Lecture 13:
Modern Architectures

Administrative: Assignment 4

Due 2/27 11:59pm

- PyTorch
- RNNs
- LSTMs

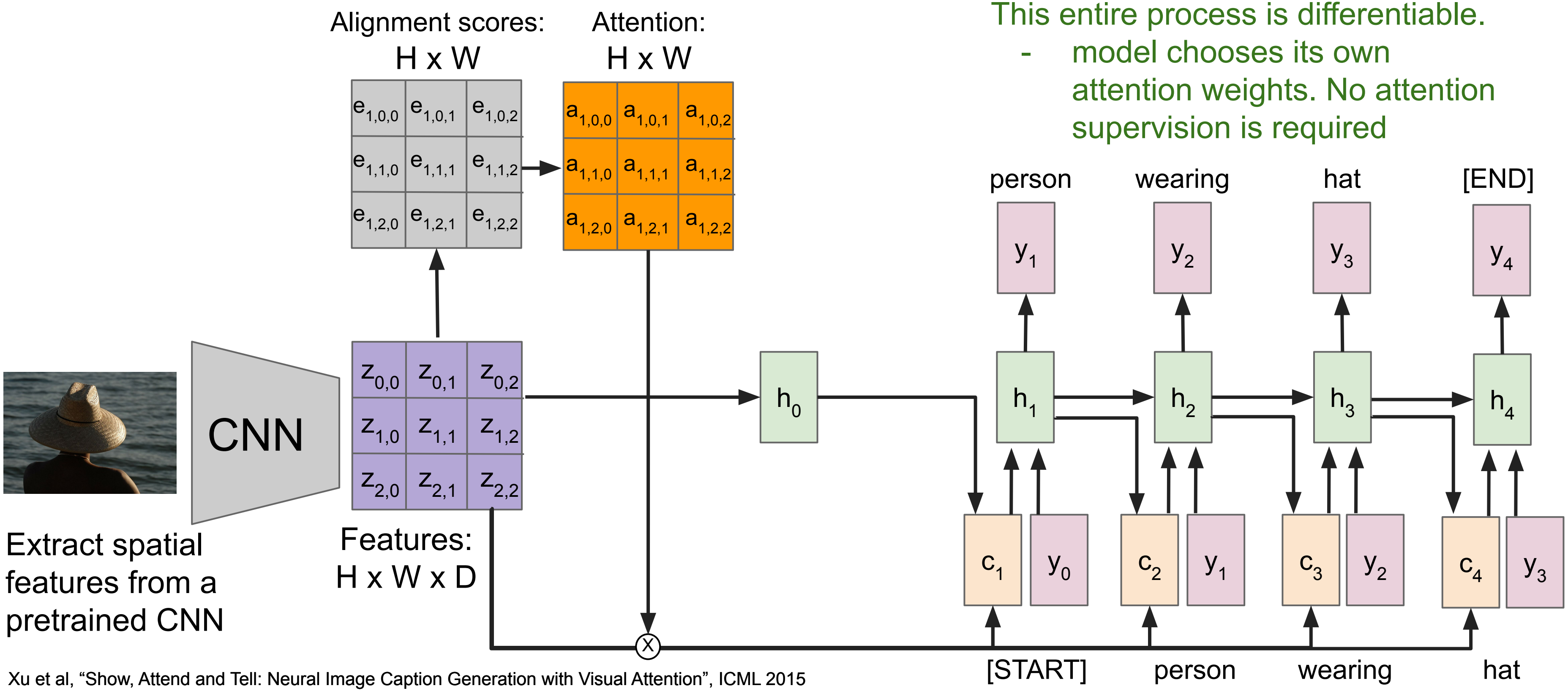
Administrative: Fridays

This Friday

Coding Agent with Ethan

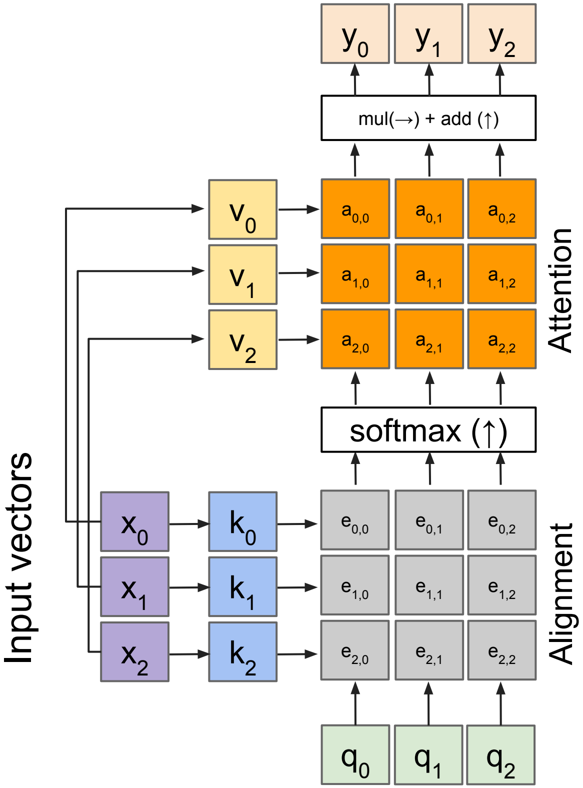
Image Captioning with RNNs & Attention

This entire process is differentiable.
- model chooses its own attention weights. No attention supervision is required



Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

General attention layer

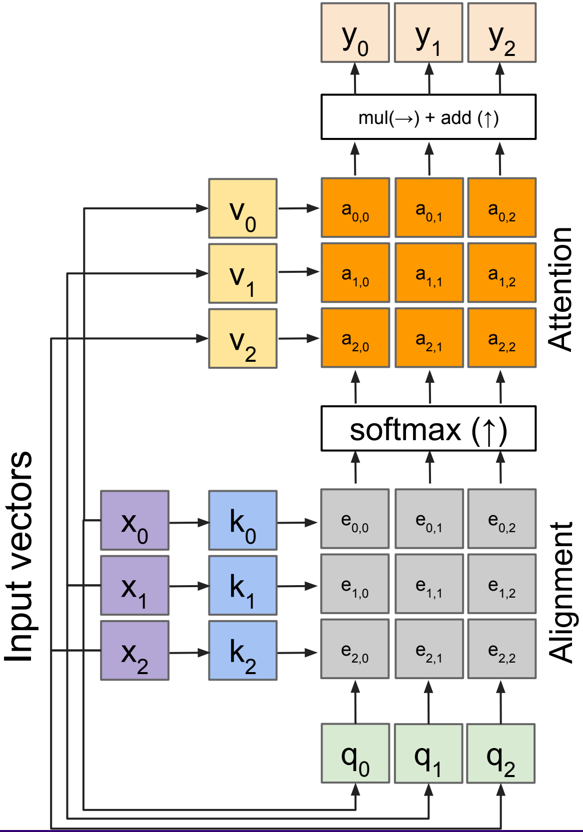


Outputs:
context vectors: **y** (shape: D_v)

Operations:
Key vectors: $\mathbf{k} = \mathbf{x}\mathbf{W}_k$
Value vectors: $\mathbf{v} = \mathbf{x}\mathbf{W}_v$
Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} v_i$

Inputs:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x D_k)

Self attention layer



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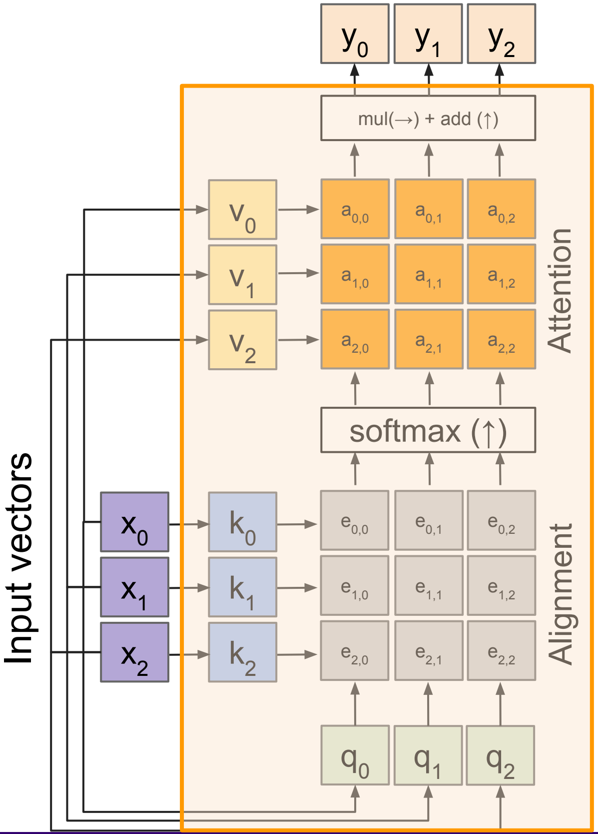
Inputs:
Input vectors: **x** (shape: N x D)

Self attention layer - attends over sets of inputs



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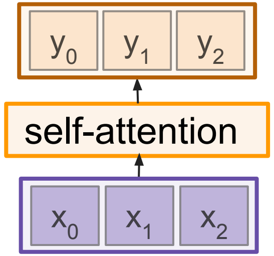
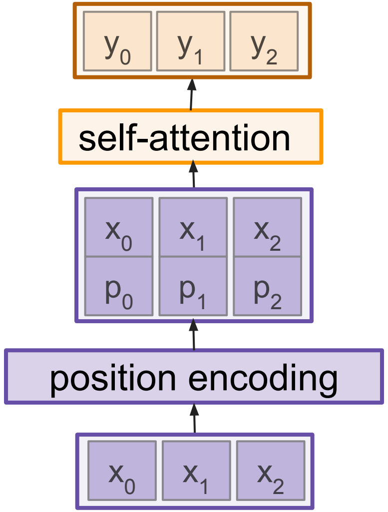


Positional encoding



Concatenate special positional encoding p_j to each input vector x_j

We use a function *pos*: $N \rightarrow R^d$ to process the position j of the vector into a d-dimensional vector

So, p_j = *pos*(j)

Options for *pos*(.)

1. Learn a lookup table:
   - Learn parameters to use for *pos*(t) for t ε [0, T)
   - Lookup table contains T x d parameters.

2. Design a fixed function with the desiderata
   -

$$p(t) = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_d$$

Intuition:

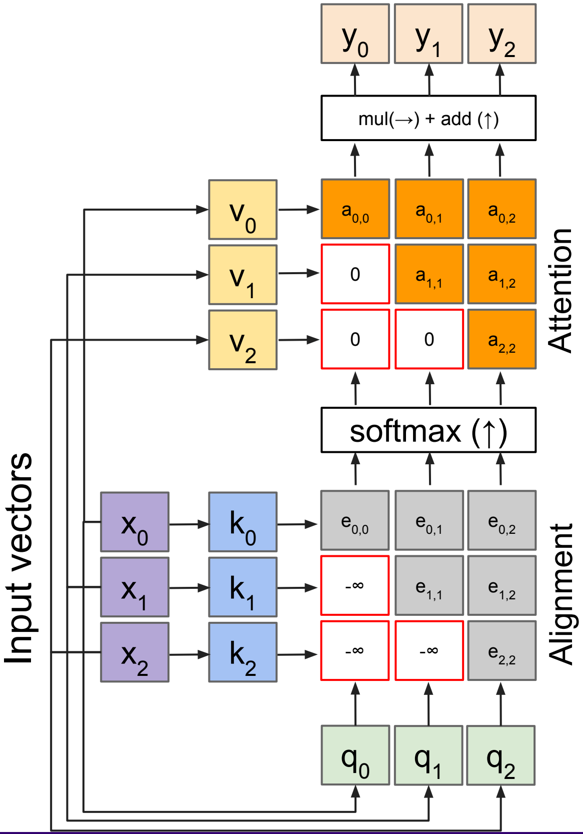
0 :	0	0	0	0	8 :	1	0	0	0
1 :	0	0	0	1	9 :	1	0	0	1
2 :	0	0	1	0	10 :	1	0	1	0
3 :	0	0	1	1	11 :	1	0	1	1
4 :	0	1	0	0	12 :	1	1	0	0
5 :	0	1	0	1	13 :	1	1	0	1
6 :	0	1	1	0	14 :	1	1	1	0
7 :	0	1	1	1	15 :	1	1	1	1

where $\omega_k = \dfrac{1}{10000^{2k/d}}$

image source

Vaswani et al, "Attention is all you need", NeurIPS 2017

Causal attention layer



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Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
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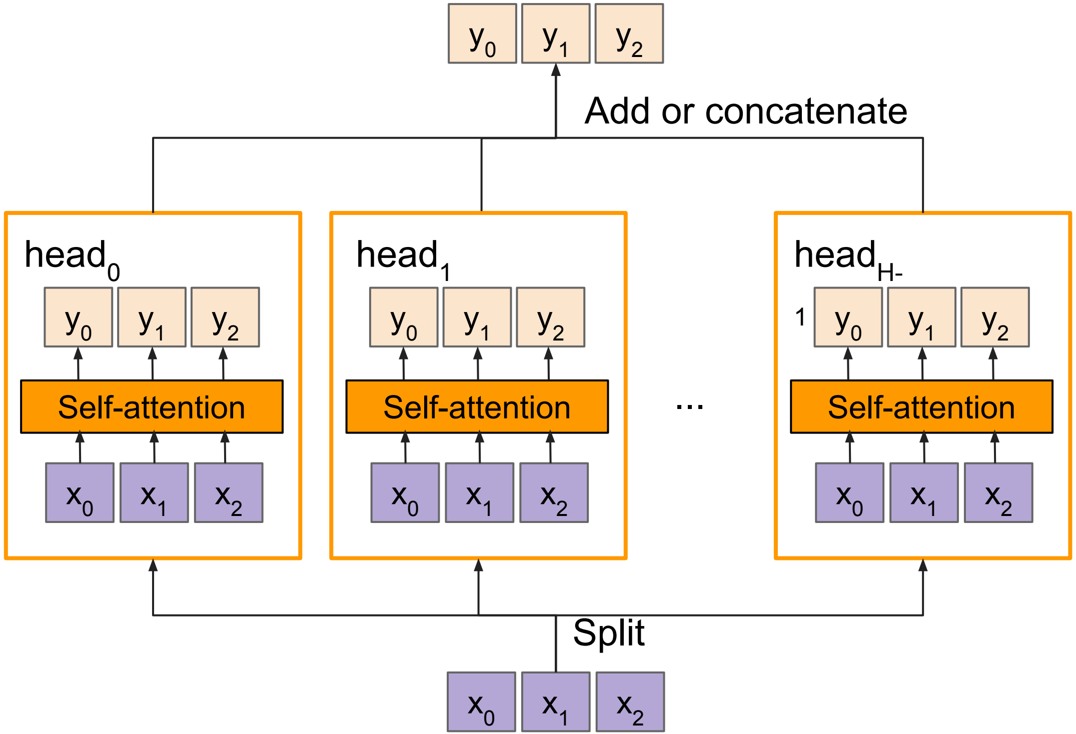
Output: $y_j = \sum_i a_{i,j} v_i$

Inputs:
Input vectors: **x** (shape: N x D)

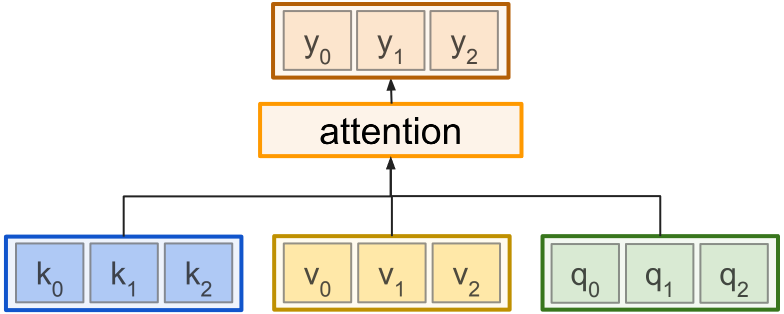
- Prevent vectors from looking at future vectors.
- Manually set alignment scores to -infinity

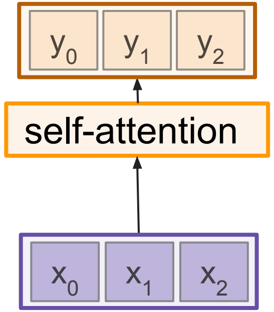
Multi-head self-attention layer

- Multiple self-attention heads in parallel

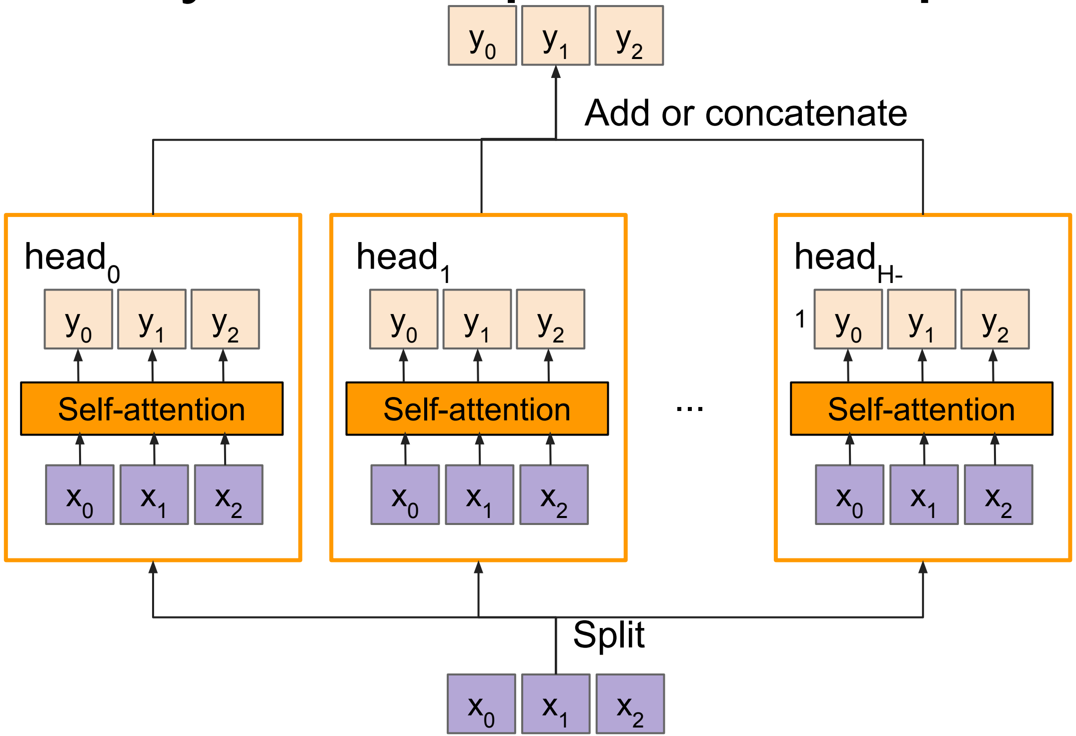


General attention versus self-attention





Attention layers can process sequential inputs



Self-attention layers are masked

Comparing RNNs to masked multi-headed attention

RNNs
(+) LSTMs work reasonably well for long sequences.
(-) Expects an ordered sequences of inputs
(-) Sequential computation: subsequent hidden states can only be computed after the previous ones are done.

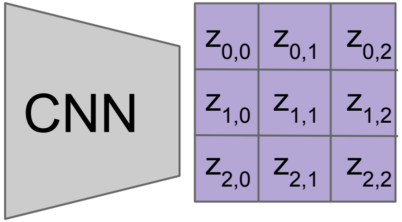
Masked multi-headed attention:
(+) Good at long sequences. Each attention calculation looks at all inputs.
(+) Can operate over unordered sets or ordered sequences with positional encodings.
(+) Parallel computation: All alignment and attention scores for all inputs can be done in parallel.
(-) Requires a lot of memory: N x M alignment and attention scalers need to be calculated and stored for a single self-attention head. (but GPUs are getting bigger and better)

Today's Agenda:

- **Attention with RNNs**
  - In Computer Vision
  - In NLP
- **General Attention Layer**
  - Self-attention
  - Positional encoding
  - Masked attention
  - Multi-head attention
- **Transformers**

Image Captioning using transformers

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, \ldots, y_T$



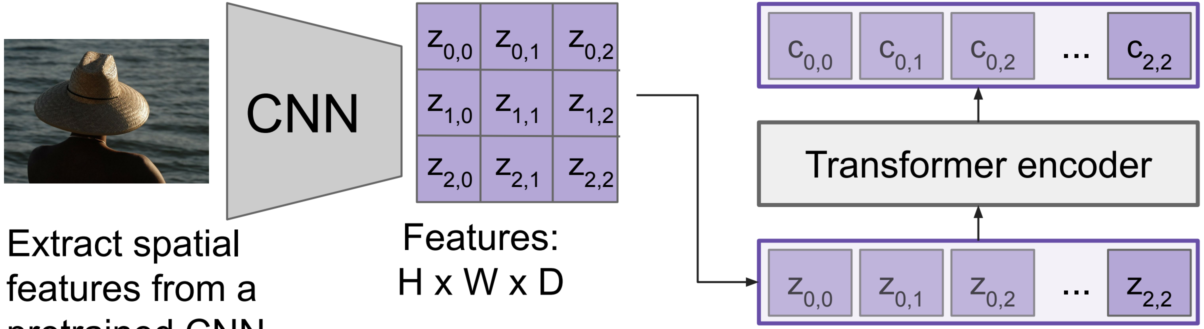
Extract spatial features from a pretrained CNN

Features: H x W x D

Image Captioning using transformers

Input: Image **I**
Output: Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

Encoder: $\mathbf{c} = T_W(\mathbf{z})$
where $\mathbf{z}$ is spatial CNN features
$T_W(.)$ is the transformer encoder



Extract spatial features from a pretrained CNN

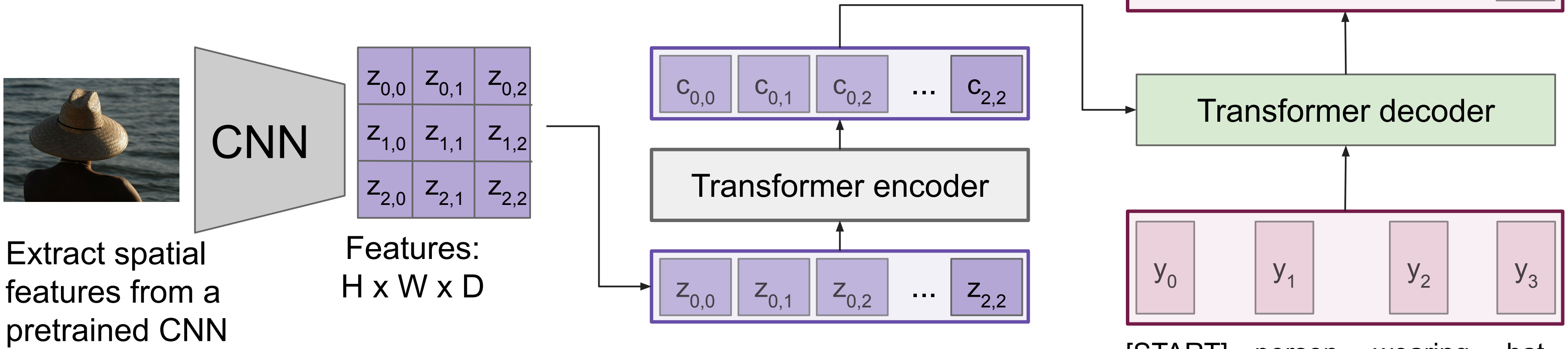
Features: H x W x D

Image Captioning using transformers

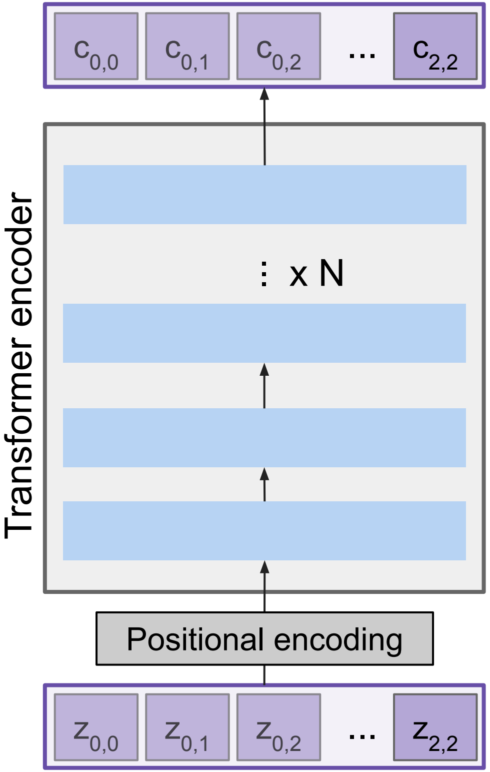
Input: Image **I**
Output: Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

Decoder: $y_t = T_D(\mathbf{y}_{0:t-1}, \mathbf{c})$
where $T_D(.)$ is the transformer decoder

Encoder: $\mathbf{c} = T_W(\mathbf{z})$
where $\mathbf{z}$ is spatial CNN features
$T_W(.)$ is the transformer encoder



The Transformer encoder block

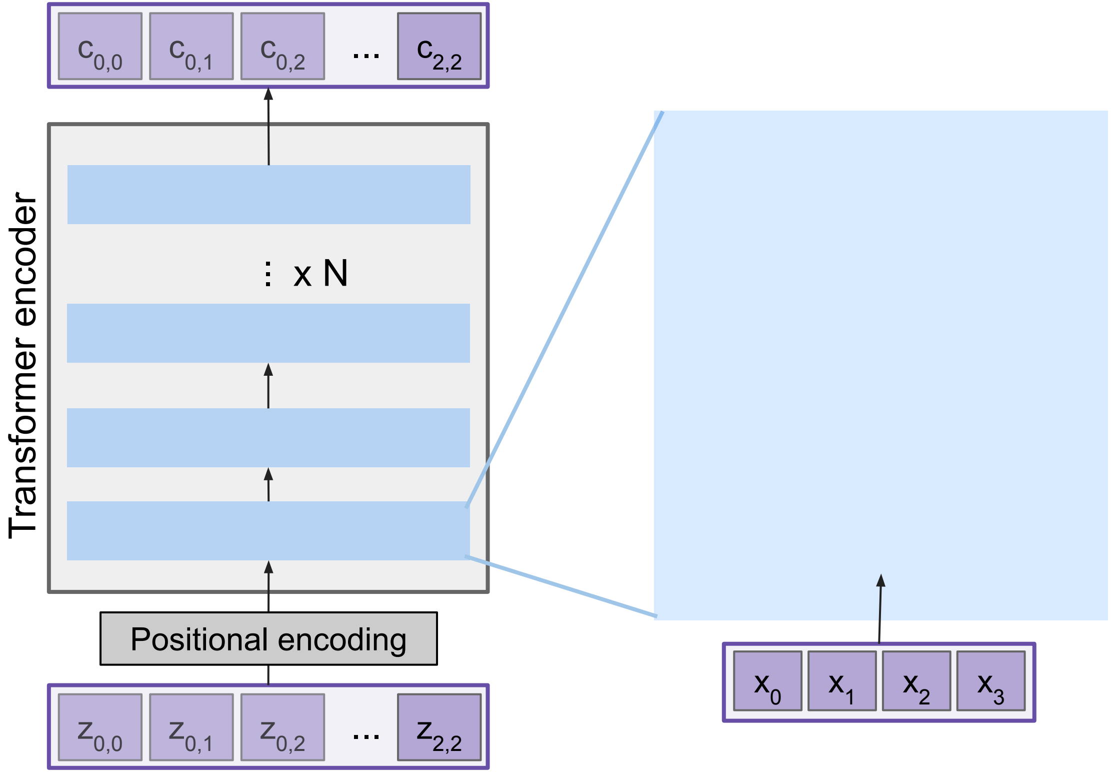


Made up of N encoder blocks.

In vaswani et al. N = 6, D_q= 512

Vaswani et al, “Attention is all you need”, NeurIPS 2017

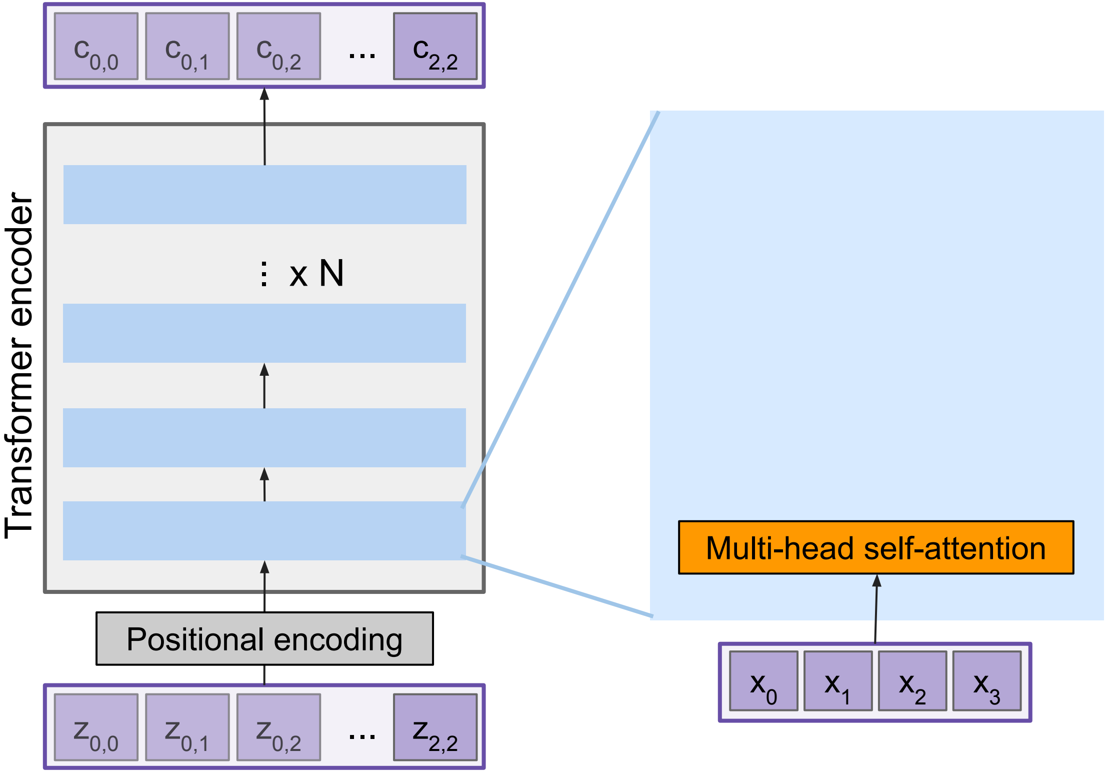
The Transformer encoder block



Let's dive into one encoder block

Vaswani et al, "Attention is all you need", NeurIPS 2017

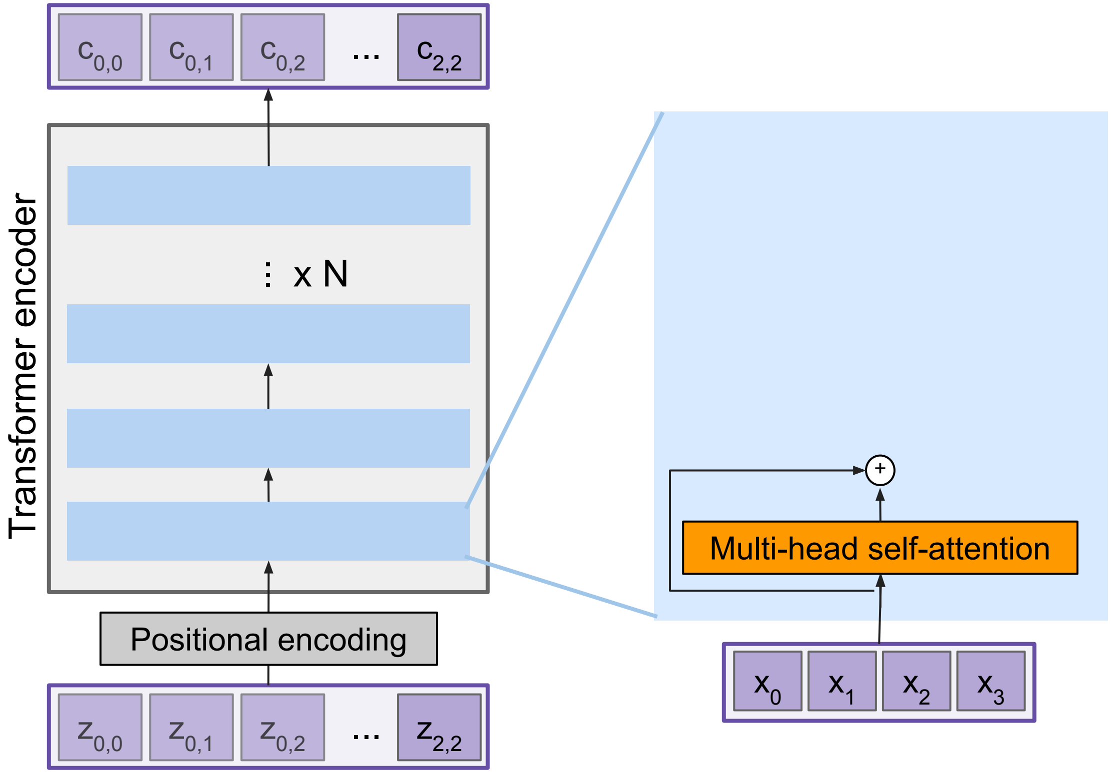
The Transformer encoder block



Attention attends over all the vectors

Vaswani et al, “Attention is all you need”, NeurIPS 2017

The Transformer encoder block



Residual connection

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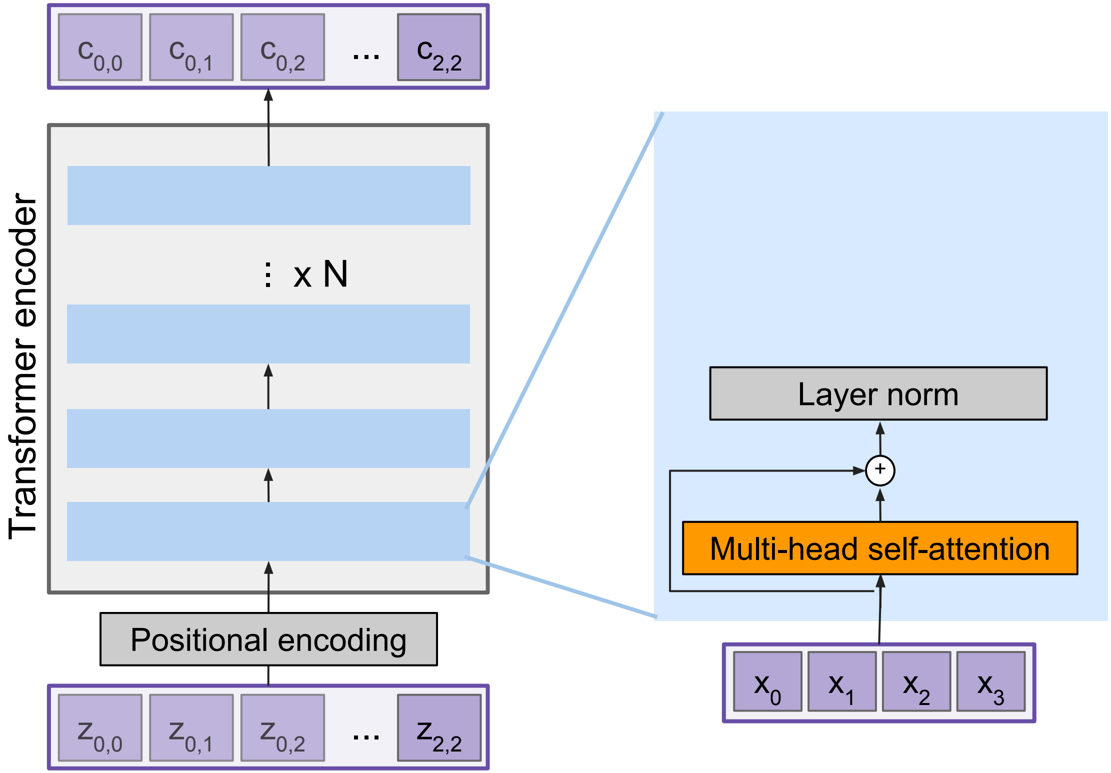
Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer encoder block



LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

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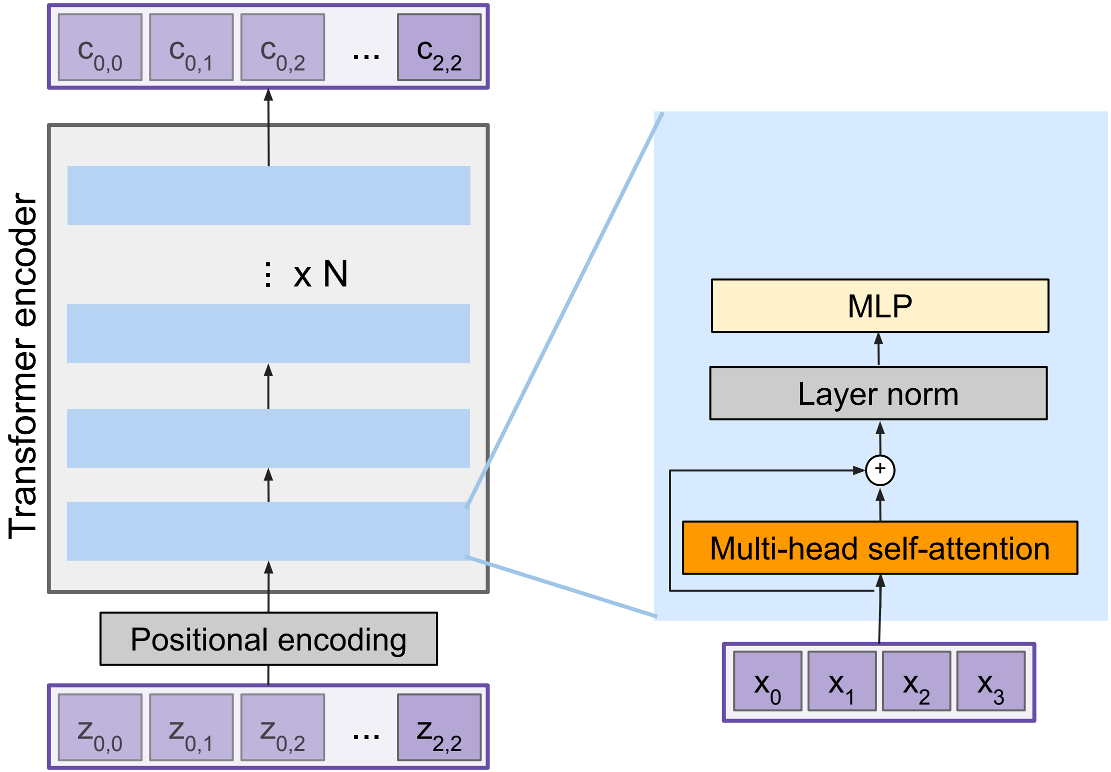
The Transformer encoder block



MLP (2 layers with GeLU) over each vector individually

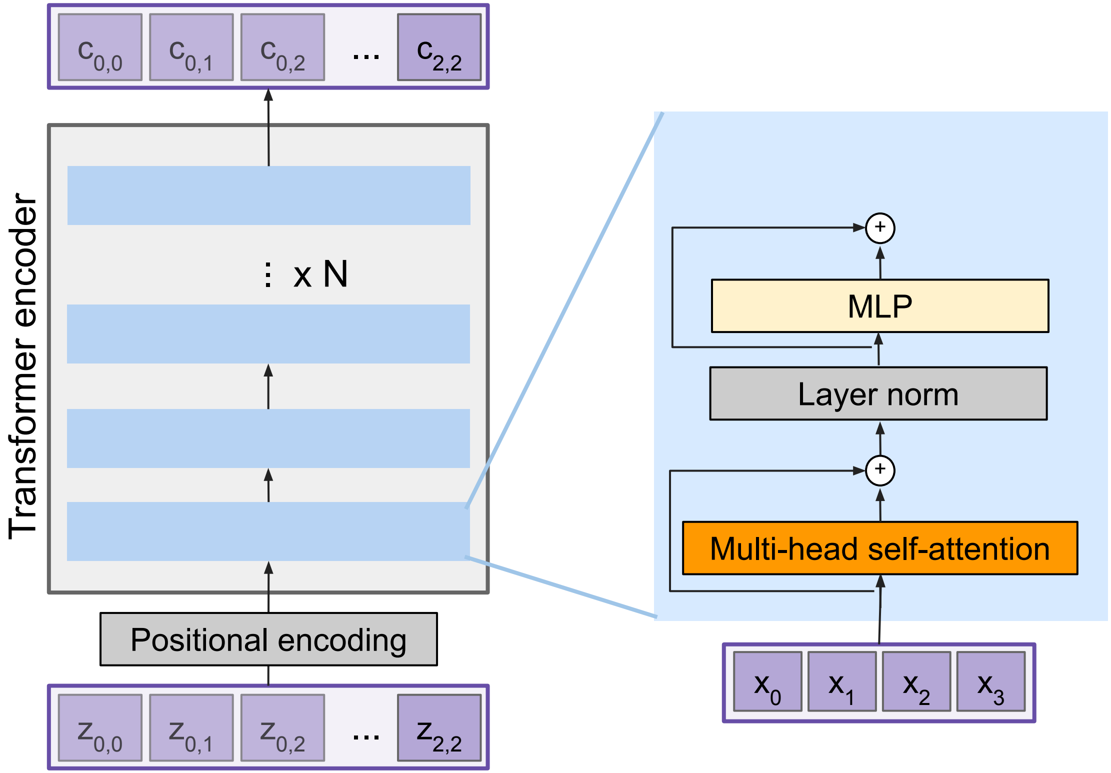
LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer encoder block



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MLP (2 layers with GeLU) over each vector individually

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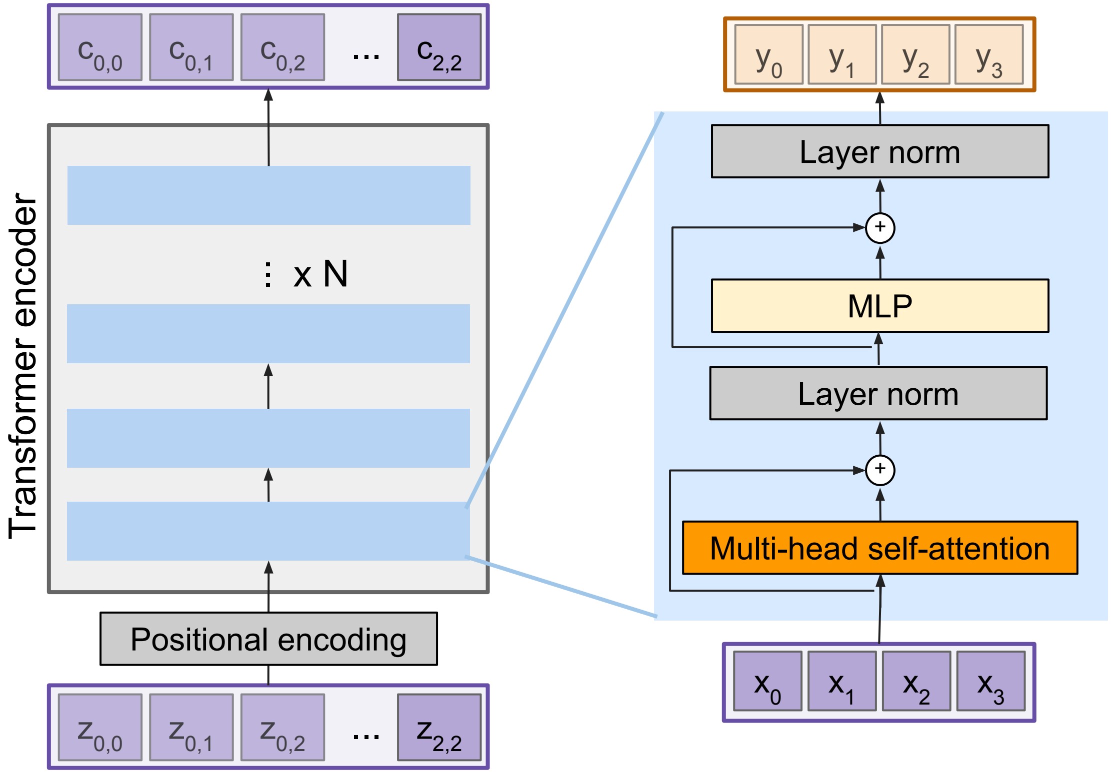
The Transformer encoder block



Transformer Encoder Block:

Inputs: Set of vectors **x**
Outputs: Set of vectors **y**

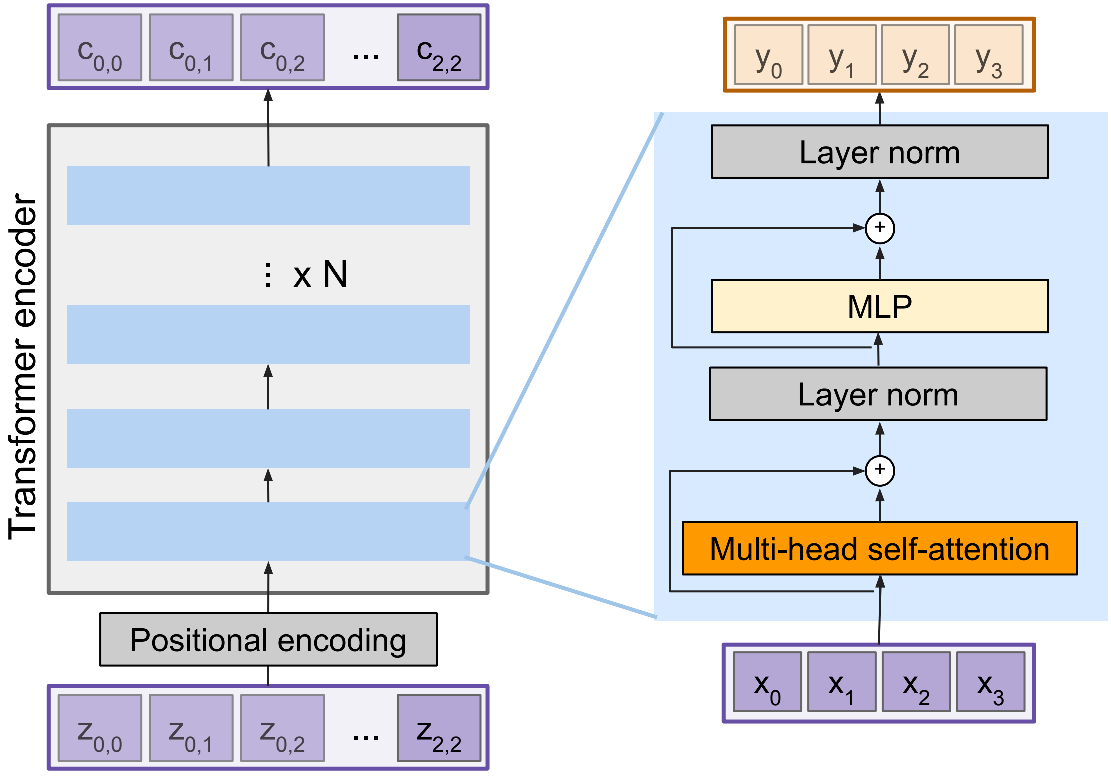
Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer encoder block



Now very common for LN to come before operations instead of after

Transformer Encoder Block:

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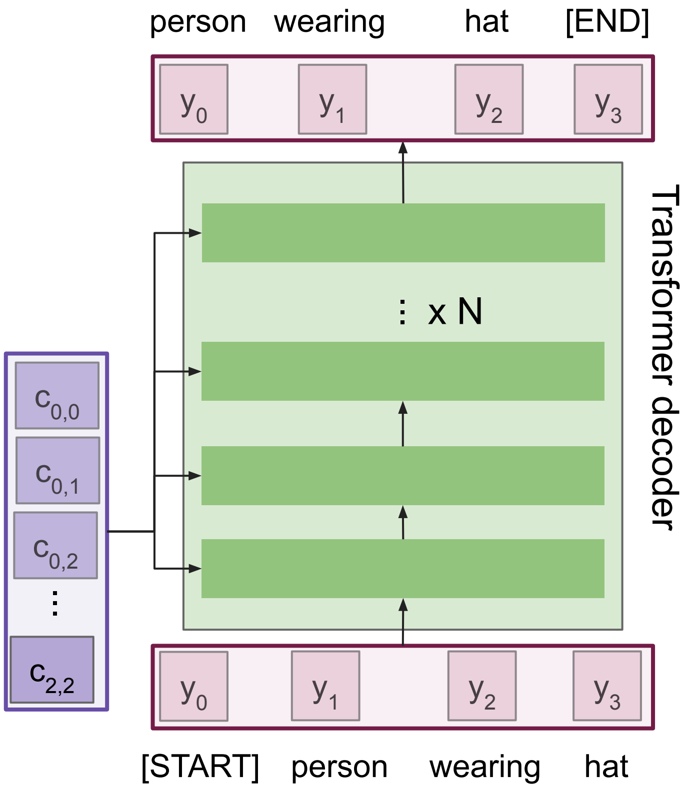
The Transformer Decoder block

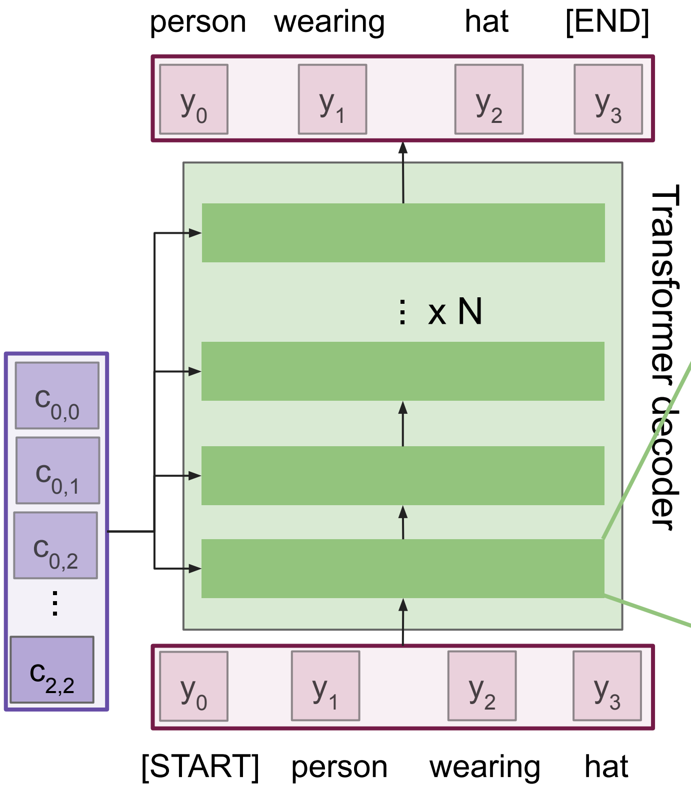


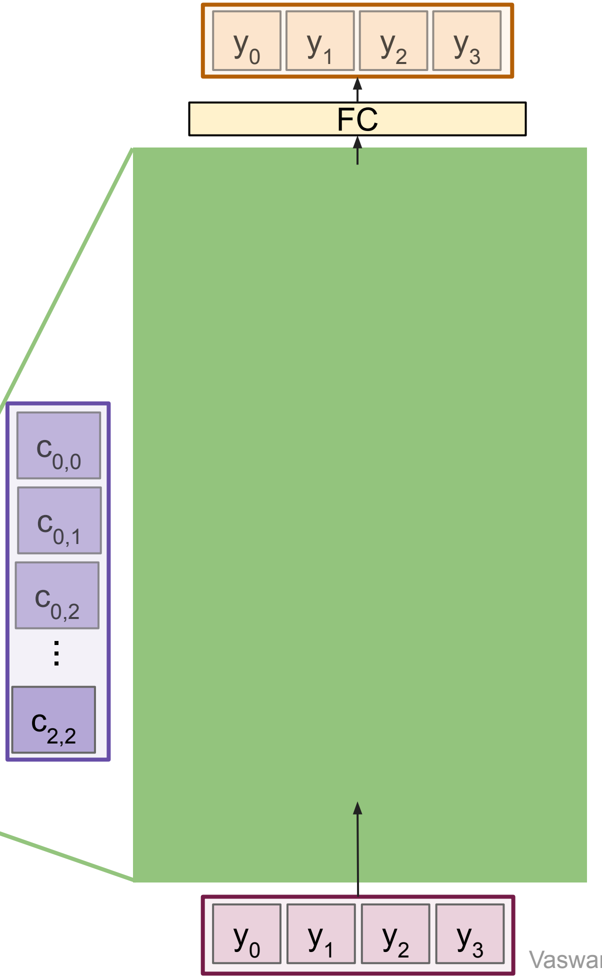
Made up of N decoder blocks.

In vaswani et al. N = 6, D_q= 512

Vaswani et al, “Attention is all you need”, NeurIPS 2017

The Transformer Decoder block

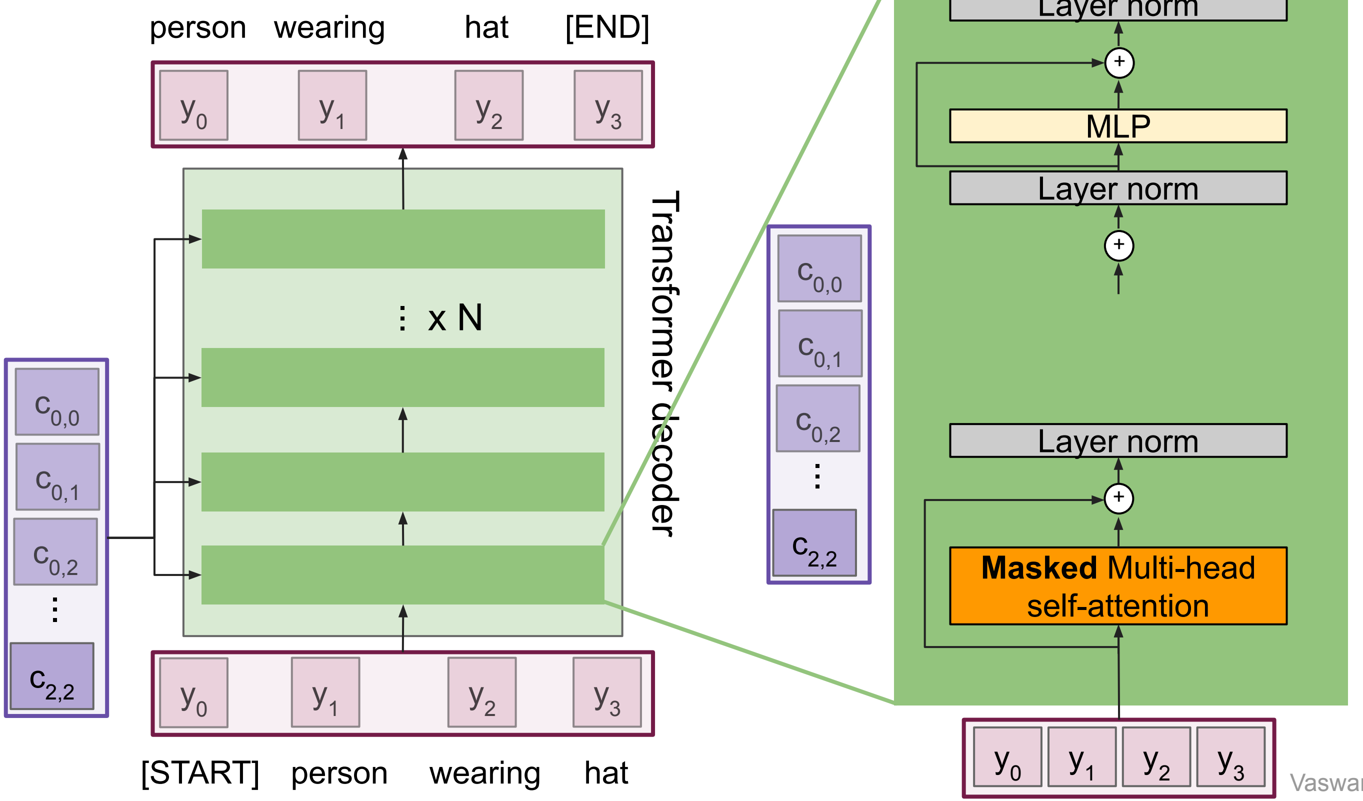




Let's dive into the transformer decoder block

Vaswani et al, “Attention is all you need”, NeurIPS 2017

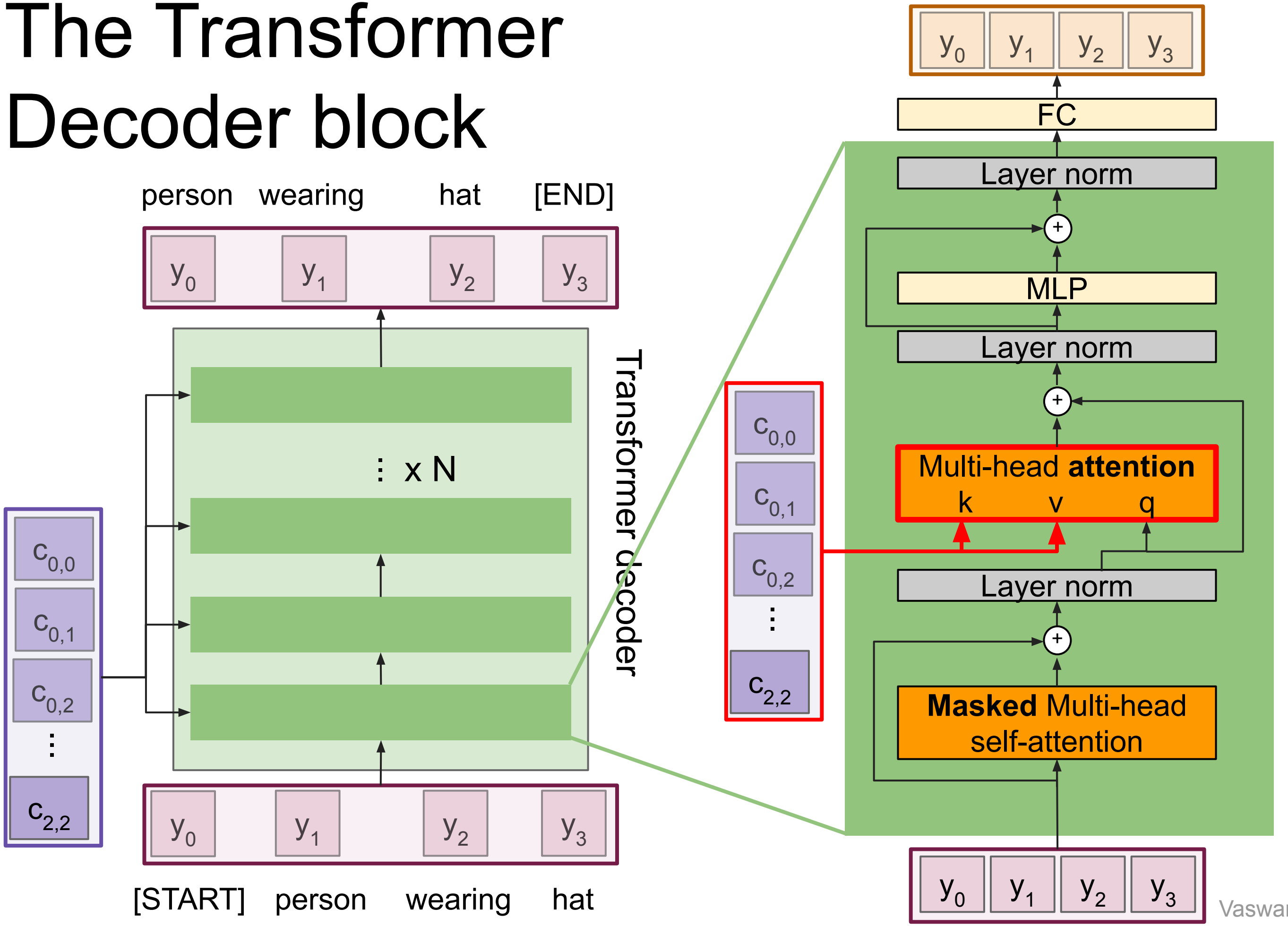
The Transformer Decoder block



Most of the network is the same the transformer encoder.

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Decoder block

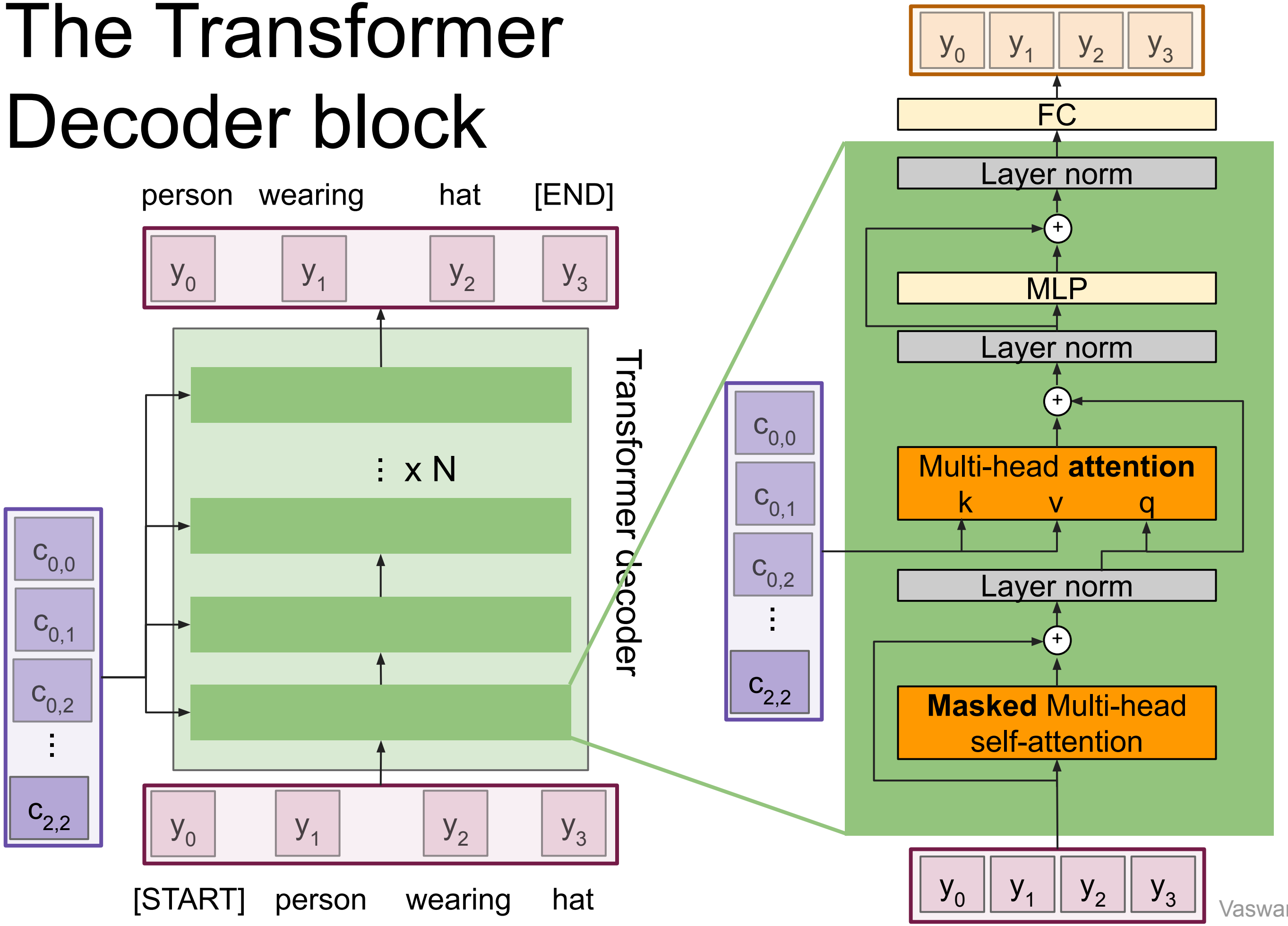


Multi-head attention block attends over the transformer encoder outputs.

For image captions, this is how we inject image features into the decoder.

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Decoder block



Transformer Decoder Block:

Inputs: Set of vectors **x** and Set of context vectors **c.**
Outputs: Set of vectors **y.**

Masked Self-attention only interacts with past inputs.

