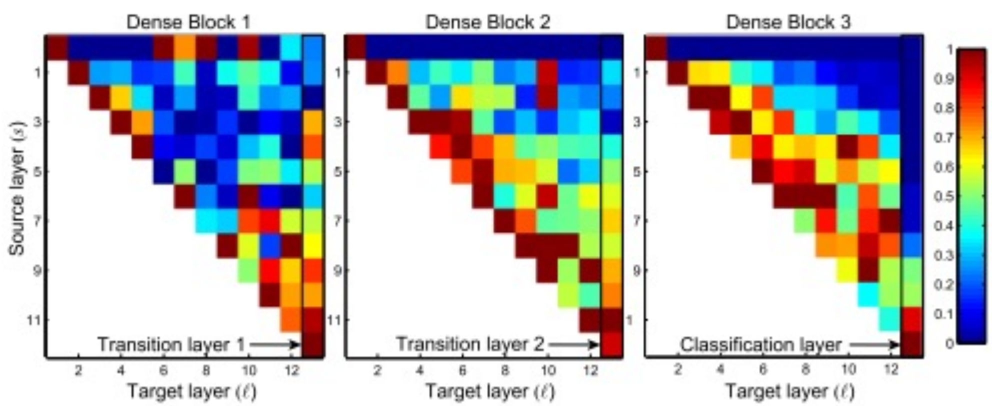
ResNeXt [Xie et al., 2016]

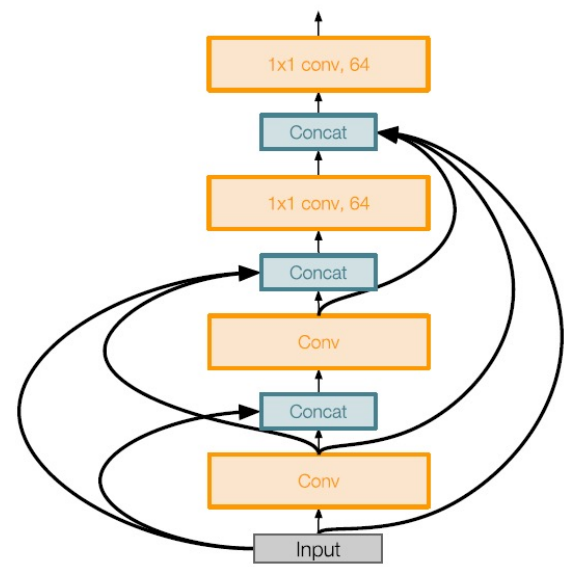
- Aggregating multiple parallel paths inside a residual block (“**cardinality**”)
- Increasing cardinality is more effective than going deeper or wider



DenseNet [Huang et al. 2017]

- Passing all the previous representation directly via concatenation of features
- Strengthens **feature propagation** and **feature reuse**





Dense Block

*source : Fei-Fei Li et al. (2018), CS231n Lecture 9, Stanford University

ResNeXt [Xie et al., 2016]

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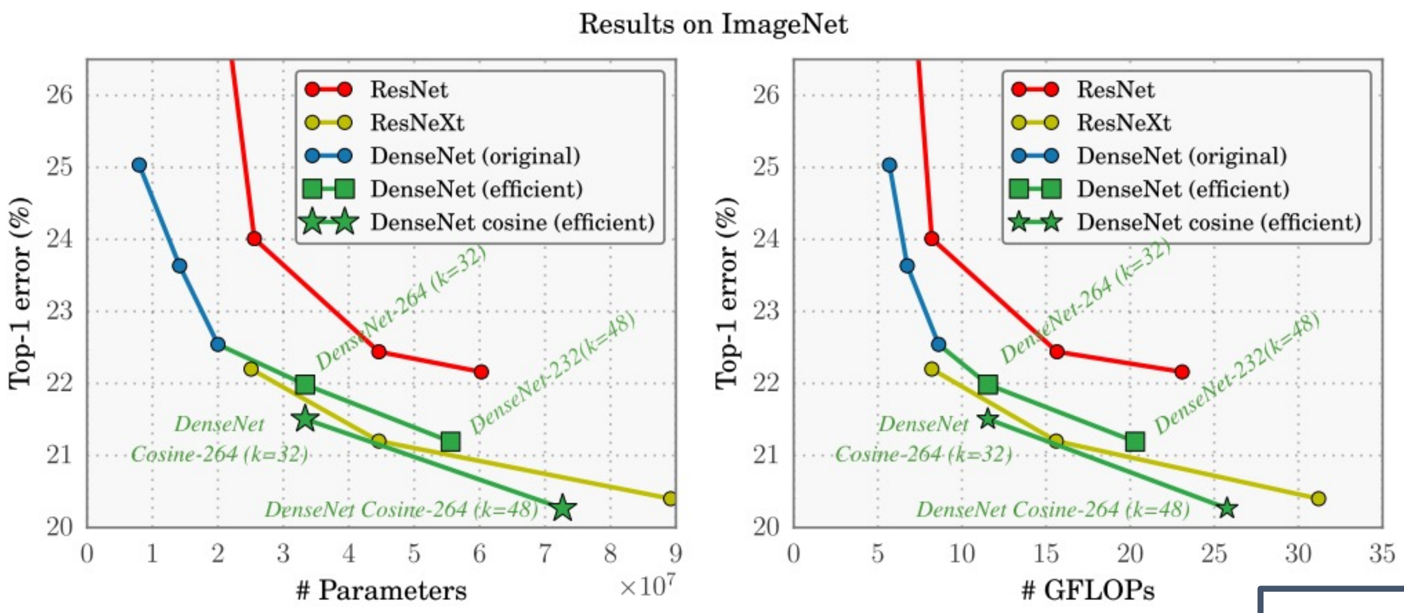

Next, NASNet

*source : Fei-Fei Li et al. (2018), CS231n Lecture 9, Stanford University

Part 1. Basics

- Evolution of CNN architectures
- Batch normalization and ResNet

Part 2. Advanced Topics

- Toward automation of network design
- Dilated and Deformable convolution
- Attention module in CNNs
- Observational Study on CNN Architectures

Part 3. Beyond CNN

- Transformer architecture for Vision
- MLP architecture for Vision

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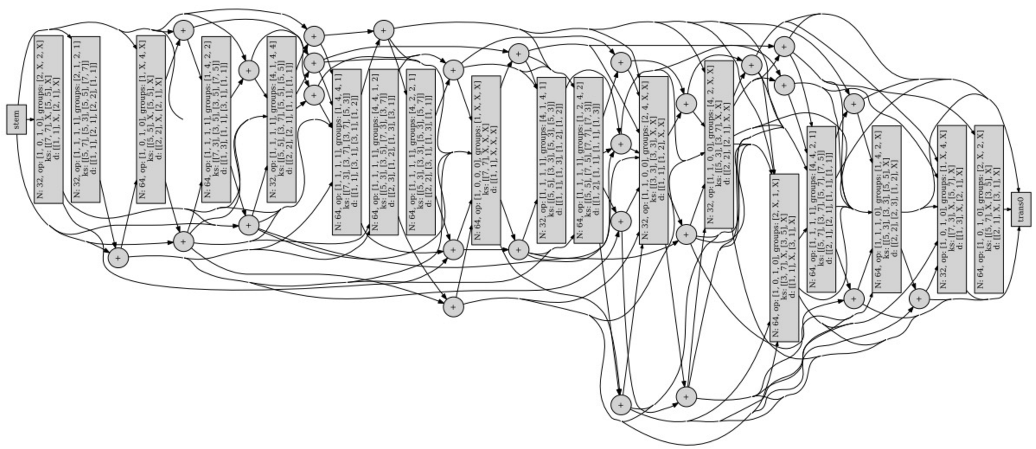
Toward Automation of Network Design

Although the CNN architecture has evolved greatly, our **design principles are still relying on heuristics**

- Smaller kernel and smaller stride, increase cardinality instead of width ...

Recently, there have been works on automatically finding a structure which can outperform existing human-crafted architectures

1. **Search space**: Naïvely searching every model is nearly impossible
2. **Searching algorithm**: Evaluating each model is very costly, and black-boxed



A sample architecture found in [Brock et al., 2018]

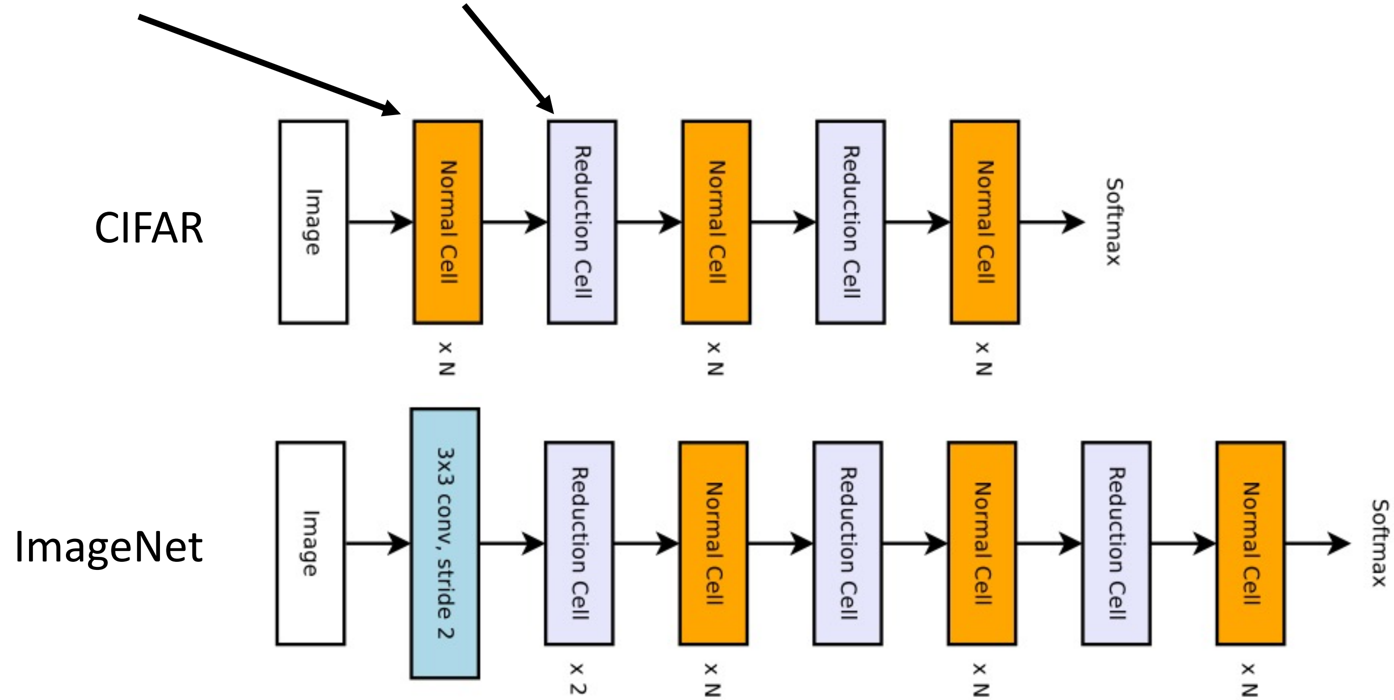
*source : Brock et al., “SMASH: One-Shot Model Architecture Search through HyperNetworks”, ICLR 2018

Designing a good search space is important in architecture searching

- **NASNet** reduces the search space by incorporating our design principles

Motivation: modern architectures are built simply: **a repeated modules**

- Try not to search the whole model, but only cells modules
- **Normal cell** and **Reduction cell** (cell w/ stride 2)

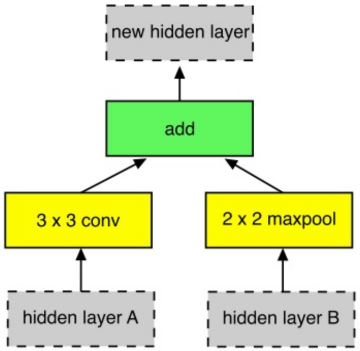


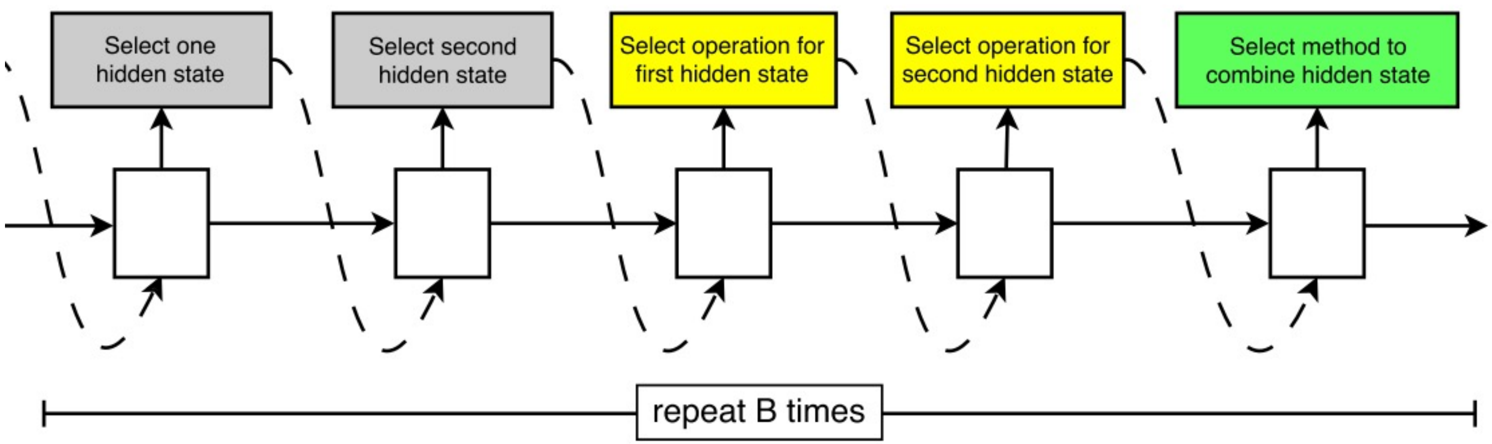
*source : Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition", CVPR 2018

Designing a good search space is important in architecture searching

- **NASNet** reduces the search space by incorporating our design principles

- Each cell consists of B **blocks**
- Each block is determined by **selecting methods**
  1. Select two hidden states from h_i, h_{i-1} or of existing block
  2. Select methods to process for each of the selected states
  3. Select a method to combine the two states
     - (1) **element-wise addition** or (2) **concatenation**



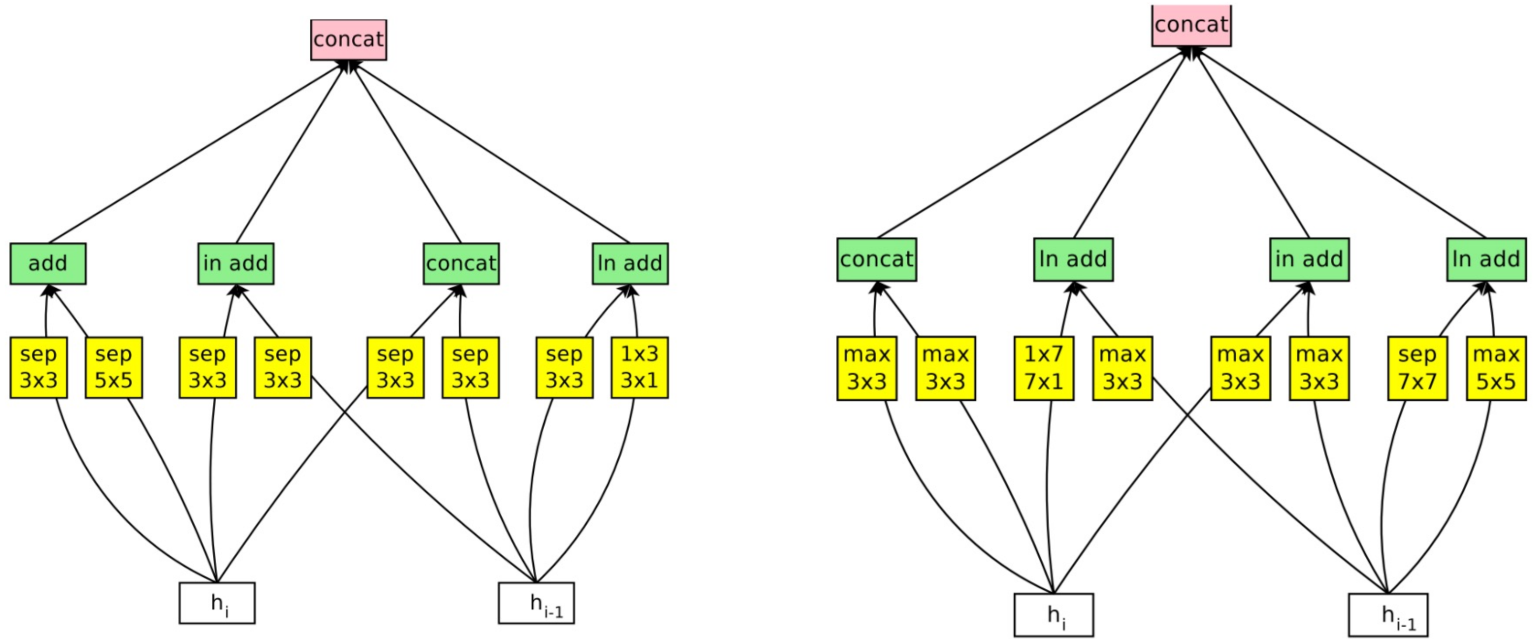


*source : Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition", CVPR 2018

Designing a good search space is important in architecture searching

- **NASNet** reduces the search space by incorporating our design principles

- Each cell consists of B **blocks**
  - **Example**: $B = 4$



Normal Cell

Reduction Cell

*source : Zoph et al., “Learning Transferable Architectures for Scalable Image Recognition”, CVPR 2018

Designing a good search space is important in architecture searching

- **NASNet** reduces the search space by incorporating our design principles

- Set of methods to be selected based on their prevalence in the CNN literature

  - identity
  - 1x7 then 7x1 convolution
  - 3x3 average pooling
  - 5x5 max pooling
  - 1x1 convolution
  - 3x3 depthwise-separable conv
  - 7x7 depthwise-separable conv
  - 1x3 then 3x1 convolution
  - 3x3 dilated convolution
  - 3x3 max pooling
  - 7x7 max pooling
  - 3x3 convolution
  - 5x5 depthwise-seperable conv

Any searching methods can be used

- **Random search** [Bergstra et al., 2012] could also work
- **RL-based search** [Zoph et al., 2016] is mainly used in this paper

*source : Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition", CVPR 2018

- The pool of workers consisted of **500 GPUs**, processing **over 4 days**

All architecture searches are performed on **CIFAR-10**

- NASNet-A: State-of-the-art error rates could be achieved
- NASNet-B/C: Extremely parameter-efficient models were also found

model	depth	# params	error rate (%)
DenseNet ($L = 40, k = 12$) [26]	40	1.0M	5.24
DenseNet($L = 100, k = 12$) [26]	100	7.0M	4.10
DenseNet ($L = 100, k = 24$) [26]	100	27.2M	3.74
DenseNet-BC ($L = 100, k = 40$) [26]	190	25.6M	3.46
Shake-Shake 26 2x32d [18]	26	2.9M	3.55
Shake-Shake 26 2x96d [18]	26	26.2M	2.86
Shake-Shake 26 2x96d + cutout [12]	26	26.2M	2.56
NAS v3 [70]	39	7.1M	4.47
NAS v3 [70]	39	37.4M	3.65
NASNet-A (6 @ 768)	-	3.3M	3.41
NASNet-A (6 @ 768) + cutout	-	3.3M	2.65
NASNet-A (7 @ 2304)	-	27.6M	2.97
NASNet-A (7 @ 2304) + cutout	-	27.6M	2.40
NASNet-B (4 @ 1152)	-	2.6M	3.73
NASNet-C (4 @ 640)	-	3.1M	3.59

*source : Zoph et al., “Learning Transferable Architectures for Scalable Image Recognition”, CVPR 2018

Toward Automation of Network Design: NASNet [Zoph et al., 2018]