Multi-head attention block is NOT self-attention. It attends over encoder outputs.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

Image Captioning using transformers

- **No recurrence at all**

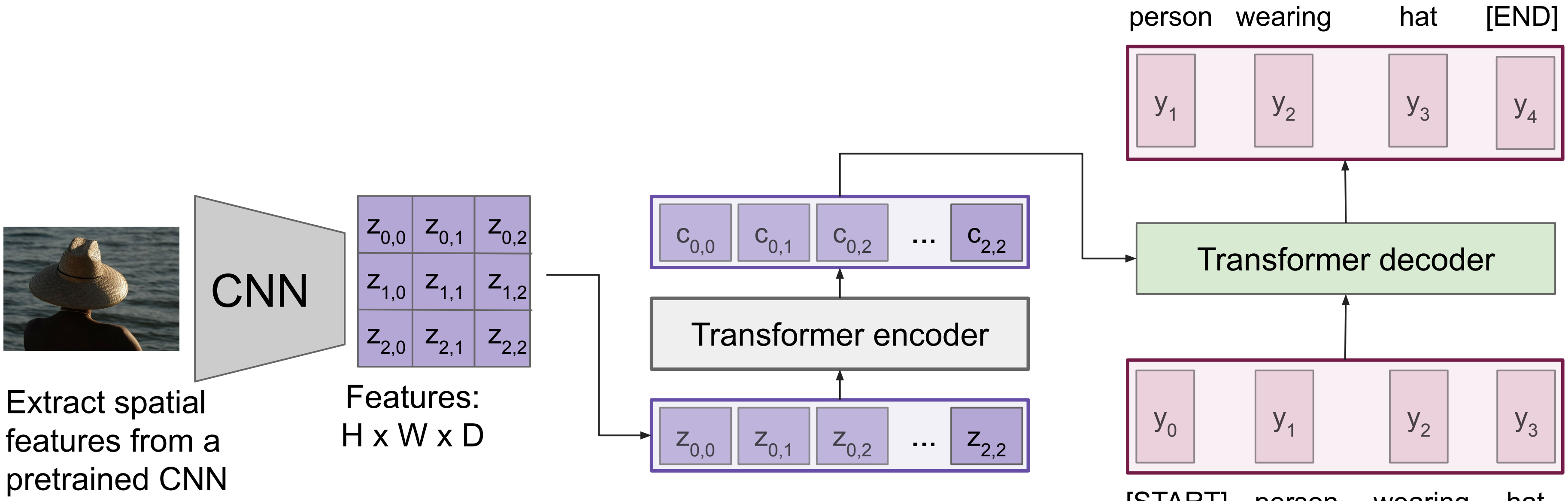


Image Captioning using transformers

- **Perhaps we don't need convolutions at all?**

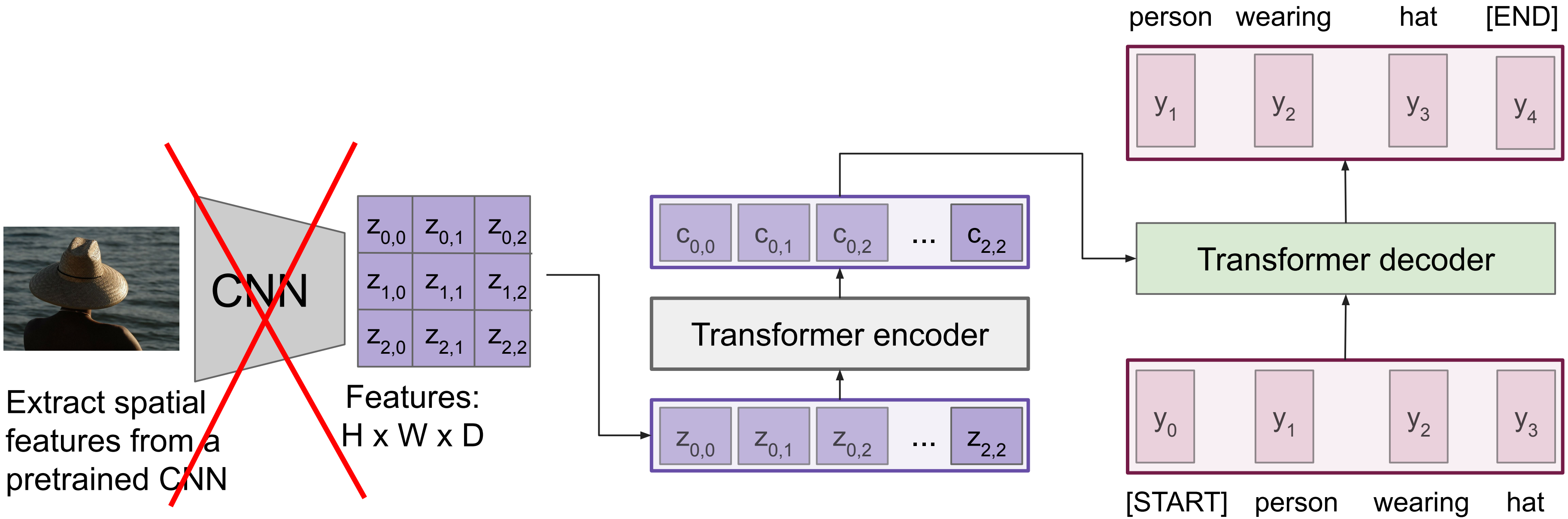
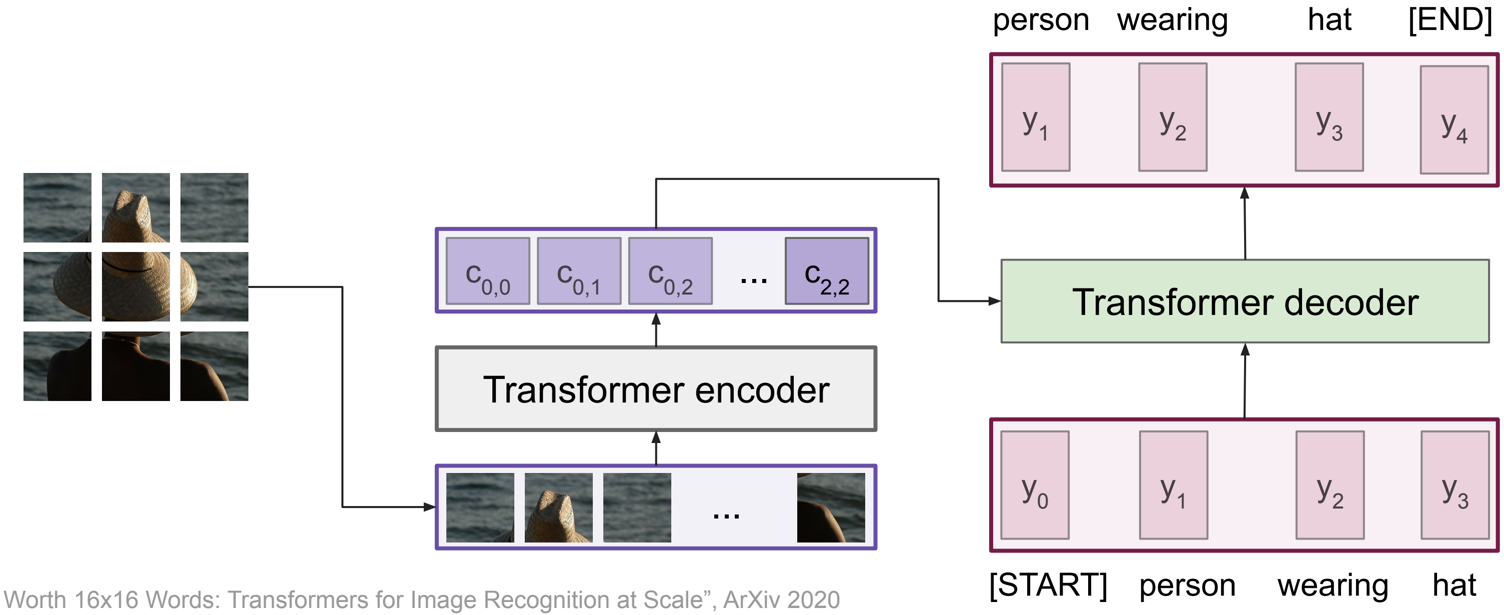


Image Captioning using ONLY transformers

- **Transformers from pixels to language**



Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020
Colab link to an implementation of vision transformers

Image Captioning using ONLY transformers

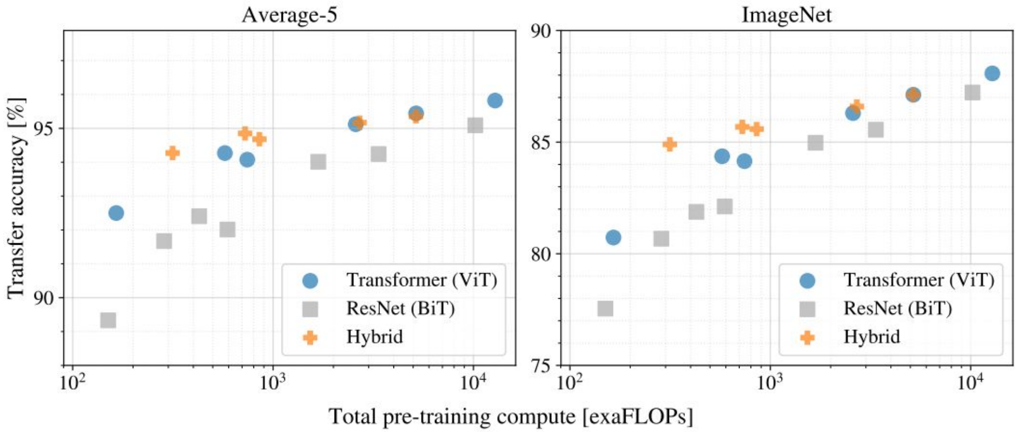


Figure 5: Performance versus cost for different architectures: Vision Transformers, ResNets, and hybrids. Vision Transformers generally outperform ResNets with the same computational budget. Hybrids improve upon pure Transformers for smaller model sizes, but the gap vanishes for larger models.

Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020
Colab link to an implementation of vision transformers

New large-scale transformer models

link to more examples

Transformers today

Model	Layers	Width	Heads	Params	Data	Training
Transformer-Base	12	512	8	65M	?	8x P100 (12 hours)
Transformer-Large	12	1024	16	213M	?	8x P100 (3.5 days)

Vaswani et al, “Attention is all you need”, NeurIPS 2017

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BERT-Base	12	768	12	119M	13GB	?
BERT-Large	24	1024	16	340M	13GB	?

Devlin et al, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", EMNLP 2018

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XLNet-Large	24	1024	16	~340M	126GB	512x TPU-v3 (2.5 days)
RoBERTa	24	1024	16	355M	160GB	1024x V100 GPUs (1 day)

Yang et al, XLNet: Generalized Autoregressive Pretraining for Language Understanding", 2019 (Google)
Liu et al, "RoBERTa: A Robustly Optimized BERT Pretraining Approach", 2019 (Meta)

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GPT-2	48	1600	25	1.5B	40GB	?

Radford et al, "Language models are unsupervised multitask learners", 2019 (OpenAI)

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GPT-2	48	1600	25	1.5B	40GB	?
Megatron-LM	72	3072	32	8.3B	174GB	512x V100 GPU (9 days)

Shoeybi et al. "Megatron-lm: Training multi-billion parameter language models using model parallelism." 2019. (Google)

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Turing-NLG	78	4256	28	17B	?	256x V100 GPUs

Microsoft, "Turing-NLG: A 17-billion parameter language model by Microsoft", 2020

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GPT-3	96	12288	96	175B	694GB	?

Brown et al, "Language Models are Few-Shot Learners", NeurIPS 2020

Transformers today

Rae et al, "Scaling Language Models: Methods, Analysis, & Insights from Training Gopher", arXiv 2021 (Google)

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BERT-Base	12	768	12	119M	13GB	?
BERT-Large	24	1024	16	340M	13GB	?
XLNet-Large	24	1024	16	~340M	126GB	512x TPU-v3 (2.5 days)
RoBERTa	24	1024	16	355M	160GB	1024x V100 GPUs (1 day)
GPT-2	48	1600	25	1.5B	40GB	?
Megatron-LM	72	3072	32	8.3B	174GB	512x V100 GPU (9 days)
Turing-NLG	78	4256	28	17B	?	256x V100 GPUs
GPT-3	96	12288	96	175B	694GB	?
Gopher	80	16384	128	280B	10.55TB	4096x TPU-v3 (38 days)

Model	Layers	Width	Heads	Params	Data	Training
Transformer-Base	12	512	8	65M	?	8x P100 (12 hours)
Transformer-Large	12	1024	16	213M	?	8x P100 (3.5 days)
BERT-Base	12	768	12	119M	13GB	?
BERT-Large	24	1024	16	340M	13GB	?
XLNet-Large	24	1024	16	~340M	126GB	512x TPU-v3 (2.5 days)
RoBERTa	24	1024	16	355M	160GB	1024x V100 GPUs (1 day)
GPT-2	48	1600	25	1.5B	40GB	?
Megatron-LM	72	3072	32	8.3B	174GB	512x V100 GPU (9 days)
Turing-NLG	78	4256	28	17B	?	256x V100 GPUs
GPT-3	96	12288	96	175B	694GB	?
Gopher	80	16384	128	280B	10.55TB	4096x TPU-v3 (38 days)
GPT-4	?	?	?	1.8T	?	?

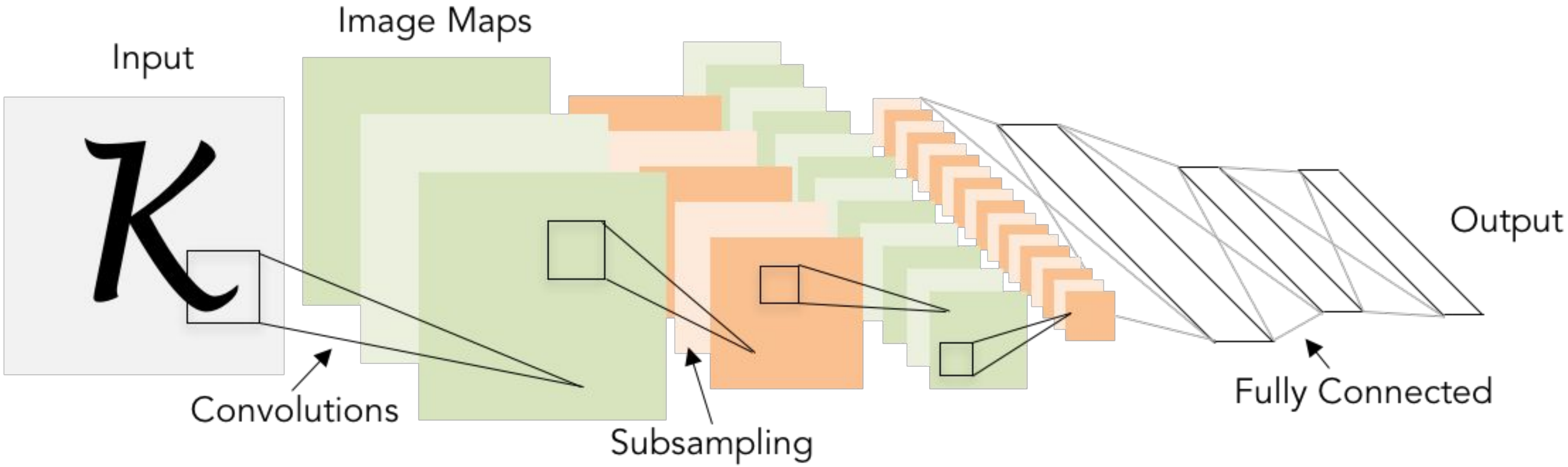
Summary

- Adding **attention** to RNNs allows them to "attend" to different parts of the input at every time step
- The **general attention layer** is a new type of layer that can be used to design new neural network architectures
- **Transformers** are a type of layer that uses **attention** and layer norm.
  - It is highly **scalable** and highly **parallelizable**
  - **Faster** training, **larger** models, **better** performance across vision and language tasks
  - They are quickly replacing RNNs, LSTMs, and may even replace convolutions.

Today: Modern Architectures

Review: LeNet-5

[LeCun et al., 1998]



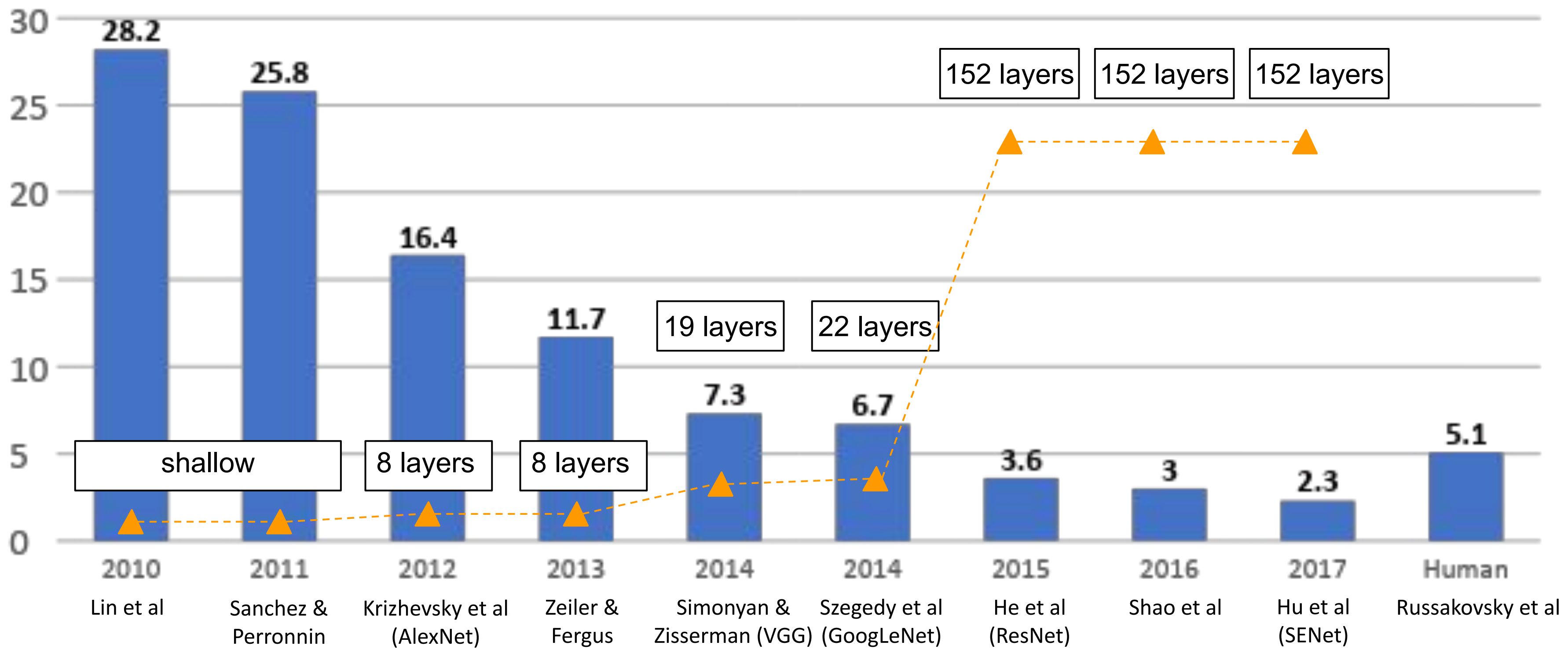
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

Today: Modern Architectures

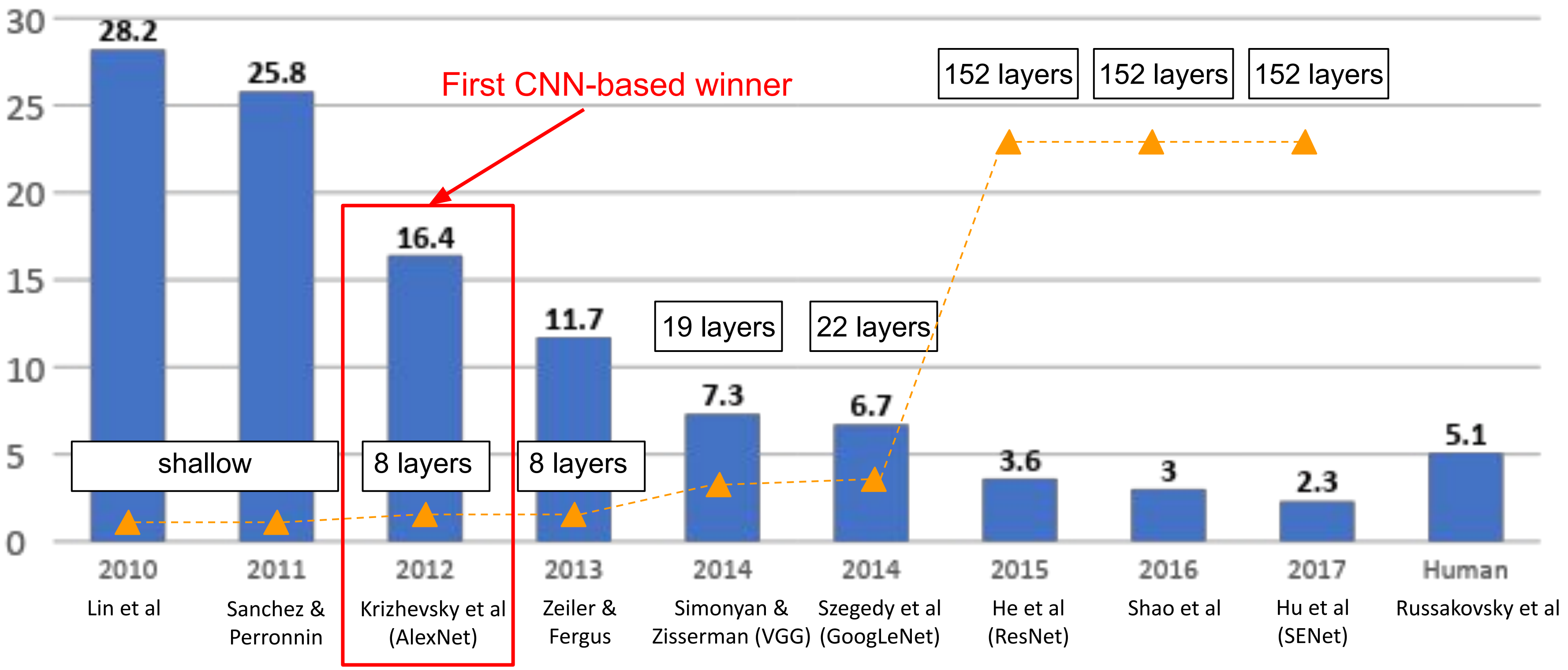
Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet
- ViT

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: AlexNet

[Krizhevsky et al. 2012]

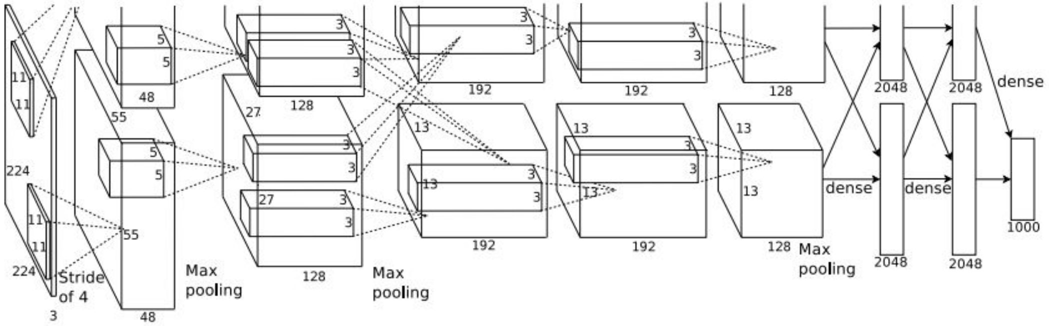


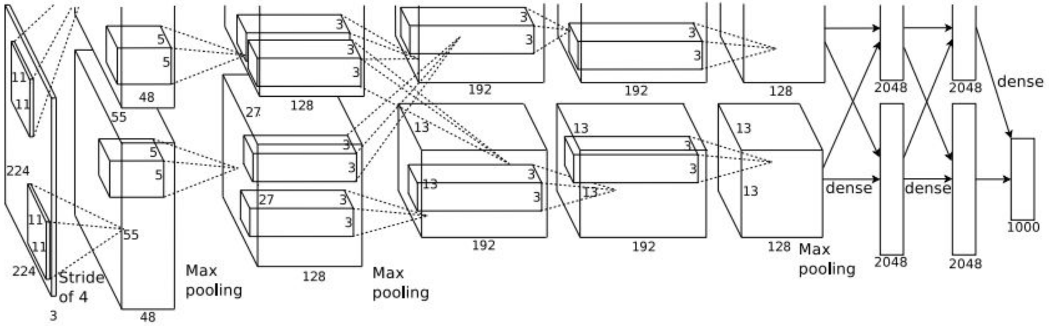
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Architecture:

CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

W' = (W - F + 2P) / S + 1

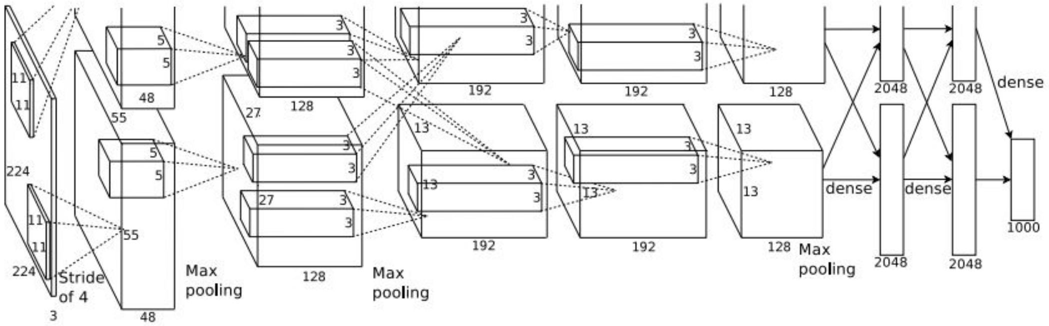
First layer (CONV1): 96 11x11 filters applied at stride 4

=>

Q: what is the output volume size? Hint: (227-11)/4+1 = 55

Case Study: AlexNet

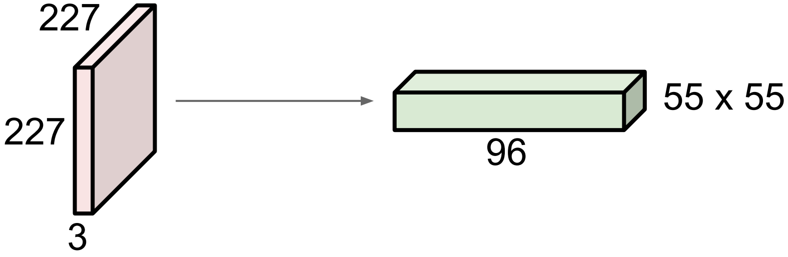
[Krizhevsky et al. 2012]



Input: 227x227x3 images

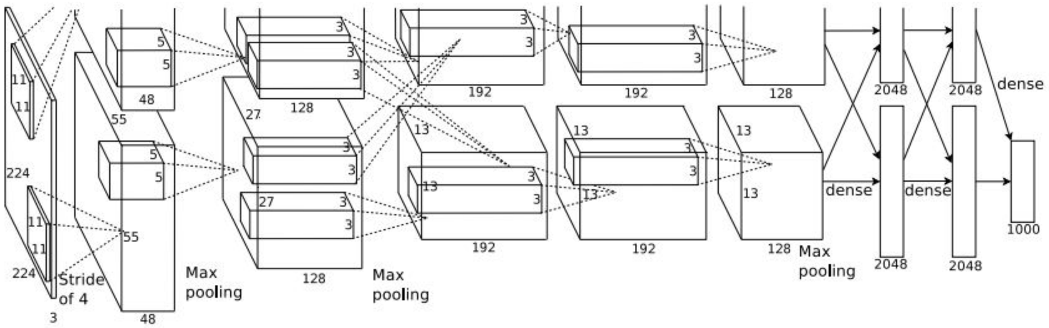
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

W' = (W - F + 2P) / S + 1



Case Study: AlexNet

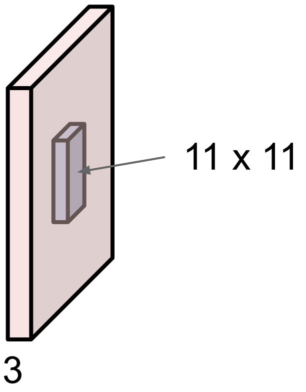
[Krizhevsky et al. 2012]



Input: 227x227x3 images

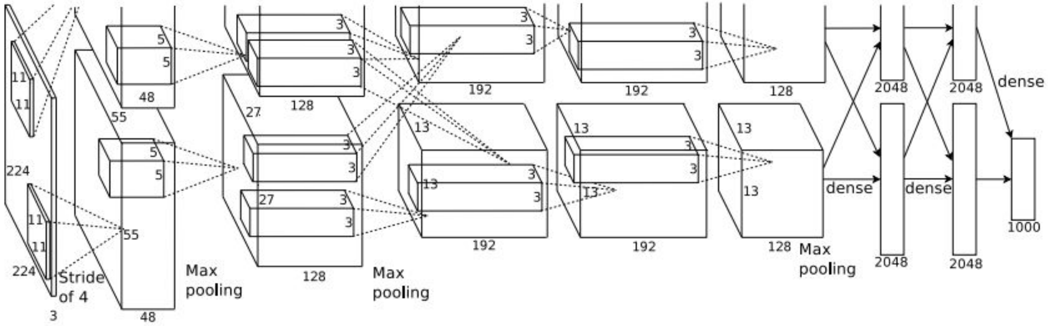
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?



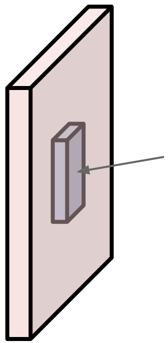
Case Study: AlexNet

[Krizhevsky et al. 2012]



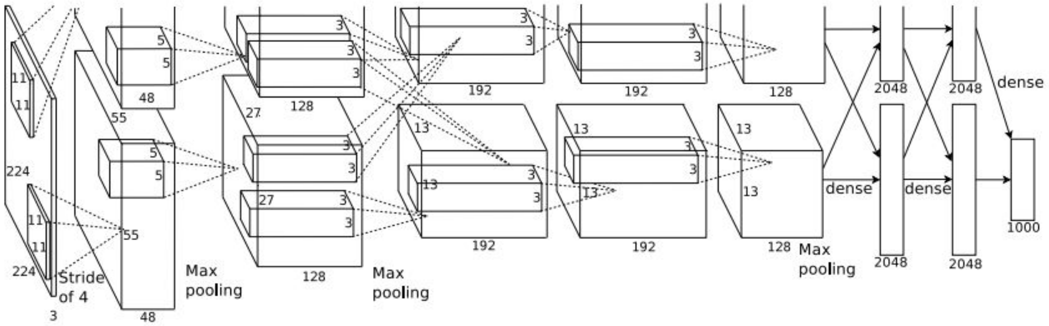
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3 + 1)*96 = **35K**



Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

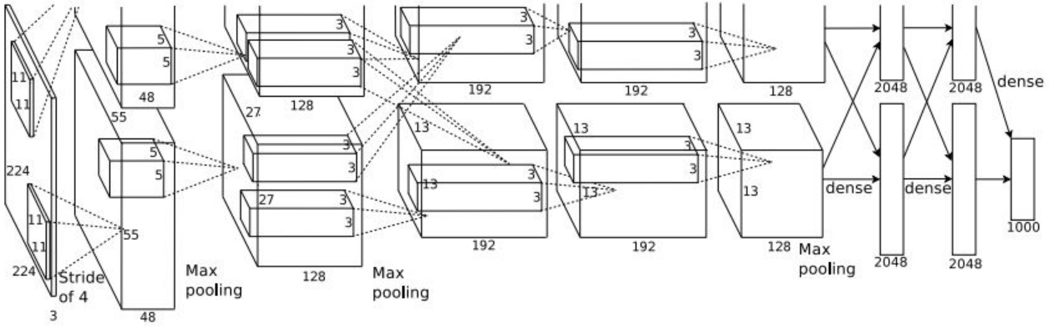
$W' = (W - F + 2P) / S + 1$

Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

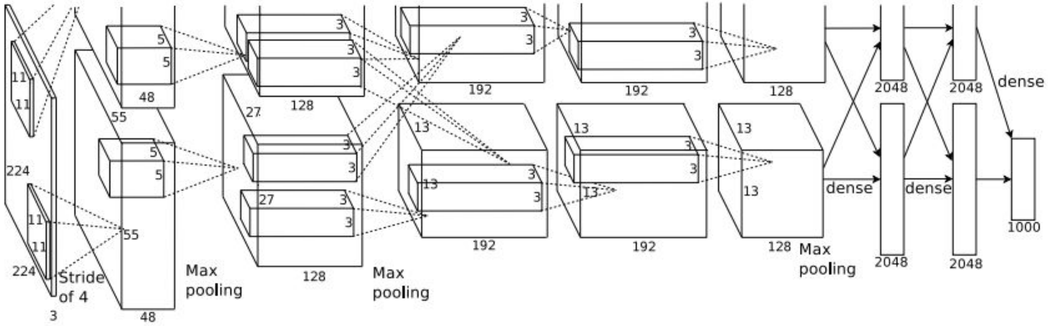
W' = (W - F + 2P) / S + 1

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky et al. 2012]

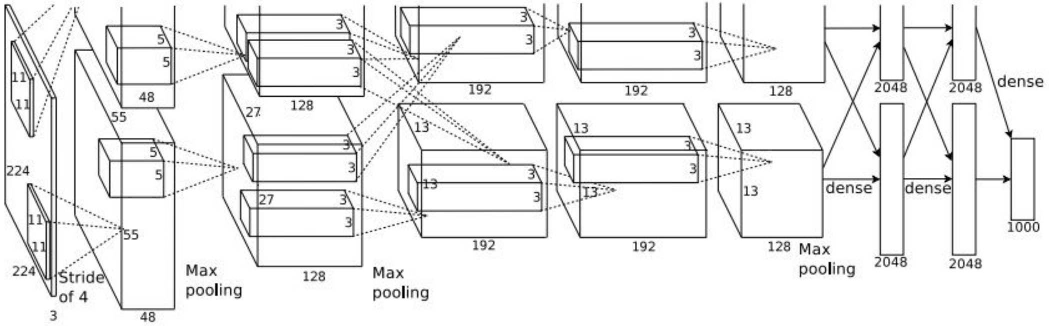


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

Case Study: AlexNet

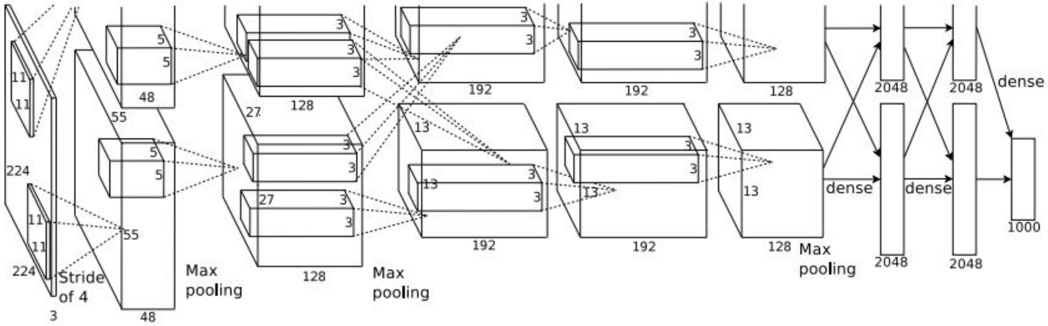
[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

Case Study: AlexNet

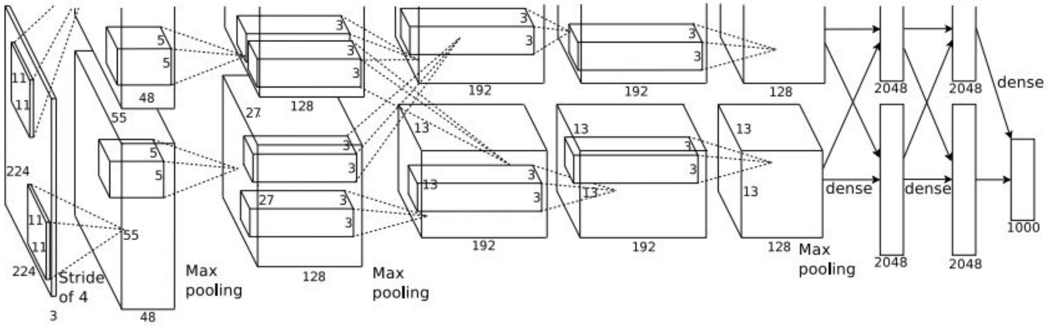
[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
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[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
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[13x13x256] MAX POOL2: 3x3 filters at stride 2
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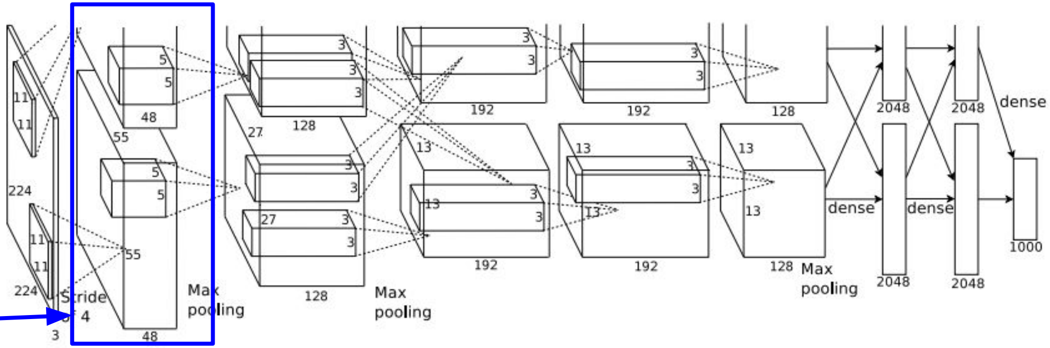
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

Case Study: AlexNet

[Krizhevsky et al. 2012]



[55x55x48] x 2

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
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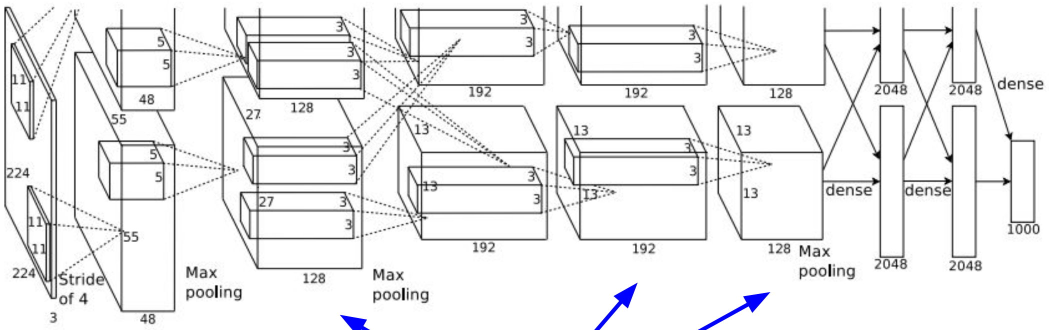
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

Case Study: AlexNet

[Krizhevsky et al. 2012]



CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
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[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
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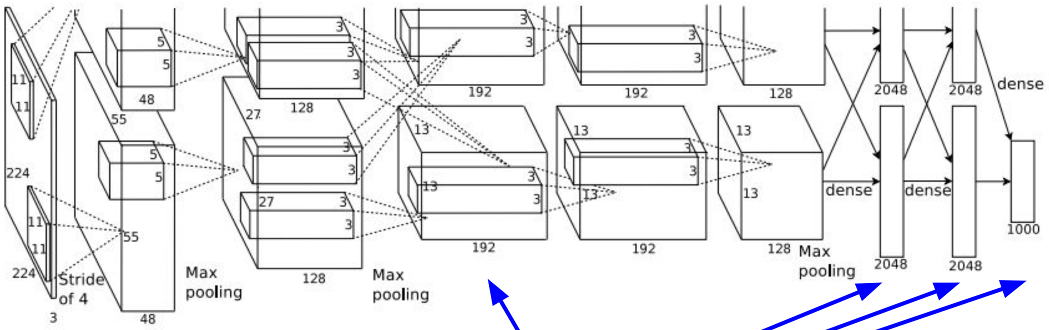
Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
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[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
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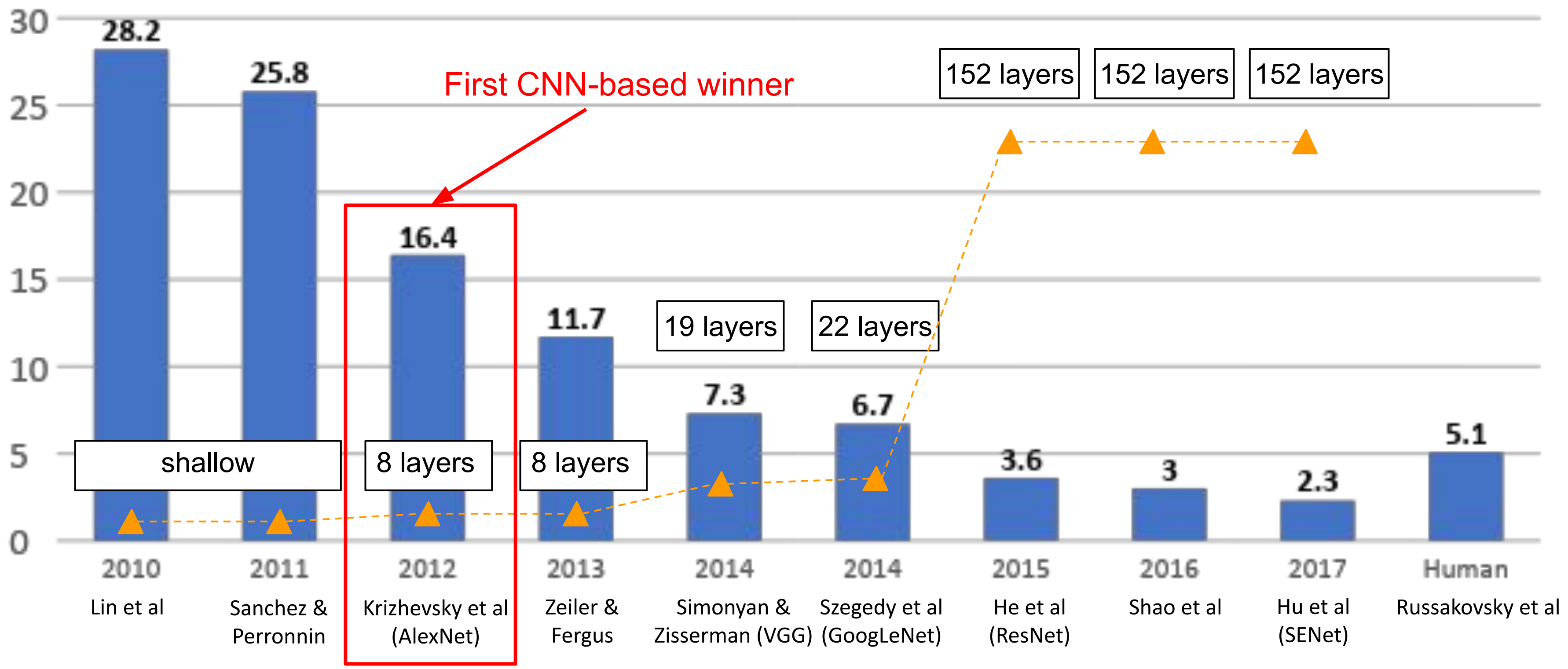
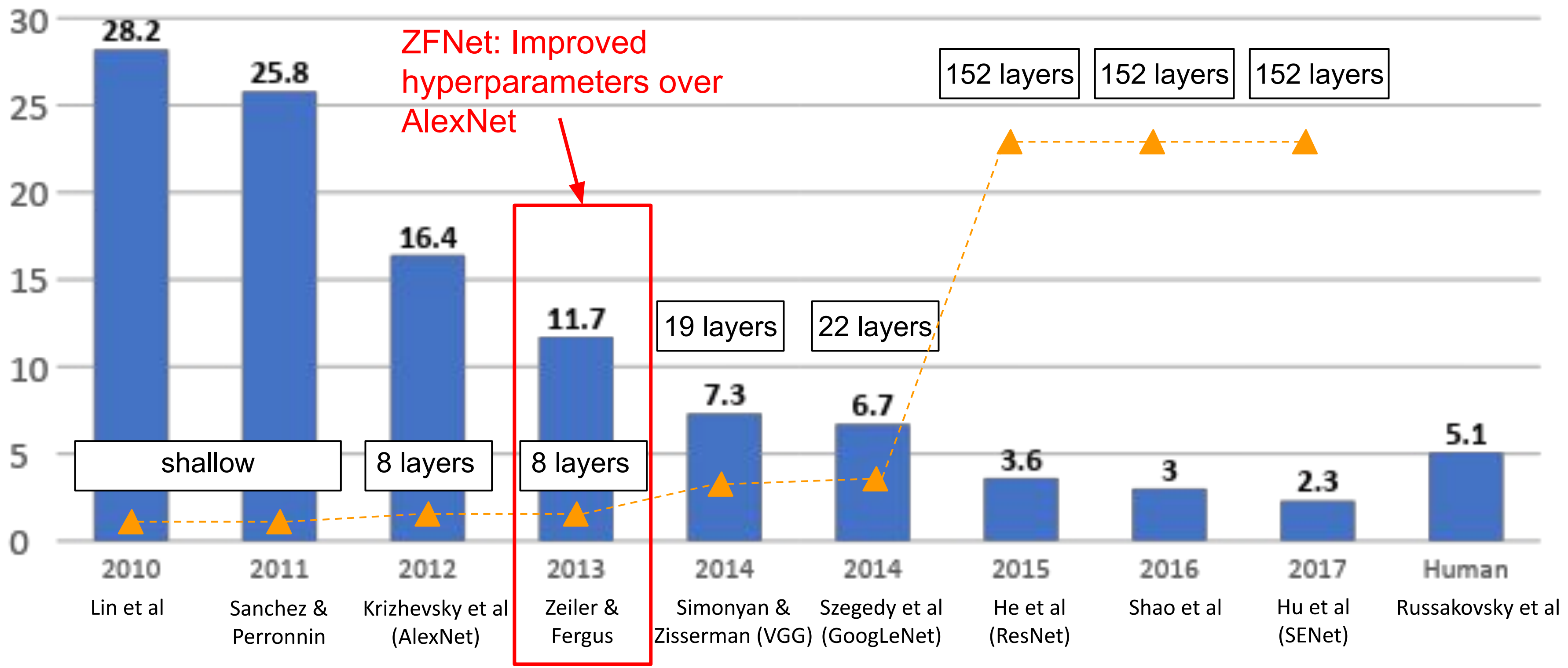
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

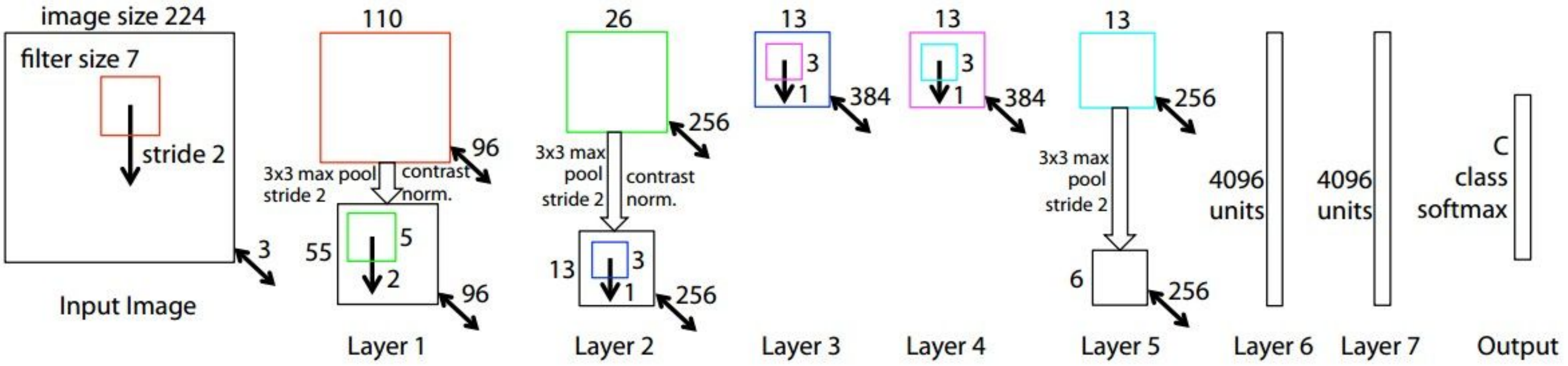


ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ZFNet

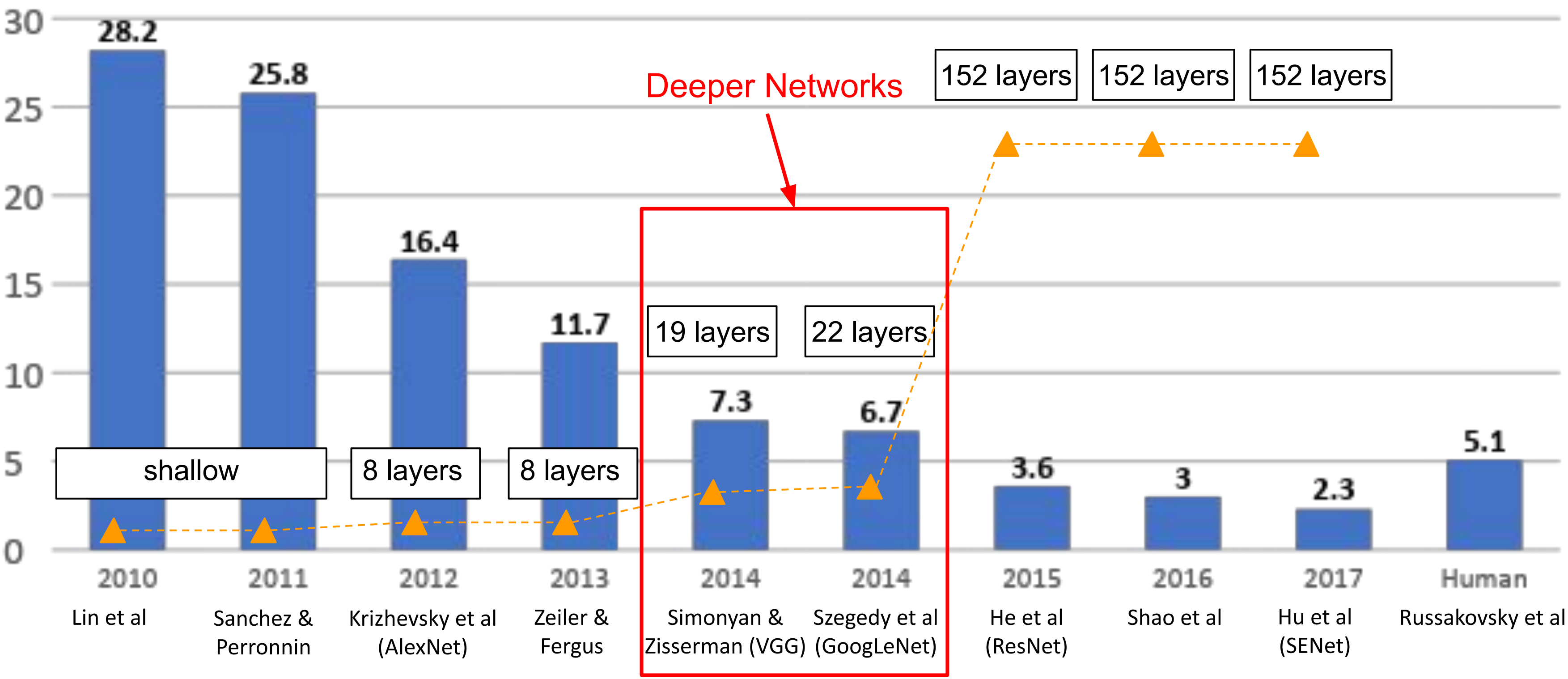
[Zeiler and Fergus, 2013]



AlexNet but:
CONV1: change from (11x11 stride 4) to (7x7 stride 2)
CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 16.4% -> 11.7%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: VGGNet

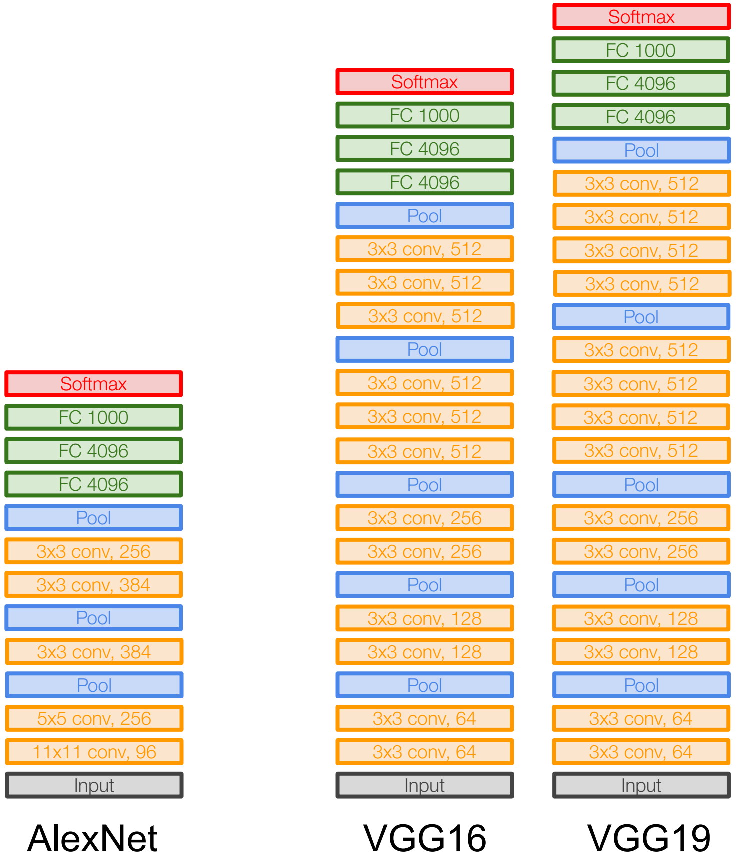
[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

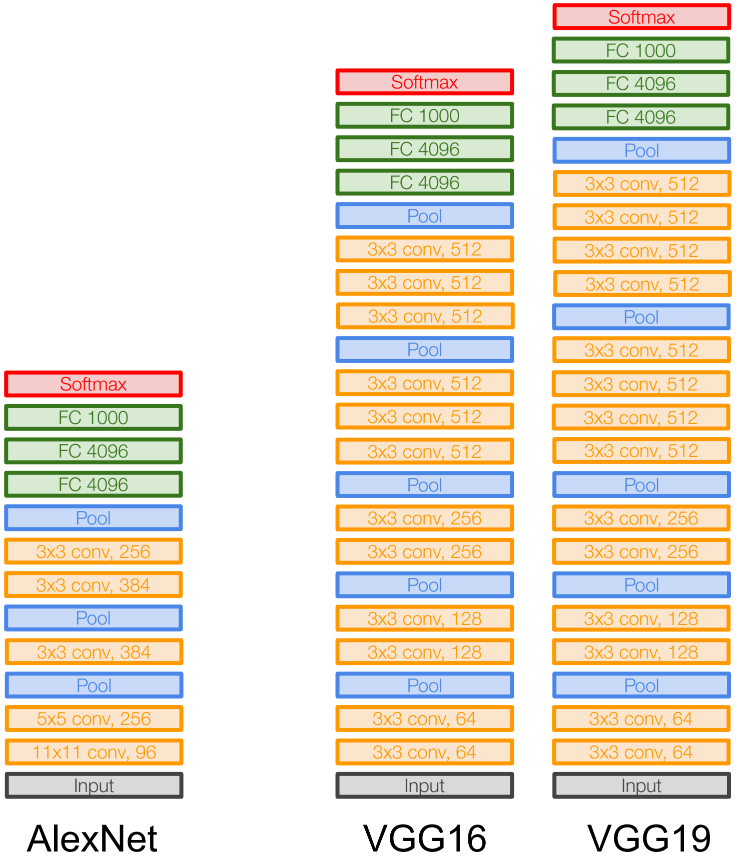
11.7% top 5 error in ILSVRC'13 (ZFNet)
-> 7.3% top 5 error in ILSVRC'14



Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)



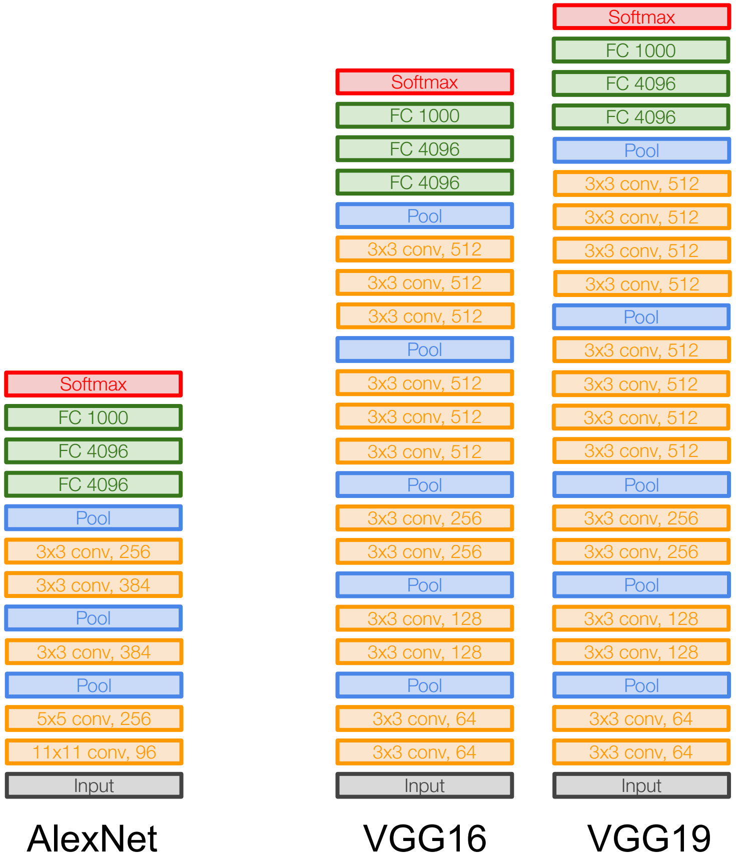
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



Case Study: VGGNet

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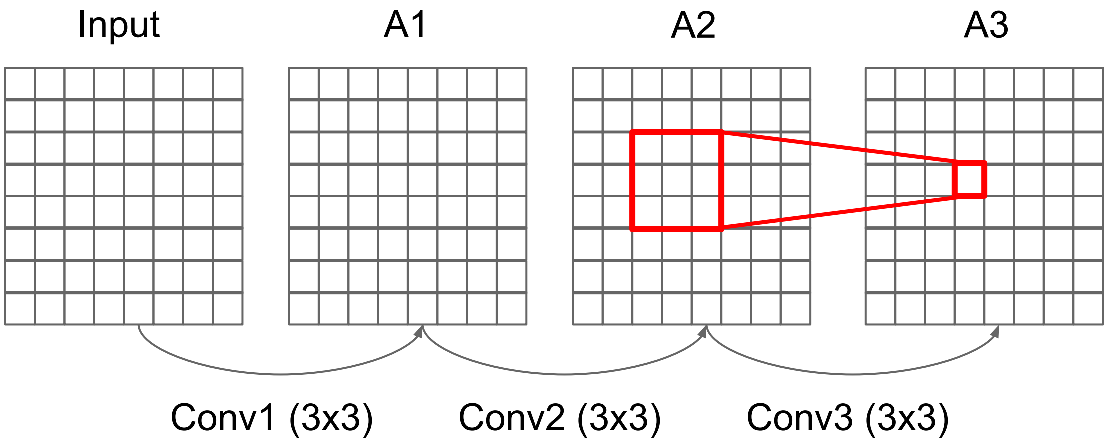

Case Study: VGGNet

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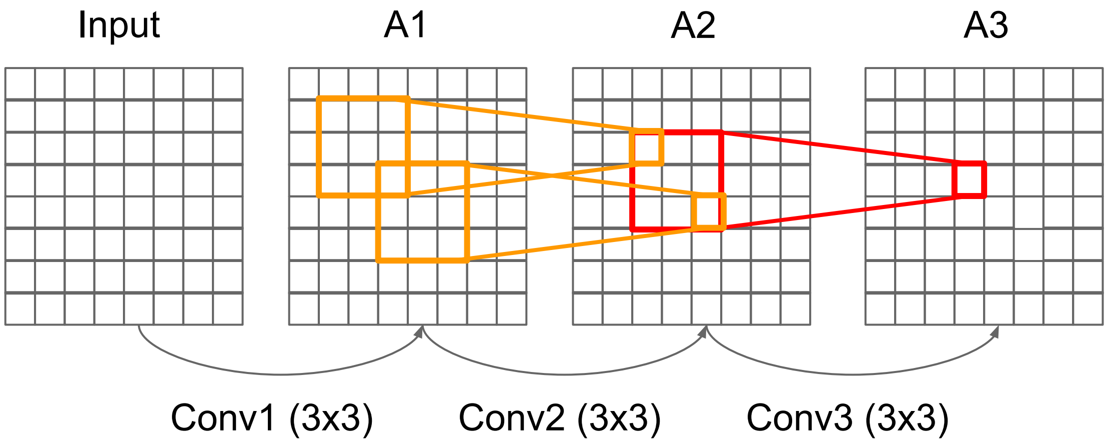

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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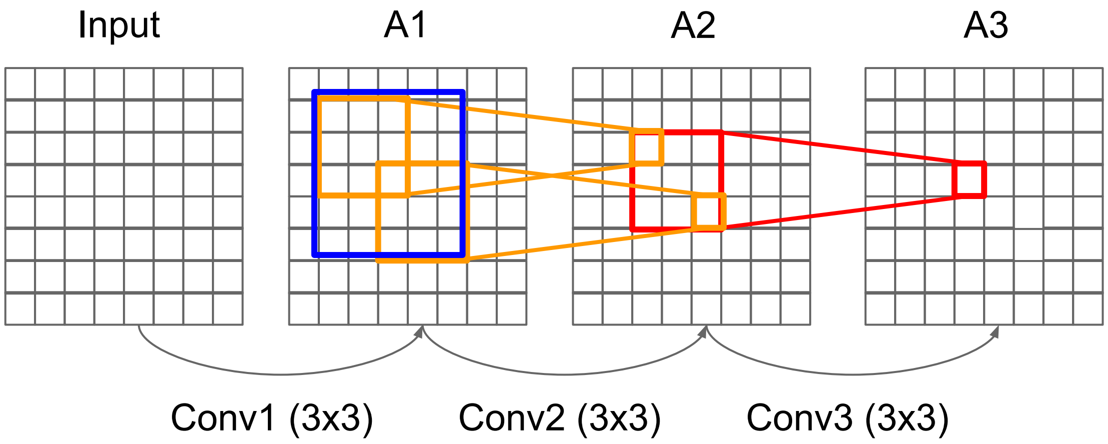
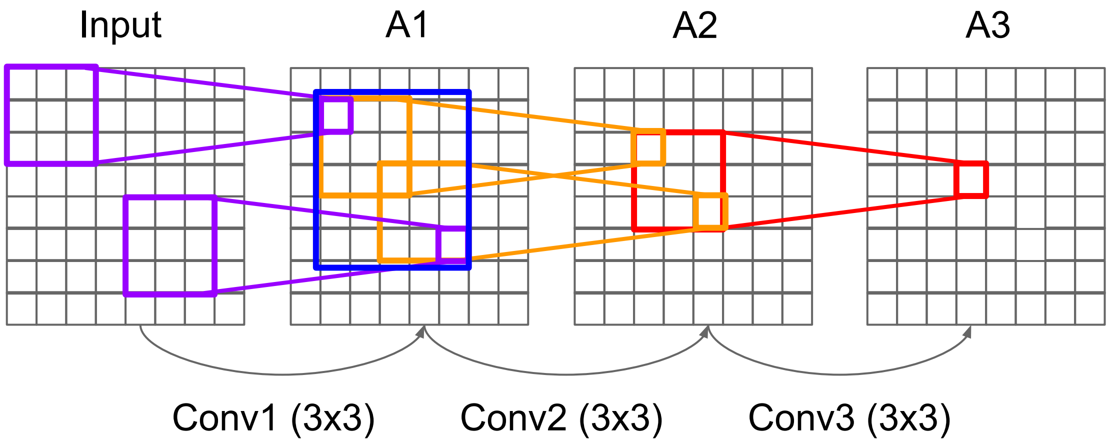


Case Study: VGGNet

[Simonyan and Zisserman, 2014]

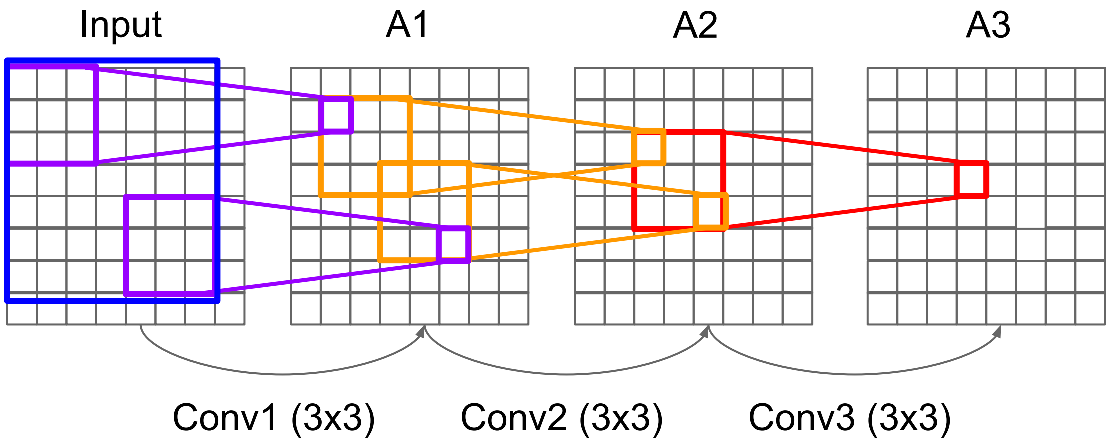
Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



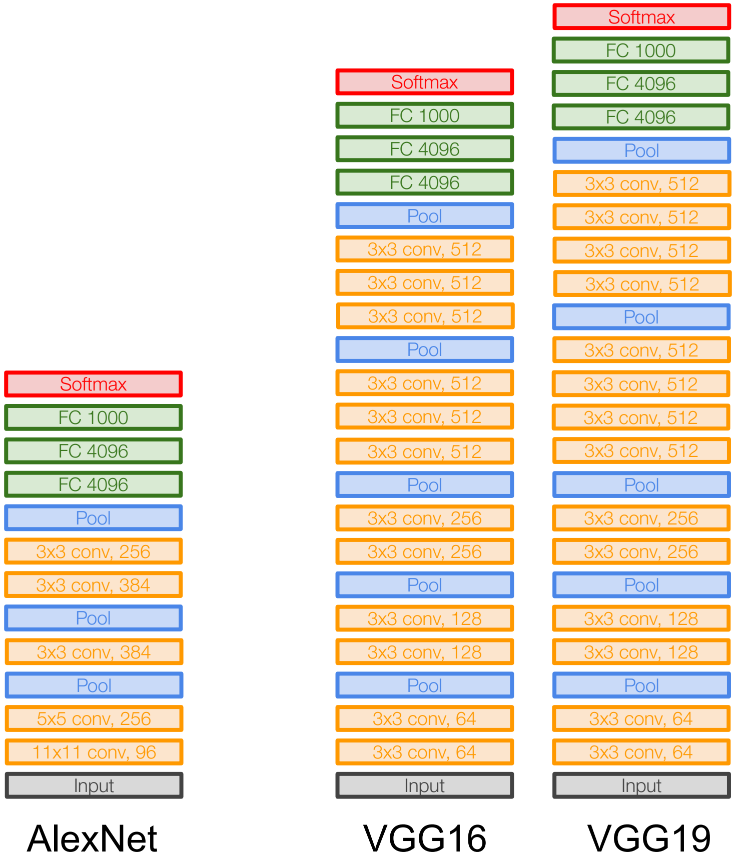
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

[7x7]



Case Study: VGGNet

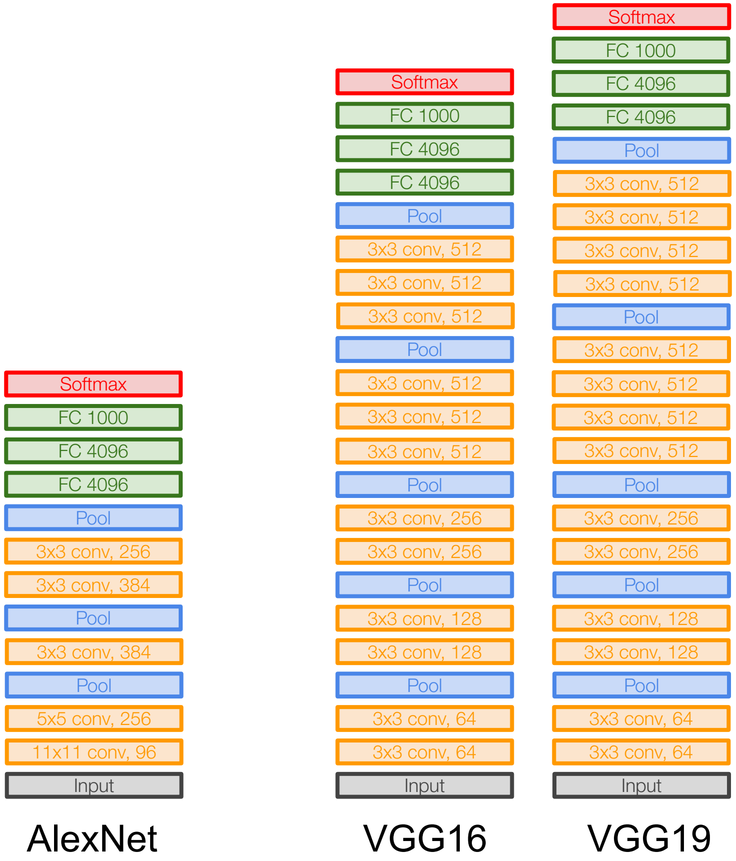
[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

And fewer parameters: 3 * (3^2C^2) vs. 7^2C^2 for C channels per layer



(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

VGG16

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
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POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)
TOTAL params: 138M parameters

VGG16

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
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POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = **102,760,448**
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

(not counting biases)

INPUT: [224x224x3]	memory: 224*224*3=150K	params: 0
CONV3-64: [224x224x64]	memory: 224*224*64=3.2M	params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]	memory: 224*224*64=3.2M	params: (3*3*64)*64 = 36,864
POOL2: [112x112x64]	memory: 112*112*64=800K	params: 0
CONV3-128: [112x112x128]	memory: 112*112*128=1.6M	params: (3*3*64)*128 = 73,728
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CONV3-256: [56x56x256]	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
POOL2: [28x28x256]	memory: 28*28*256=200K	params: 0
CONV3-512: [28x28x512]	memory: 28*28*512=400K	params: (3*3*256)*512 = 1,179,648
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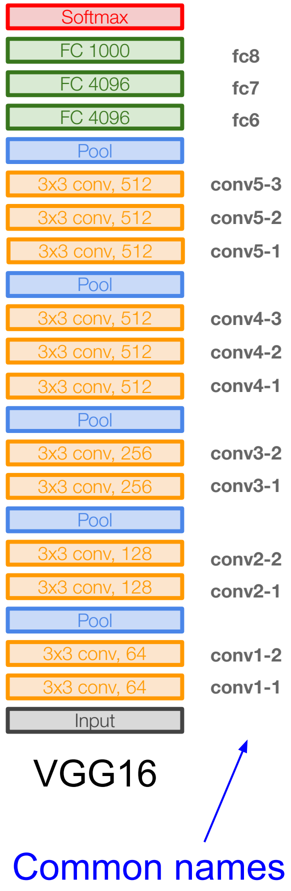
CONV3-512: [14x14x512]	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]	memory: 7*7*512=25K	params: 0
FC: [1x1x4096]	memory: 4096	params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]	memory: 4096	params: 4096*4096 = 16,777,216
FC: [1x1x1000]	memory: 1000	params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)