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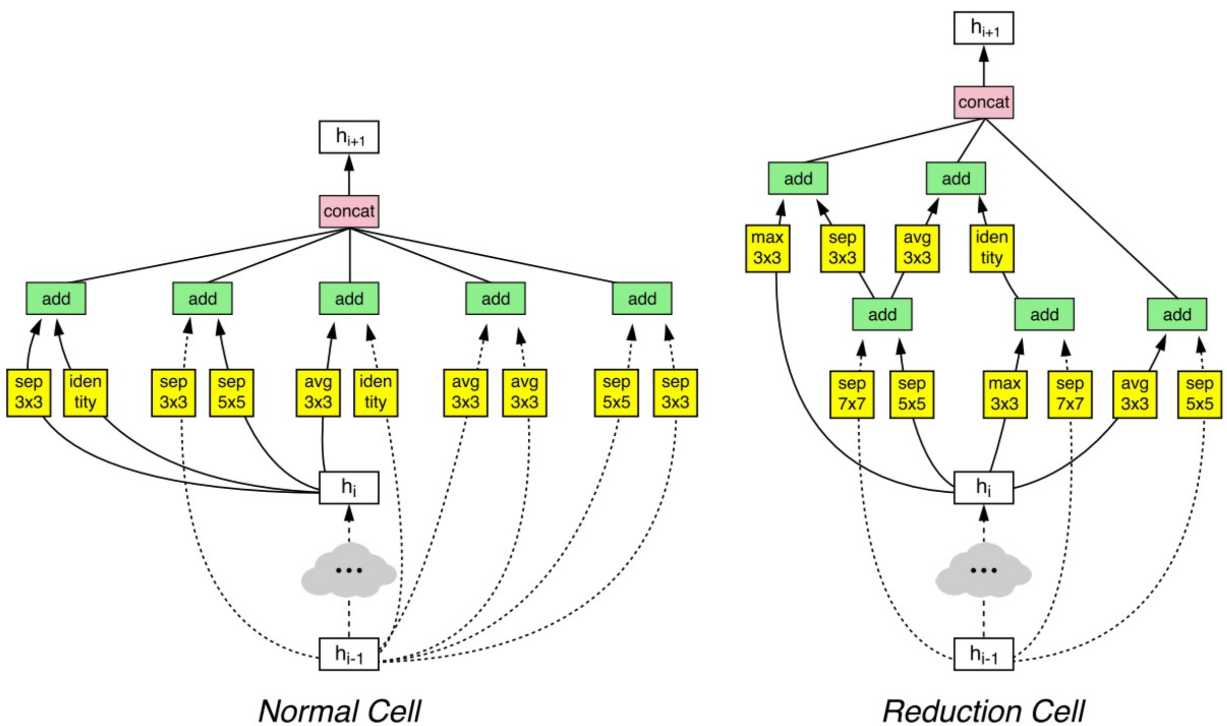

NASNet-A

*source : Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition", CVPR 2018

- The pool of workers consisted of **500 GPUs**, processing **over 4 days**

All architecture searches are performed on **CIFAR-10**

Cells found in CIFAR-10 could also transferred well into ImageNet

Model	image size	# parameters	Mult-Adds	Top 1 Acc. (%)	Top 5 Acc. (%)
Inception V2 [29]	224×224	11.2 M	1.94 B	74.8	92.2
NASNet-A (5 @ 1538)	**299×299**	**10.9 M**	**2.35 B**	**78.6**	**94.2**
Inception V3 [59]	299×299	23.8 M	5.72 B	78.0	93.9
Xception [9]	299×299	22.8 M	8.38 B	79.0	94.5
Inception ResNet V2 [57]	299×299	55.8 M	13.2 B	80.4	95.3
NASNet-A (7 @ 1920)	**299×299**	**22.6 M**	**4.93 B**	**80.8**	**95.3**
ResNeXt-101 (64 x 4d) [67]	320×320	83.6 M	31.5 B	80.9	95.6
PolyNet [68]	331×331	92 M	34.7 B	81.3	95.8
DPN-131 [8]	320×320	79.5 M	32.0 B	81.5	95.8
SENet [25]	**320×320**	**145.8 M**	**42.3 B**	**82.7**	**96.2**
NASNet-A (6 @ 4032)	**331×331**	**88.9 M**	**23.8 B**	**82.7**	**96.2**

*source : Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition", CVPR 2018

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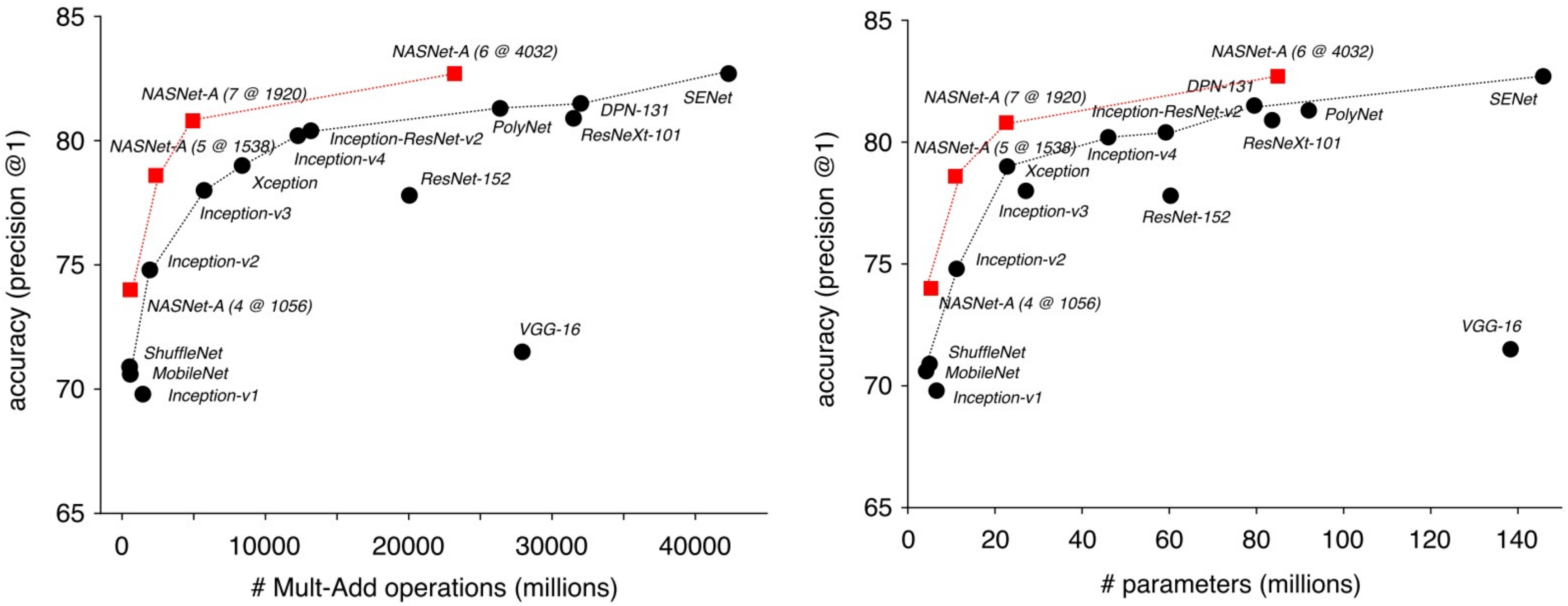


*source : Zoph et al., “Learning Transferable Architectures for Scalable Image Recognition”, CVPR 2018

Architecture searching is still an active research area

- AmoebaNet [Real et al., 2018]
- Efficient-NAS (ENAS) [Pham et al., 2018]
- NAONet [Luo et al., 2018]

Model	Error(%)	#params	GPU Days
DenseNet-BC [19]	3.46	25.6M	/
ResNeXt-29 [43]	3.58	68.1M	/
NASNet-A [48]	3.41	3.3M	2000
NASNet-B [48]	3.73	2.6M	2000
NASNet-C [48]	3.59	3.1M	2000
Hier-EA [28]	3.75	15.7M	300
AmoebaNet-A [38]	3.34	3.2M	3150
AmoebaNet-B [38]	3.37	2.8M	3150
AmoebaNet-B [38]	3.04	13.7M	3150
AmoebaNet-B [38]	2.98	34.9M	3150
AmoebaNet-B + Cutout [38]	2.13	34.9M	3150
ENAS [37]	3.54	4.6M	0.45
PNAS [27]	3.41	3.2M	225
DARTS + Cutout [29]	2.83	4.6M	4
NAONet	3.18	10.6M	200
NAONet	2.98	28.6M	200
NAONet + Cutout	2.07	128M	200
NAONet-WS	3.53	3.7M	0.4

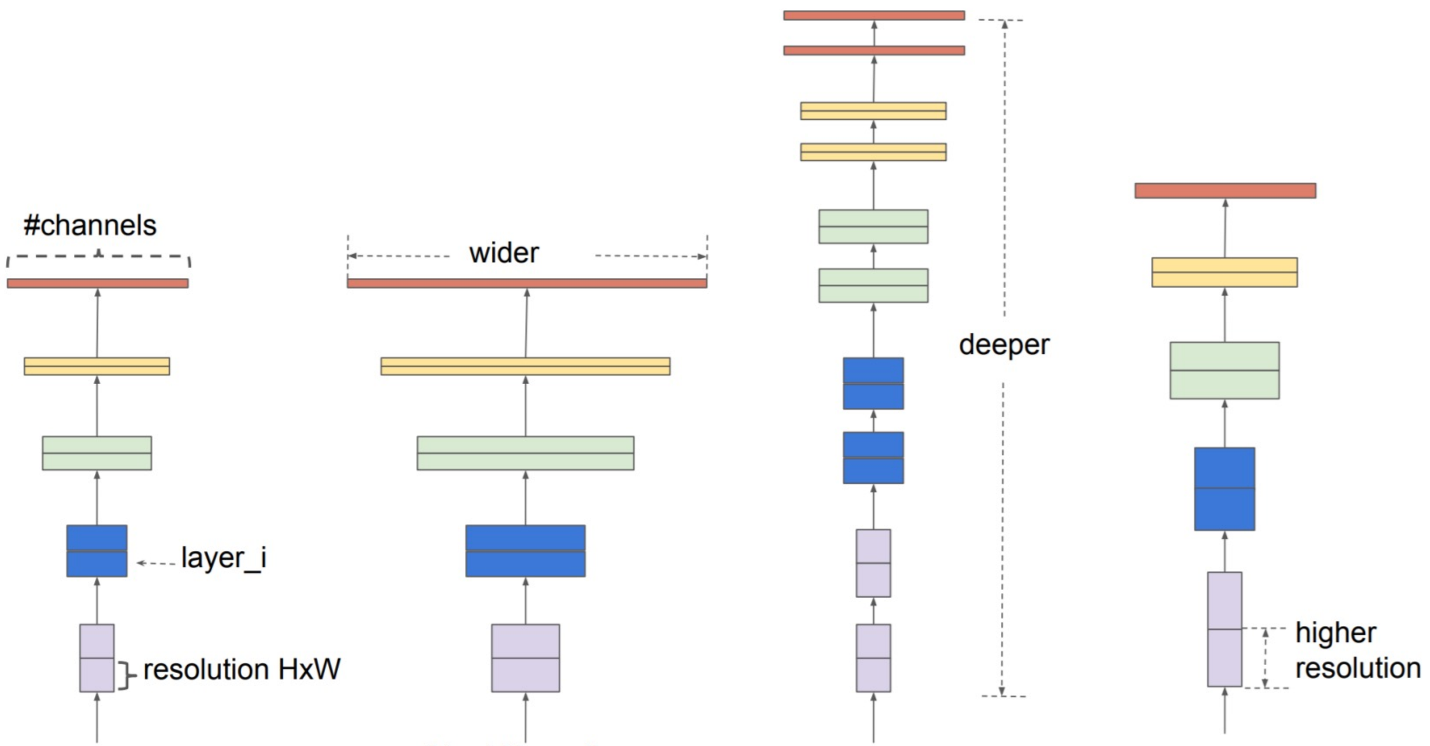
Next, EfficientNet

*source : Luo et al., “Neural Architecture Optimization”, Arxiv 2018

Although **Scaling up** CNNs is widely used to achieve better generalization, the process of scaling has never been understood

- The common way is scaling model depth, width, and image resolution

Question: Is there a principled scaling method for better accuracy and efficiency?



(a) baseline (b) width scaling (c) depth scaling (d) resolution scaling

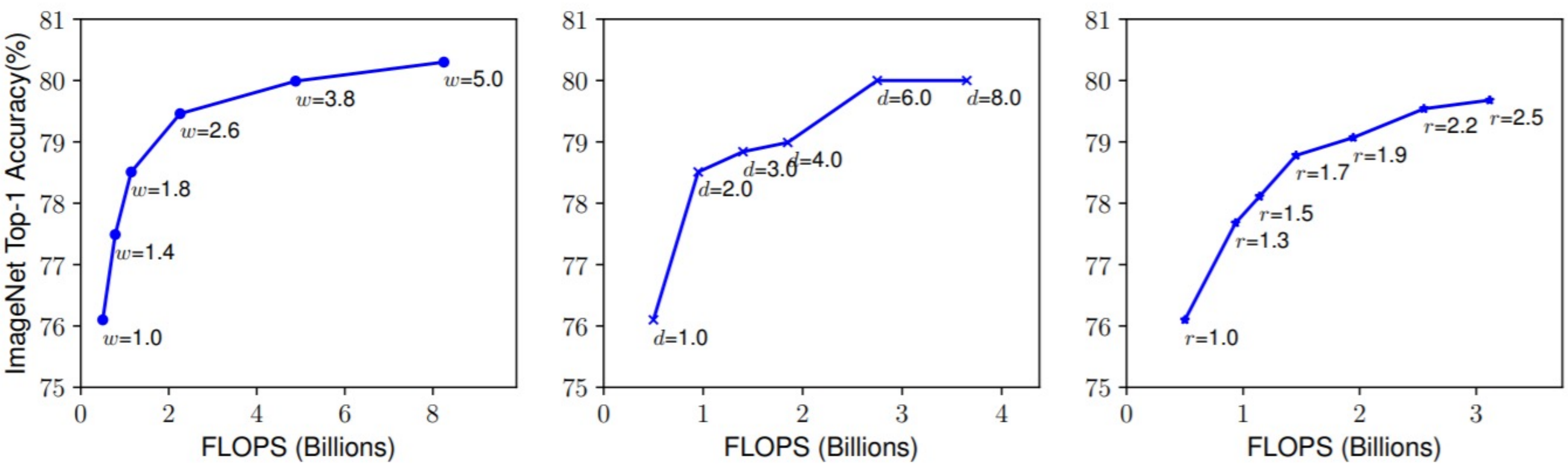
*source : Tan et al., "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", ICML 2019

The state-of-the-art ILSVRC classification in 2019 (top-5 error rate 2.9%)

- **EfficientNet** uniformly scales network width, depth, and resolution with a set of fixed scaling coefficients (called ***"compound scaling"***)

Motivation: There exists certain relationship between network width, depth and image resolution

- Scaling single dimension has a limitation
    - Gain diminishes for bigger models.

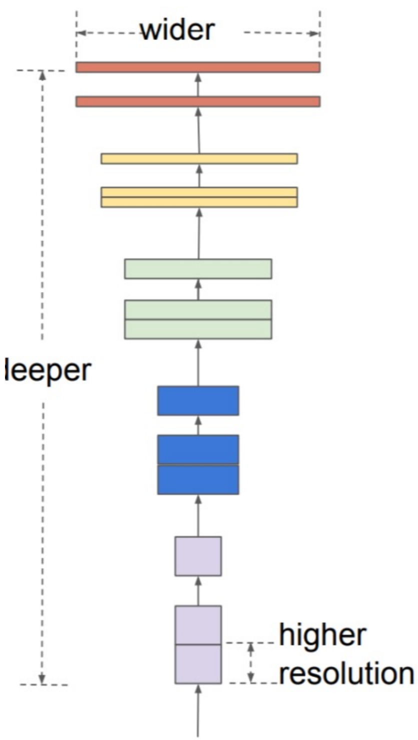


Depth w **Width d** **Resolution r**

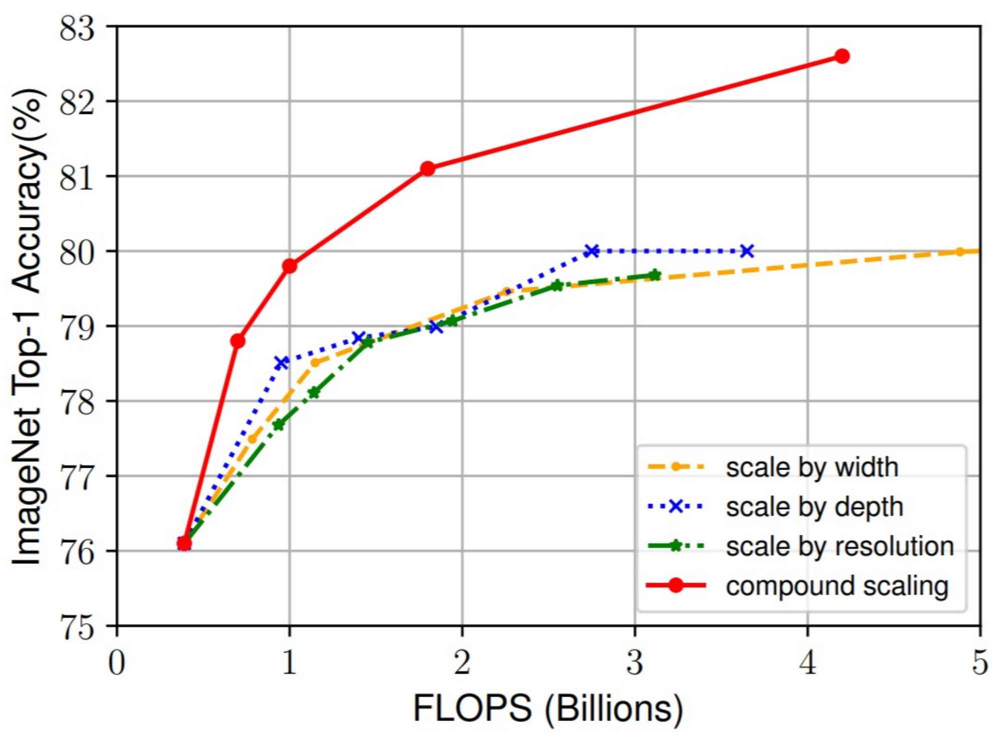
- Scaling all together with a fixed ratio

*source : Tan et al., "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", ICML 2019

- **Compound scaling:** Scaling all together with a fixed ratio ϕ in a principled way
  - Depth $d = \alpha^{\phi}, \alpha \geq 1$
  - Width $w = \beta^{\phi}, \beta \geq 1$
  - Resolution $r = \gamma^{\phi}, \gamma \geq 1$
  - Finding α, β, γ under compound constraint $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$
    - **Why?** Such scaling approximately increases total FLOPS by $(\alpha \cdot \beta^2 \cdot \gamma^2)^{\phi} \approx 2^{\phi}$



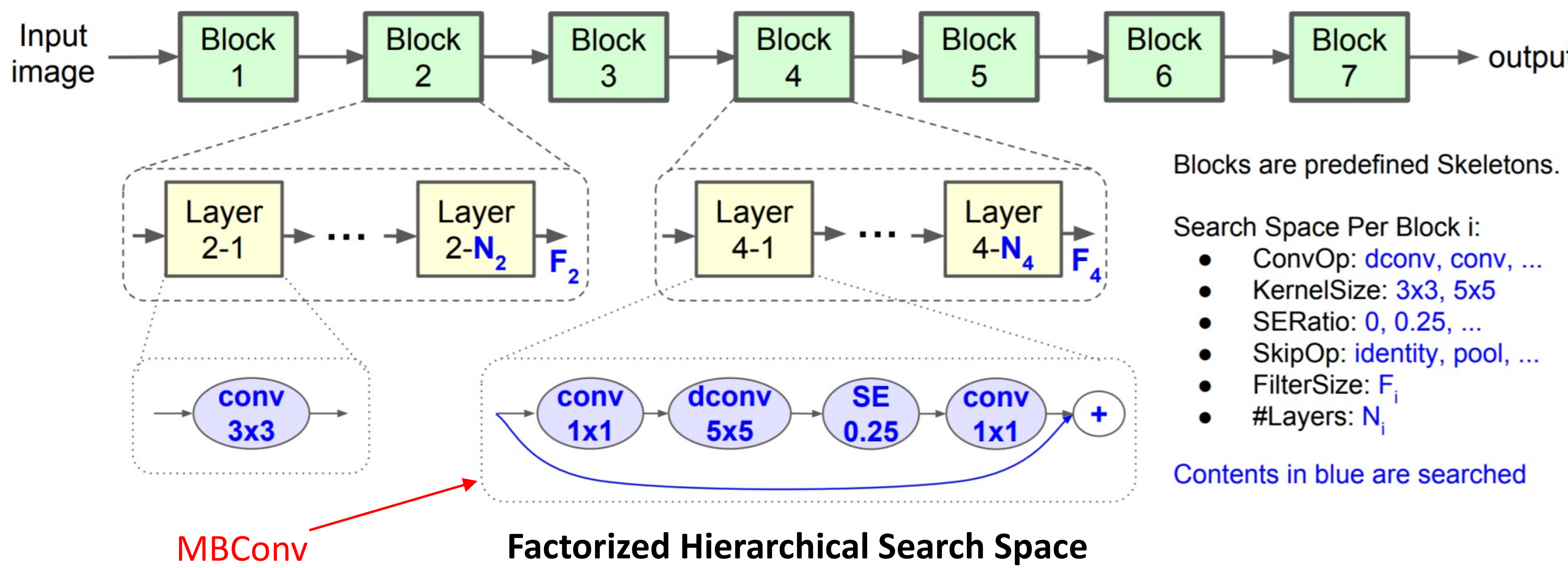
(e) compound scaling



*source : Tan et al., “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, ICML 2019

Having a good baseline network is also critical!