TOTAL params: 138M parameters

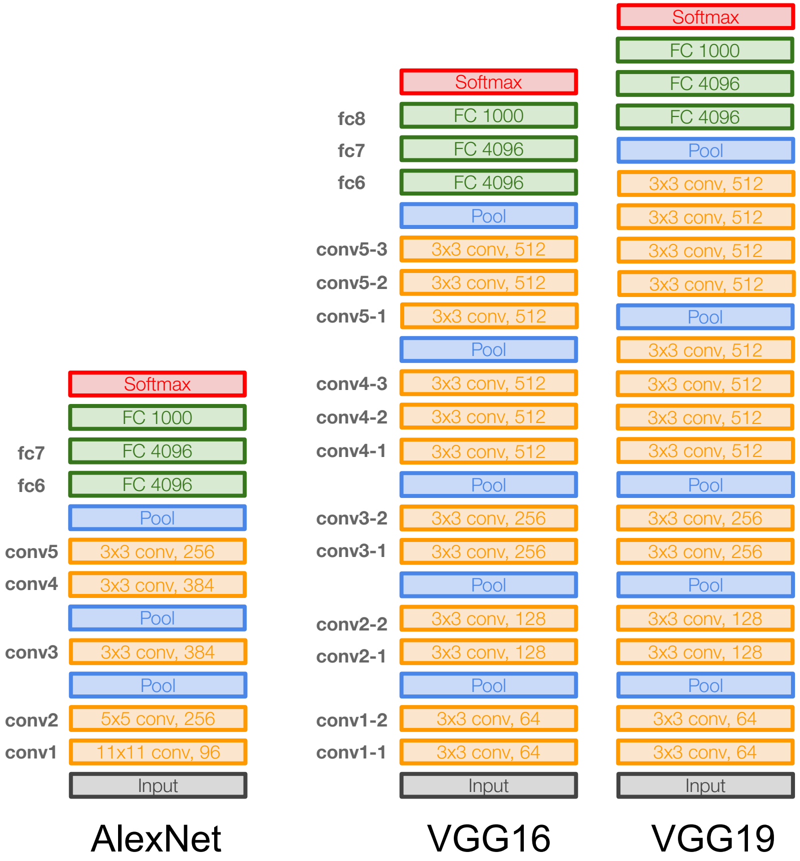


Case Study: VGGNet

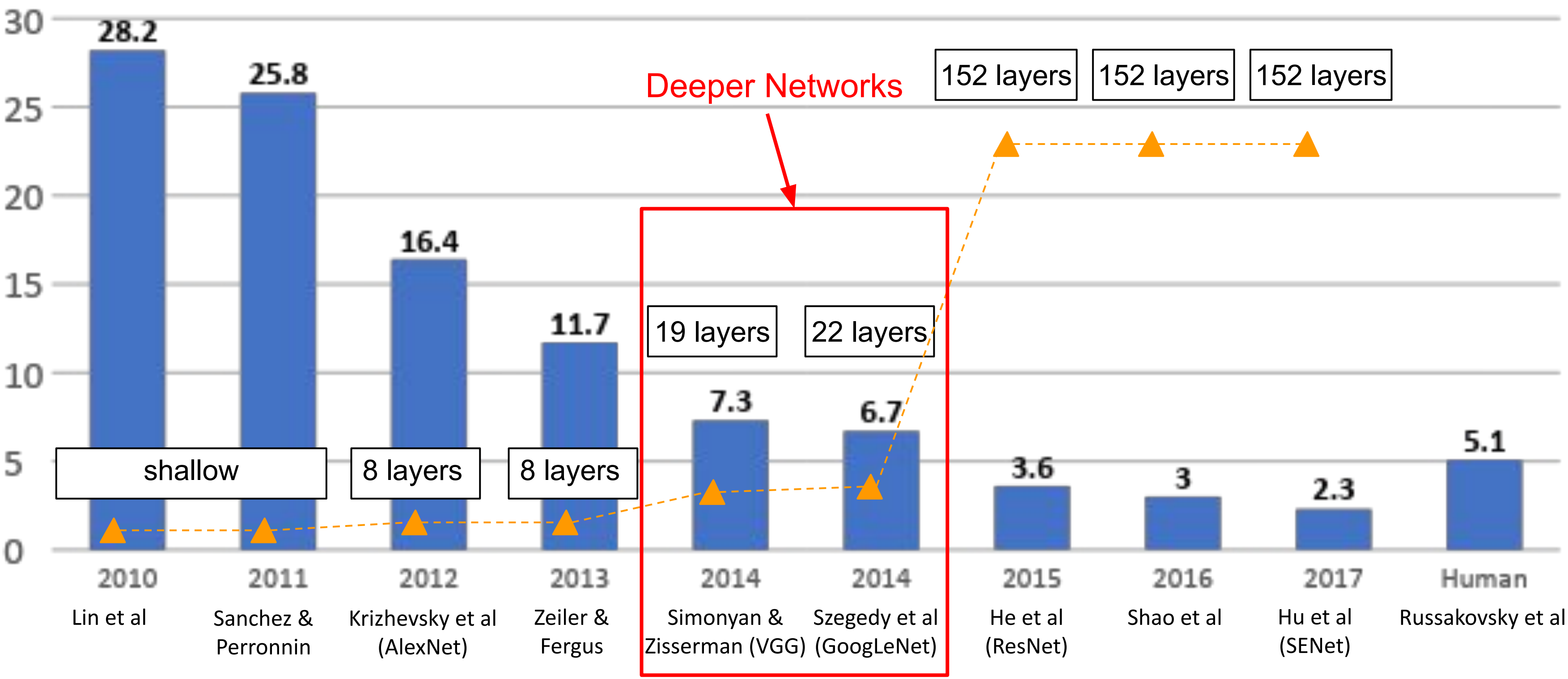
[Simonyan and Zisserman, 2014]

Details:

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as Krizhevsky 2012
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

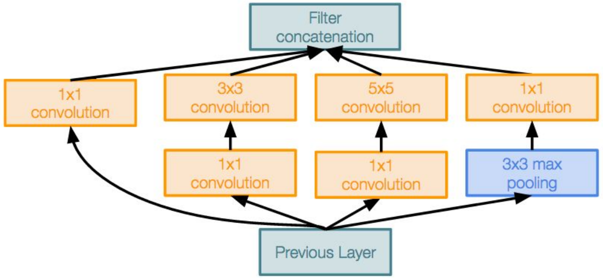


Case Study: GoogLeNet

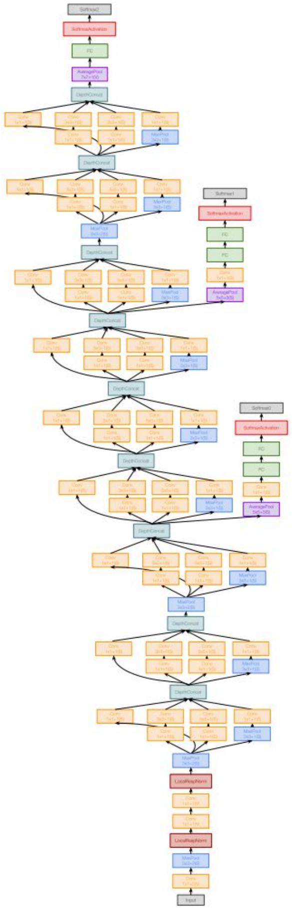
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- ILSVRC'14 classification winner (6.7% top 5 error)
- 22 layers
- Only 5 million parameters!
  12x less than AlexNet
  27x less than VGG-16
- Efficient "Inception" module
- No FC layers



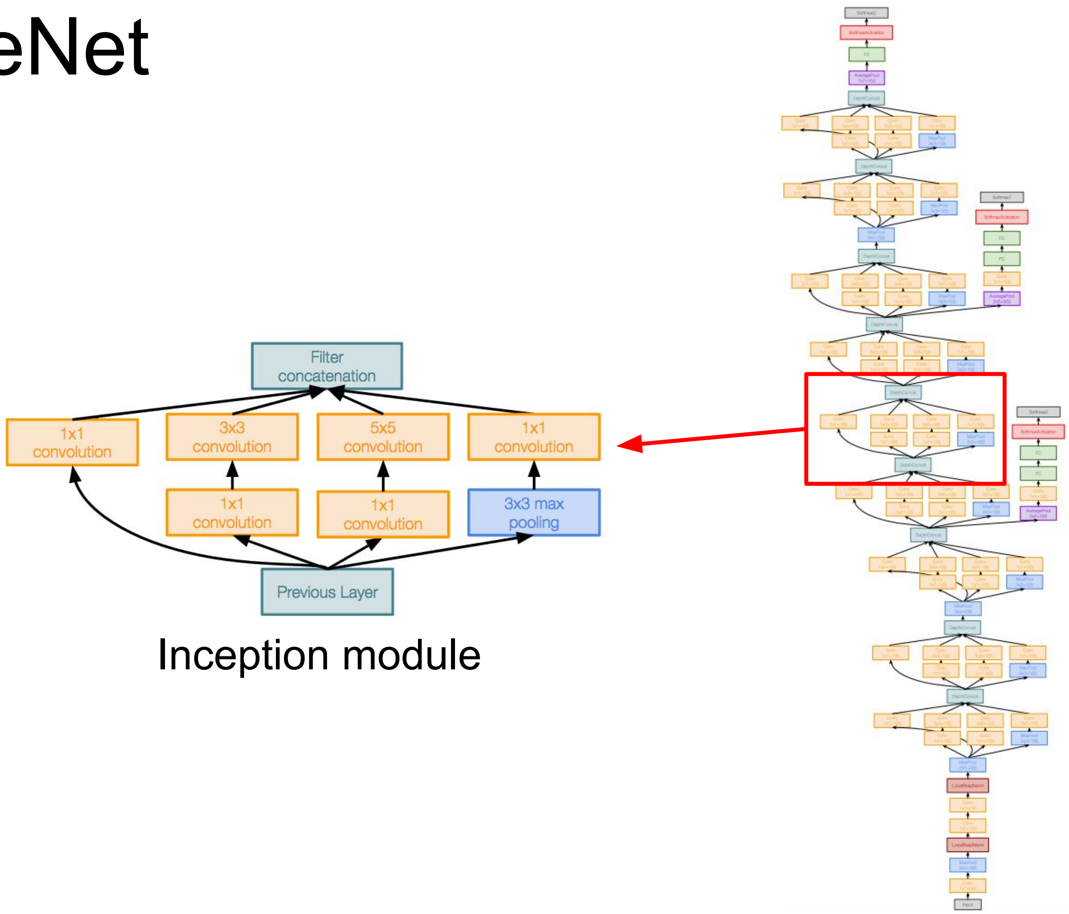
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

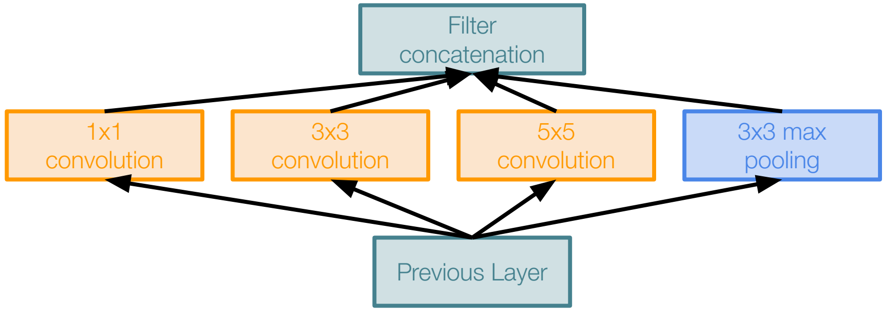
"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other



Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

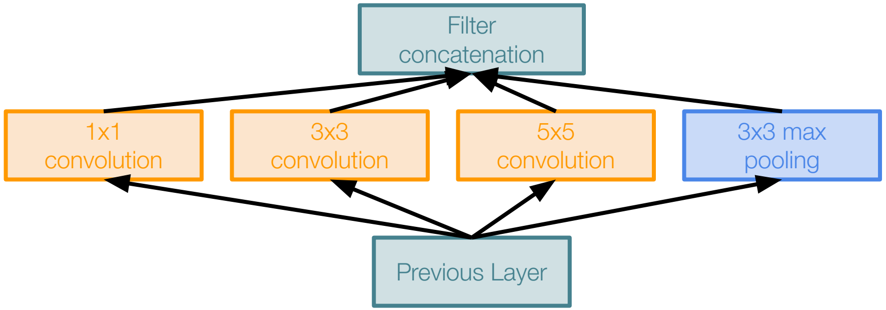
Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
- Pooling operation (3x3)

Concatenate all filter outputs together channel-wise

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
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Q: What is the problem with this?
[Hint: Computational complexity]

Case Study: GoogLeNet

[Szegedy et al., 2014]

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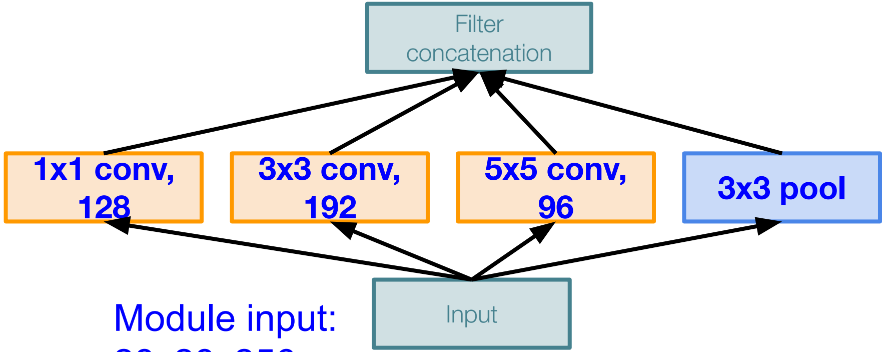
[Hint: Computational complexity]

Example:



Module input: 28x28x256

Naive Inception module

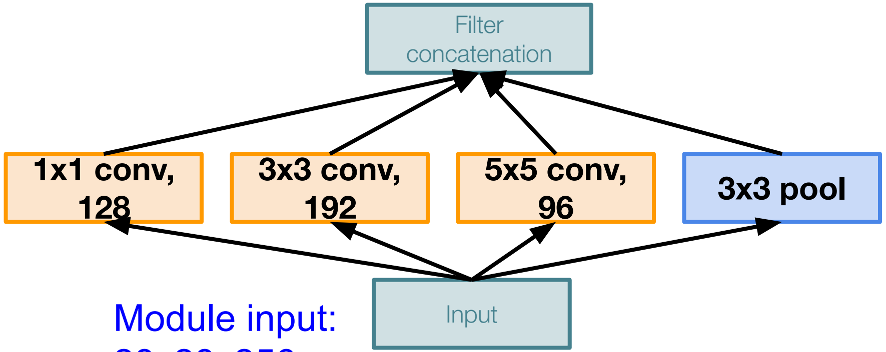
Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q1: What are the output sizes of all different filter operations?



Module input: 28x28x256

Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

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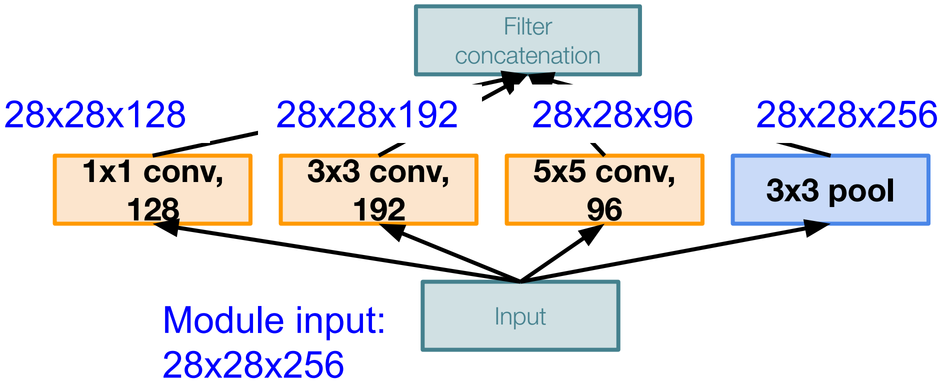
Example:

Q1: What are the output sizes of all different filter operations?



Naive Inception module

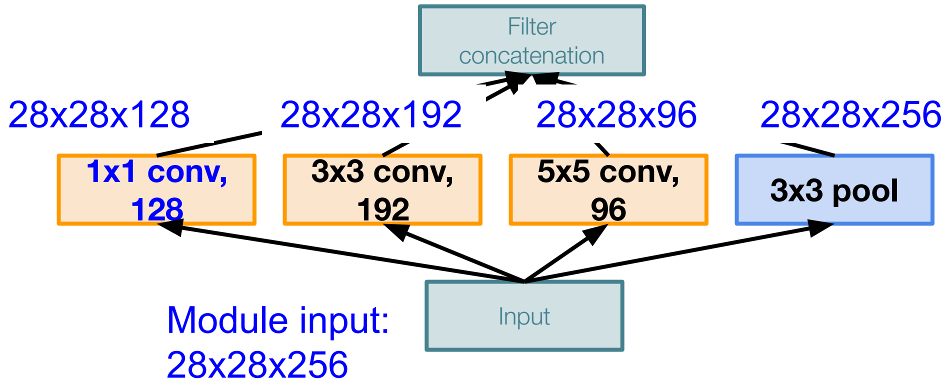
Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2:What is output size after filter concatenation?



Naive Inception module

Case Study: GoogLeNet

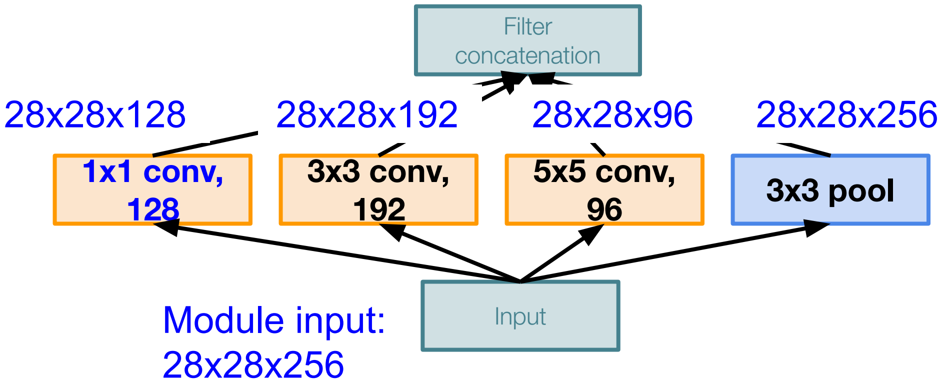
[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2:What is output size after filter concatenation?

28x28x(128+192+96+256) = 28x28x672



Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
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Example:

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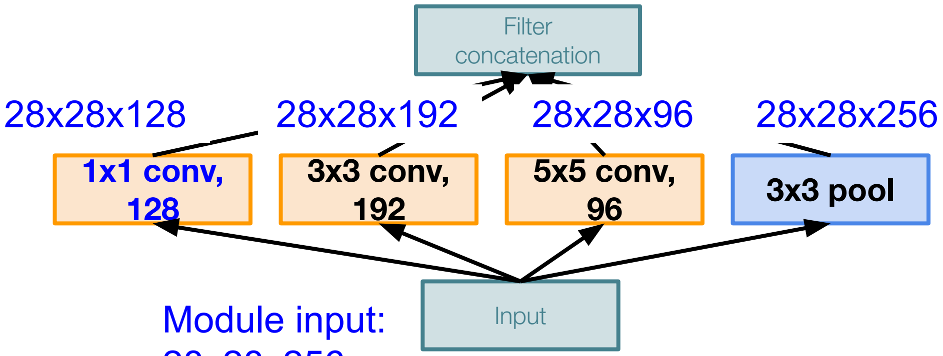
28x28x(128+192+96+256) = 28x28x672



Module input: 28x28x256

Naive Inception module

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x**192x3x3x256**

[5x5 conv, 96] 28x28x**96x5x5x256**

Total: 854M ops

Case Study: GoogLeNet

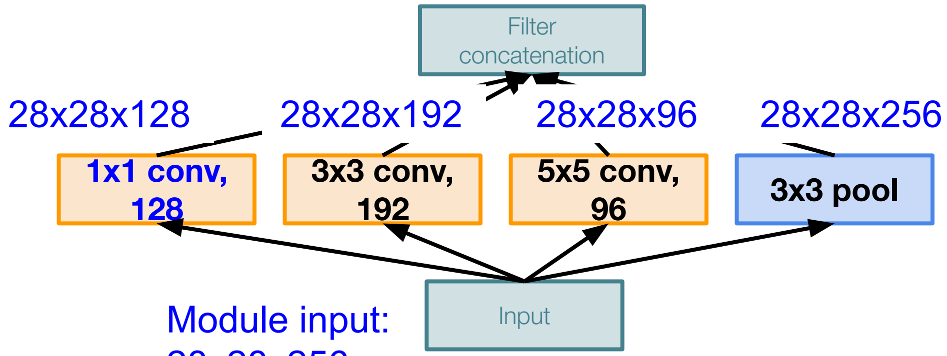
[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2:What is output size after filter concatenation?

28x28x(128+192+96+256) = 28x28x672



Module input: 28x28x256

Naive Inception module

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x**192x3x3x256**
[5x5 conv, 96] 28x28x**96x5x5x256**
Total: 854M ops

Very expensive compute

Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Case Study: GoogLeNet

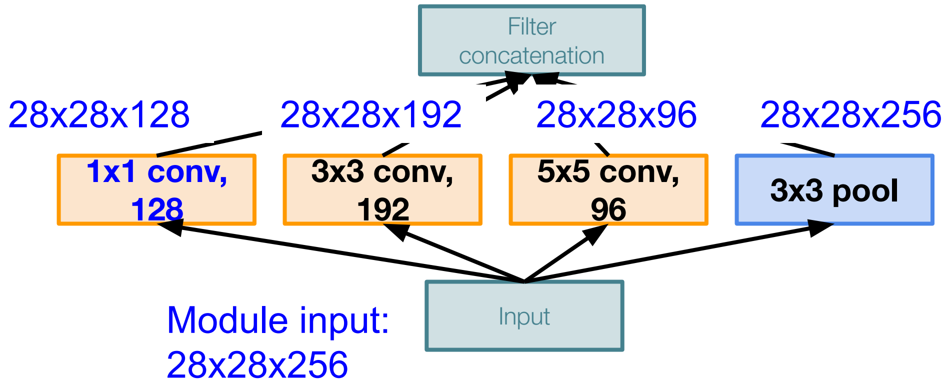
[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2:What is output size after filter concatenation?

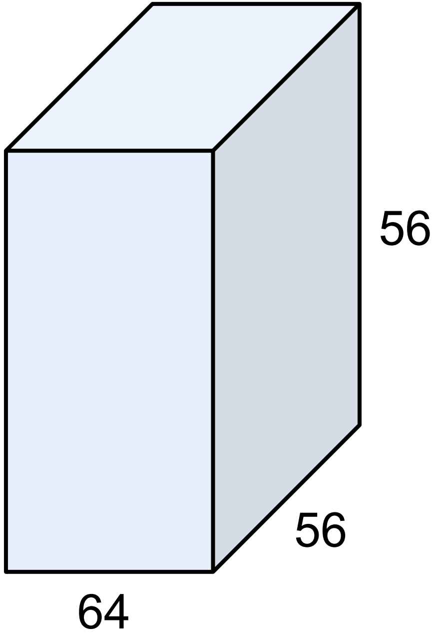
28x28x(128+192+96+256) = **529k**



Naive Inception module

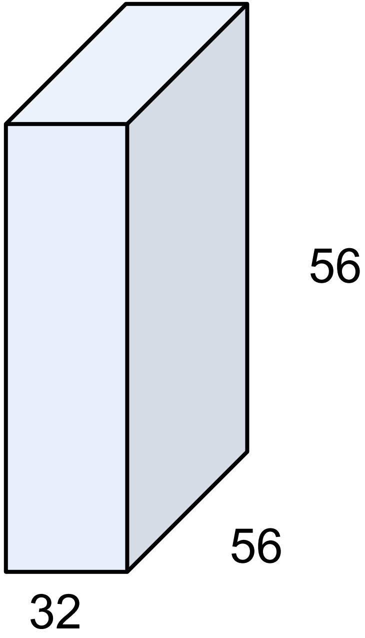
Solution: “bottleneck” layers that use 1x1 convolutions to reduce feature channel size

Review: 1x1 convolutions



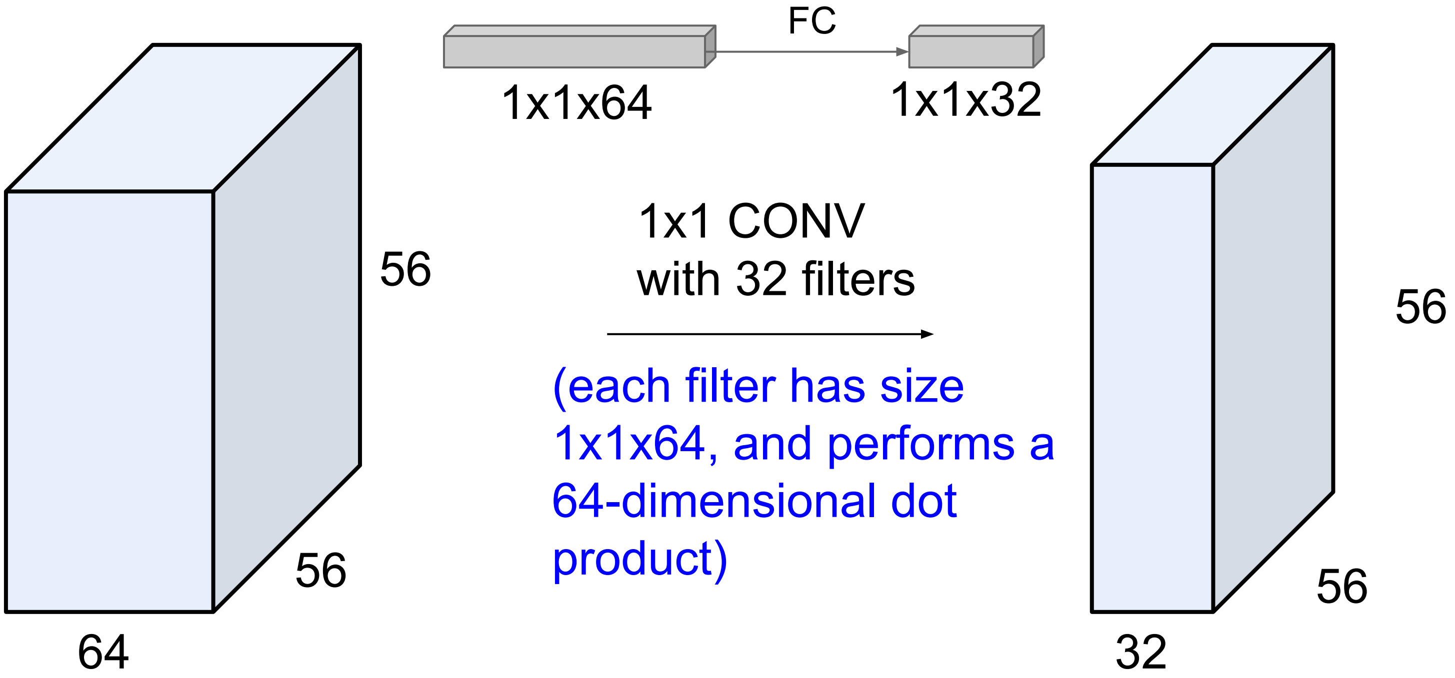
1x1 CONV
with 32 filters

(each filter has size 1x1x64, and performs a 64-dimensional dot product)



Review: 1x1 convolutions

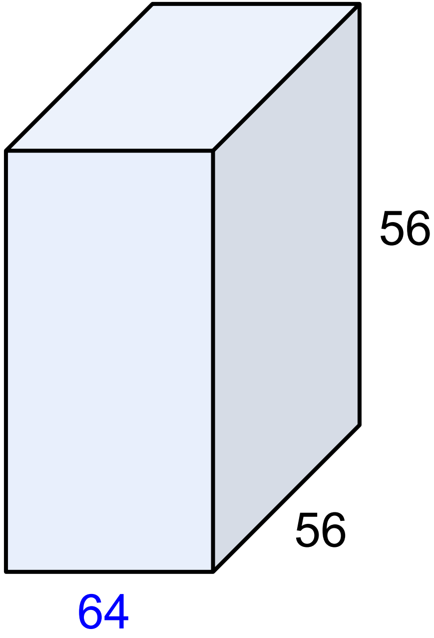
Alternatively, interpret it as applying the same FC layer on each input pixel

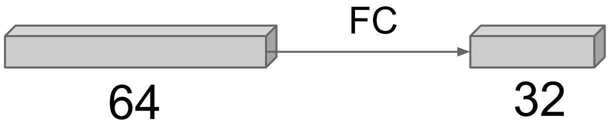


(each filter has size 1x1x64, and performs a 64-dimensional dot product)

Review: 1x1 convolutions

Alternatively, interpret it as applying the same FC layer on each input pixel

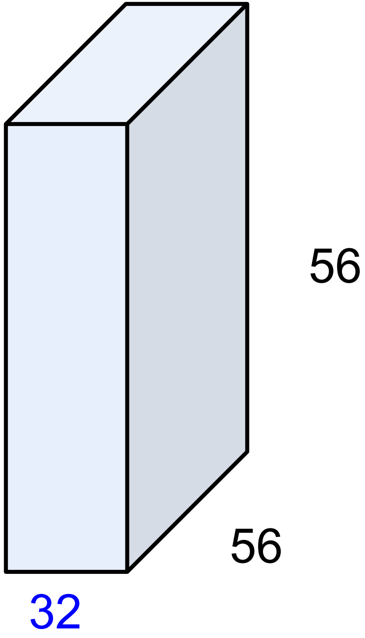




1x1 CONV
with 32 filters

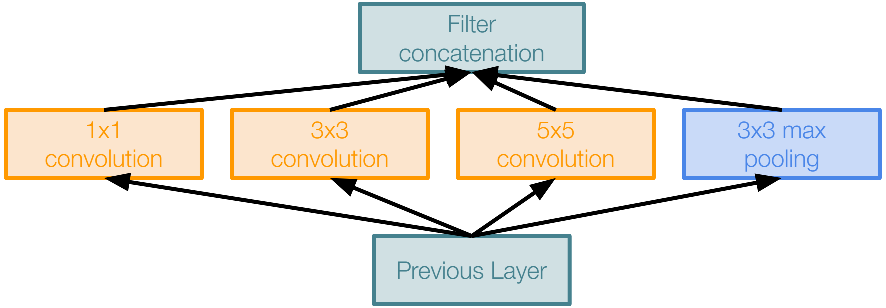
preserves spatial dimensions, reduces depth!