- Multi-objective neural architecture search
  - Optimizing both **accuracy** and **FLOPS**
  - Search space is the same as MnasNet [Tan et al., 2019]
- Mobile-size baseline, called **EfficientNet-B0**
  - Main building block is mobile inverted bottleneck, **MBConv**
  - Adding squeeze-and-excitation (SE) optimization [Hu et al., 2018]



Factorized Hierarchical Search Space

*source : Tan et al., "Mnasnet: Platform-aware neural architecture search for mobile", CVPR 2019

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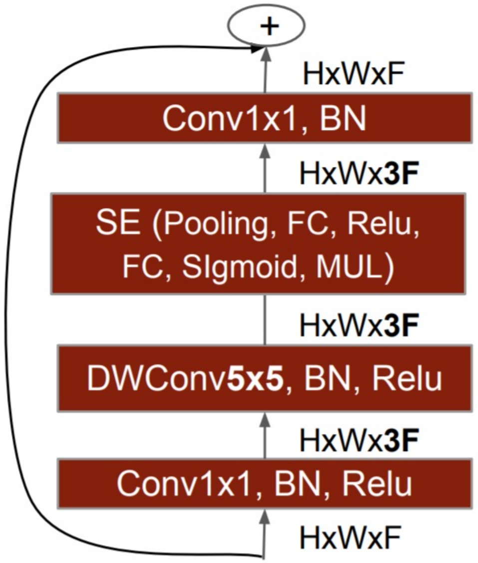
  - DWConv denotes depthwise convolution [Howard et al ., 2017]

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Architecture of EfficientNet-B0



MBConv

*source : Tan et al., “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, ICML 2019
Tan et al., “Mnasnet: Platform-aware neural architecture search for mobile”, CVPR 2019

From EfficientNet-B0 to B7

- **EfficientNet-B0**: Baseline model with $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$
- **EfficientNet-B1 to B7**: Scaling up EfficientNet-B0 with different ϕ

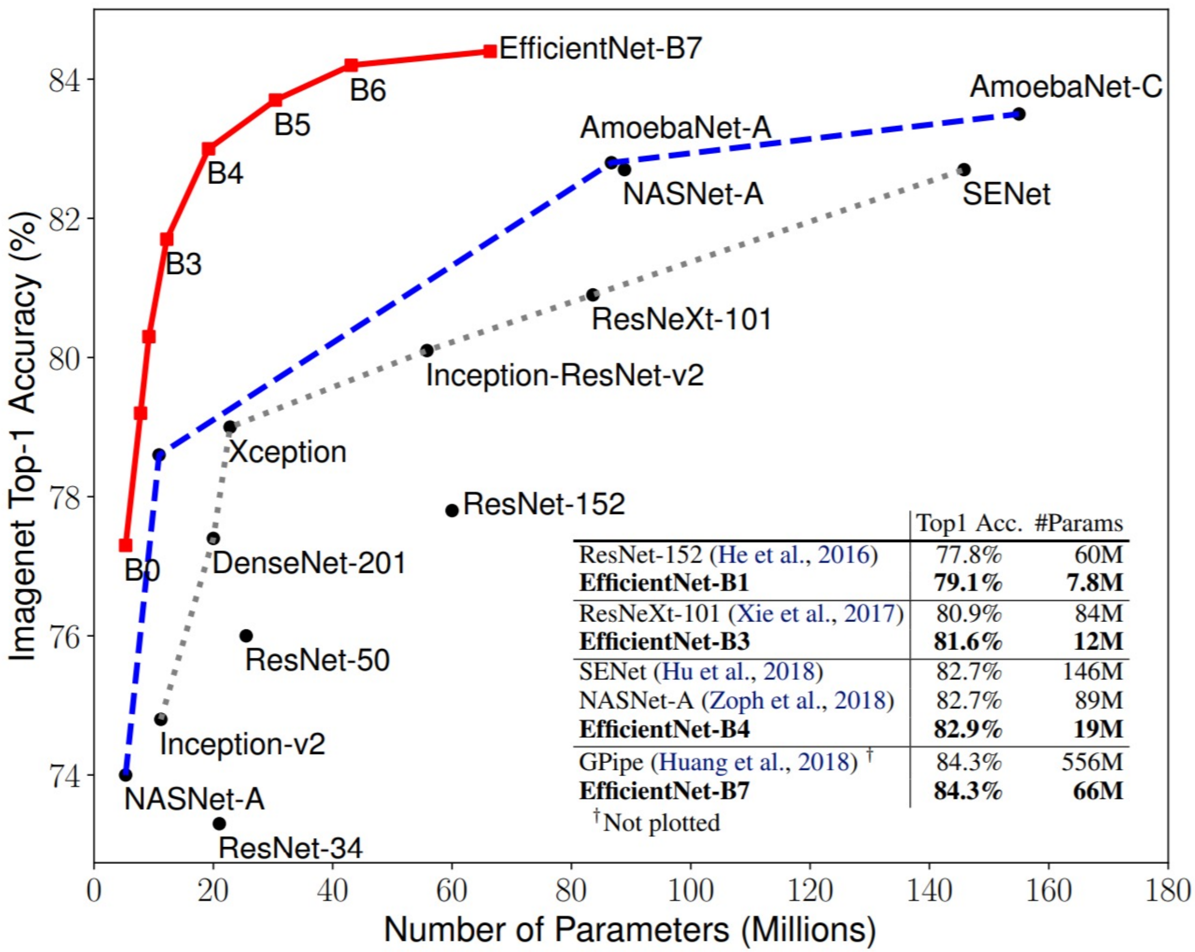
Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	**77.1%**	**93.3%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**79.1%**	**94.4%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**80.1%**	**94.9%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.6%**	**95.7%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**82.9%**	**96.4%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.6%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.0%**	**96.8%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.3%**	**97.0%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

*source : Tan et al., "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", ICML 2019

Principle of Network Scaling: EfficientNet [Tan et al., 2019]

From EfficientNet-B0 to B7

- **EfficientNet-B0**: Baseline model with $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$
- **EfficientNet-B1 to B7**: Scaling up EfficientNet-B0 with different ϕ



EfficientNet-B7 achieves new state-of-the-art 84.3% top-1 accuracy but being 1.3x smaller than NASNet-A.

EfficientNet-B1 is 7.6x smaller and 5.7x faster than ResNet-152

Next, Dilated Conv

*source : Luo et al., “Neural Architecture Optimization”, Arxiv 2018

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Objects in real-world often contain sophisticated spatial information

- Multiple scales
- Irregular shapes

Drawbacks: geometric transformations are assumed fixed and known

- Different size and shape of kernels may be required
- But, regular kernels have fixed-size and shape

Scale:

Deformation:

*source : https://jifengdai.org/slides/Deformable_Convolutional_Networks_Oral.pdf

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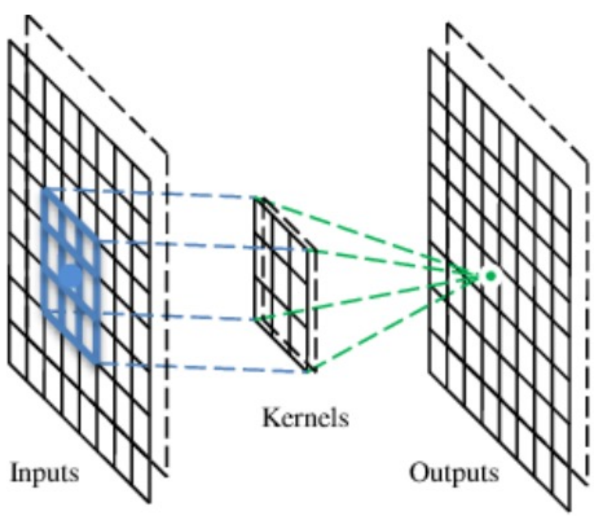
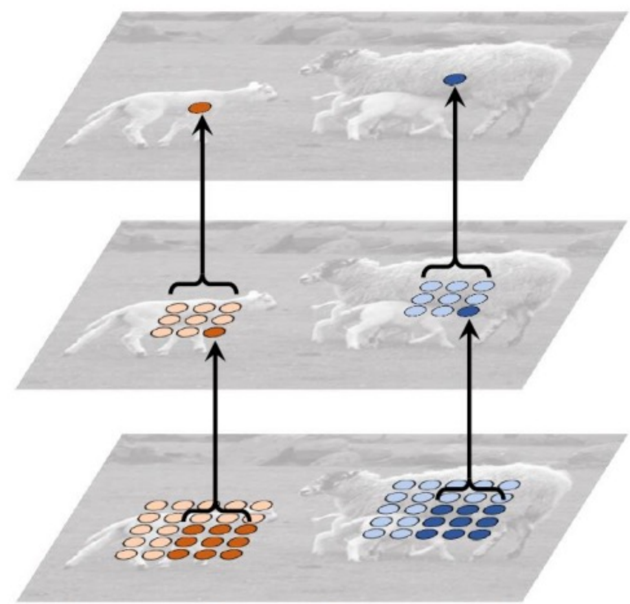


regular convolution



2 layers of regular convolution

*source : https://jifengdai.org/slides/Deformable_Convolutional_Networks_Oral.pdf

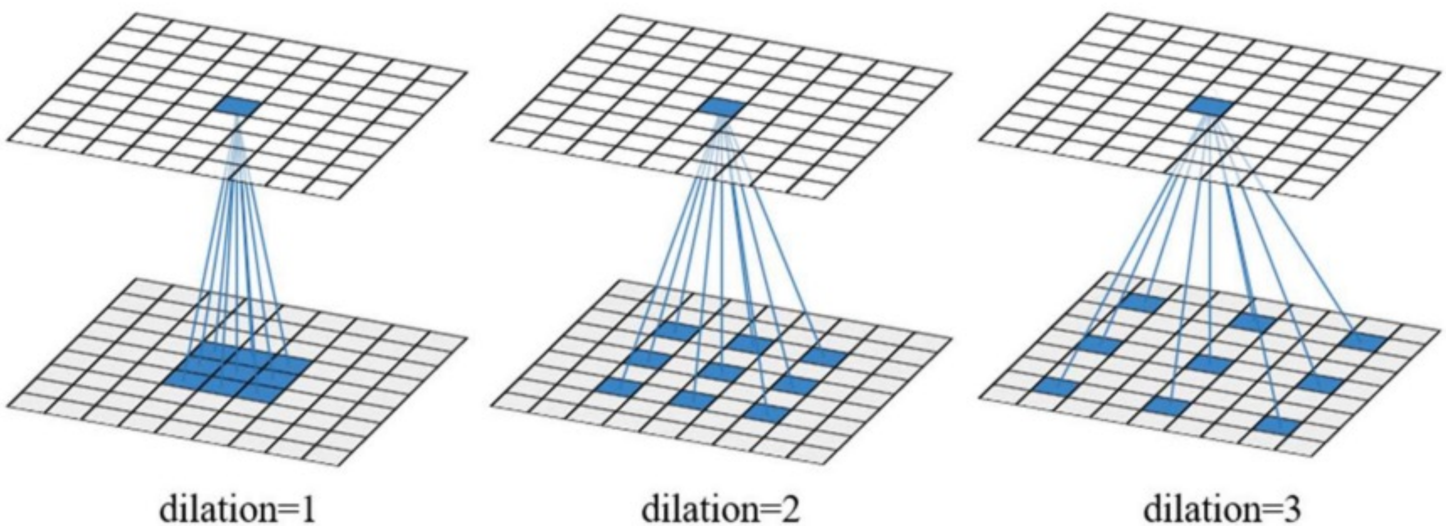
Dilated Convolution [Chen et al., 2017]

Motivation: Images in real-world usually contain **multi-scale objects**

- Regular convolution has a fixed-size of field of view
- Different size of kernels are required for multi-scale objects
- But, large-size of kernels may increase computational costs

Dilated convolution: Filling with **zero values** inside of large-size of kernels for efficient computation

- It can enlarge field-of-view to incorporate multi-scale context

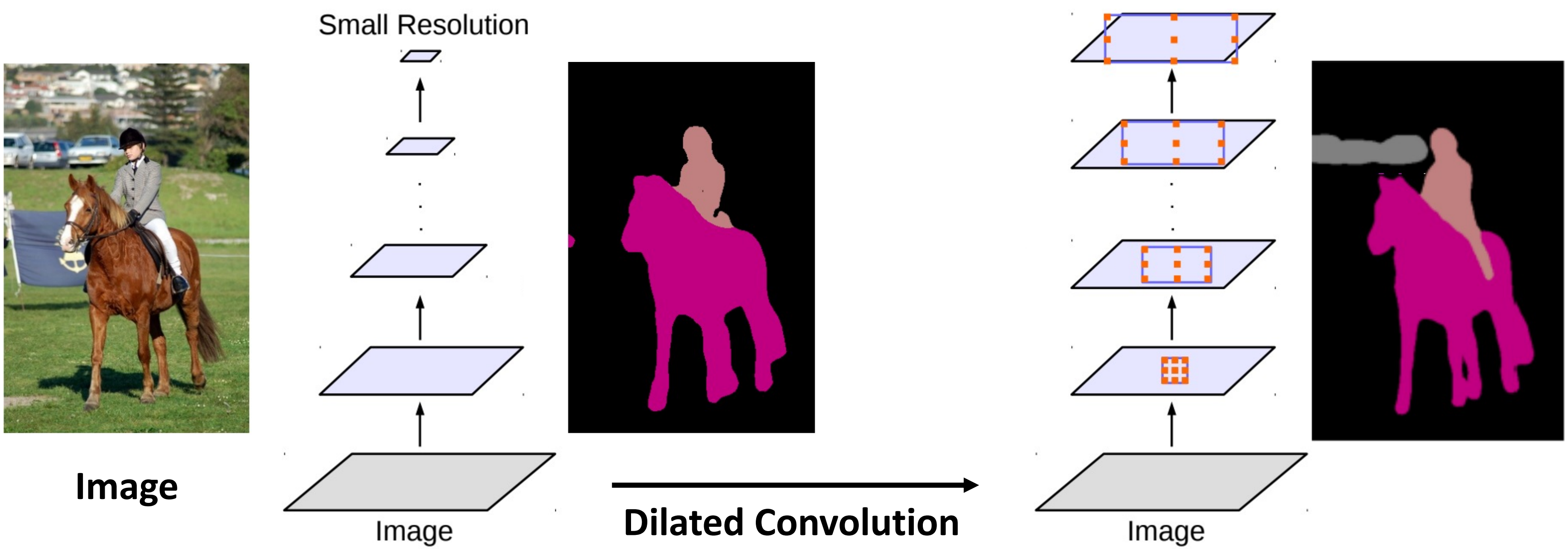


*source: Chen et al., "Rethinking atrous convolution for semantic image segmentation", ArXiv, 2019

Motivation: Images in real-world usually contain **multi-scale objects**

- Regular convolution has a fixed-size of field of view
- Different size of kernels are required for multi-scale objects
- But, large-size of kernels may increase computational costs

- **Example: Dilated convolution** in semantic segmentation



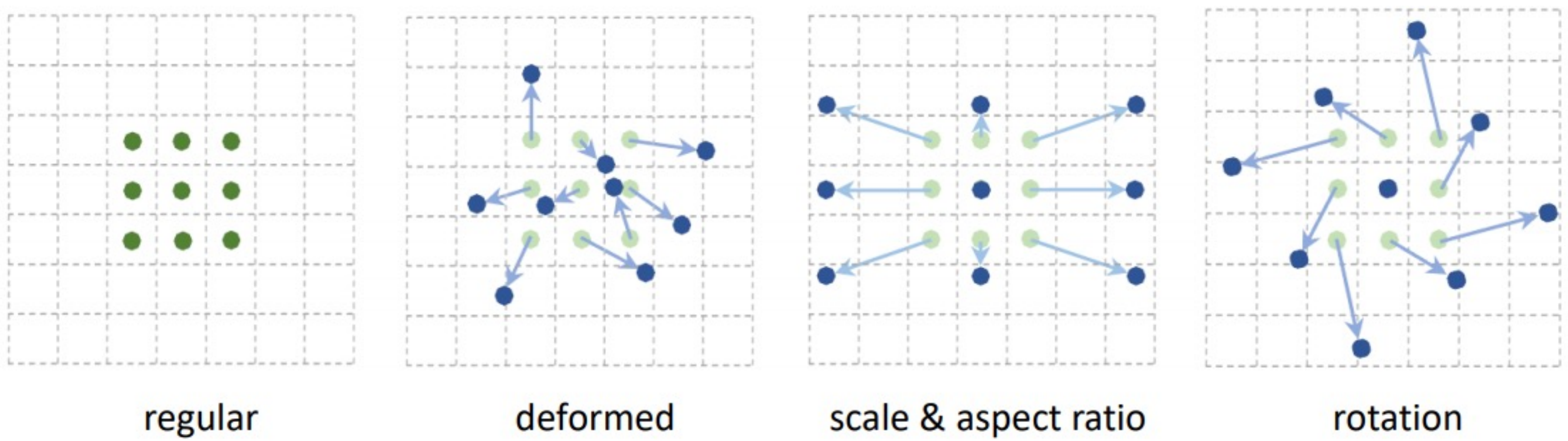
*source: Chen et al., "Rethinking atrous convolution for semantic image segmentation", ArXiv, 2019

Motivation: Shape of objects in the real world are usually irregular

- Different shape of kernels are required for irregular objects
- Regular convolution has a fixed-shape of kernel

Deformable convolution: Learning sampling location of kernels to capture irregular shape of objects

- Adding **offset field** to generate irregular sampling locations



Different types of sampling locations

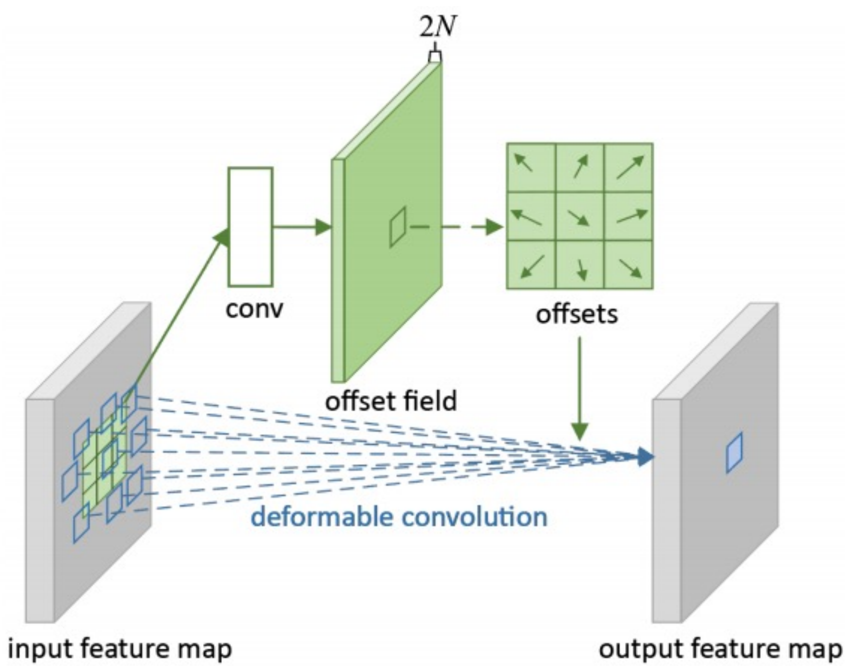
*source : https://jifengdai.org/slides/Deformable_Convolutional_Networks_Oral.pdf

Motivation: Shape of objects in the real world are usually irregular

- Different shape of kernels are required for irregular objects
- Regular convolution has a fixed-shape of kernel

Deformable convolution: Learning sampling location of kernels to capture irregular shape of objects

- Adding **offset field** to generate irregular sampling locations



Regular convolution

$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n)$$

Deformable convolution

$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta\mathbf{p}_n)$$

where $\Delta\mathbf{p}_n$ is generated by a sibling branch of regular convolution (offset field)

*source : https://jifengdai.org/slides/Deformable_Convolutional_Networks_Oral.pdf

Motivation: Shape of objects in the real world are usually irregular

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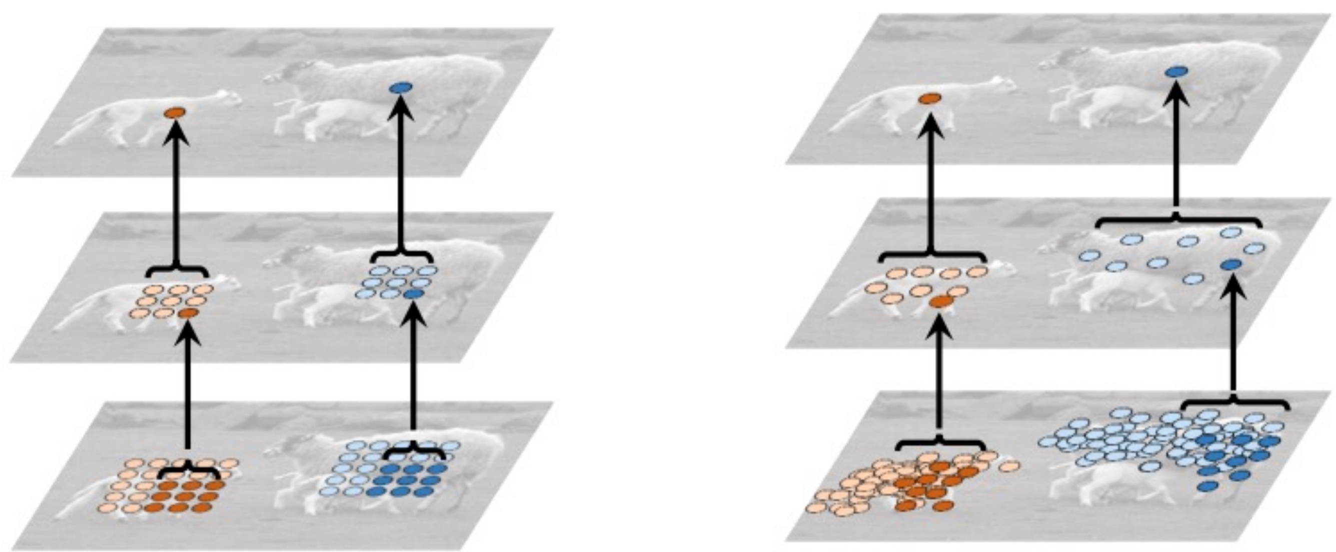

(a) standard convolution (b) deformable convolution

*source : https://jifengdai.org/slides/Deformable_Convolutional_Networks_Oral.pdf

Motivation: Shape of objects in the real world are usually irregular

- Different shape of kernels are required for irregular objects
- Regular convolution has a fixed-shape of kernel

Learned offsets in the **deformable convolution** layers are highly adaptive to the image content

- Different size and shape of kernels for multiple objects

Visualizations of sampling locations

Next, SENet

*source: Dai et al., "Deformable Convolutional Networks", ICCV, 2017

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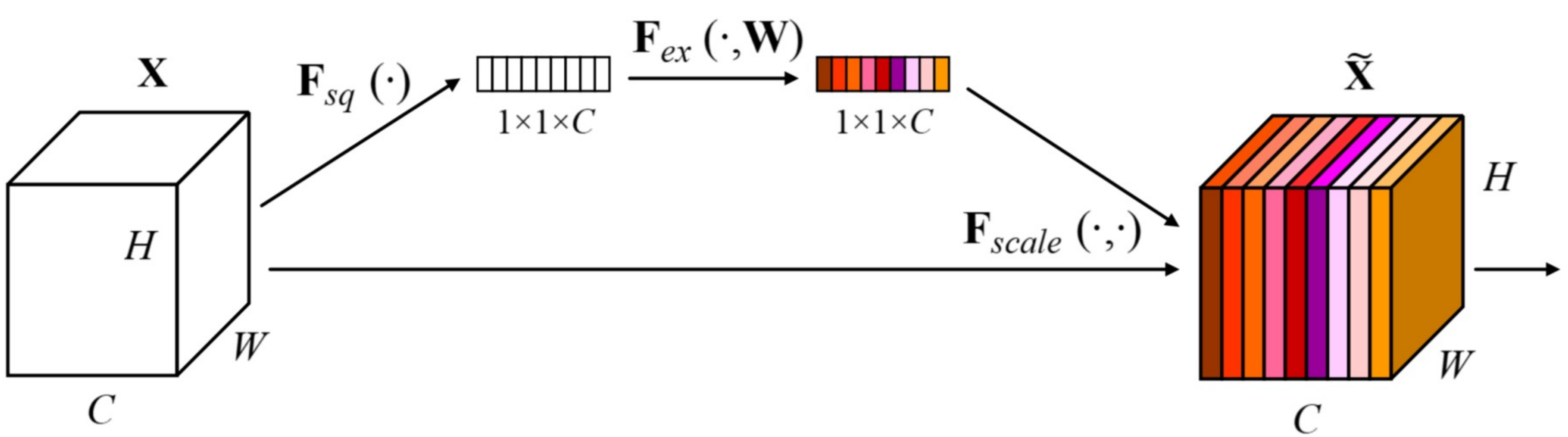
Motivation: The deeper the model, the more feature maps are generated

- Many of them might be important for classification task
- Others might redundant or less important

Squeeze and Excitation Network [Hu et al., 2018]

- It selectively emphasizes informative feature maps and suppress less useful ones via global information in two steps
- **Squeeze** step: obtaining global information by shrinking feature maps
  - Global average pooling
- **Excitation** step: recalibrating weights of features by learning channel-wise weights
  - MLP of two fully-connected layers



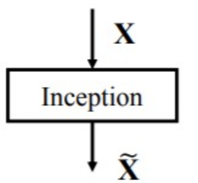
*source: Hu et al., "Squeeze-and-Excitation Networks", CVPR, 2018

Motivation: The deeper the model, the more feature maps are generated

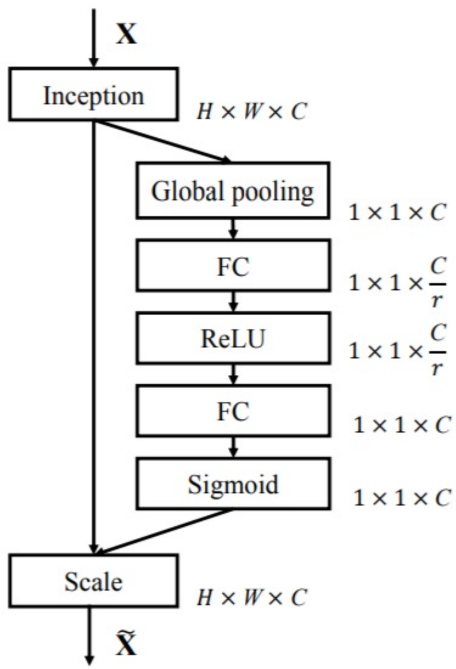
- Many of them might be important for classification task
- Others might redundant or less important

SE block integrates to Inception and ResNet module

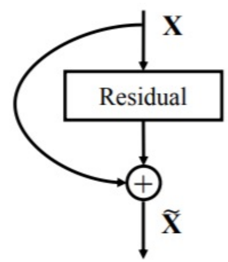
- SENet ranked first in the ILSVRC’17 (2.99% → **2.25%**)



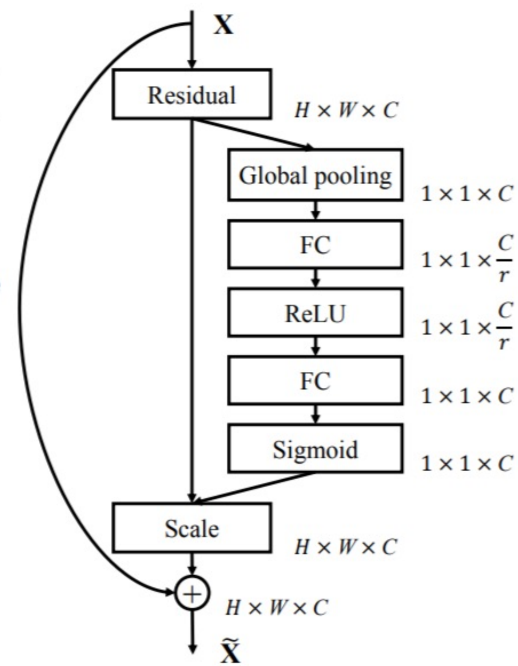
Inception Module



SE-Inception Module



ResNet Module



SE-ResNet Module

*source: Hu et al., “Squeeze-and-Excitation Networks”, CVPR, 2018

Motivation: The deeper the model, the more feature maps are generated

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SE block integrates to Inception and ResNet module

- SENet ranked first in the ILSVRC'17 (2.99% → **2.25%**)

	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]	$19.9^{\dagger}$	$4.9^{\dagger}$	20.37	5.21	11.75	$19.80_{(0.57)}$	$4.79_{(0.42)}$	11.76

Next, Convolutional Block Attention Module

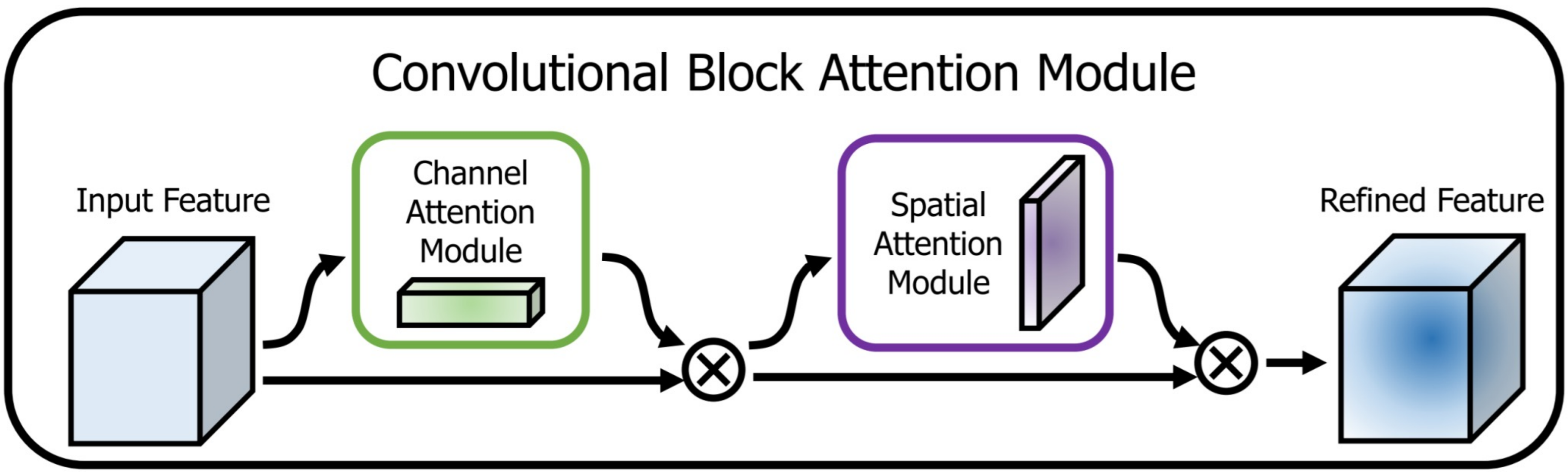
*source: Hu et al., "Squeeze-and-Excitation Networks", CVPR, 2018

Motivation: SENet only considers the contribution of feature maps

- It ignores the spatial locality of the object in image
- The spatial location of the object has a vital role in understanding image

Convolutional Block Attention Module (CBAM) [Woo et al., 2018]

- Learning 'what' and 'where' to attend in the channel and spatial axes respectively
- **Channel** and **Spatial** attention modules



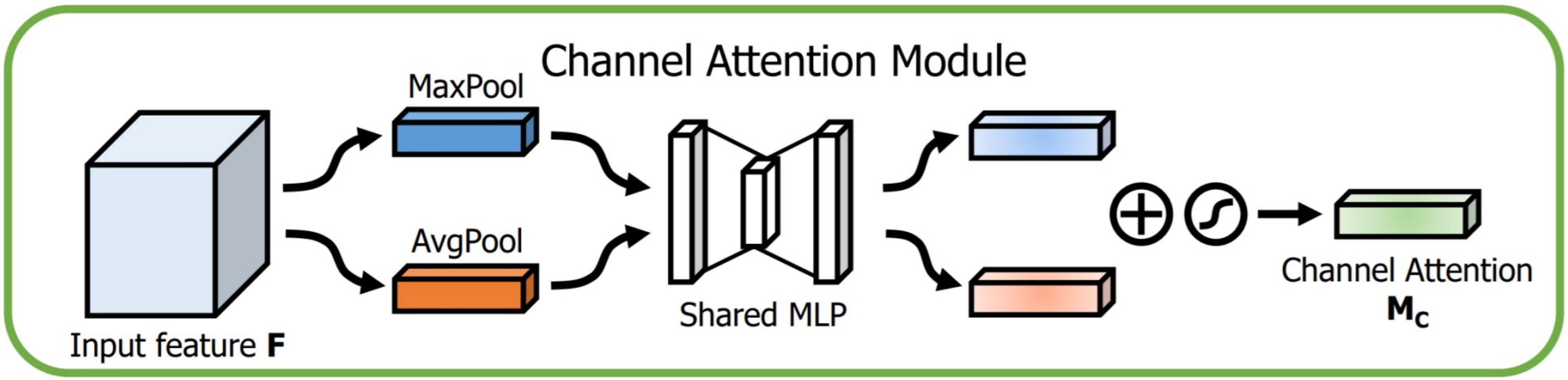
*source: Woo et al., "CBAM: Convolutional block attention module", ECCV, 2018

Motivation: SENet only considers the contribution of feature maps

- It ignores the spatial locality of the object in image
- The spatial location of the object has a vital role in understanding image

Channel attention module: It helps "what" to focus

- Both **average-pooling** and **max-pooling** are important
- **Max-pooling** provides the information of distinctive object features
- Both pooled features share a MLP with two fully-connected layers



$$\mathbf{M_c}(\mathbf{F}) = \sigma(MLP(AvgPool(\mathbf{F})) + MLP(MaxPool(\mathbf{F})))$$

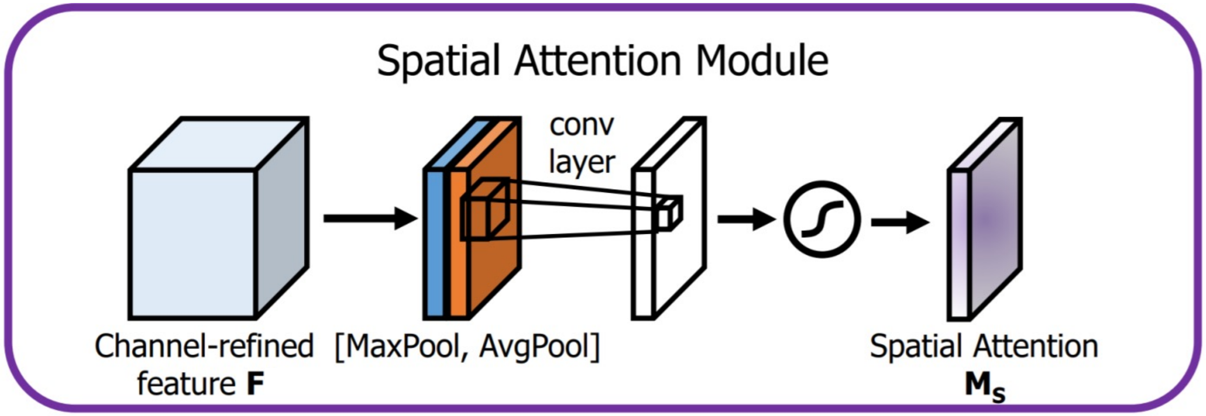
*source: Woo et al., "CBAM: Convolutional block attention module", ECCV, 2018

Motivation: SENet only considers the contribution of feature maps

- It ignores the spatial locality of the object in image
- The spatial location of the object has a vital role in understanding image

Spatial attention module: It helps "where" to focus

- Again, Both **average-pooling** and **max-pooling** are important
- It aggregates channel information of feature maps by using two pooling operations
- Capturing **spatial locality** via convolution



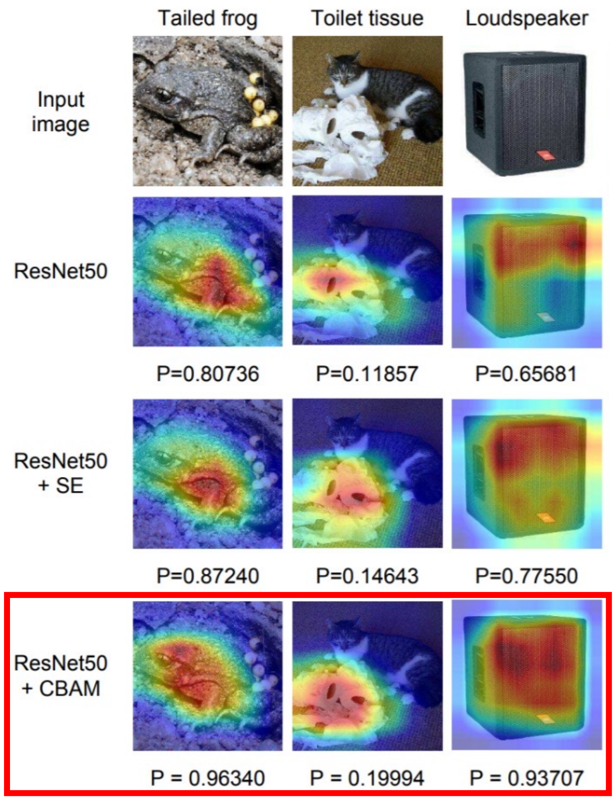
$$\mathbf{M_s}(\mathbf{F}) = \sigma(Conv([AvgPool(\mathbf{F}); MaxPool(\mathbf{F})]))$$

*source: Woo et al., "CBAM: Convolutional block attention module", ECCV, 2018

Motivation: SENet only considers the contribution of feature maps

- It ignores the spatial locality of the object in image
- The spatial location of the object has a vital role in understanding image

- **CBAM** module integrated with ResNet outperforms SE module



Grad-CAM visualization

Architecture	Param.	GFLOPs	Top-1 Error (%)	Top-5 Error (%)
ResNet18 [5]	11.69M	1.814	29.60	10.55
ResNet18 [5] + SE [28]	11.78M	1.814	29.41	10.22
ResNet18 [5] + CBAM	11.78M	1.815	**29.27**	**10.09**
ResNet34 [5]	21.80M	3.664	26.69	8.60
ResNet34 [5] + SE [28]	21.96M	3.664	26.13	8.35
ResNet34 [5] + CBAM	21.96M	3.665	**25.99**	**8.24**
ResNet50 [5]	25.56M	3.858	24.56	7.50
ResNet50 [5] + SE [28]	28.09M	3.860	23.14	6.70
ResNet50 [5] + CBAM	28.09M	3.864	**22.66**	**6.31**
ResNet101 [5]	44.55M	7.570	23.38	6.88
ResNet101 [5] + SE [28]	49.33M	7.575	22.35	6.19
ResNet101 [5] + CBAM	49.33M	7.581	**21.51**	**5.69**
WideResNet18 [6] (widen=1.5)	25.88M	3.866	26.85	8.88
WideResNet18 [6] (widen=1.5) + SE [28]	26.07M	3.867	26.21	8.47
WideResNet18 [6] (widen=1.5) + CBAM	26.08M	3.868	**26.10**	**8.43**
WideResNet18 [6] (widen=2.0)	45.62M	6.696	25.63	8.20
WideResNet18 [6] (widen=2.0) + SE [28]	45.97M	6.696	24.93	7.65
WideResNet18 [6] (widen=2.0) + CBAM	45.97M	6.697	**24.84**	**7.63**
ResNeXt50 [7] (32x4d)	25.03M	3.768	22.85	6.48
ResNeXt50 [7] (32x4d) + SE [28]	27.56M	3.771	**21.91**	6.04
ResNeXt50 [7] (32x4d) + CBAM	27.56M	3.774	21.92	**5.91**
ResNeXt101 [7] (32x4d)	44.18M	7.508	21.54	5.75
ResNeXt101 [7] (32x4d) + SE [28]	48.96M	7.512	21.17	5.66
ResNeXt101 [7] (32x4d) + CBAM	48.96M	7.519	**21.07**	**5.59**

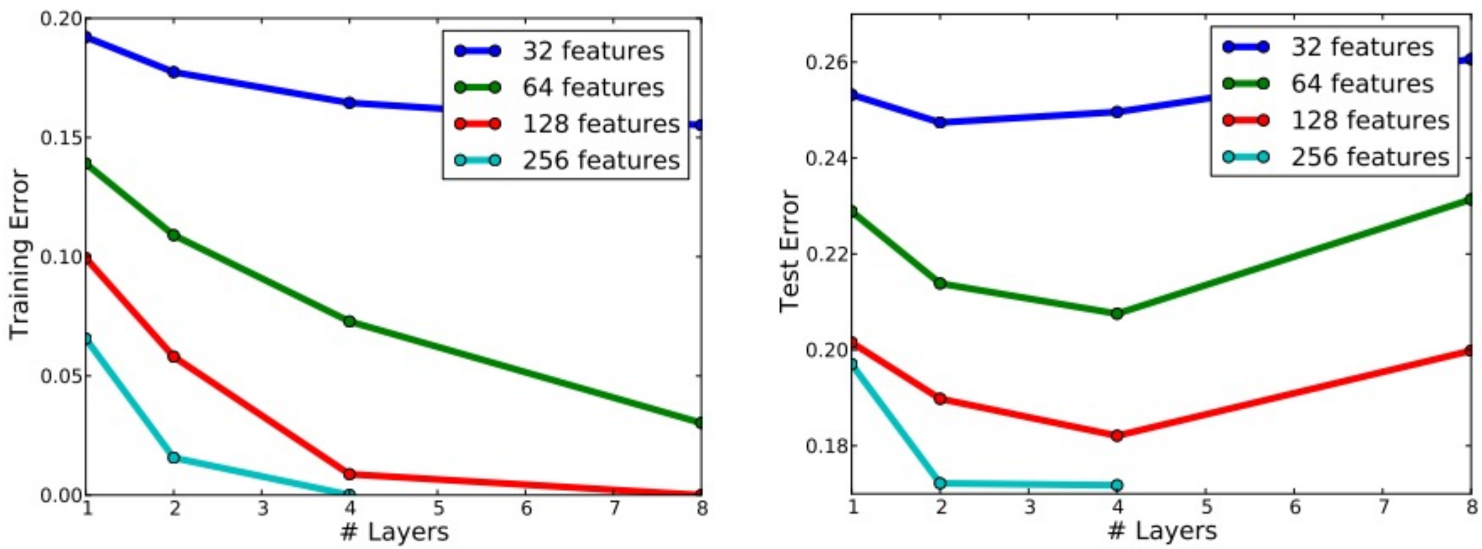
*source: Woo et al., “CBAM: Convolutional block attention module”, ECCV, 2018

ResNet improved generalization by revolution of depth

Quiz: But, does it fully explain why deep ResNets generalize well?