Projects depth to lower dimension (combination of feature maps)

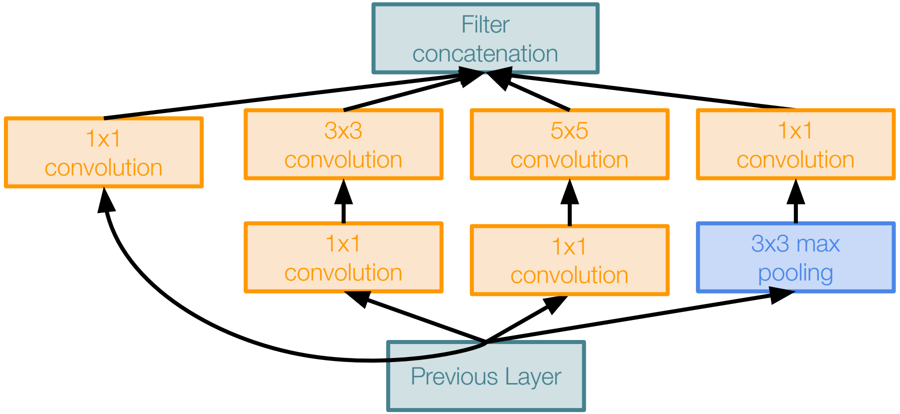


Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

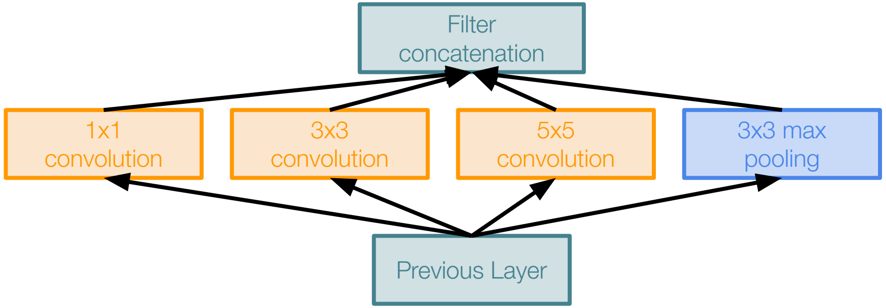


Inception module with dimension reduction

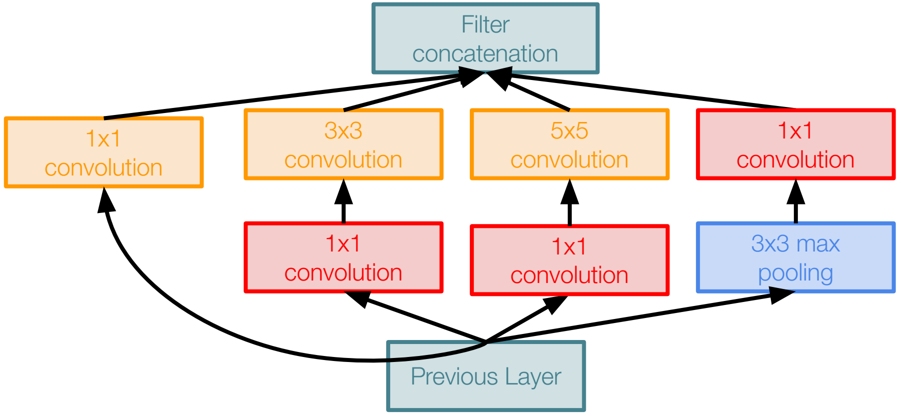
Case Study: GoogLeNet

[Szegedy et al., 2014]

1x1 conv “bottleneck” layers



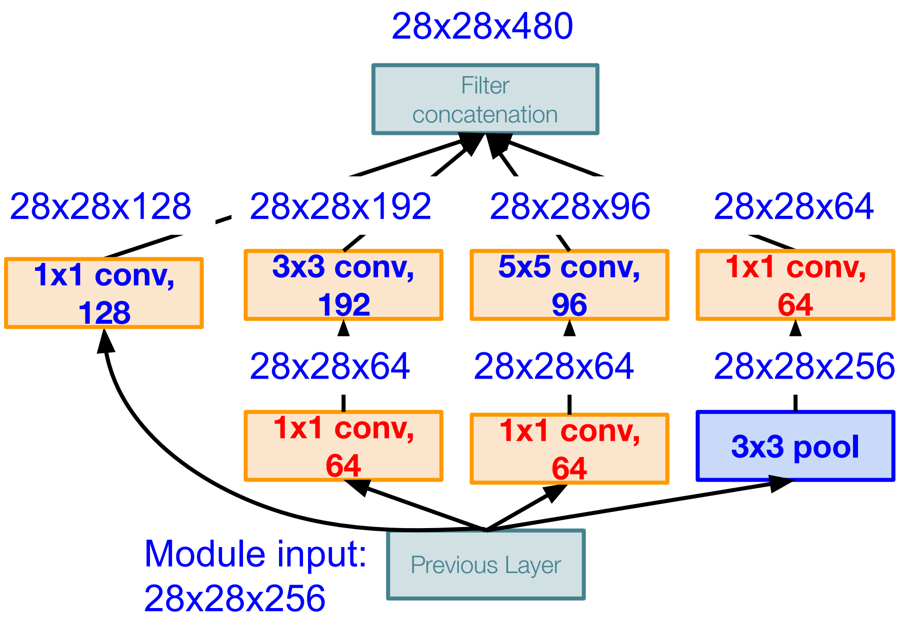
Naive Inception module



Inception module with dimension reduction

Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

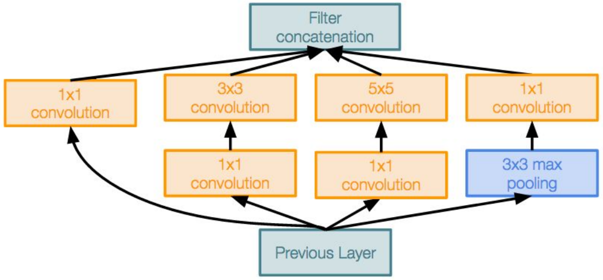
Conv Ops:
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

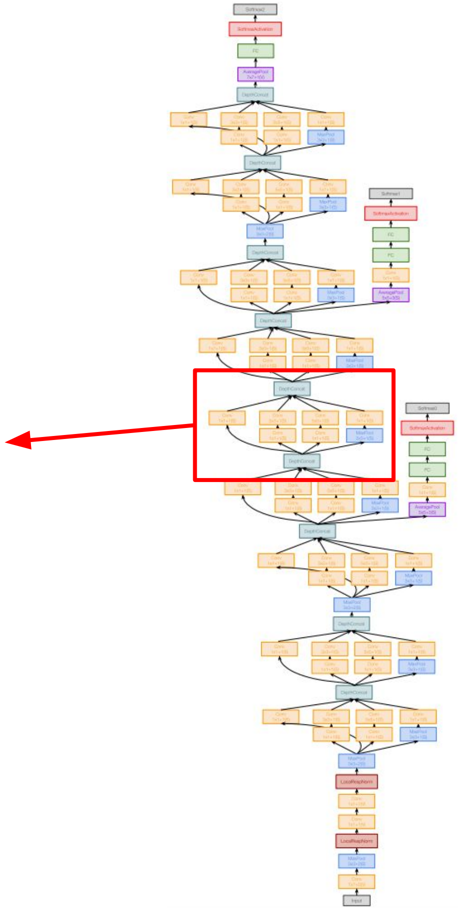
Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules
with dimension reduction
on top of each other



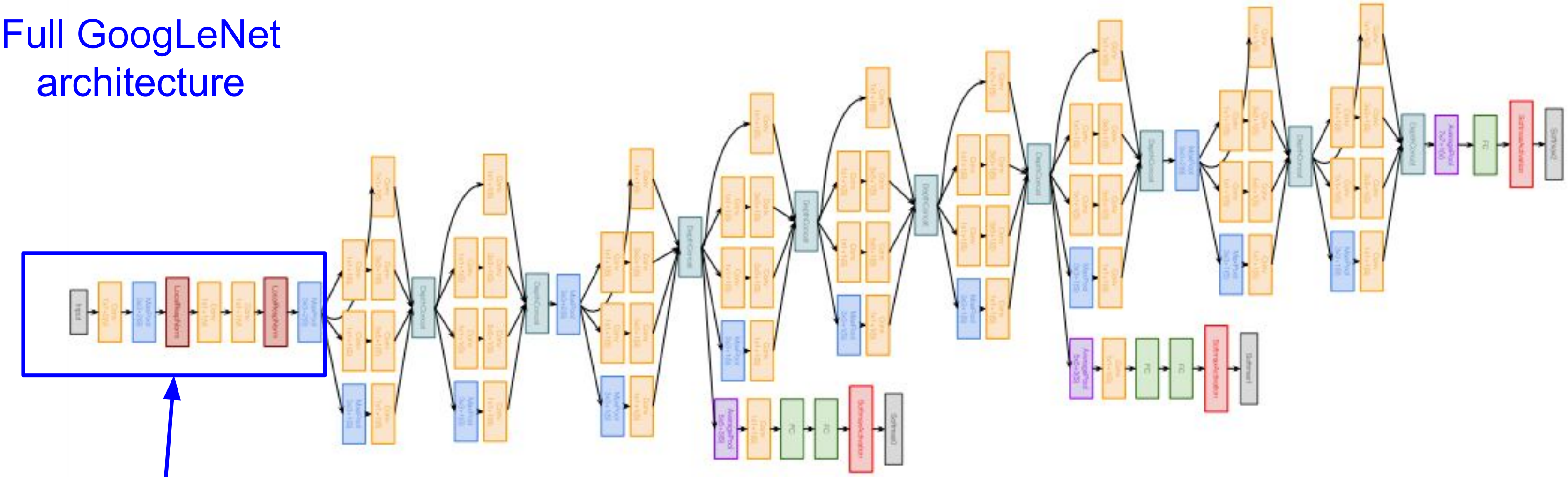
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

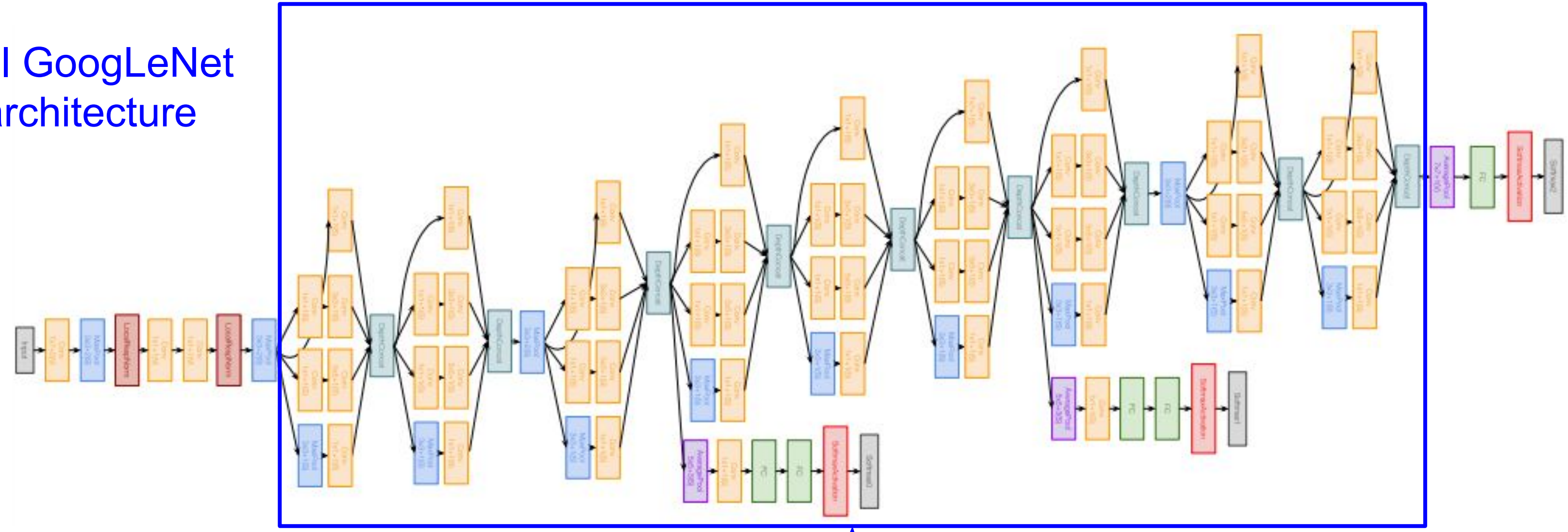


Stem Network:
Conv-Pool-
2x Conv-Pool

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

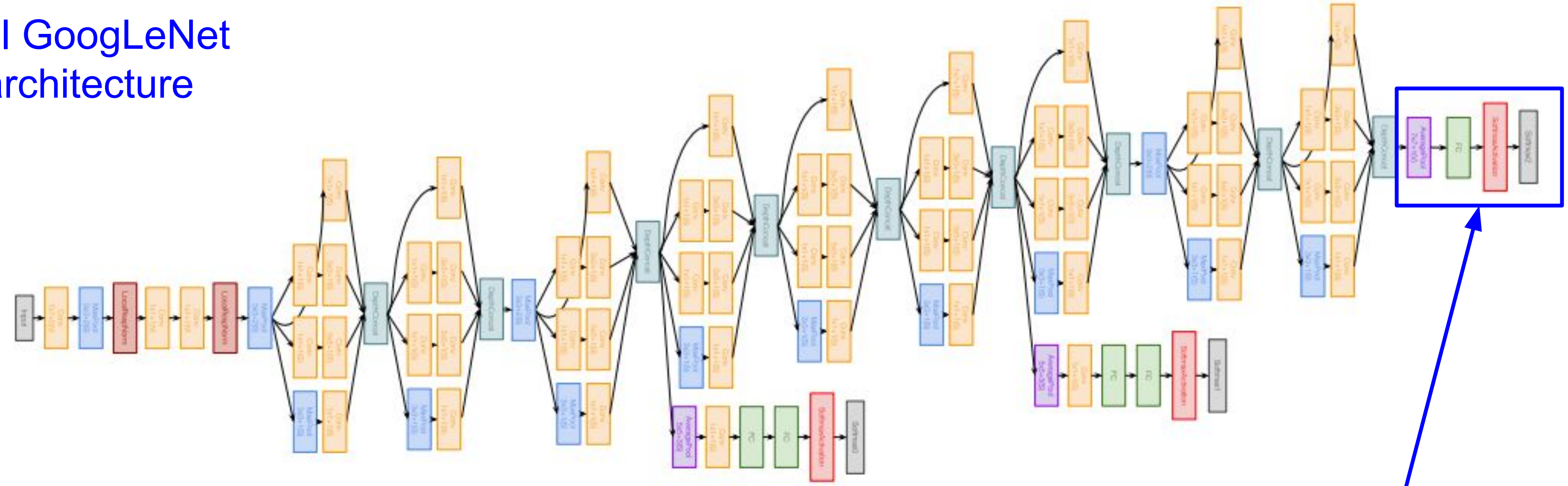


Stacked Inception Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

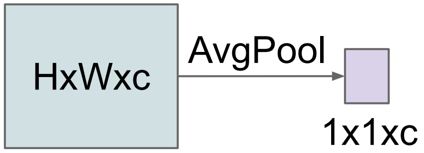
Full GoogLeNet architecture



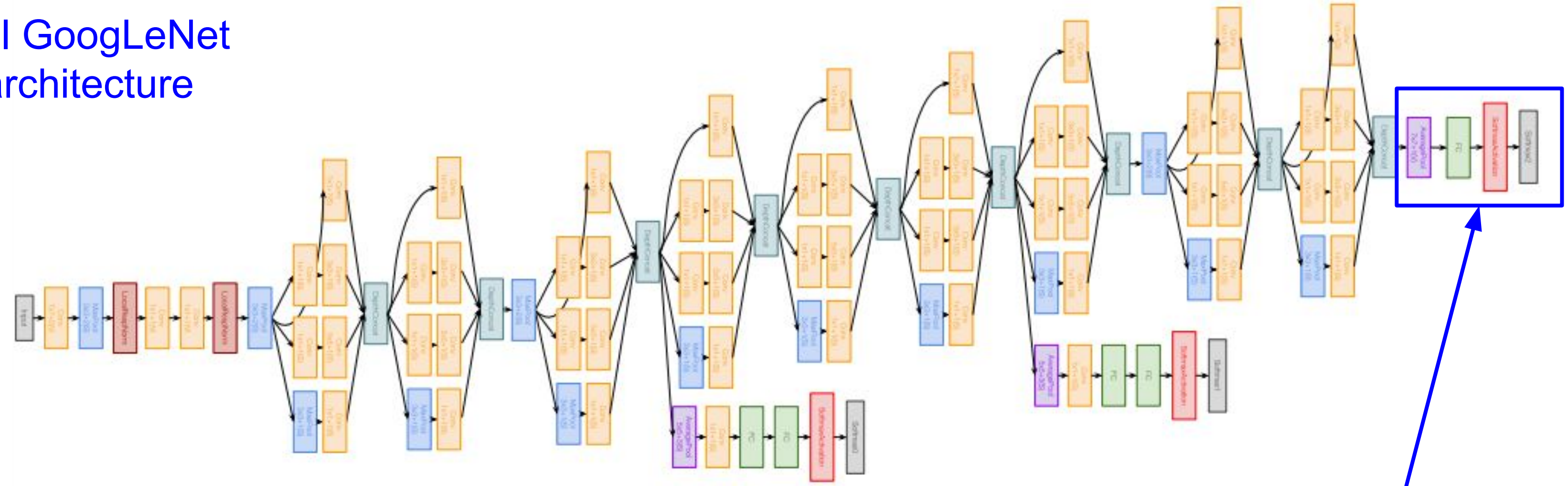
Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]



Full GoogLeNet architecture



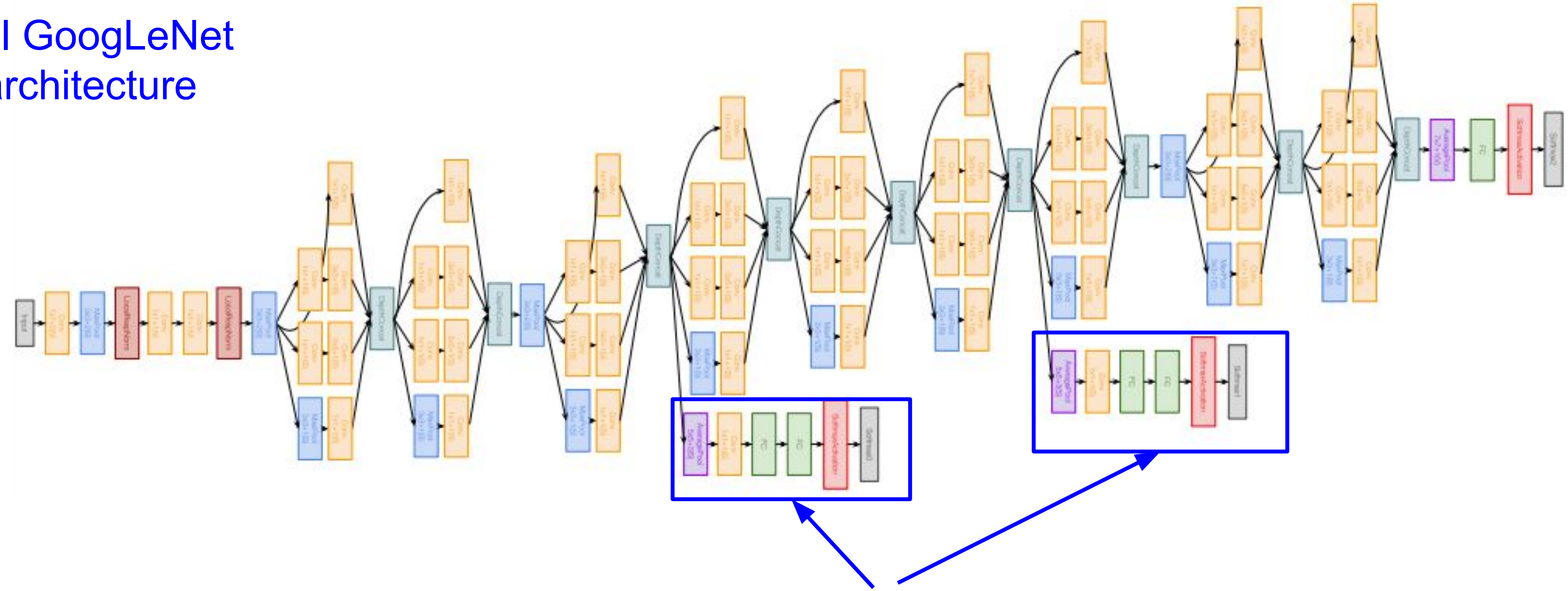
Note: after the last convolutional layer, a global average pooling layer is used that spatially averages across each feature map, before final FC layer. No longer multiple expensive FC layers!

Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

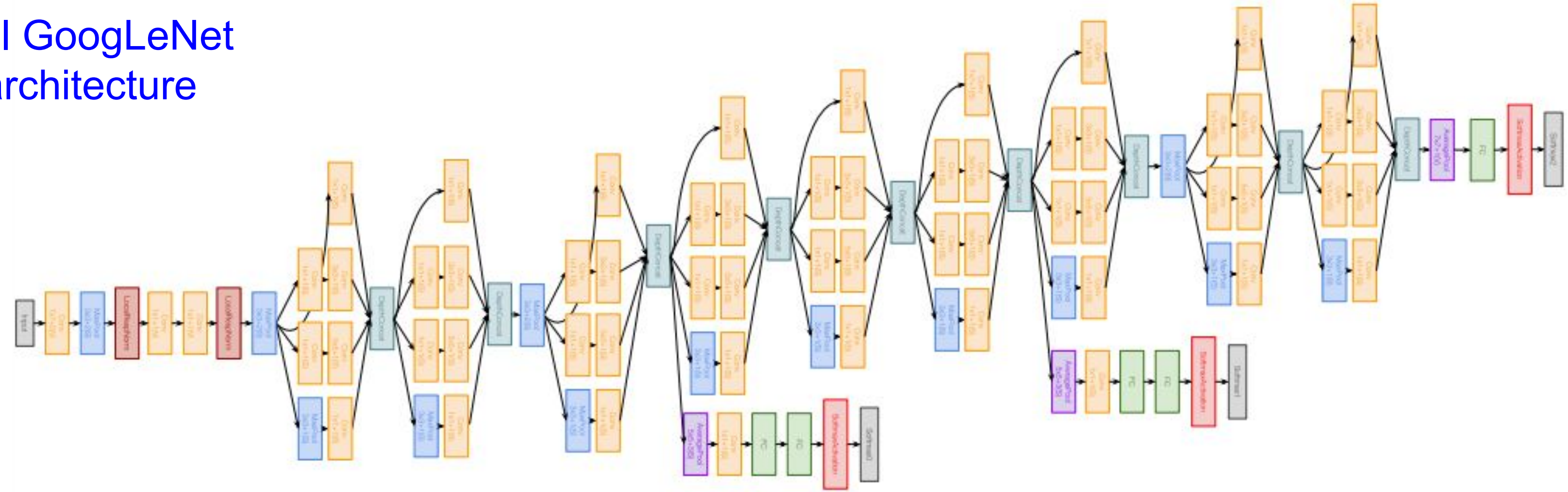


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



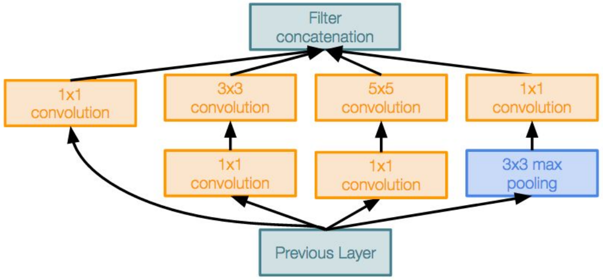
22 total layers with weights
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

Case Study: GoogLeNet

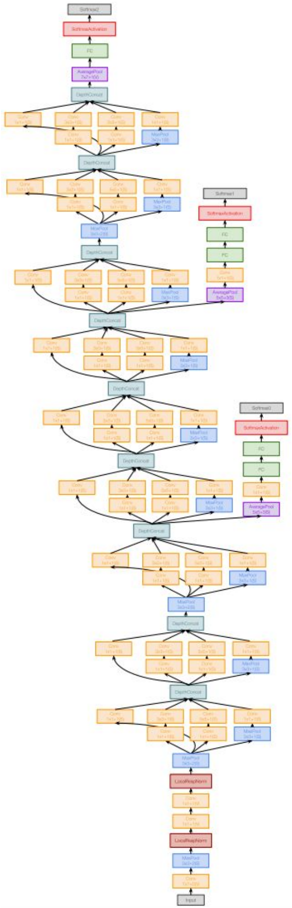
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

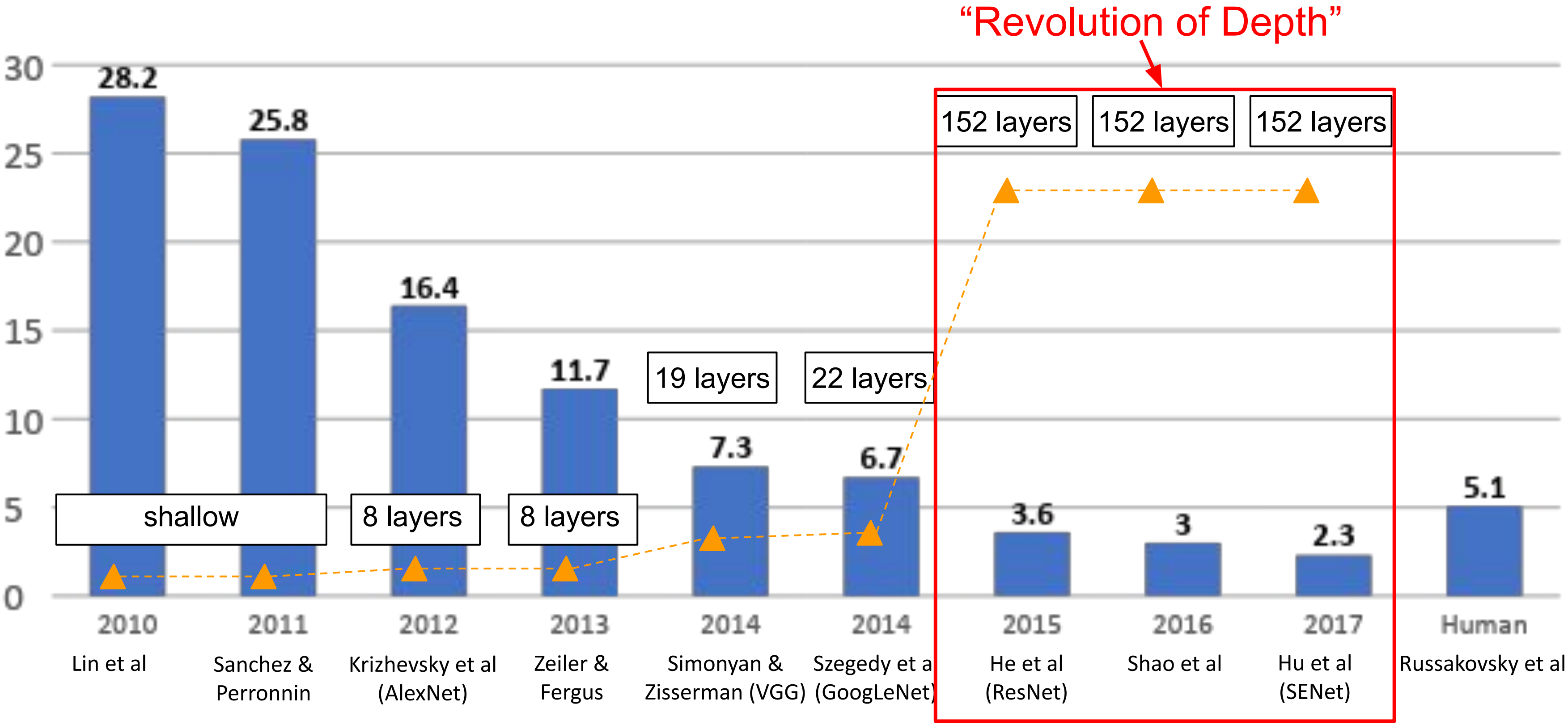
- 22 layers
- Efficient "Inception" module
- Avoids expensive FC layers
- 12x less params than AlexNet
- 27x less params than VGG-16
- ILSVRC'14 classification winner (6.7% top 5 error)



Inception module



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

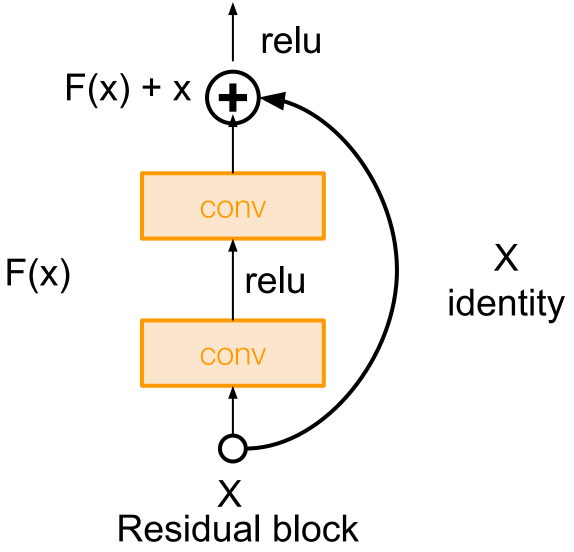


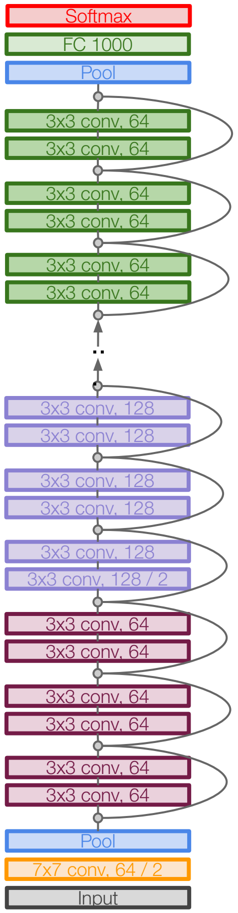
Case Study: ResNet

[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!





Case Study: ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

Case Study: ResNet

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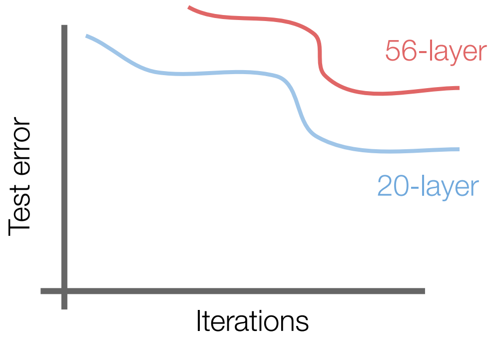

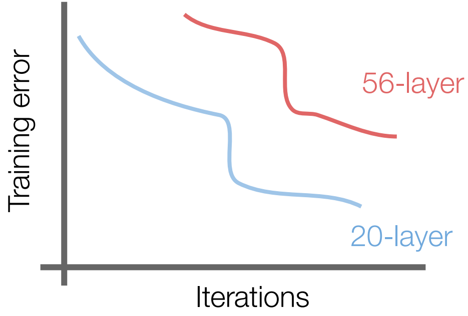

Case Study: ResNet

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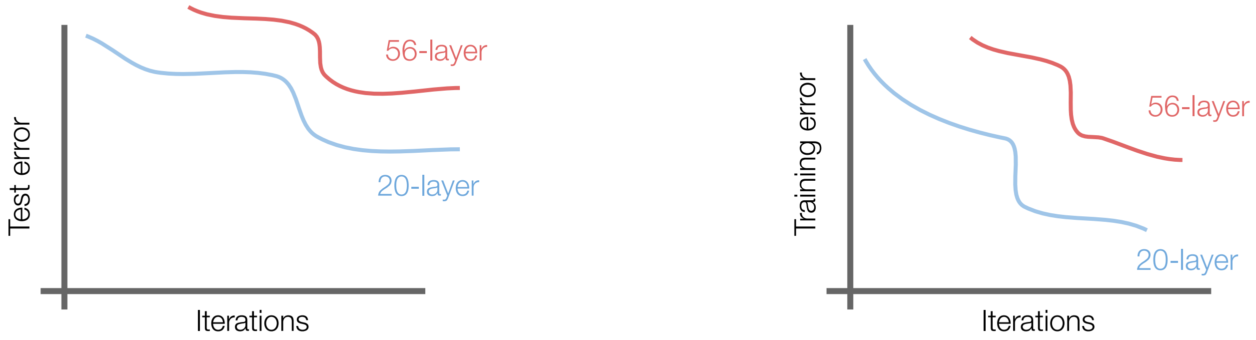


56-layer model performs worse on both test and training error
-> The deeper model performs worse, but it’s not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

Fact: Deep models have more representation power (more parameters) than shallower models.

Hypothesis: the problem is an *optimization* problem, **deeper models are harder to optimize**

Case Study: ResNet

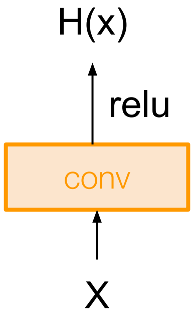
[He et al., 2015]

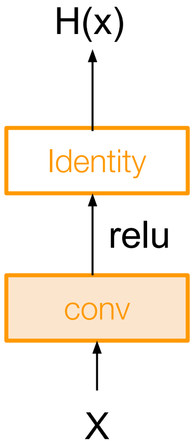
Fact: Deep models have more representation power (more parameters) than shallower models.

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

What should the deeper model learn to be at least as good as the shallower model?

A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

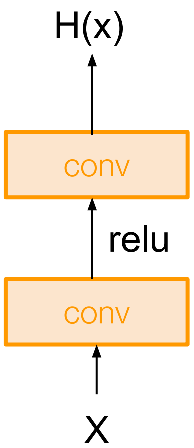




Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping

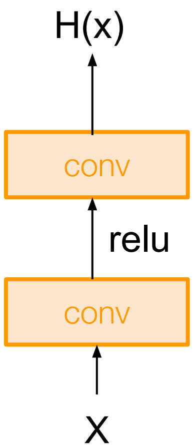


“Plain” layers

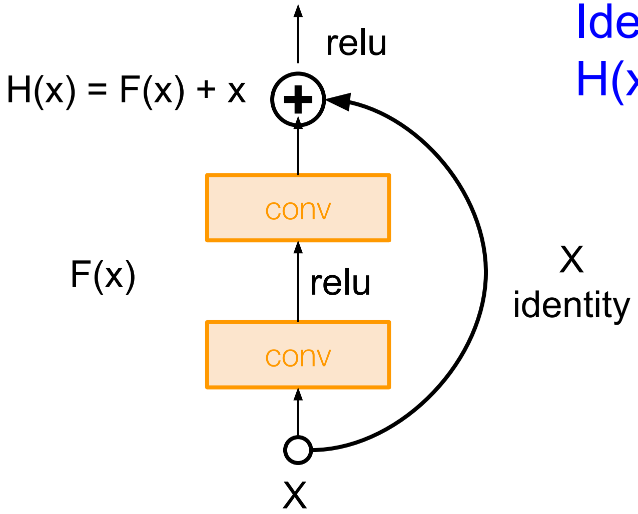
Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



“Plain” layers



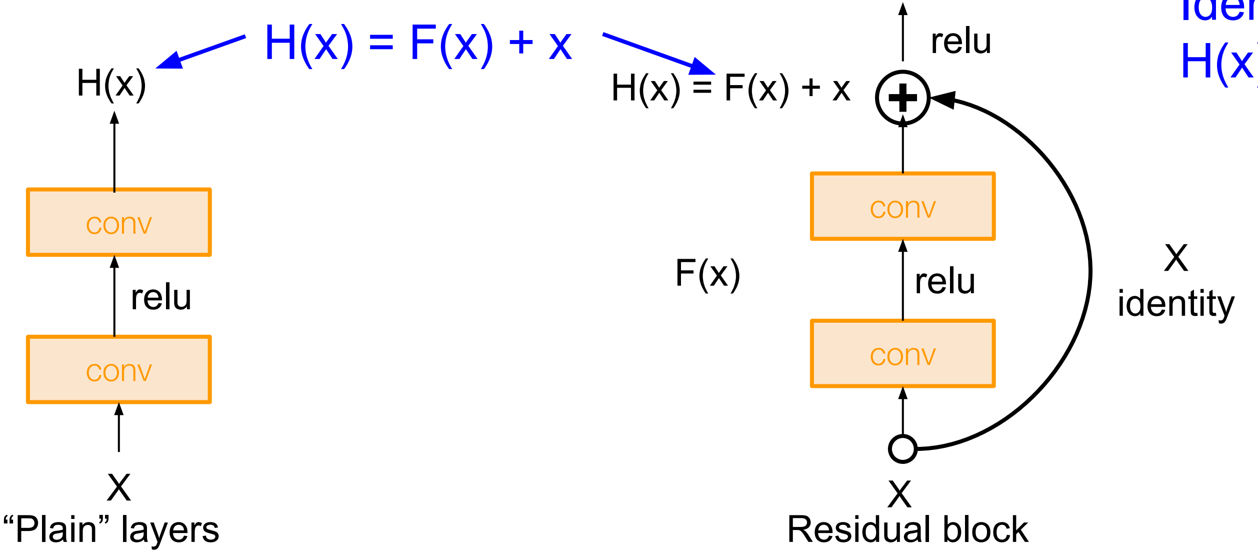
Residual block

Identity mapping:
H(x) = x if F(x) = 0

Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



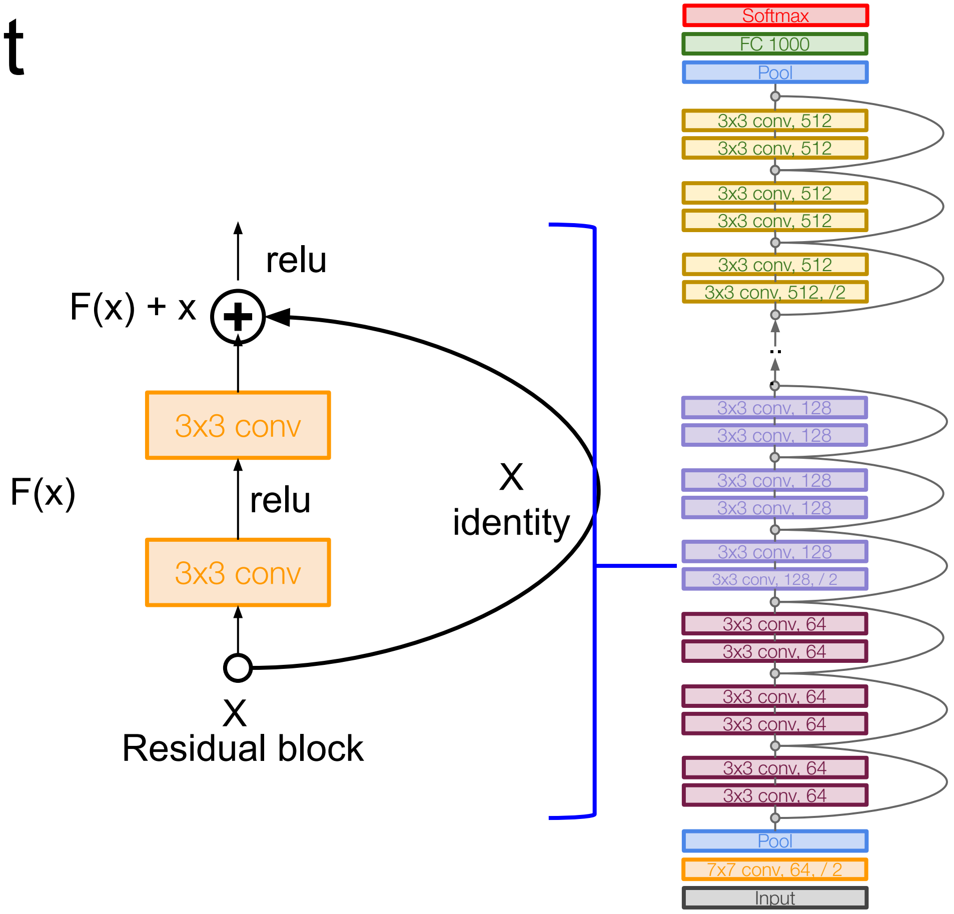
Identity mapping:
$H(x) = x$ if $F(x) = 0$

Use layers to fit **residual** $F(x) = H(x) - x$ instead of $H(x)$ directly

Case Study: ResNet

[He et al., 2015]

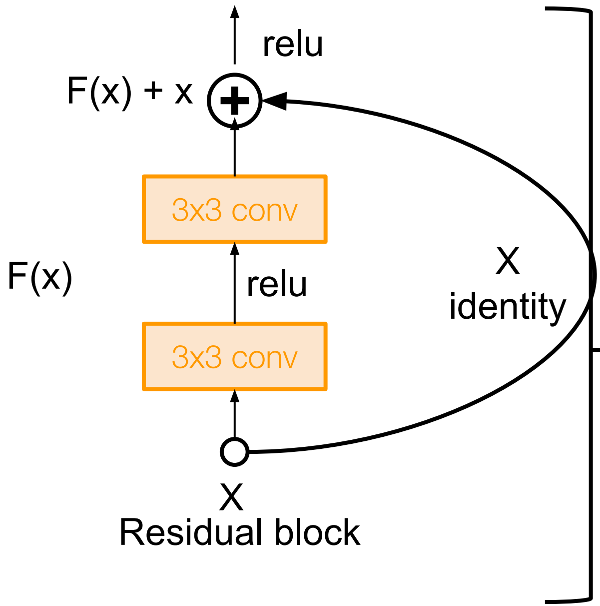
Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers

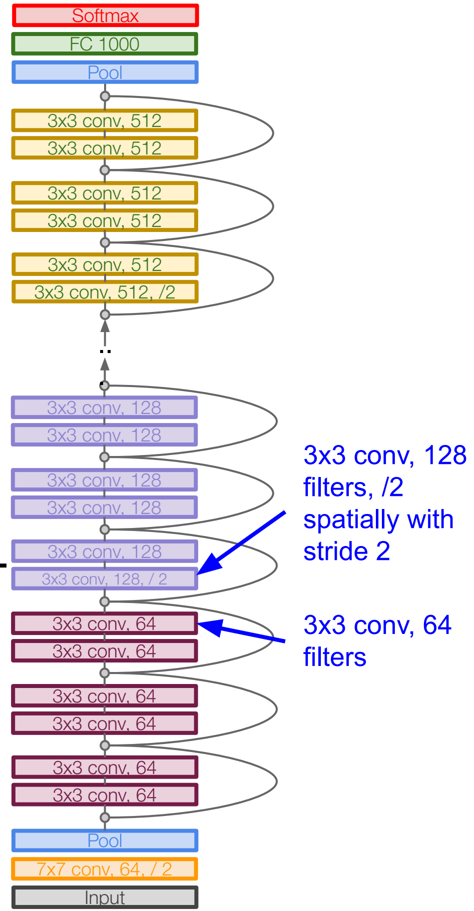


Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
  Reduce the activation volume by half.





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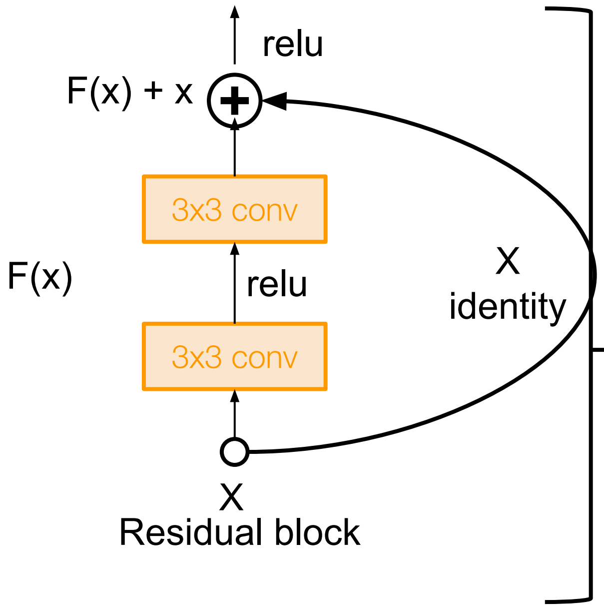
- Additional conv layer at the beginning (stem)

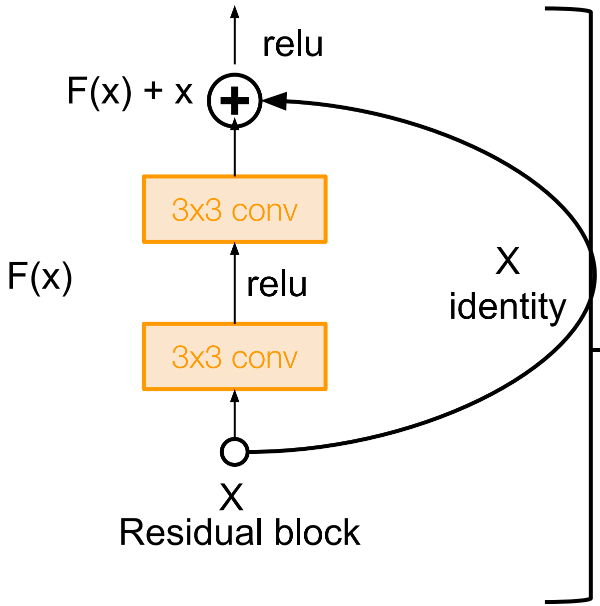


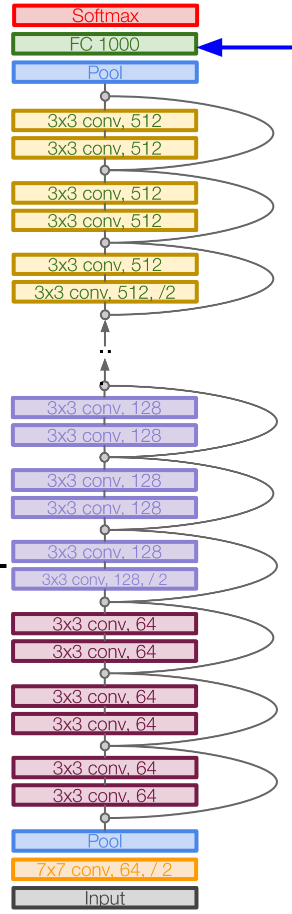
Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning (stem)
- No FC layers at the end (only FC 1000 to output classes)
- (In theory, you can train a ResNet with input image of variable sizes)





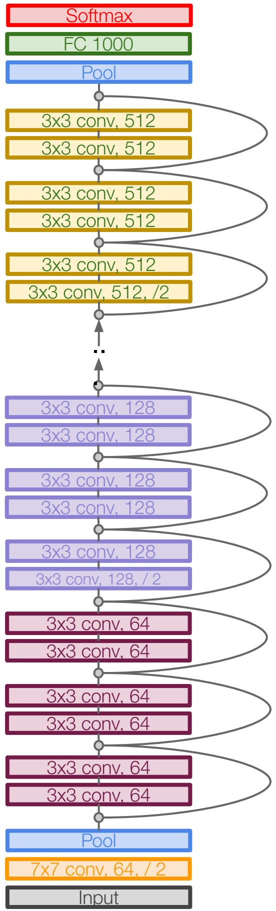
No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

Case Study: ResNet

[He et al., 2015]

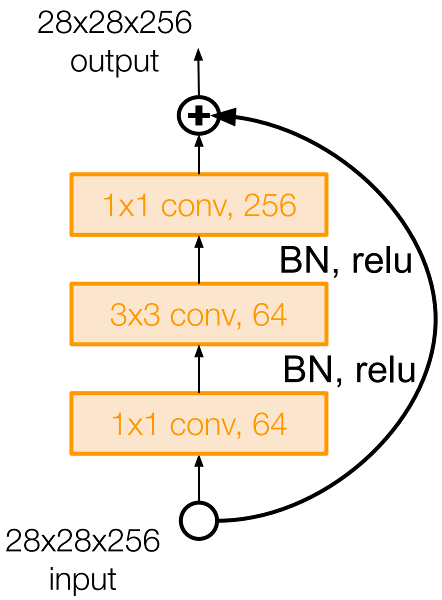
Total depths of 18, 34, 50, 101, or 152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

For deeper networks (ResNet-50+), use “bottleneck” layer to improve efficiency (similar to GoogLeNet)



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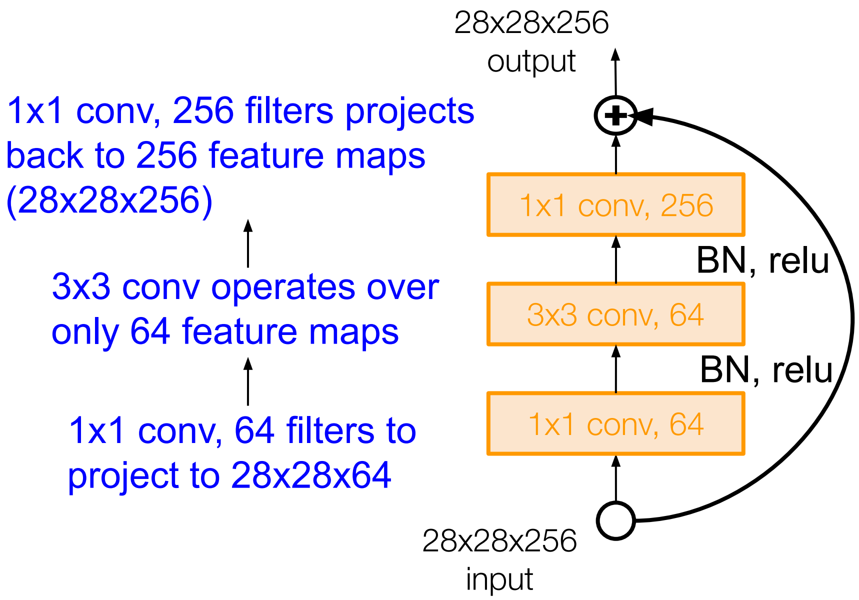

Case Study: ResNet

[He et al., 2015]

Training ResNet in practice:

- Batch Normalization after every CONV layer
- Xavier initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

Case Study: ResNet

[He et al., 2015]

Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lower training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

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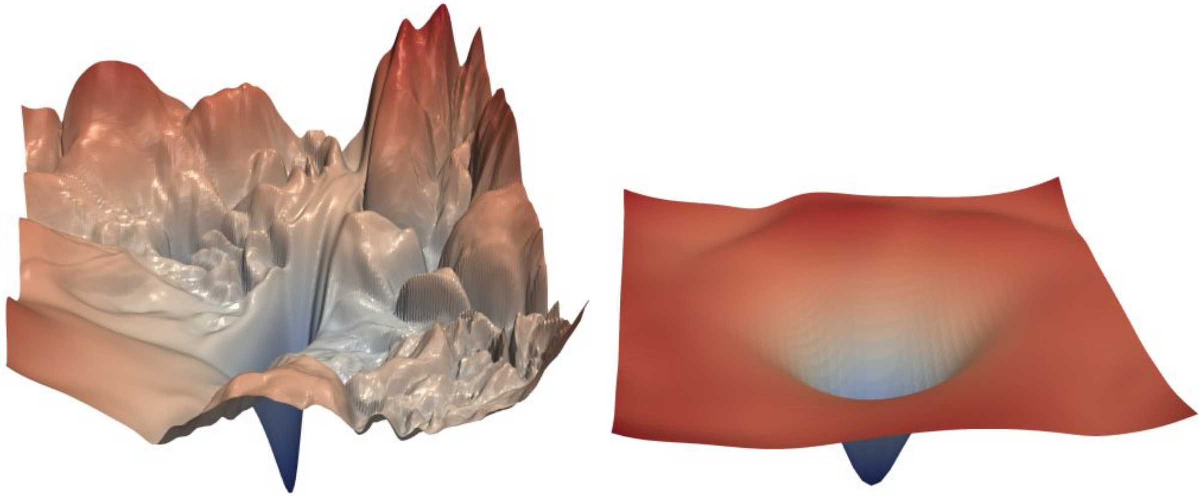
ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

Case Study: ResNet

[He et al., 2015]

Skip connections smooth out the loss landscape, easier optimization

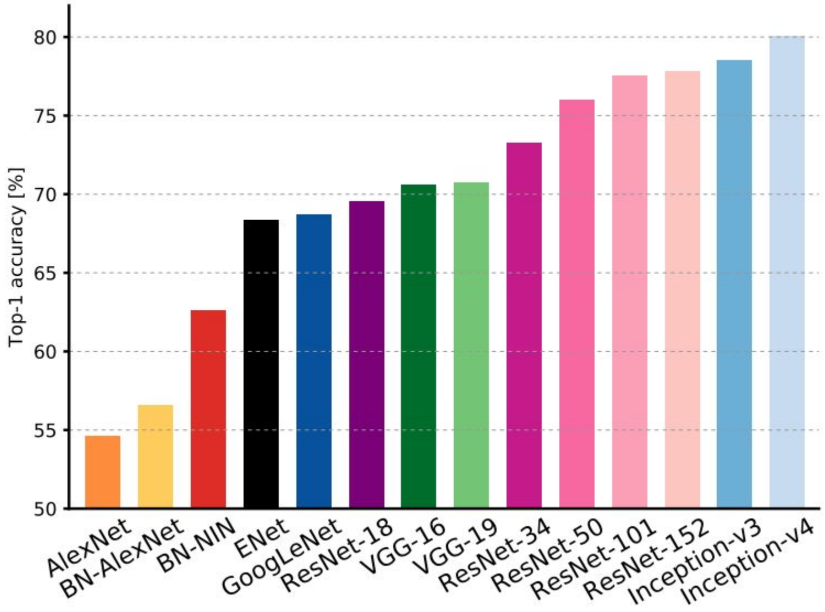


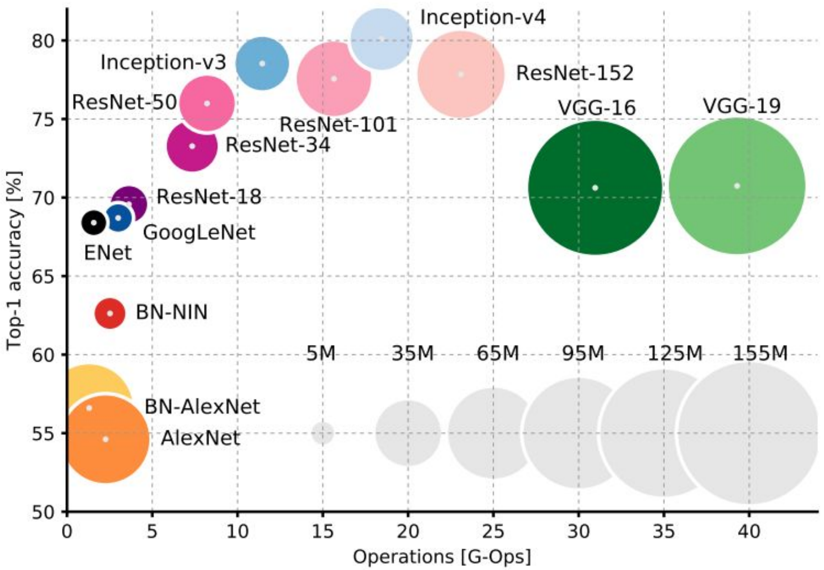
(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

Li, H., Xu, Z., Taylor, G., Studer, C., & Goldstein, T. (2018). Visualizing the Loss Landscape of Neural Nets. *Advances in Neural Information Processing Systems (NeurIPS)*

Comparing complexity...

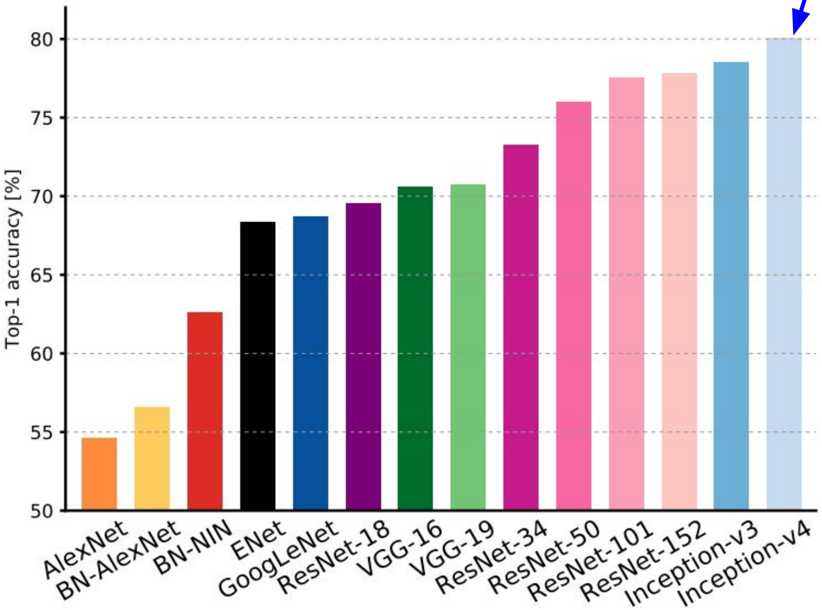


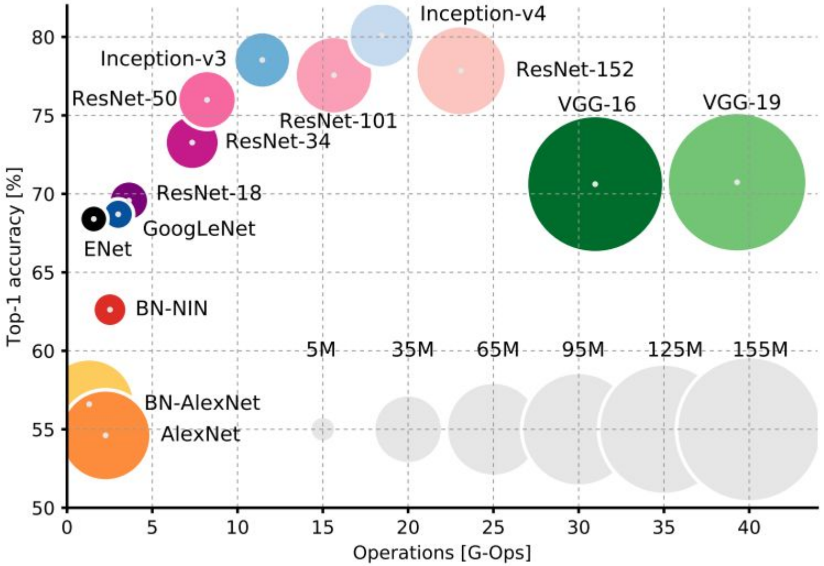


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

Inception-v4: Resnet + Inception!

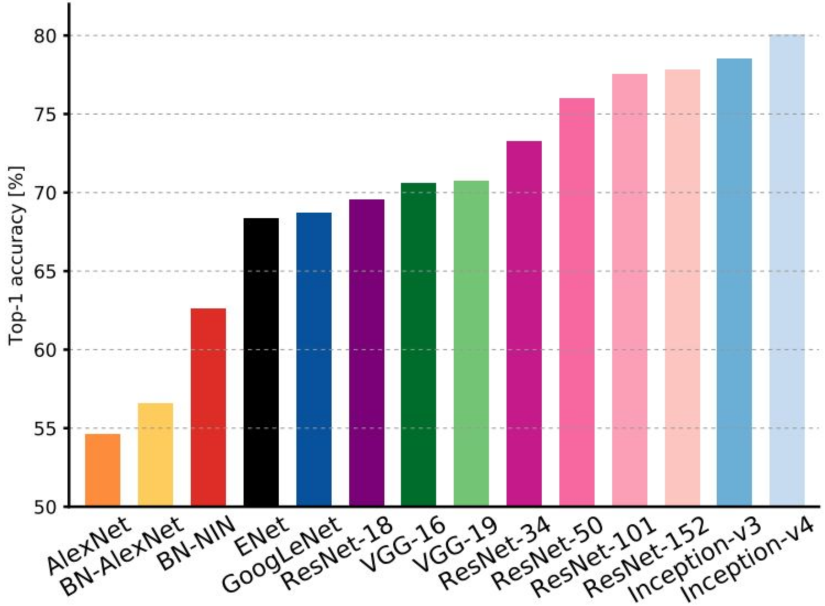


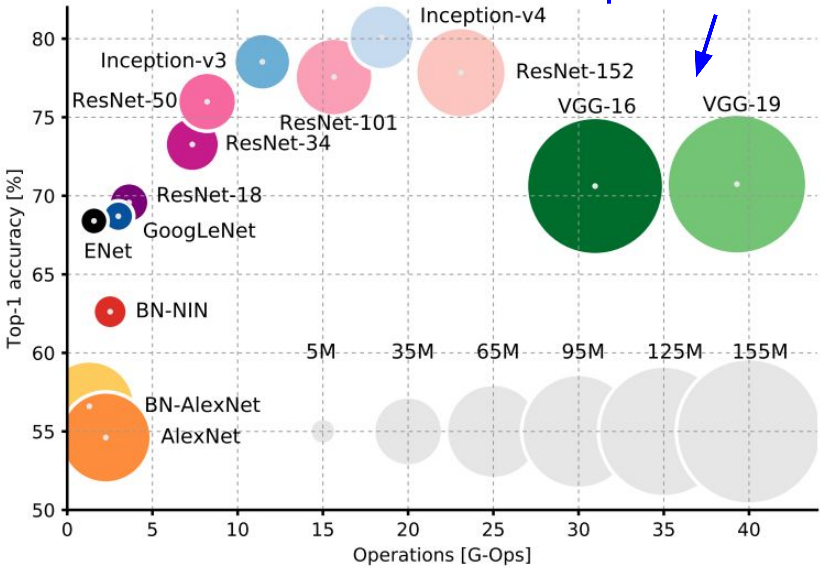


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

VGG: most parameters, most operations

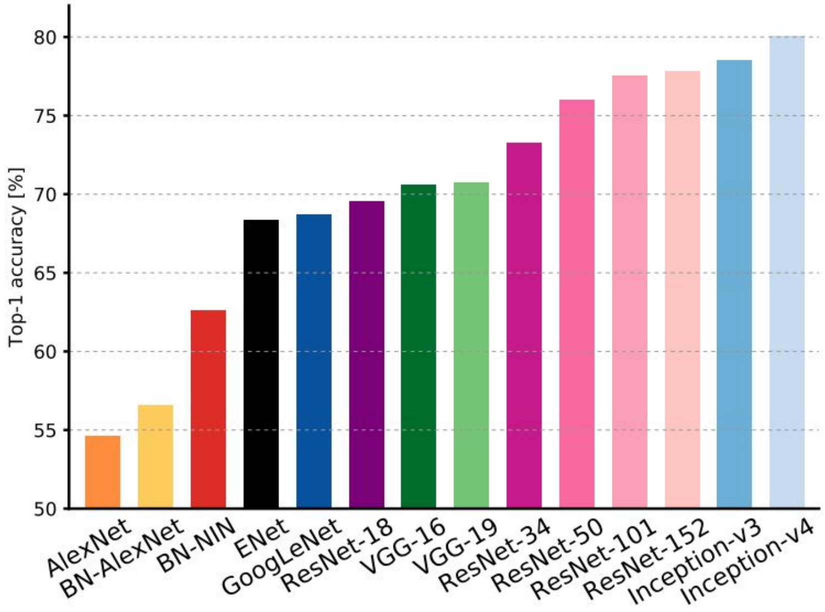


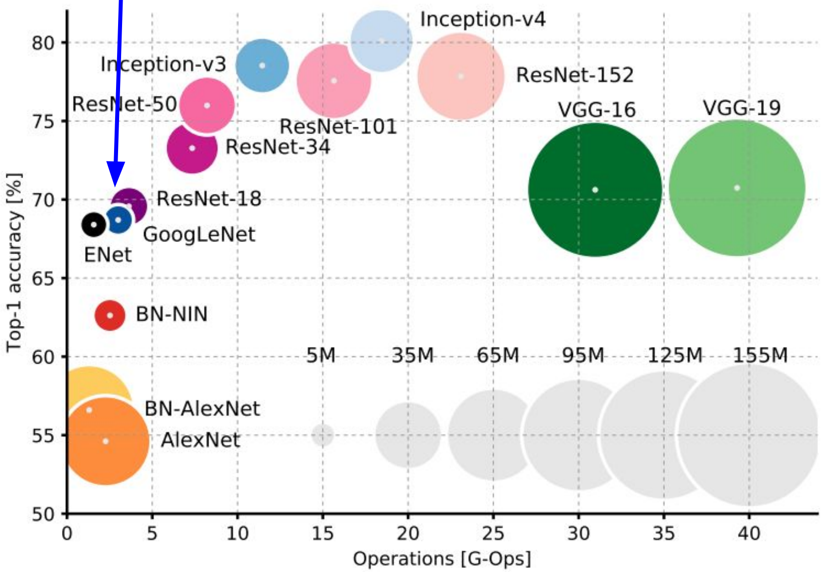


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

GoogLeNet:
most efficient

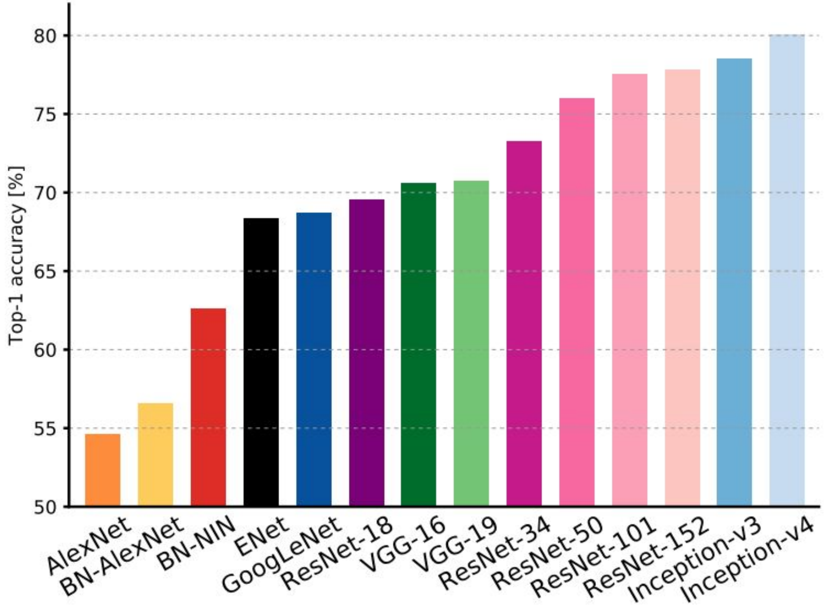


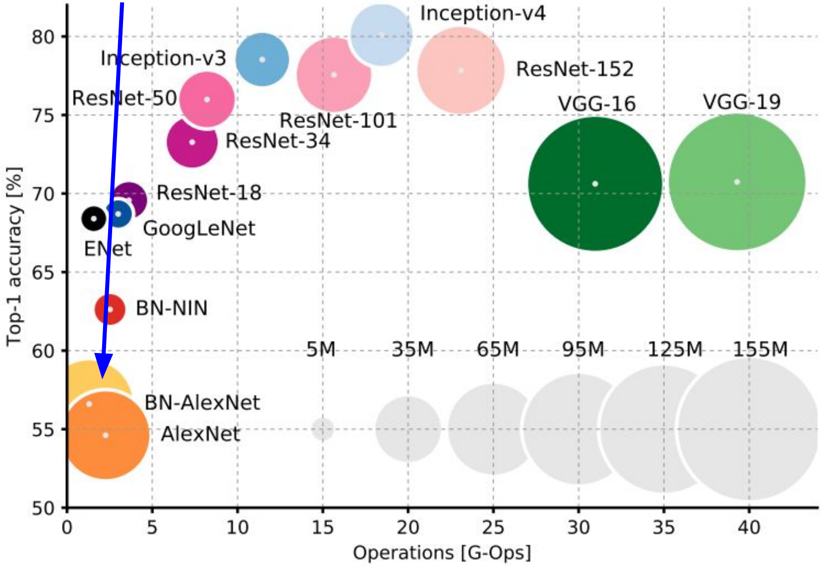


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

AlexNet:
Smaller compute, still memory heavy, lower accuracy

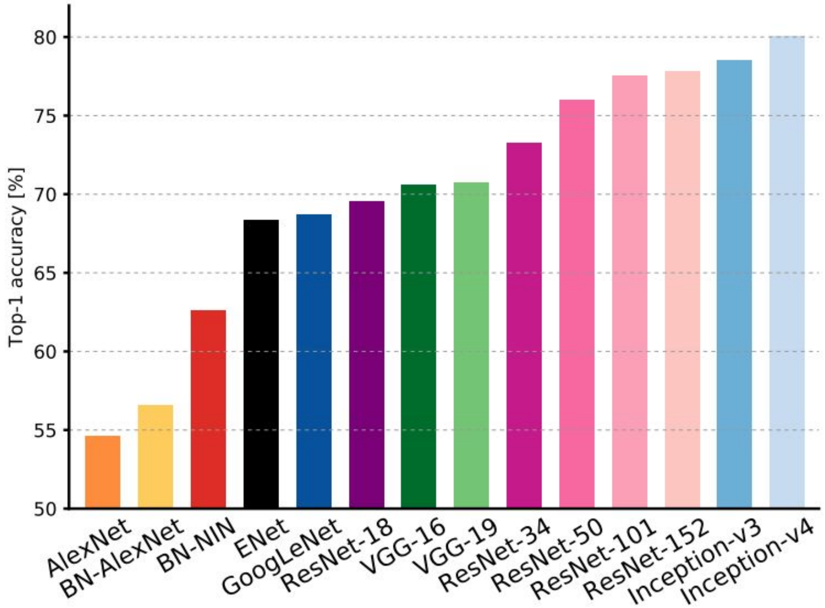


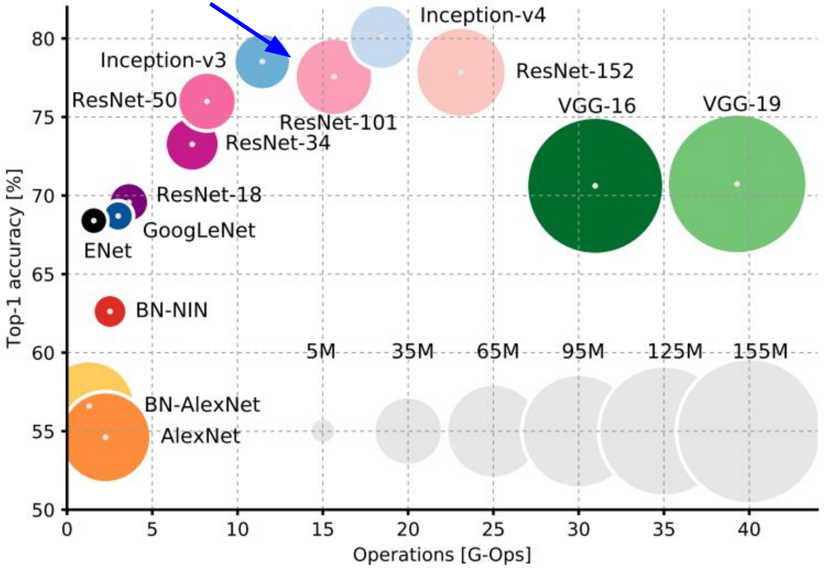


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy





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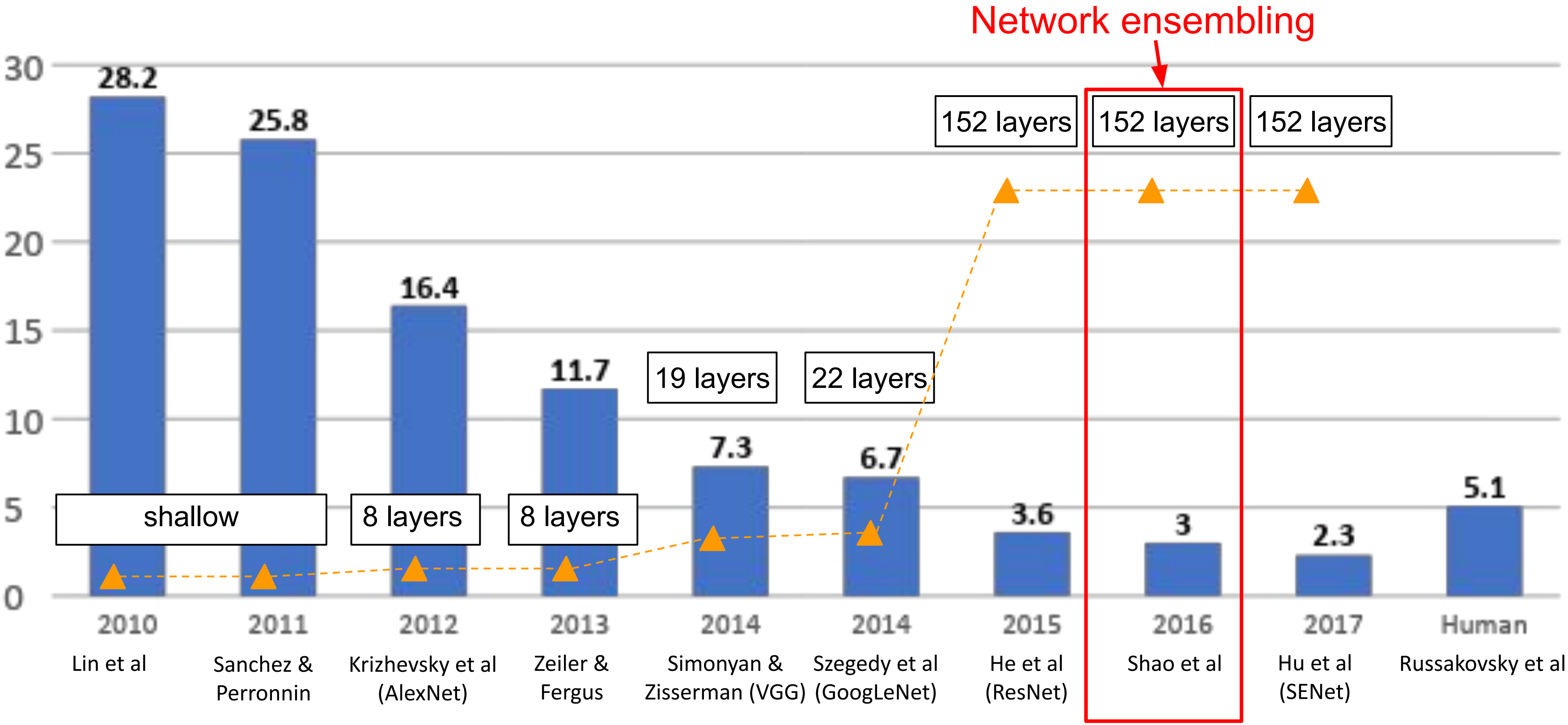
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Improving ResNets...