Increasing depth **does not always mean** better generalization

- Naïve CNNs are very easy to overfit on deeper networks [Eigen et al., 2014]

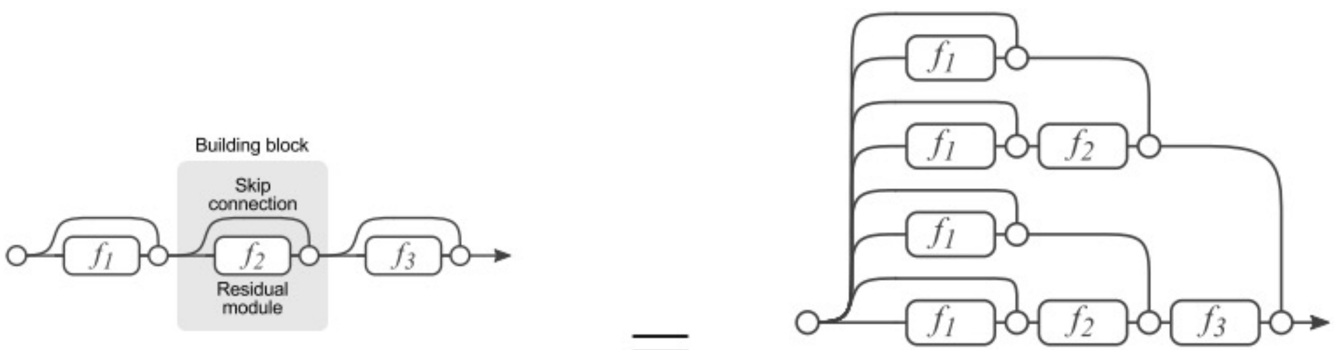


*source : Eigen et al., "Understanding Deep Architectures using a Recursive Convolutional Network", Arxiv 2014

Veit et al. (2016): ResNet can be viewed as a collection of many paths, instead of a single ultra-deep network

- Each module in a ResNet receives a **mixture of 2^{n-1} different distributions**

$$
\begin{aligned}
y_3 &= y_2 + f_3(y_2) \\
&= [\boxed{y_1 + f_2(y_1)}] + f_3(\boxed{y_1 + f_2(y_1)}) \\
&= [\boxed{y_0 + f_1(y_0)} + f_2(\boxed{y_0 + f_1(y_0)})] + f_3(\boxed{y_0 + f_1(y_0)} + f_2(\boxed{y_0 + f_1(y_0)}))
\end{aligned}
$$



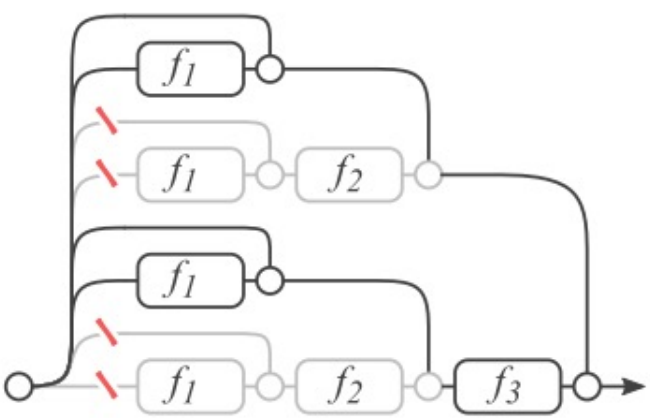
(a) Conventional 3-block residual network

(b) Unraveled view of (a)

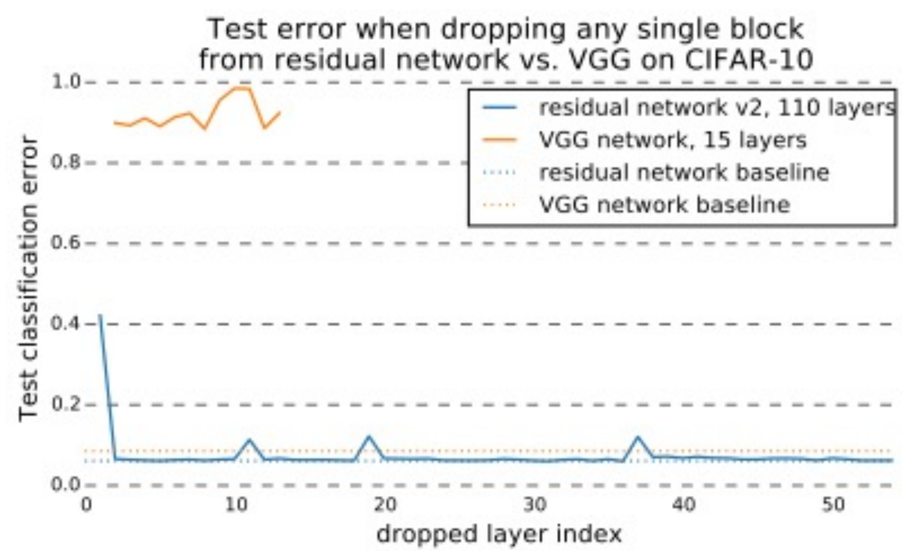
*source : Veit et al., “ResNets behave like ensembles of relatively shallow nets”, NIPS 2016

Veit et al. (2016): ResNet can be viewed as a collection of many paths, instead of a single ultra-deep network

- Deleting a module in ResNet has a minimal effect on performance
- Similar effect as removing 2^{n-1} paths out of 2^n: still 2^{n-1} paths alive!



(a) Deleting f_2 from unraveled view



Next, visualizing loss functions in CNN

*source : Veit et al., "ResNets behave like ensembles of relatively shallow nets", NIPS 2016

Trainability of neural nets is highly dependent on network architecture

- However, the effect of each choice on the underlying loss surface is unclear
  - Why are we able to minimize highly non-convex neural loss?
  - Why do the resulting minima generalize?

Li et al. (2018) analyzes **random-direction 2D plot of loss** around local minima

$$f(\alpha, \beta) = L(\theta^* + \alpha\delta + \beta\eta)$$

Local minima **Random directions**

- δ and η are sampled from a random Gaussian distribution
- To remove some scaling effect, δ and η are normalized filter-wise

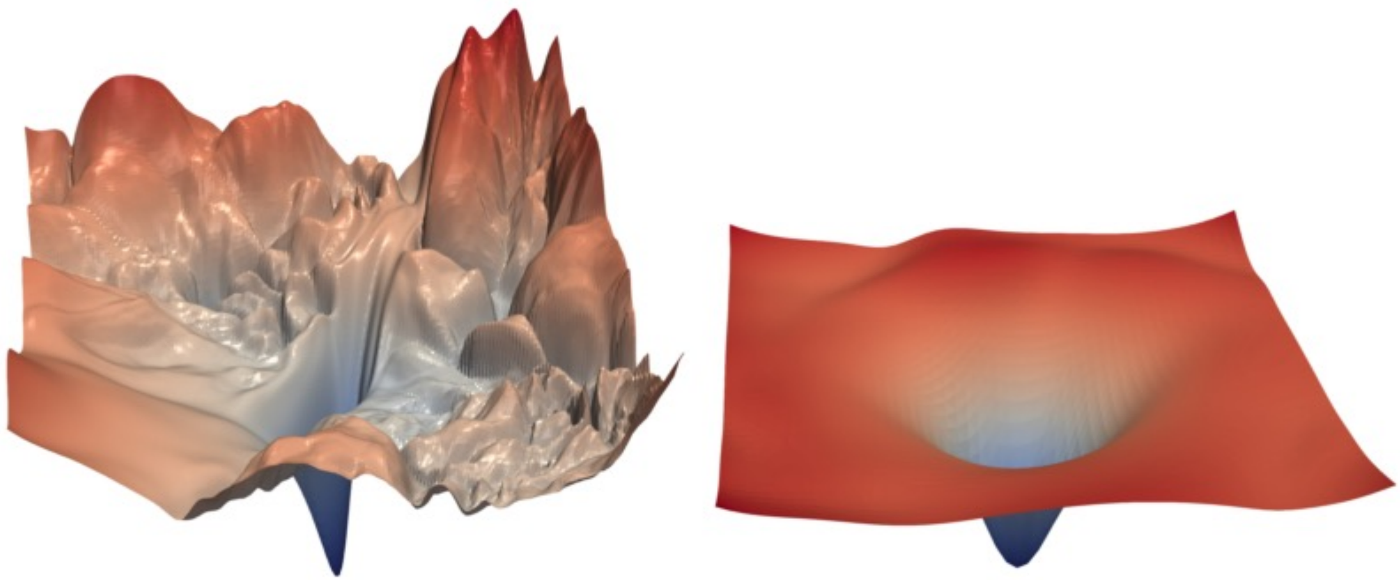
$$\delta_{i,j} \leftarrow \frac{\delta_{i,j}}{||\delta_{i,j}||}||\theta_{i,j}||$$

i^{th} layer, j^{th} filter

*source : Li et al., "Visualizing the loss landscape of neural nets", ICLR Workshop 2018

Li et al. (2018) analyzes **random-direction 2D plot of loss** around local minima

Modern architectures prevent the loss to be chaotic as depth increases



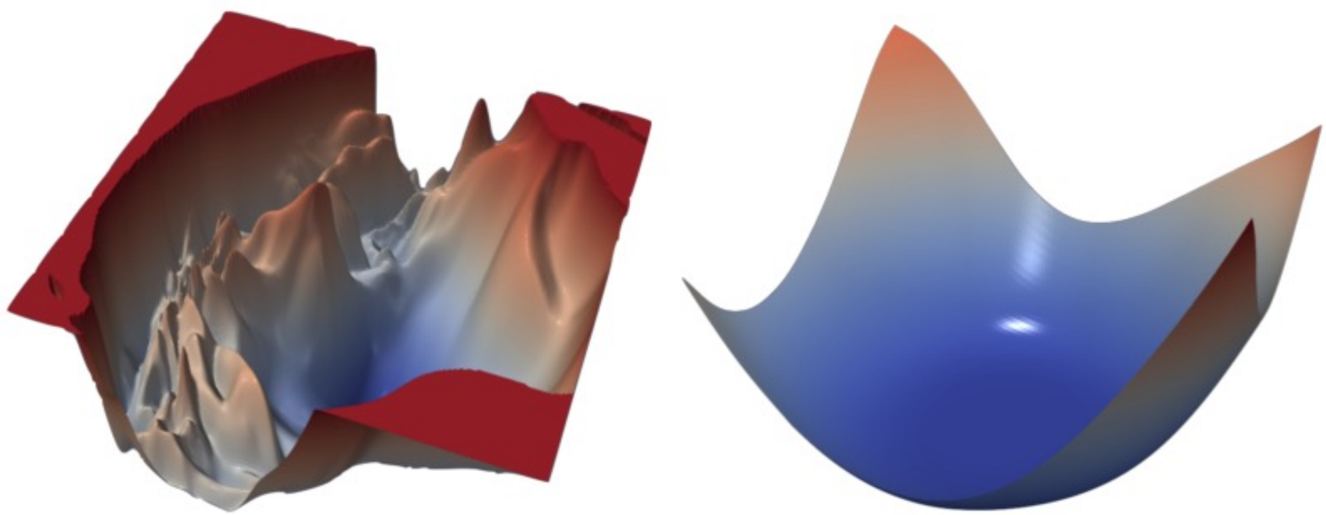
(a) without skip connections (b) with skip connections

ResNet-56

*source : Li et al., "Visualizing the loss landscape of neural nets", ICLR Workshop 2018

Li et al. (2018) analyzes **random-direction 2D plot of loss** around local minima

Modern architectures prevent the loss to be chaotic as depth increases



(a) 110 layers, no skip connections

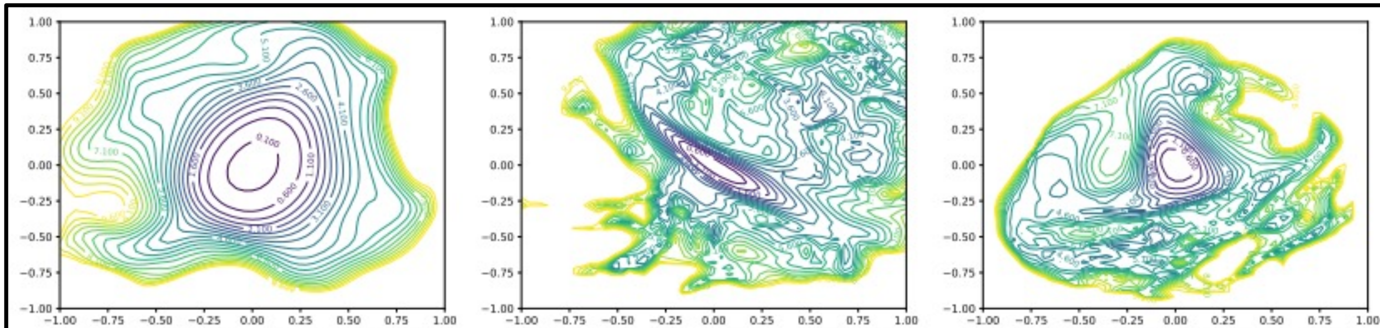
(b) DenseNet, 121 layers

*source : Li et al., “Visualizing the loss landscape of neural nets”, ICLR Workshop 2018

Li et al. (2018) analyzes **random-direction 2D plot of loss** around local minima

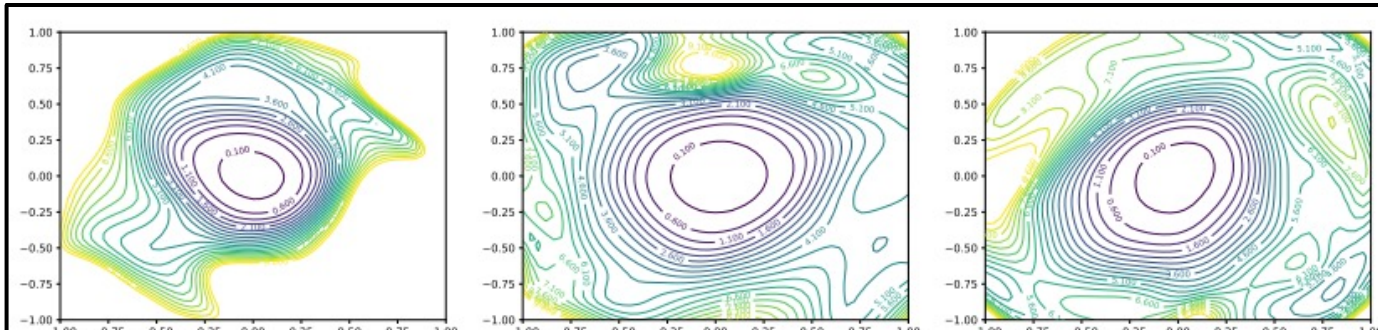
Modern architectures prevent the loss to be chaotic as depth increases

ResNet, **no shortcuts** ⇒ sharp minima



(d) ResNet-20-noshort, 8.18% (e) ResNet-56-noshort, 13.31% (f) ResNet-110-noshort, 16.44%

ResNet ⇒ flat minima



(a) ResNet-20, 7.37% (b) ResNet-56, 5.89% (c) ResNet-110, 5.79%

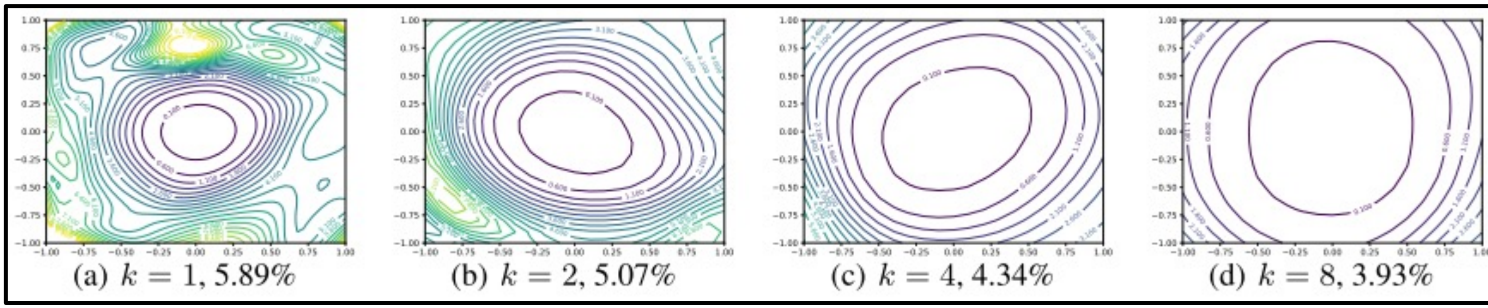
*source : Li et al., “Visualizing the loss landscape of neural nets”, ICLR Workshop 2018

Li et al. (2018) analyzes **random-direction 2D plot of loss** around local minima

Wide-ResNet lead the network toward more flat minimizer

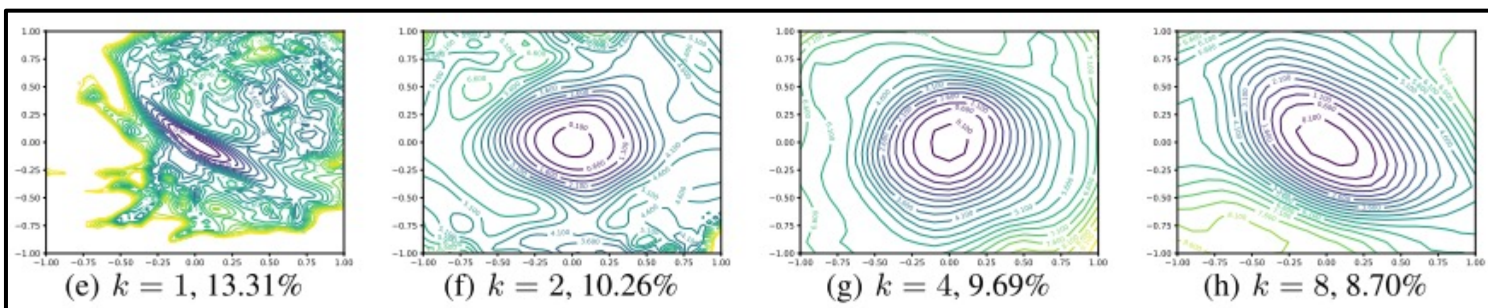
- WideResNet-56 with **width-multiplier** $k = 1, 2, 4, 8$
- Increased width flatten the minimizer in ResNet

WRN-56



(a) $k = 1$, 5.89% (b) $k = 2$, 5.07% (c) $k = 4$, 4.34% (d) $k = 8$, 3.93%

WRN-56, **no shortcuts**



(e) $k = 1$, 13.31% (f) $k = 2$, 10.26% (g) $k = 4$, 9.69% (h) $k = 8$, 8.70%

Next, minimum energy paths in CNNs

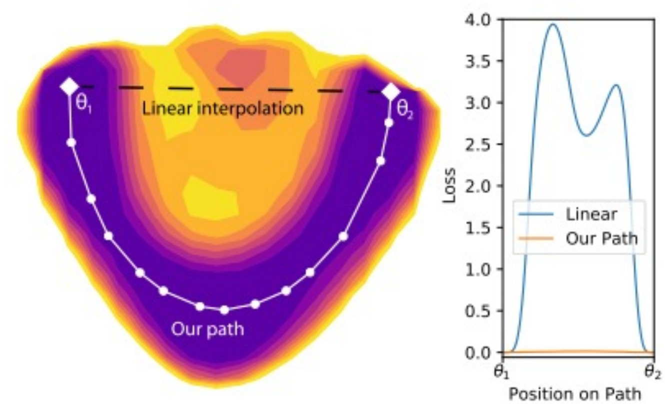
*source : Li et al., "Visualizing the loss landscape of neural nets", ICLR Workshop 2018

Draxler et al. (2018) analyzes **minimum energy paths** [Jónsson et al., 1998] between two local minima θ_1 and θ_2 of a given model:

$$p(\theta_i, \theta_2)^* = \underset{\text{path } p:\ \theta_1 \to \theta_2}{\operatorname{argmin}} \left(\max_{\theta \in p} L(\theta) \right)$$

- They found a path $\theta_1 \to \theta_2$ with almost zero barrier
  - A path that **keeps low loss constantly** both in training and test
- The gap vanishes as the model grows, especially on modern architectures
  - e.g. ResNet, DenseNet

- Minima of a loss of deep neural networks are perhaps on a single connected manifold



DenseNet-40-12

*source : Draxler et al., “Essentially no barriers in neural network energy landscape”, ICML 2018

Essentially no barriers in neural network energy landscape [Draxler et al., 2018]

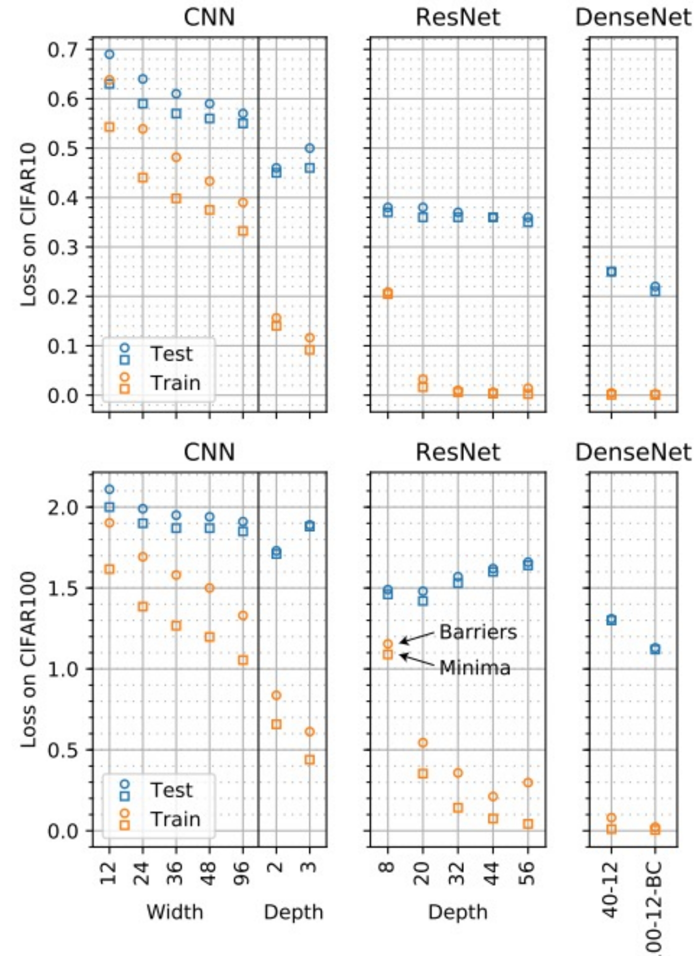
For a given model with two local minima θ_1 and θ_2, they applied **AutoNEB** [Kolsbjerg et al., 2016] to find a minimum energy path

- A state-of the-art for connecting minima from molecular statistical mechanics

- The deeper and wider an architecture, the lower are the saddles between minima

- They essentially vanish for current-day deep architectures

- The **test accuracy** is also preserved
  - **CIFAR-10**: < +0.5%
  - **CIFAR-100**: < +2.2%



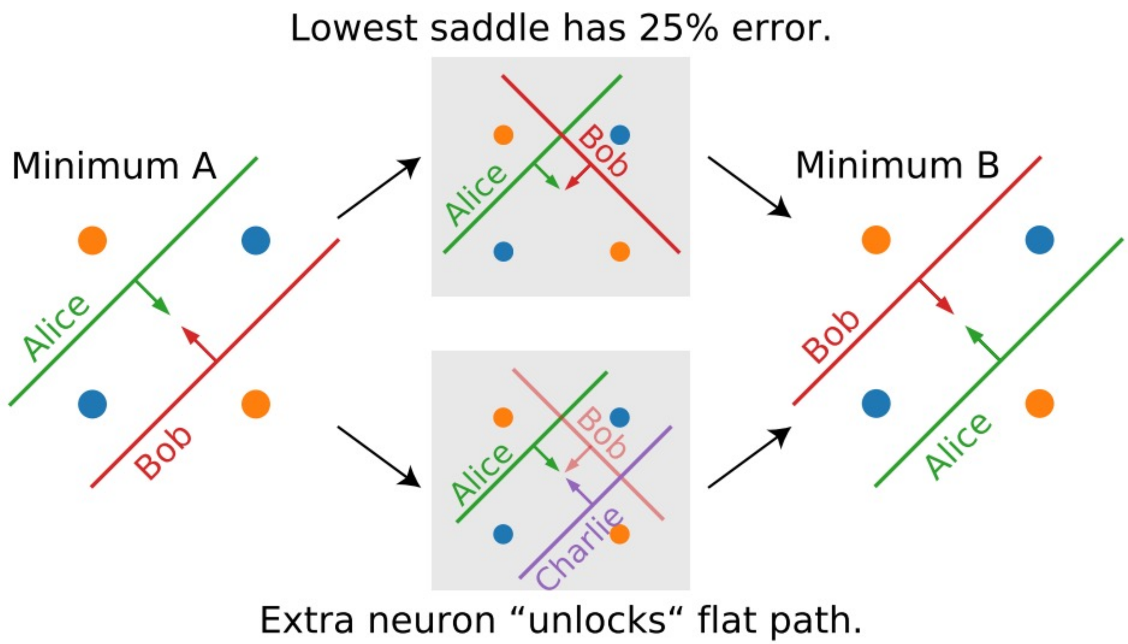
*source : Draxler et al., "Essentially no barriers in neural network energy landscape", ICML 2018

Essentially no barriers in neural network energy landscape [Draxler et al., 2018]

- The deeper and wider an architecture, the lower are the barriers
- They essentially vanish for current-day deep architectures

Why do this phenomenon happen?

- **Parameter redundancy** may help to flatten the neural loss



*source : Draxler et al., "Essentially no barriers in neural network energy landscape", ICML 2018

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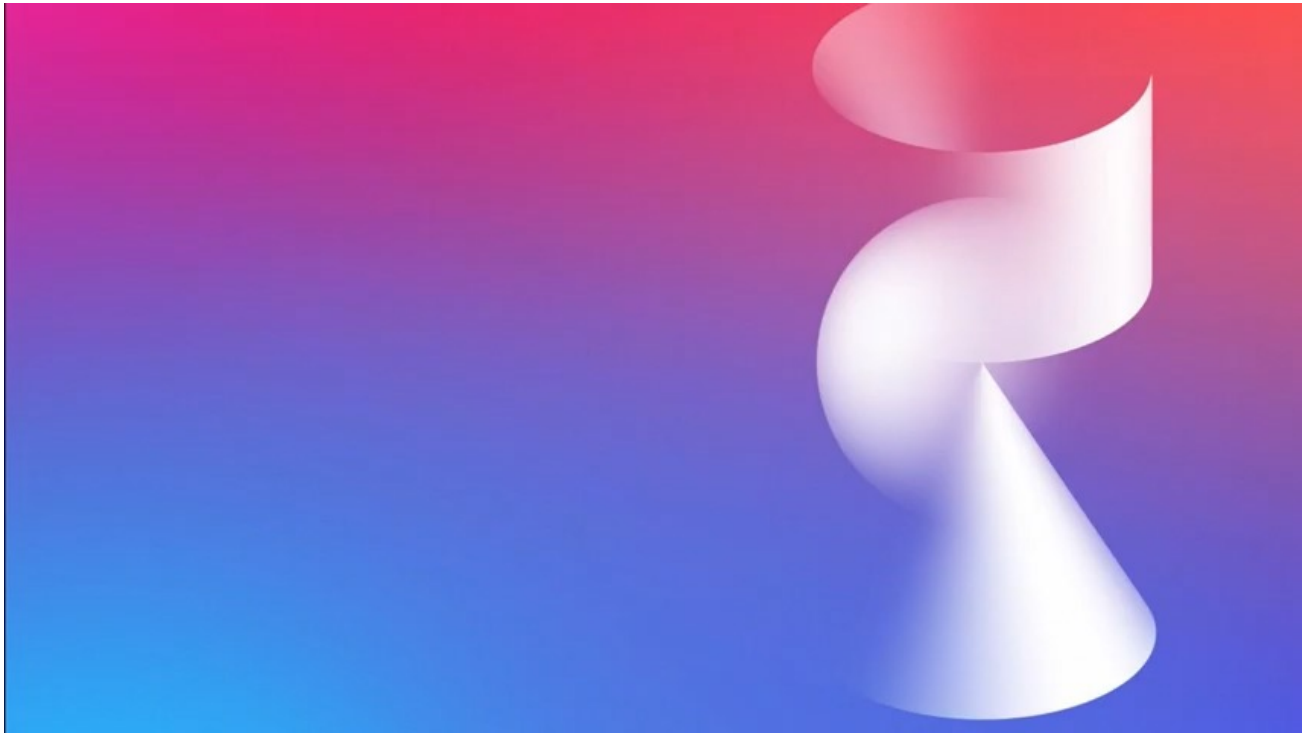
Success of Transformer in Language: GPT-3

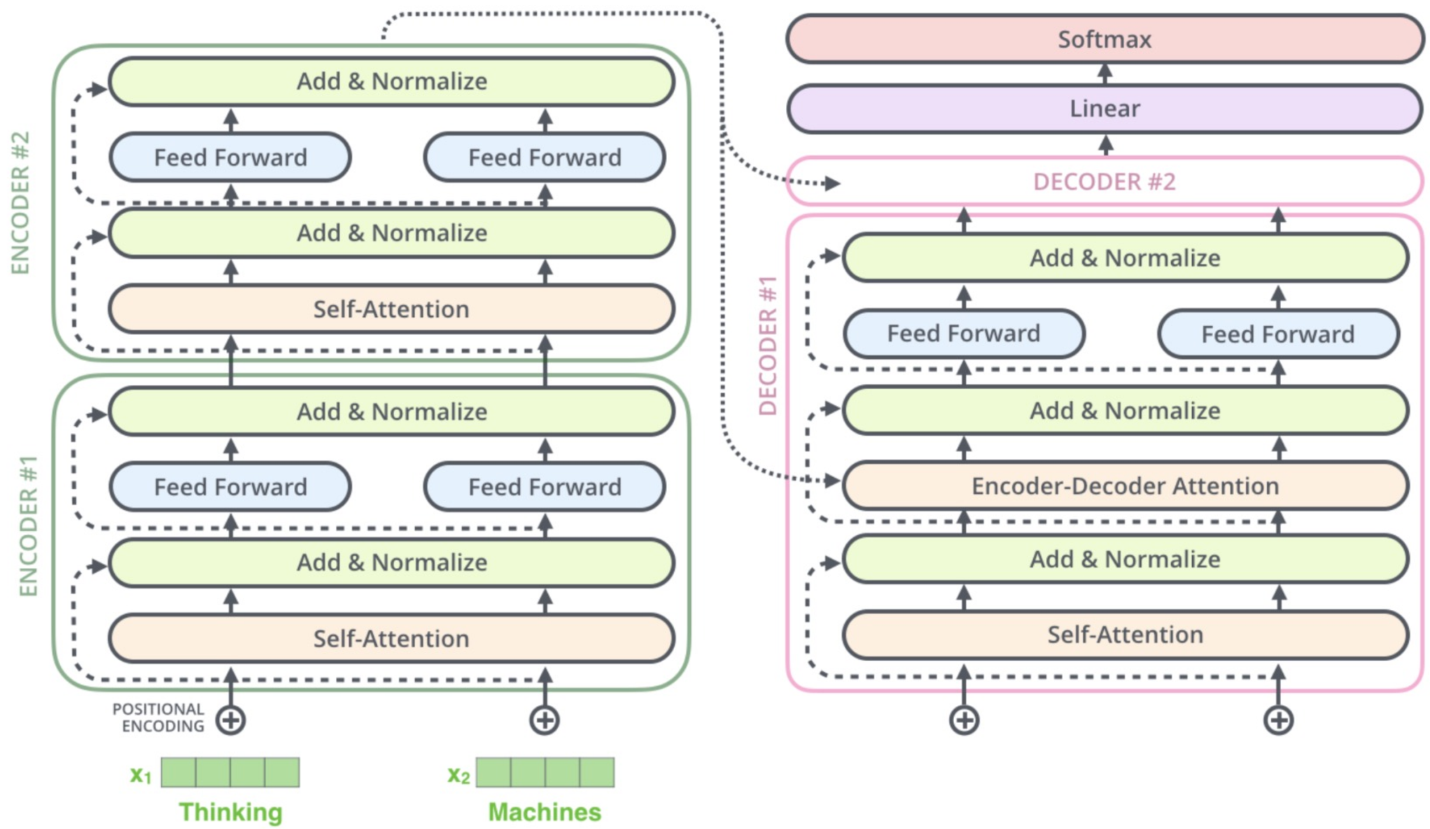
- In 2020, **GPT-3** achieved near-human results in various tasks
- OpenAI even trained a model with **175 billion** parameters (**350 GB** of memory) and showed near-human performance on various **few-shot** tasks



*source : https://youtu.be/CSe3_u9P-RM
Draxler et al., "Essentially no barriers in neural network energy landscape", ICML 2018

What is Transformer?

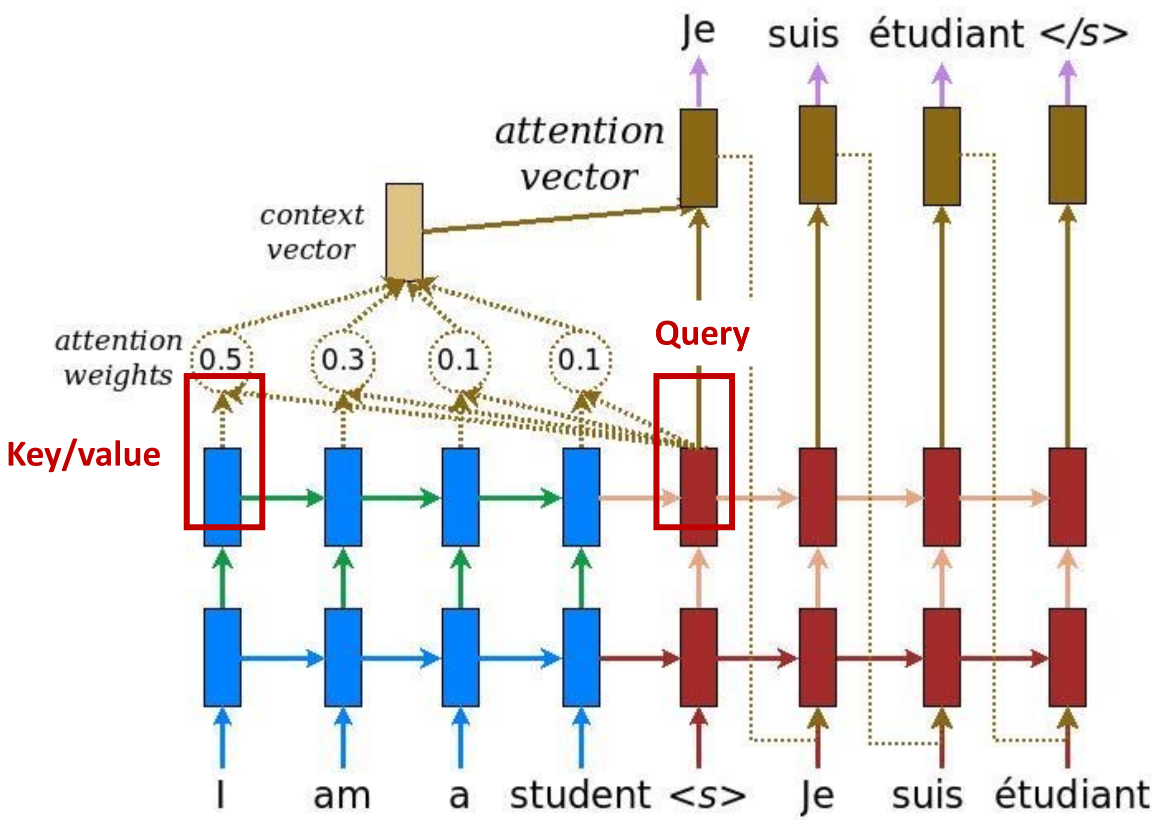
- Transformer [Vaswani et al., 2017] has an **encoder-decoder** structure and they are composed of multiple block with **self-attention** module



*source: http:// http://jalammar.github.io/illustrated-transformer

What is Transformer?

- Transformer [Vaswani et al., 2017] has an **encoder-decoder** structure and they are composed of multiple block with **self-attention** module
- The self-attention is a function of **query** (e.g., “Je”) and **key/value** (e.g., “I”)
  - It shows powerful performances in learning **sequential input-output relations**



Attention mechanism can be used for other type of input data, e.g. image

- Self-attention operation scales **quadratically** with the sequence length

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Question: How to transform an image to **sequence data**?

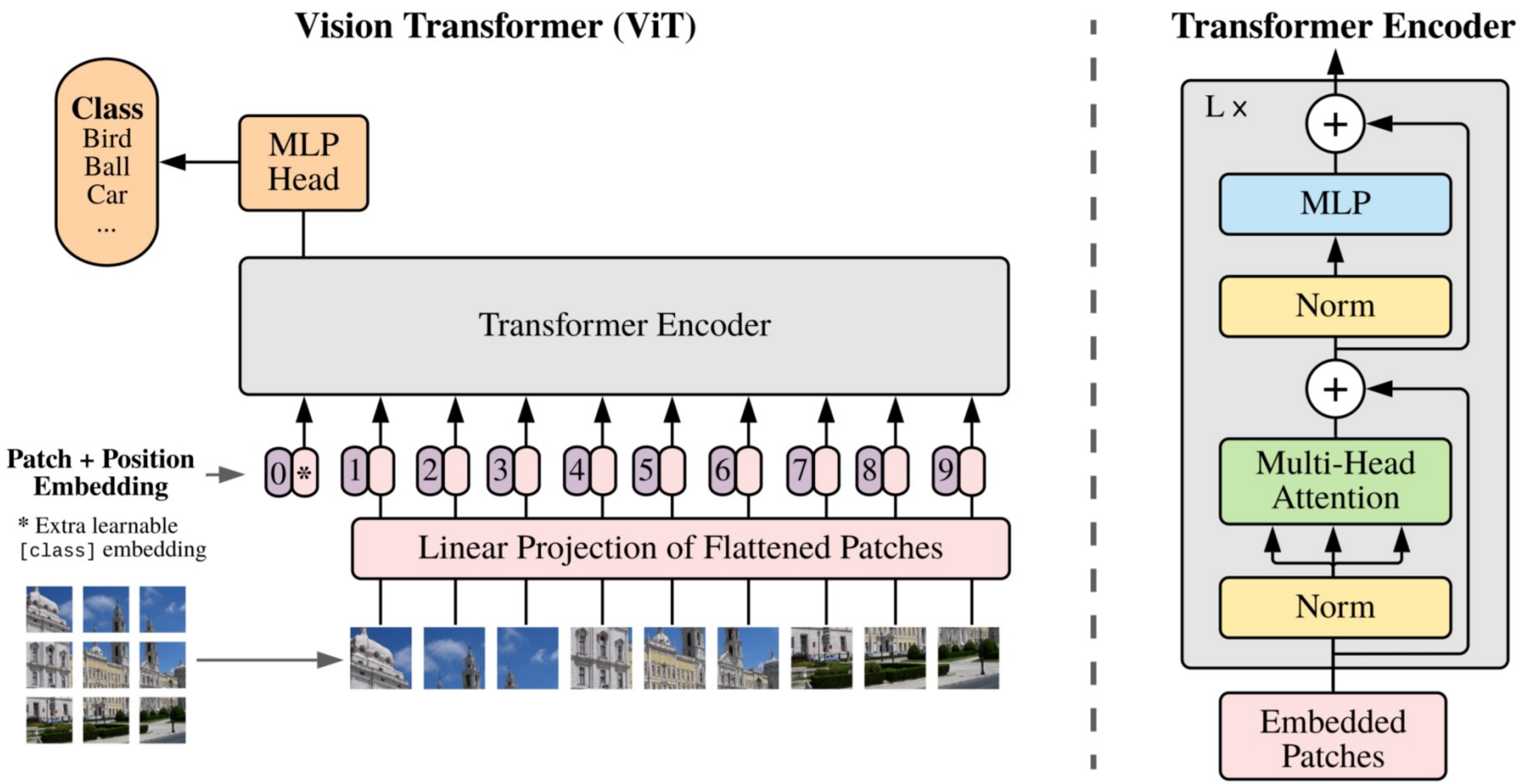
- Dosovitskiy et al. (2021): splits an **image** into **patches**

Sequence of patch images

*source: [Chen et al. 2020] Generative Pretraining from Pixels, ICML 2020
[Dosovitskiy et al. 2021] An image is worth 16x16 words: Transformers for image recognition at scale, ICLR 2021

Vision Transformer [Dosovitskiy et al., 2021]

- Splitting an image into fixed-size patches (16x16)
  - Linearly embedding each of them
- Adding position embedding & [class] token



*source: [Dosovitskiy et al. 2021] An image is worth 16x16 words: Transformers for image recognition at scale, ICLR 2021

Vision Transformer [Dosovitskiy et al., 2021]

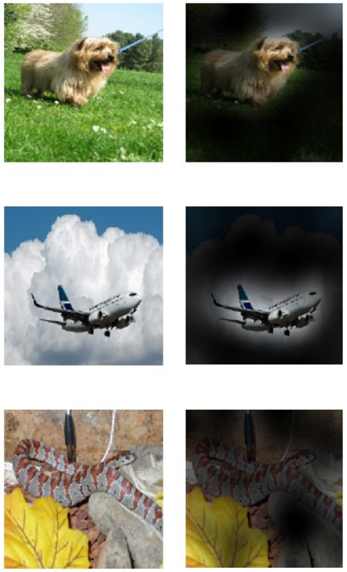
- Splitting an image into fixed-size patches (16x16)
  - Linearly embedding each of them
- Adding position embedding & [class] token

- **Dosovitskiy et al.** (2021) pre-trains models on larger datasets (14M-300M images)
  - Vision Transformer achieves **competitive performances** compared to CNNs

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21k (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** $\pm$ 0.04	87.76 $\pm$ 0.03	85.30 $\pm$ 0.02	87.54 $\pm$ 0.02	88.4/88.5*
ImageNet ReaL	**90.72** $\pm$ 0.05	90.54 $\pm$ 0.03	88.62 $\pm$ 0.05	90.54	90.55
CIFAR-10	**99.50** $\pm$ 0.06	99.42 $\pm$ 0.03	99.15 $\pm$ 0.03	99.37 $\pm$ 0.06	–
CIFAR-100	**94.55** $\pm$ 0.04	93.90 $\pm$ 0.05	93.25 $\pm$ 0.05	93.51 $\pm$ 0.08	–
Oxford-IIIT Pets	**97.56** $\pm$ 0.03	97.32 $\pm$ 0.11	94.67 $\pm$ 0.15	96.62 $\pm$ 0.23	–
Oxford Flowers-102	99.68 $\pm$ 0.02	**99.74** $\pm$ 0.00	99.61 $\pm$ 0.02	99.63 $\pm$ 0.03	–
VTAB (19 tasks)	**77.63** $\pm$ 0.23	76.28 $\pm$ 0.46	72.72 $\pm$ 0.21	76.29 $\pm$ 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

Vision Transformer **CNNs**

Input Attention



*source: [Dosovitskiy et al. 2021] An image is worth 16x16 words: Transformers for image recognition at scale, ICLR 2021

Various architectures now are based on Vision Transformer

1. **Modification for patch splitting**
   - Token-to-Token Vision Transformer [Li et al., 2021]
   - Swin Transformer [Liu et al., 2021]
2. **Modification for hierarchical structure**
   - Pooling-based Vision Transformer [Heo et al., 2021]
   - Swin Transformer [Liu et al., 2021]

Question: What's a good way to split an **image** into a **sequence of patches**?

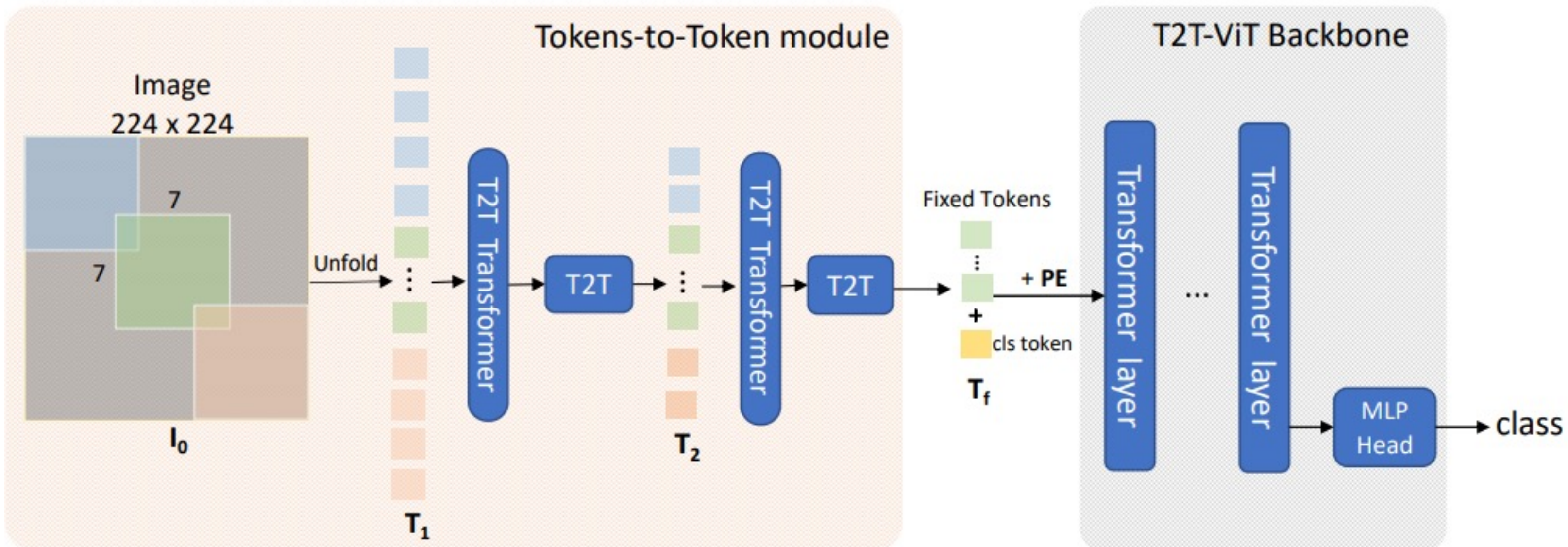
- Vision Transformer splits an image into a **fixed grid-shape** of **non-overlapping** patches

Sequence of patch images

*source : He et al., "Deep residual learning for image recognition". CVPR 2016

Token-to-Token Vision Transformer [Li et al., 2021]

- **(Soft-split)** Splitting an image into overlapping patches
- **(Re-structurization)** Rearranging patch sequences into 2D image shape
- Iterating re-structurization and soft-split before Transformer backbone



*source: [Li et al. 2021] Tokens-to-Token ViT: Training Vision Transformers from Scratch on ImageNet, ICCV 2021

Token-to-Token Vision Transformer [Li et al., 2021]

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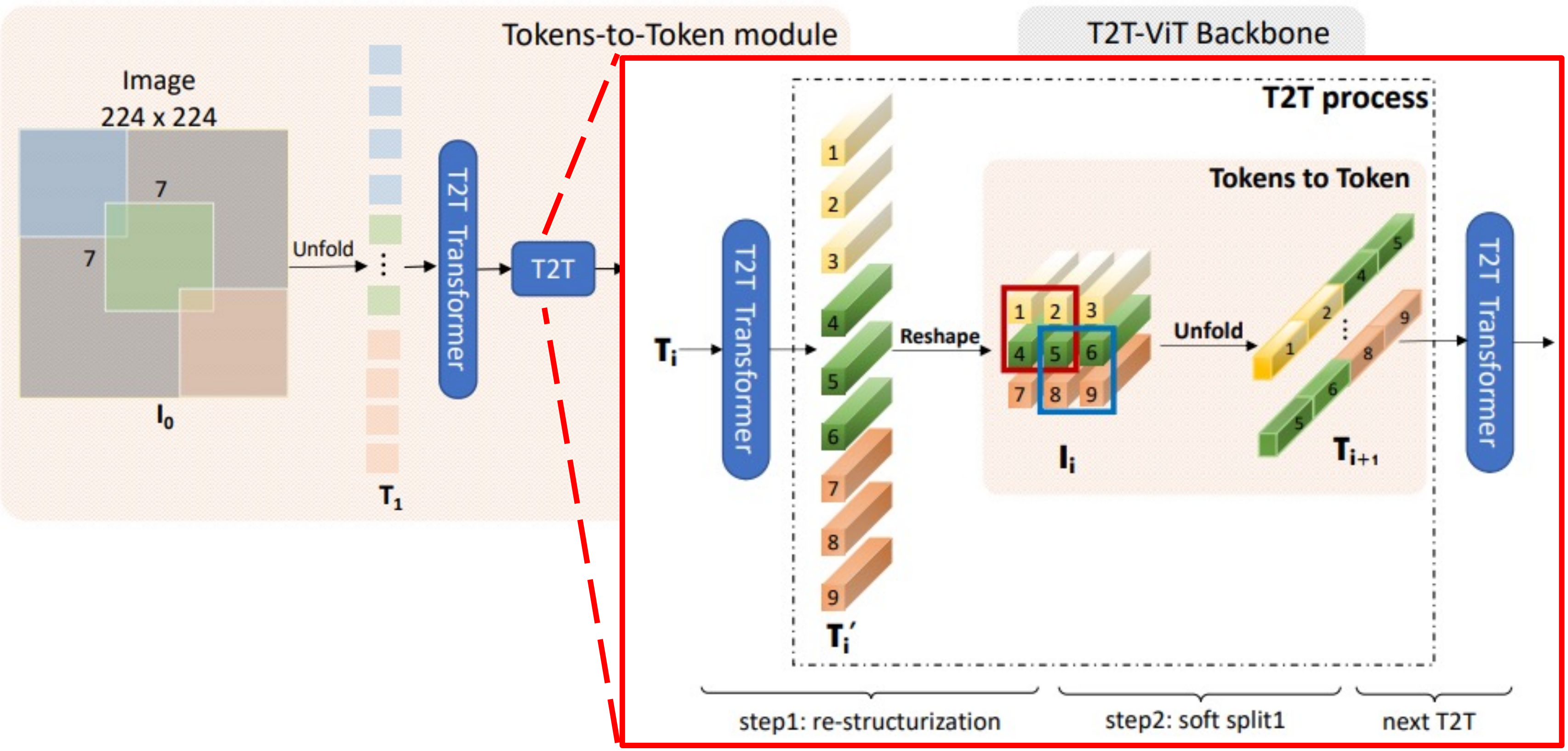
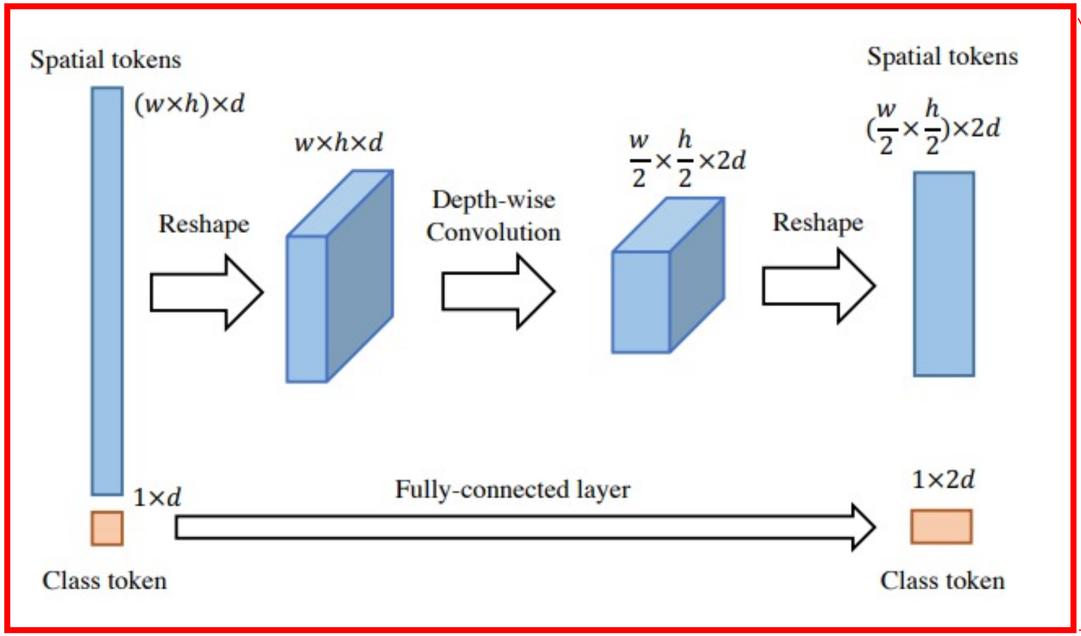
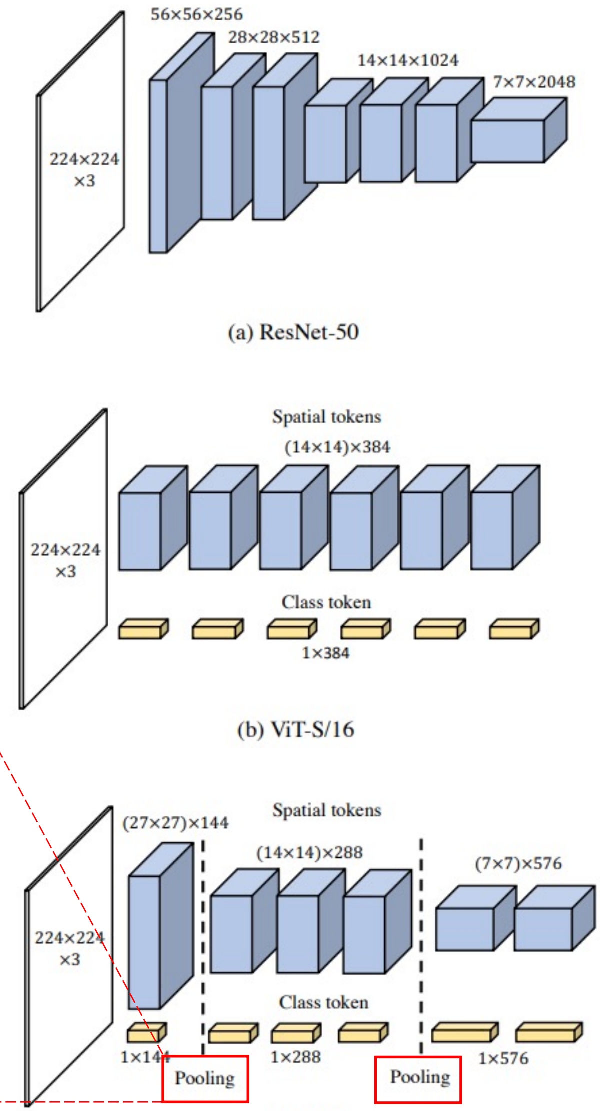


*source: [Li et al. 2021] Tokens-to-Token ViT: Training Vision Transformers from Scratch on ImageNet, ICCV 2021

Pooling-based Vision Transformer [Heo et al., 2021]

- Design of a hierarchical structure
  - **Motivation:** ResNet gradually downsamples the features from the input to the output
- Downsampling via the pooling layer based on depth-wise convolution
- Spatial reduction with small parameters





(a) ResNet-50

(b) ViT-S/16

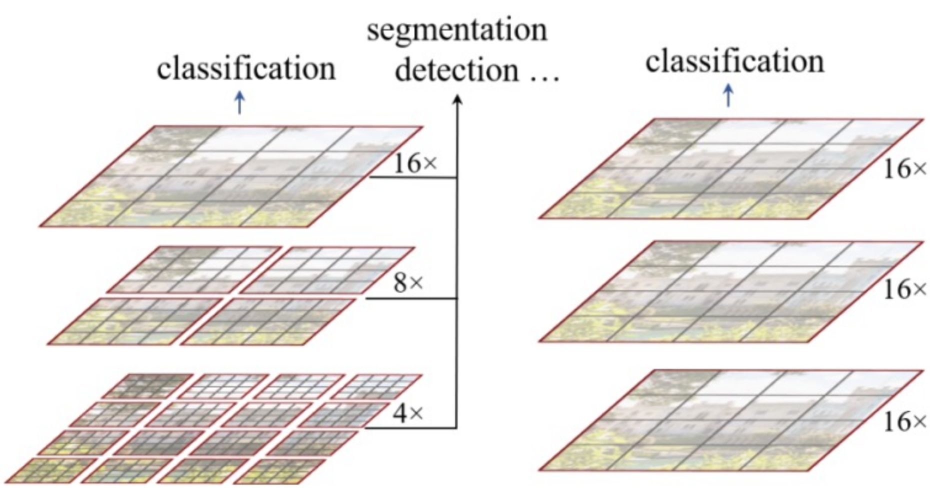
(c) PiT-S

*source: [Heo et al. 2021] Rethinking Spatial Dimensions of Vision Transformers , ICCV 2021

Swin Transformer [Liu et al., 2021]

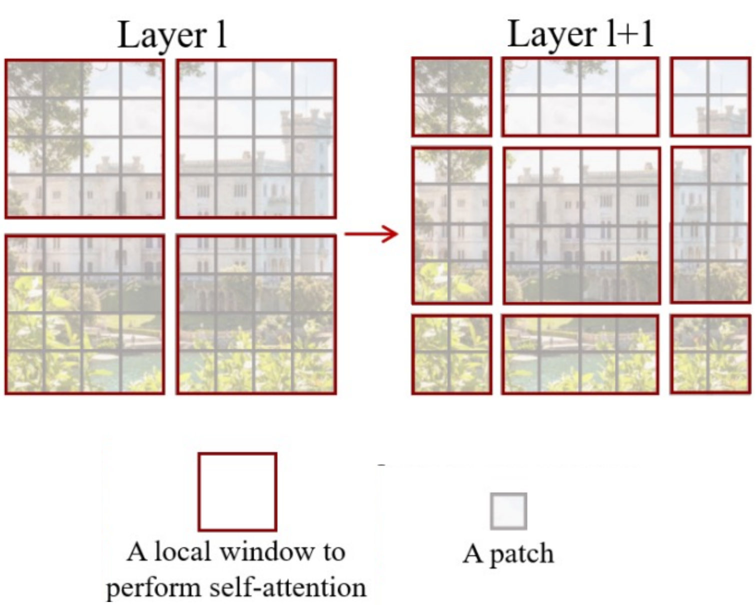
- Design of a hierarchical structure
- Various spatial resolutions (e.g., patch-shape) can be handled via shifted windows
- Efficient self-attention computation by using shifted windows scheme
- Concatenating 2 × 2 neighboring patches for downsampling operation
- Powerful performances in dense prediction tasks

  e.g., object detection and semantic segmentation



(a) Swin Transformer (ours) (b) ViT

Shifted window scheme

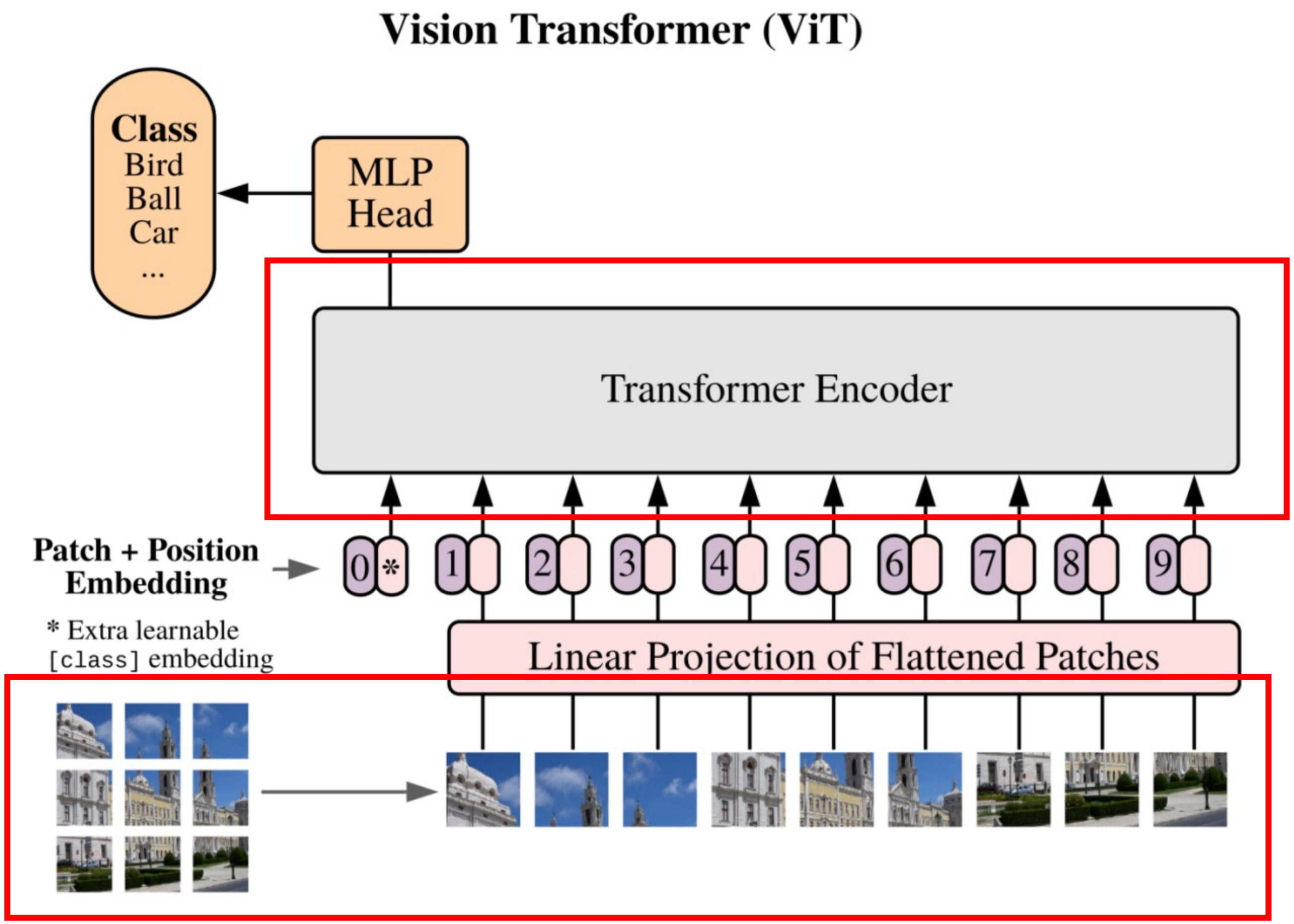


*source: [Liu et al. 2021] Swin Transformer: Hierarchical Vision Transformer using Shifted Windows, ICCV 2021

Table of Contents

Question: Is the success of **Vision Transformers** due to

1. the powerful Transformer architecture?
2. using patches as the input representation?



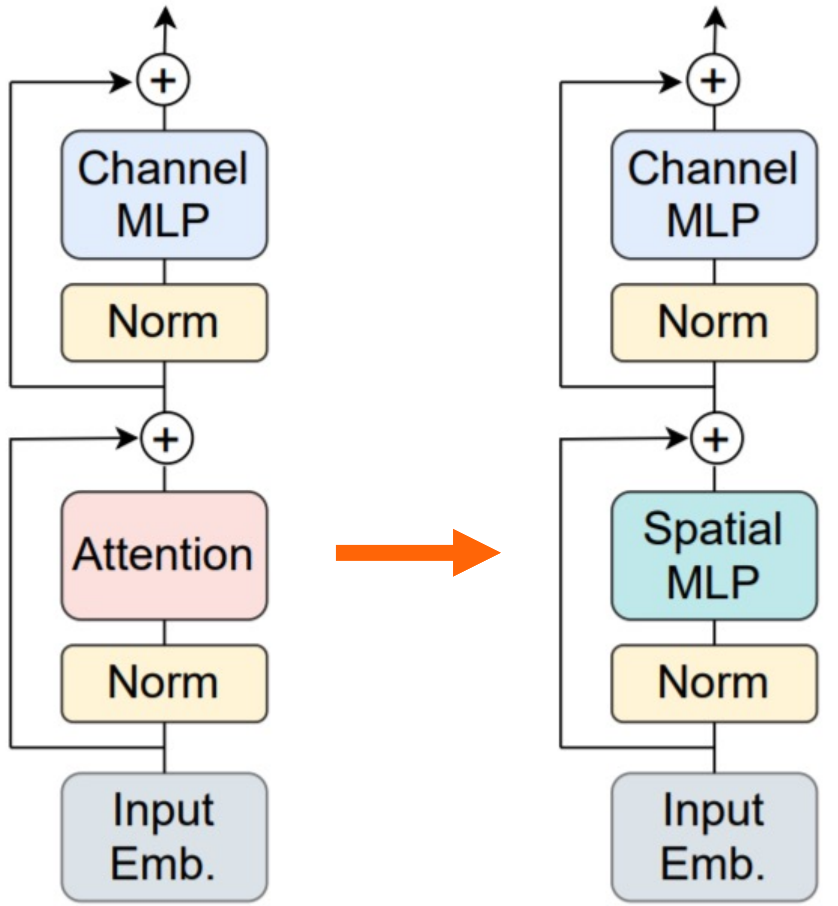
*source: [Dosovitskiy et al. 2021] An image is worth 16x16 words: Transformers for image recognition at scale, ICLR 2021

- **Tolstikhin et al.** (2021) suggests MLP module as an alternative of self-attention module
  - For a given Image I,

$$Z = \mathrm{MLP}\big(\mathrm{Norm}(Y)\big) + Y$$
$$= \sigma(\mathrm{Norm}(Y)W_1)W_2 + Y$$

$$Y = \color{red}{\mathrm{SelfAttn}}\big(\mathrm{Norm}(X)\big) + X$$

$$X = \mathrm{InputEmbed}(I)$$



Transformer architectures **MLP architectures**

$$Z = \mathrm{MLP}\big(\mathrm{Norm}(Y)\big) + Y$$
$$= \sigma(\mathrm{Norm}(Y)W_1)W_2 + Y$$

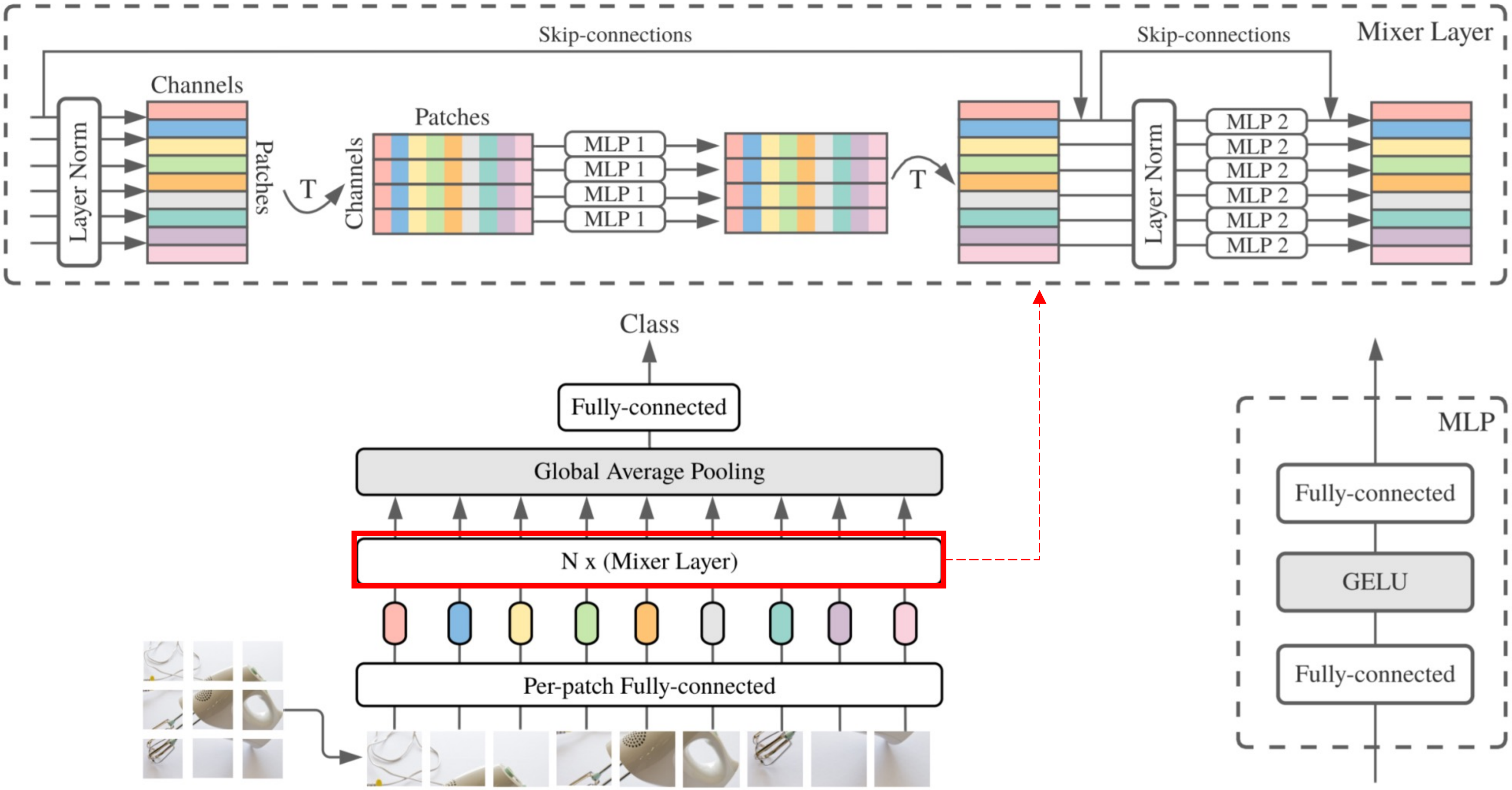
$$Y = \color{red}{\mathrm{MLP}}\big(\mathrm{Norm}(X)\big) + X$$

$$X = \mathrm{InputEmbed}(I)$$

*source : [Yu et al., 2021] MetaFormer is Actually What You Need for Vision, arxiv 2021

MLP-Mixer [Tolstikhin et al., 2021]

- Replacing the self-attention into MLP layers
- Removing position embedding & [class] token
- Mixing spatial & channel dimension separately



MLP-Mixer [Tolstikhin et al., 2021]

- Replacing the self-attention into MLP layers
- Removing position embedding & [class] token
- Mixing spatial & channel dimension separately

- **MLP-Mixer** shows competitive performances compared to Vision Transformers

	ImNet top-1	ReaL top-1	Avg 5 top-1	VTAB-1k 19 tasks	Throughput img/sec/core	TPUv3 core-days
Pre-trained on ImageNet-21k (public)						
HaloNet [51]	85.8	—	—	—	120	0.10k
Mixer-L/16	84.15	87.86	93.91	74.95	105	0.41k
ViT-L/16 [14]	85.30	88.62	94.39	72.72	32	0.18k
BiT-R152x4 [22]	85.39	—	94.04	70.64	26	0.94k
Pre-trained on JFT-300M (proprietary)						
NFNet-F4+ [7]	89.2	—	—	—	46	1.86k
Mixer-H/14	87.94	90.18	95.71	75.33	40	1.01k
BiT-R152x4 [22]	87.54	90.54	95.33	76.29	26	9.90k
ViT-H/14 [14]	88.55	90.72	95.97	77.63	15	2.30k

Summary

- The **larger** the network, the **more difficult** it is to design
    1. Optimization difficulty
    2. Generalization difficulty

- **ImageNet challenge** contributed greatly to development of CNN architectures
- **ResNet**: Optimization ⇒ Generalization
    - Many variants of ResNet have been emerged
    - Very recent trends towards **network design and scaling**

- Many types of **CNN modules** are explored to capture detailed spatial information
    - Dilated and deformable convolution
    - Attention based modules
    - Many **observational study** supports the advantages of modern CNN architectures

- Recently, various types of architectures using **patch-based input shape** are explored
    - Transformer architecture: **Vision Transformer**
    - MLP architecture: **MLP-Mixer**

References

[Jónsson et al., 1998] Jónsson, H., Mills, G., & Jacobsen, K. W. (1998). Nudged elastic band method for finding minimum energy paths of transitions. In Classical and quantum dynamics in condensed phase simulations (pp. 385-404).
link : https://www.worldscientific.com/doi/abs/10.1142/9789812839664_0016

[LeCun et al., 1998] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.
link : https://ieeexplore.ieee.org/abstract/document/726791/

[Bergstra et al., 2012] Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. Journal of Machine Learning Research, 13(Feb), 281-305.
link : http://www.jmlr.org/papers/v13/bergstra12a.html

[Krizhevsky et al., 2012] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105).
link : http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks

[Farabet et al., 2013] Farabet, C., Couprie, C., Najman, L., & LeCun, Y. (2013). Learning hierarchical features for scene labeling. IEEE transactions on pattern analysis and machine intelligence, 35(8), 1915-1929.
link : https://ieeexplore.ieee.org/abstract/document/6338939/

[Eigen et al., 2014] Eigen, D., Rolfe, J., Fergus, R., & LeCun, Y. (2013). Understanding Deep Architectures using a Recursive Convolutional Network. ArXiv Preprint ArXiv:1312.1847, 1–9.
link : http://arxiv.org/abs/1312.1847

[Simonyan et al., 2014] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
link: https://arxiv.org/abs/1409.1556

References

[Zeiler et al., 2014] Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In European conference on computer vision (pp. 818-833). Springer, Cham.
link : https://link.springer.com/chapter/10.1007/978-3-319-10590-1_53

[Ioffe et al., 2015] Ioffe, S. & Szegedy, C.. (2015). Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. Proceedings of the 32nd International Conference on Machine Learning, in PMLR 37:448-456
link : http://proceedings.mlr.press/v37/ioffe15.html

[Ren et al., 2015] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*(pp. 91-99).
link : http://papers.nips.cc/paper/5638-faster-r-cnn-towards-real-time-object-detection-with-region-proposal-networks

[Russakovsky et al., 2015] Russakovsky, O. et al. (2015). Imagenet large scale visual recognition challenge. International Journal of Computer Vision, 115(3), 211-252.
link : https://link.springer.com/article/10.1007/s11263-015-0816-y

[Szegedy et al., 2015] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015). Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9).
link : https://www.cv-foundation.org/openaccess/content_cvpr_2015/html/Szegedy_Going_Deeper_With_2015_CVPR_paper.html

[Han et al., 2016] Han, D., Kim, J., & Kim, J. (2017, July). Deep pyramidal residual networks. In Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on (pp. 6307-6315). IEEE.
link : https://ieeexplore.ieee.org/document/8100151/

[Yu et al., 2016] Yu, F., & Koltun, V.. (2016) Multi-Scale Context Aggregation by Dilated Convolutions. In International Conference on Learning Representations.
link : https://arxiv.org/abs/1511.07122

References

[He et al., 2016a] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
link : https://ieeexplore.ieee.org/document/7780459/

[He et al., 2016b] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Identity mappings in deep residual networks. In European conference on computer vision (pp. 630-645). Springer, Cham.
link : https://link.springer.com/chapter/10.1007/978-3-319-46493-0_38

[Huang et al., 2016] Huang, G., Sun, Y., Liu, Z., Sedra, D., & Weinberger, K. Q. (2016). Deep networks with stochastic depth. In European Conference on Computer Vision (pp. 646-661).
link : https://link.springer.com/chapter/10.1007/978-3-319-46493-0_39

[Kolsbjerg et al., 2016] Kolsbjerg, E. L., Groves, M. N., & Hammer, B. (2016). An automated nudged elastic band method. The Journal of chemical physics, 145(9), 094107.
link : https://aip.scitation.org/doi/abs/10.1063/1.4961868

[Targ et al., 2016] Targ, S., Almeida, D., & Lyman, K. (2016). Resnet in Resnet: generalizing residual architectures. arXiv preprint arXiv:1603.08029.
link : https://arxiv.org/abs/1603.08029

[Veit et al., 2016] Veit, A., Wilber, M. J., & Belongie, S. (2016). Residual networks behave like ensembles of relatively shallow networks. In Advances in Neural Information Processing Systems (pp. 550-558).
link : http://papers.nips.cc/paper/6556-residual-networks-behave-like-ensembles-of-relatively-shallow-networks

[Xie et al., 2016] Xie, S., Girshick, R., Dollár, P., Tu, Z., & He, K. (2017, July). Aggregated residual transformations for deep neural networks. In Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on (pp. 5987-5995). IEEE.
link : http://openaccess.thecvf.com/content_cvpr_2017/papers/Xie_Aggregated_Residual_Transformations_CVPR_2017_paper.pdf

References

[Zagoruyko et al., 2016] Zagoruyko, S. and Komodakis, N. (2016). Wide Residual Networks. In Proceedings of the British Machine Vision Conference (pp. 87.1-87.12).
link : http://www.bmva.org/bmvc/2016/papers/paper087/index.html

[Zoph et al., 2016] Zoph, B., & Le, Q. V. (2016). Neural architecture search with reinforcement learning. arXiv preprint arXiv:1611.01578.
link : https://arxiv.org/abs/1611.01578

[Chen et al., 2017] Chen, Y., Li, J., Xiao, H., Jin, X., Yan, S., & Feng, J. (2017). Dual path networks. In Advances in Neural Information Processing Systems (pp. 4467-4475).
link : https://papers.nips.cc/paper/7033-dual-path-networks

[Huang et al., 2017] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017, July). Densely Connected Convolutional Networks. In CVPR (Vol. 1, No. 2, p. 3).
link : http://openaccess.thecvf.com/content_cvpr_2017/papers/Huang_Densely_Connected_Convolutional_CVPR_2017_paper.pdf

[Szegedy et al., 2017] Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. A. (2017, February). Inception-v4, inception-resnet and the impact of residual connections on learning. In AAAI (Vol. 4, p. 12).
link : https://www.aaai.org/ocs/index.php/AAAI/AAAI17/paper/download/14806/14311

[Dai et al., 2017] Dai, J., Qi, H., Xiong, Y., Li, Y., Zhang, G., Hu, H., & Wei, Y. (2017). Deformable convolutional networks. In *Proceedings of the IEEE international conference on computer vision* (pp. 764-773).
link : https://arxiv.org/abs/1703.06211v3

[Chen et al., 2017] Chen, L. C., Papandreou, G., Schroff, F., & Adam, H. (2017). Rethinking atrous convolution for semantic image segmentation. *arXiv preprint arXiv:1706.05587*.
link : https://arxiv.org/abs/1706.05587

[Howard et al., 2017] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*.
link: https://arxiv.org/abs/1704.04861

References

[Draxler et al., 2018] Draxler, F., Veschgini, K., Salmhofer, M. & Hamprecht, F. (2018). Essentially No Barriers in Neural Network Energy Landscape. Proceedings of the 35th International Conference on Machine Learning, in PMLR 80:1309-1318.
link : http://proceedings.mlr.press/v80/draxler18a.html

[Luo et al., 2018] Luo, R., Tian, F., Qin, T., Chen, E. & Liu, T. (2018) Neural Architecture Optimization. arXiv preprint arXiv:1808.07233.
link : https://arxiv.org/abs/1808.07233

[Li et al., 2018] Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the loss landscape of neural nets. arXiv preprint arXiv:1712.09913.
link : https://arxiv.org/abs/1712.09913

[Pham et al., 2018] Pham, H., Guan, M., Zoph, B., Le, Q. & Dean, J.. (2018). Efficient Neural Architecture Search via Parameters Sharing. Proceedings of the 35th International Conference on Machine Learning, in PMLR 80:4095-4104
link : http://proceedings.mlr.press/v80/pham18a.html

[Real et al., 2018] Real, E., Aggarwal, A., Huang, Y., & Le, Q. V. (2018). Regularized evolution for image classifier architecture search. arXiv preprint arXiv:1802.01548.
link : https://arxiv.org/abs/1802.01548

[Zoph et al., 2018] Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2017). Learning transferable architectures for scalable image recognition. arXiv preprint arXiv:1707.07012, 2(6).
link : http://openaccess.thecvf.com/content_cvpr_2018/papers/Zoph_Learning_Transferable_Architectures_CVPR_2018_paper.pdf

[Brock et al., 2018] Brock, A., Lim, T., Ritchie, J. M., & Weston, N. (2018). SMASH: one-shot model architecture search through hypernetworks. In International Conference on Learning Representations.
link : https://openreview.net/forum?id=rydeCEhs-

References

[Hu et al., 2018] Hu, J., Shen, L., & Sun, G. (2018). Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 7132-7141).
link : https://arxiv.org/abs/1709.01507

[Woo et al., 2018] Woo, S., Park, J., Lee, J. Y., & Kweon, I. S. (2018). Cbam: Convolutional block attention module. In *Proceedings of the European conference on computer vision (ECCV)* (pp. 3-19).
link : https://arxiv.org/abs/1807.06521v2

[Tan et al., 2019] Tan, M., Chen, B., Pang, R., Vasudevan, V., Sandler, M., Howard, A., & Le, Q. V. (2019). Mnasnet: Platform-aware neural architecture search for mobile. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 2820-2828).
link : https://arxiv.org/abs/1807.11626

[Dosovitskiy et al., 2021] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*.
link : https://arxiv.org/abs/2010.11929

[Liu et al., 2021] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., ... & Guo, B. (2021). Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 10012-10022).
link :
https://openaccess.thecvf.com/content/ICCV2021/html/Liu_Swin_Transformer_Hierarchical_Vision_Transformer_Using_Shifted_Windows_ICCV_2021_paper.html

[Tolstikhin et al., 2021] Tolstikhin, I. O., Houlsby, N., Kolesnikov, A., Beyer, L., Zhai, X., Unterthiner, T., ... & Dosovitskiy, A. (2021). Mlp-mixer: An all-mlp architecture for vision. *Advances in Neural Information Processing Systems*, *34*.
link : https://proceedings.neurips.cc/paper/2021/hash/cba0a4ee5ccd02fda0fe3f9a3e7b89fe-Abstract.html

References

[Heo et al., 2021] Heo, B., Yun, S., Han, D., Chun, S., Choe, J., & Oh, S. J. (2021). Rethinking spatial dimensions of vision transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 11936-11945).
link : https://arxiv.org/abs/2103.16302

[Li et al., 2021] Yuan, L., Chen, Y., Wang, T., Yu, W., Shi, Y., Jiang, Z. H., ... & Yan, S. (2021). Tokens-to-token vit: Training vision transformers from scratch on imagenet. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 558-567).
link : https://arxiv.org/abs/2101.11986