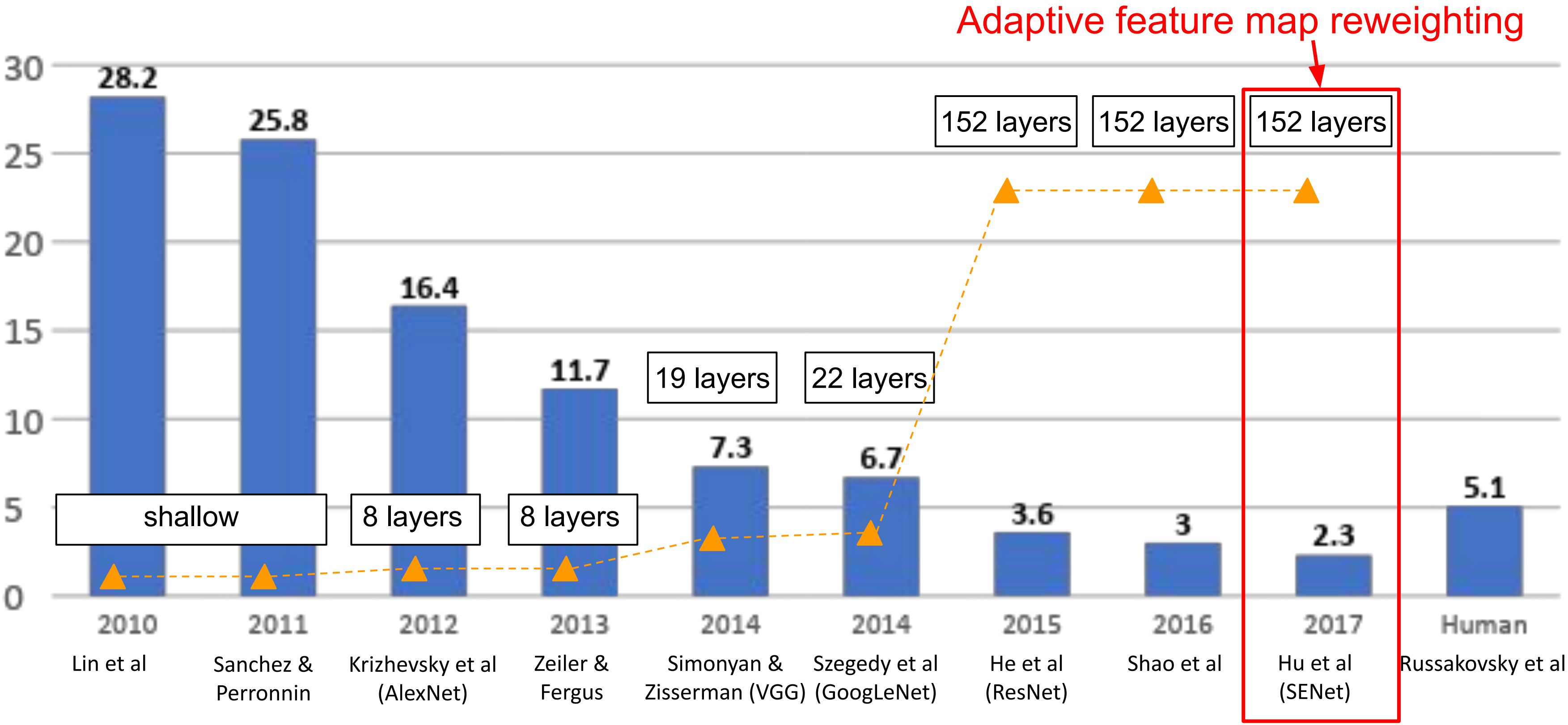
"Good Practices for Deep Feature Fusion"

[Shao et al. 2016]

- Multi-scale ensembling of Inception, Inception-Resnet, Resnet, Wide Resnet models
- ILSVRC'16 classification winner

	Inception-v3	Inception-v4	Inception-Resnet-v2	Resnet-200	Wrn-68-3	Fusion（Val.）	Fusion（Test）
Err. (%)	4.20	4.01	3.52	4.26	4.65	2.92 (-0.6)	2.99

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

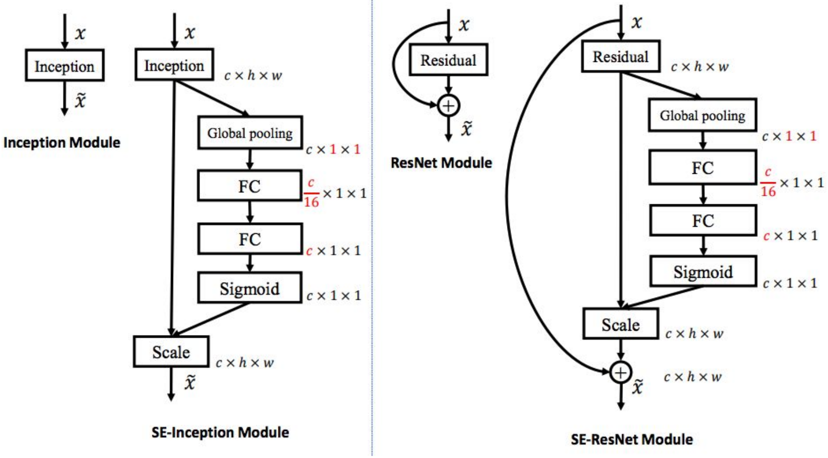


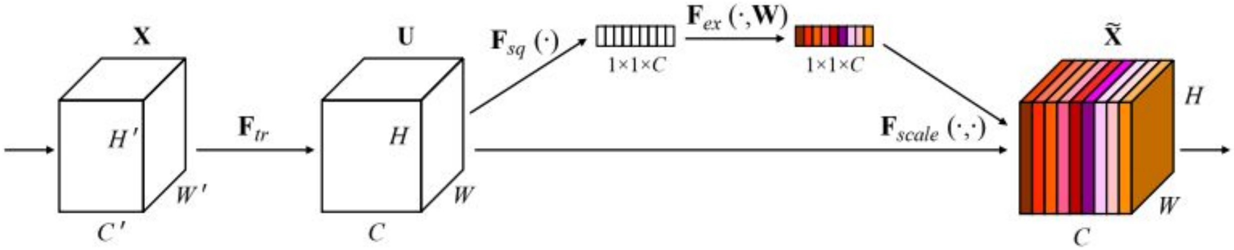
Improving ResNets...

Squeeze-and-Excitation Networks (SENet)

[Hu et al. 2017]

- Add a “feature recalibration” module that learns to adaptively reweight feature maps
- Global information (global avg. pooling layer) + 2 FC layers used to determine feature map weights
- ILSVRC’17 classification winner (using ResNeXt-152 as a base architecture)





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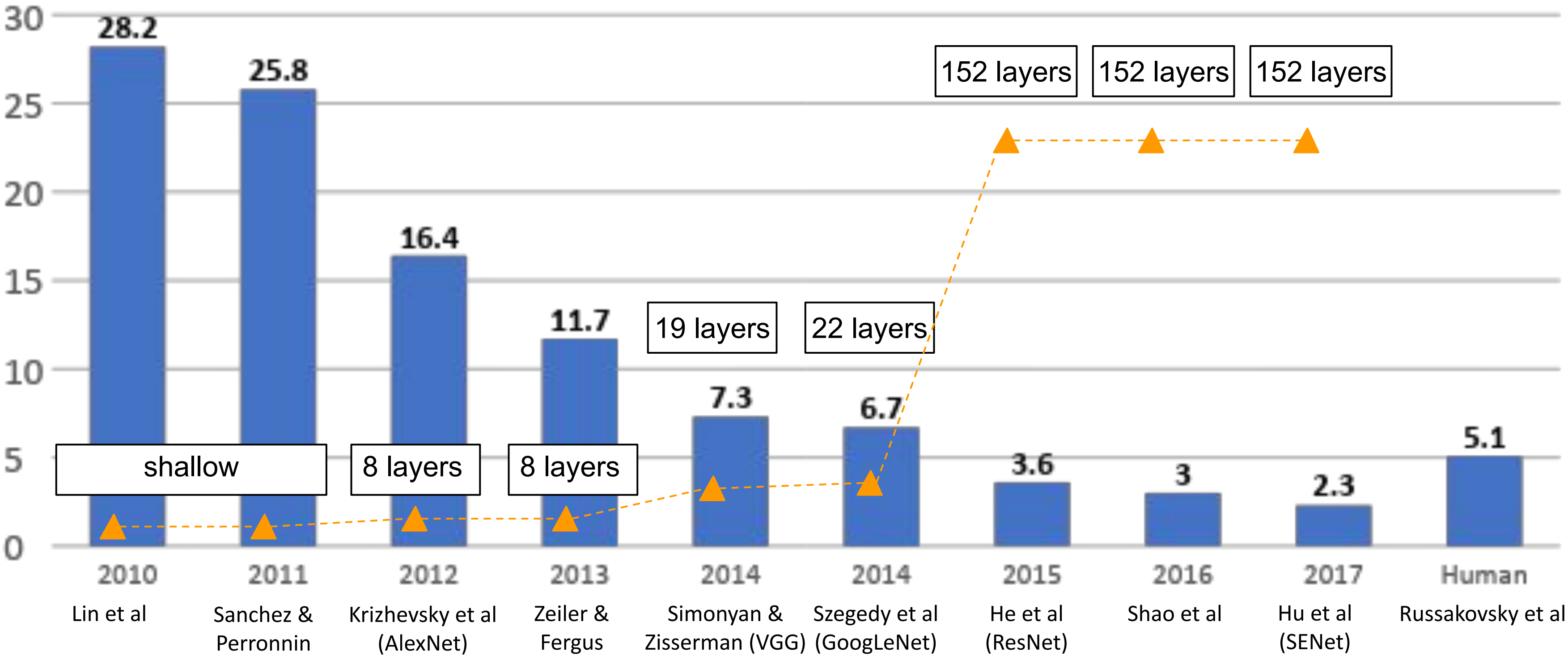

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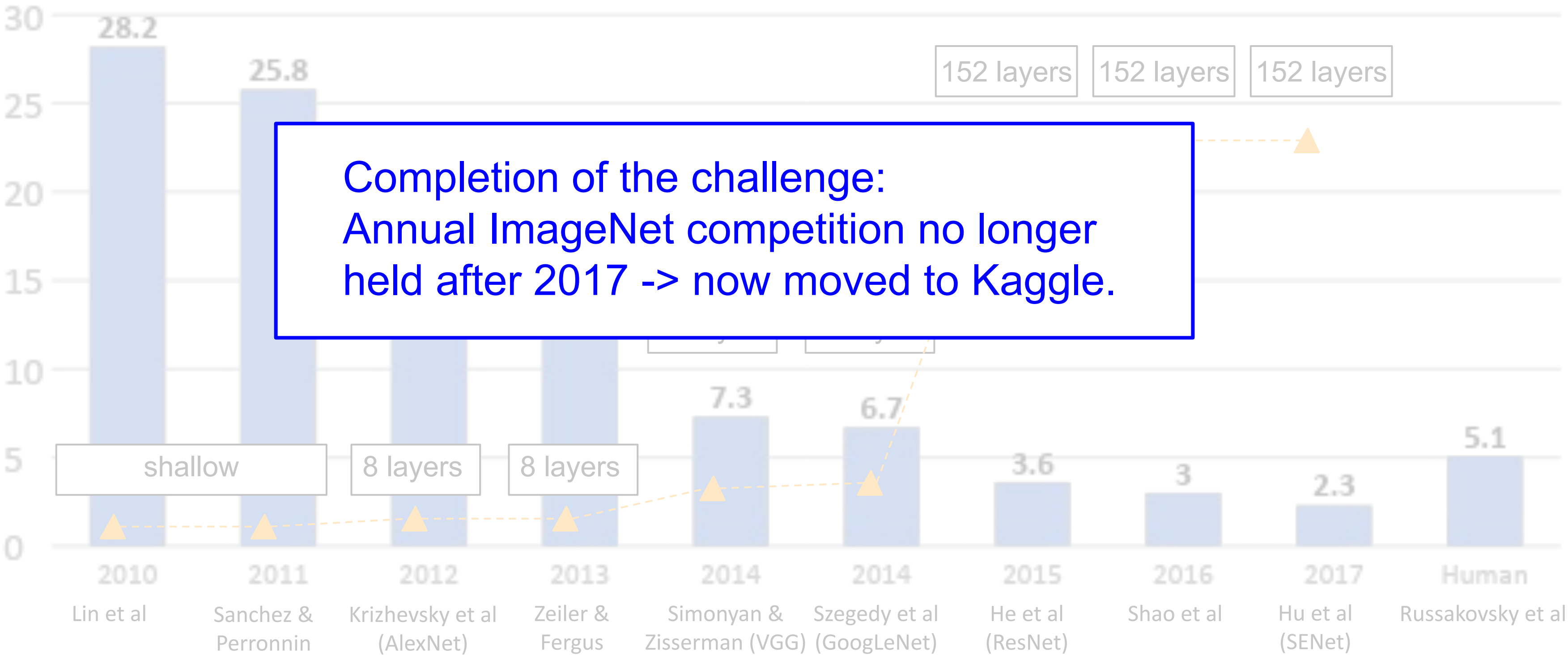
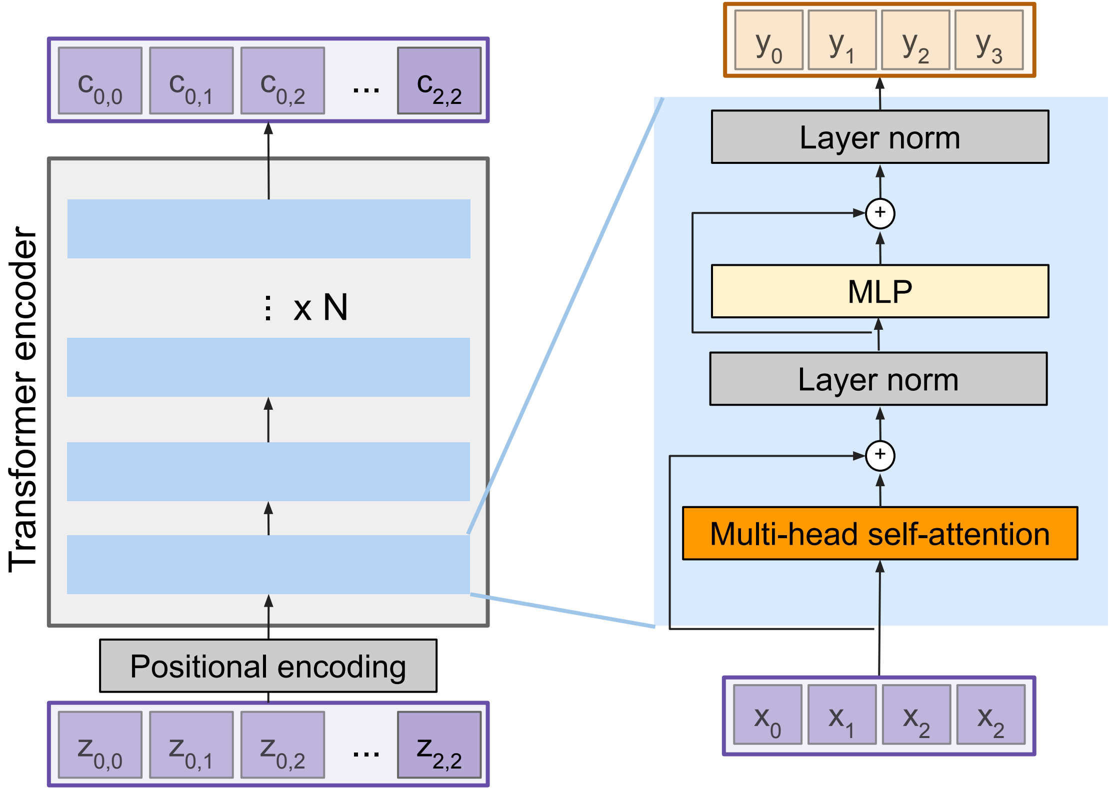


Completion of the challenge:
Annual ImageNet competition no longer held after 2017 -> now moved to Kaggle.

How have transformers affected architectures?



Transformer Encoder Block:

Inputs: Set of vectors **x**
Outputs: Set of vectors **y**

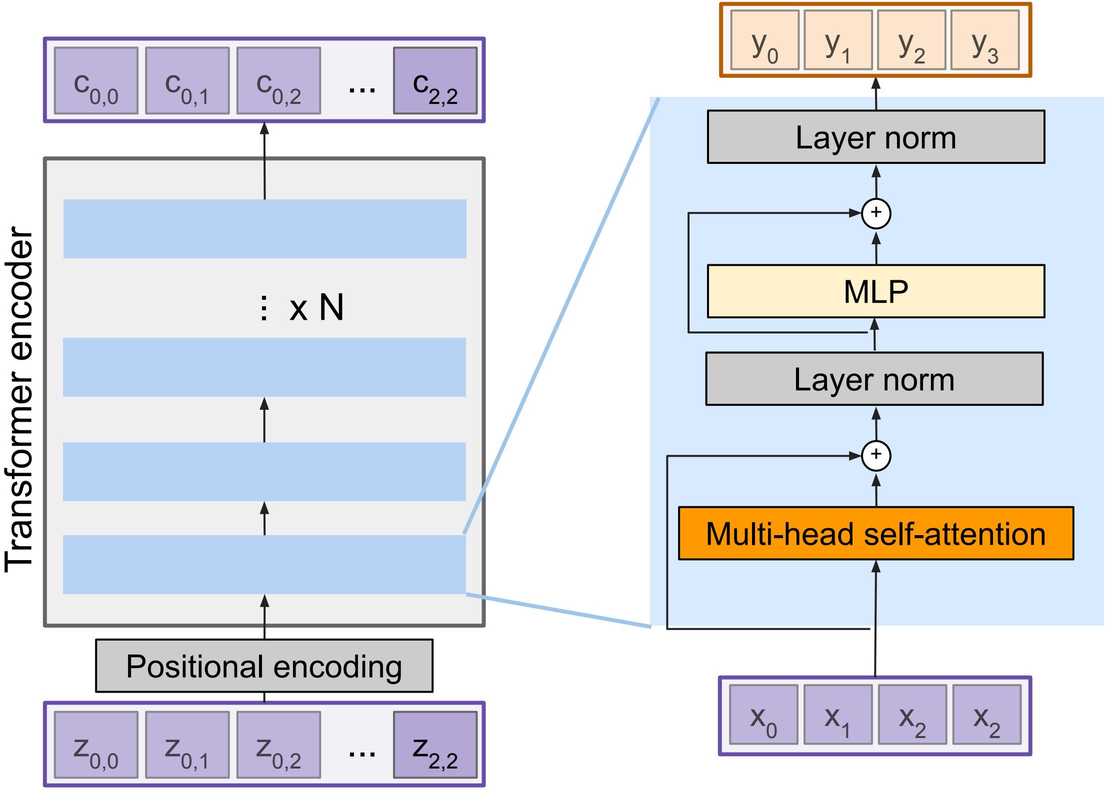
Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

Notice the residual connections!!

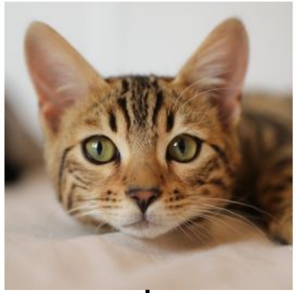


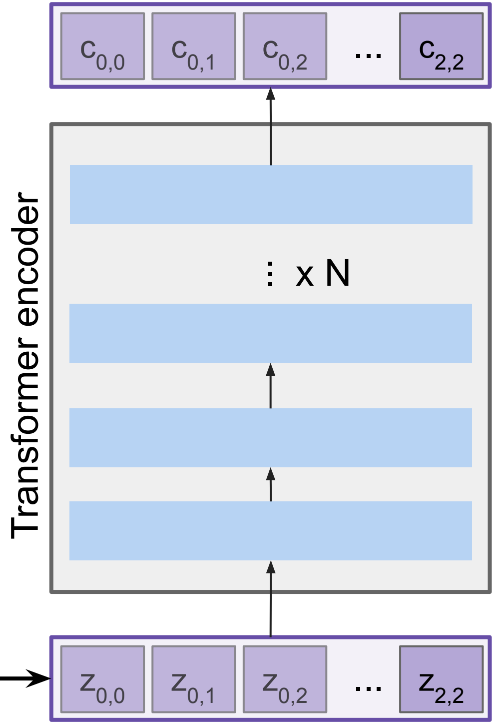
Residual connections inherited from ResNet's design.

Allows for better gradients to flow through all the transformers blocks.

Vaswani et al, "Attention is all you need", NeurIPS 2017

How to incorporate transformers to vision?





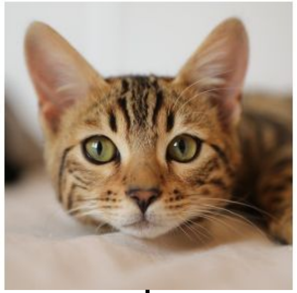
Idea #1: pass the image pixels into the transformer encoder.

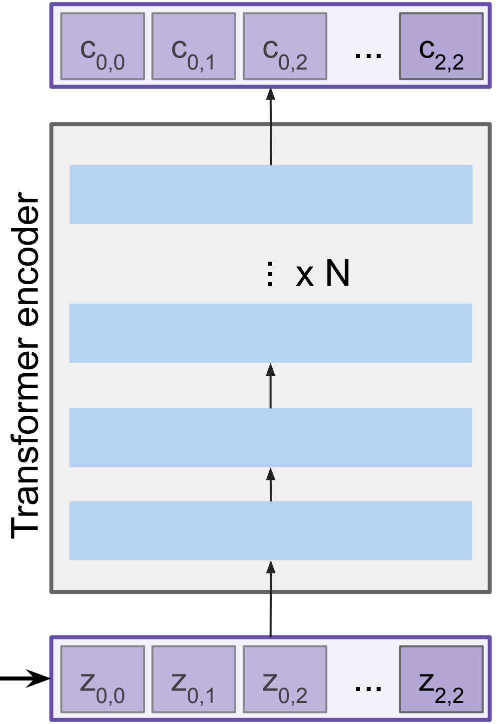
So, each $z_{0,0}$ is a pixel.

What is the problem with this idea?

Cat image is free for commercial use

How to incorporate transformers to vision?





Cat image is free for commercial use

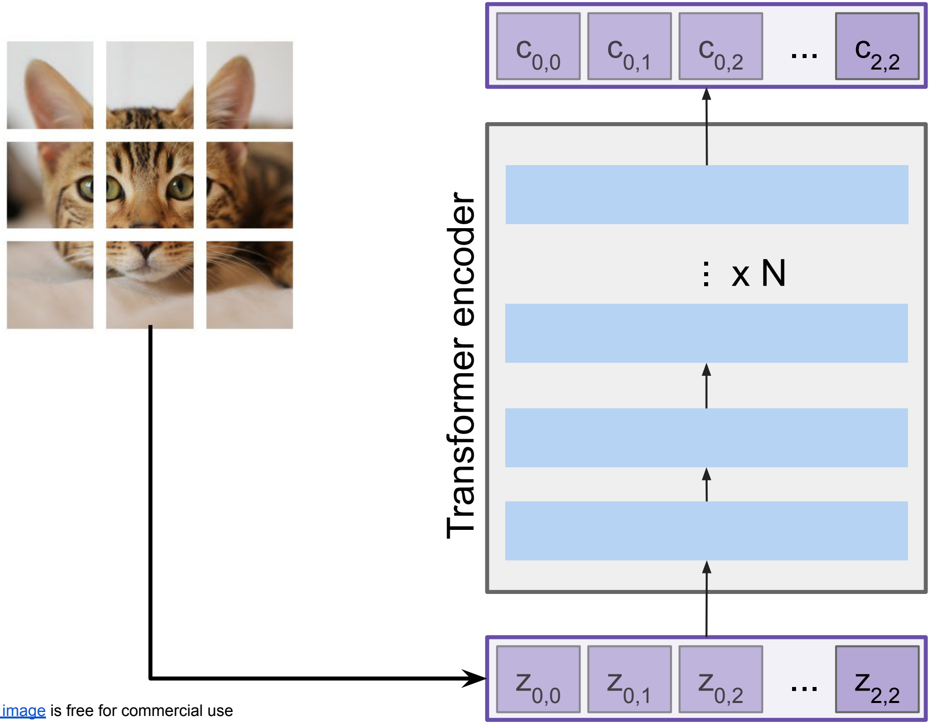
Idea #1: pass the image pixels into the transformer encoder.

So, each $z_{0,0}$ is a pixel.

Q. What is the problem with this idea?

A. Memory issue: Assume images are 224x224 pixels. This means that self attention will produce $224^4 = 10^9$ values!

How to incorporate transformers to vision?



Idea #2: Divide image into patches and pass those patches into the transformer

So, each $z_{0,0}$ is a 16x16x3 patch.

Q. What operation do you know already that operates over patches?

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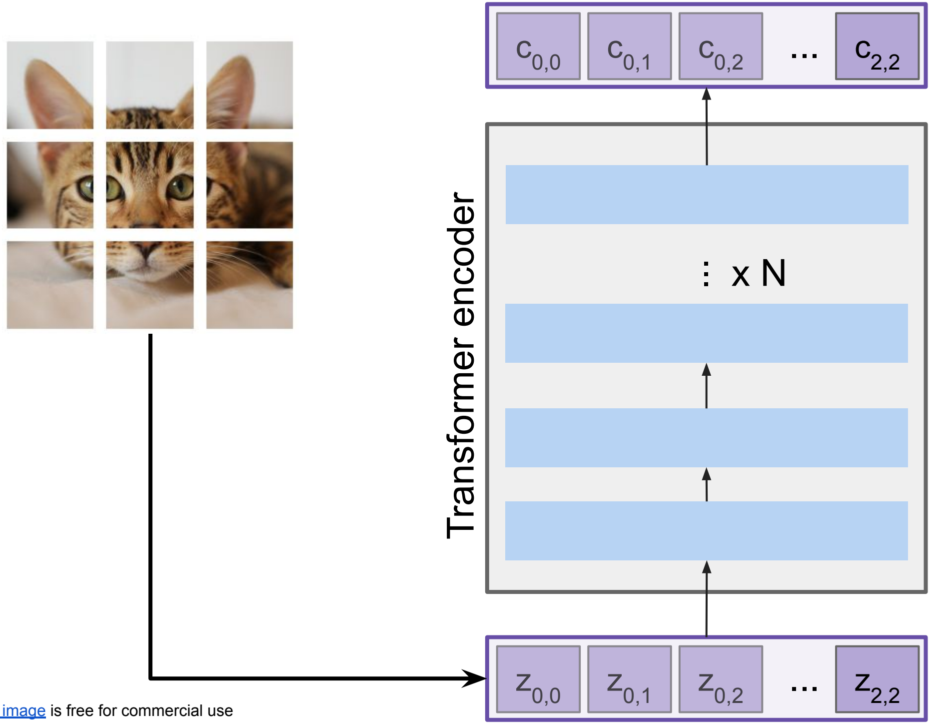
Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

How to incorporate transformers to vision?



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Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Idea #2: Divide image into patches and pass those patches into the transformer

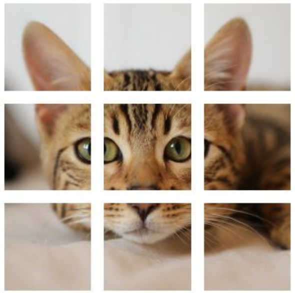
So, each $z_{0,0}$ is a 16x16x3 patch.

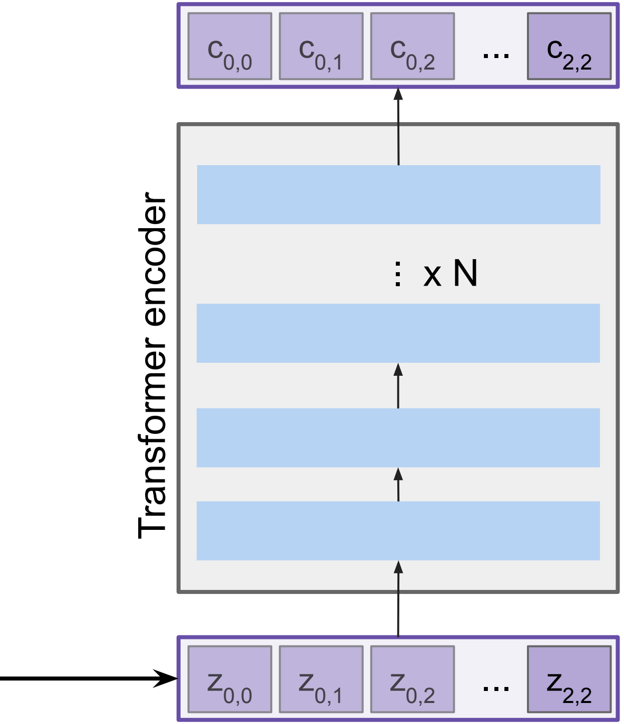
Q. What operation do you know already that operates over patches?

Yes it's a convolution.

Q. What is the kernel size and stride and padding?

How to incorporate transformers to vision?





Idea #2: Divide image into patches and pass those patches into the transformer

So, each $z_{0,0}$ is a 16x16x3 patch.

Q. Does this solve the memory problem?

A. 14^2 x 14^2 = 38416, much less than 10^9

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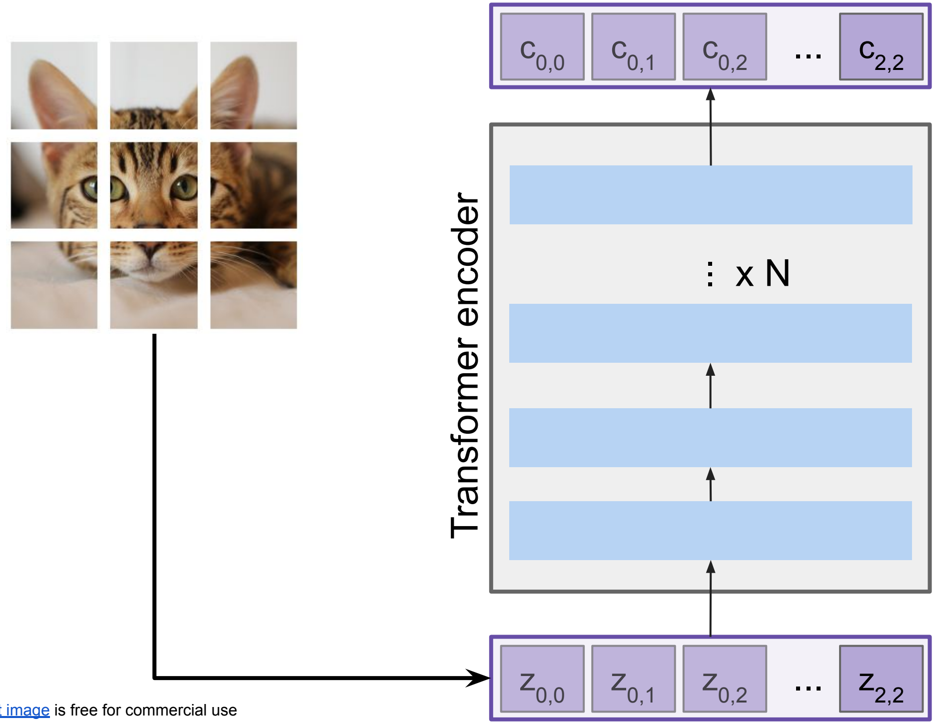
Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Position encoding



Since transformers are permutation invariant, we want to add position encoding to each patch.

- Patches are 768D.
- Position encoding is some learned 768D.

Pick any consistent ordering of patches (e.g. top left patch is always first).

Simply Add position encoding and patch representation.

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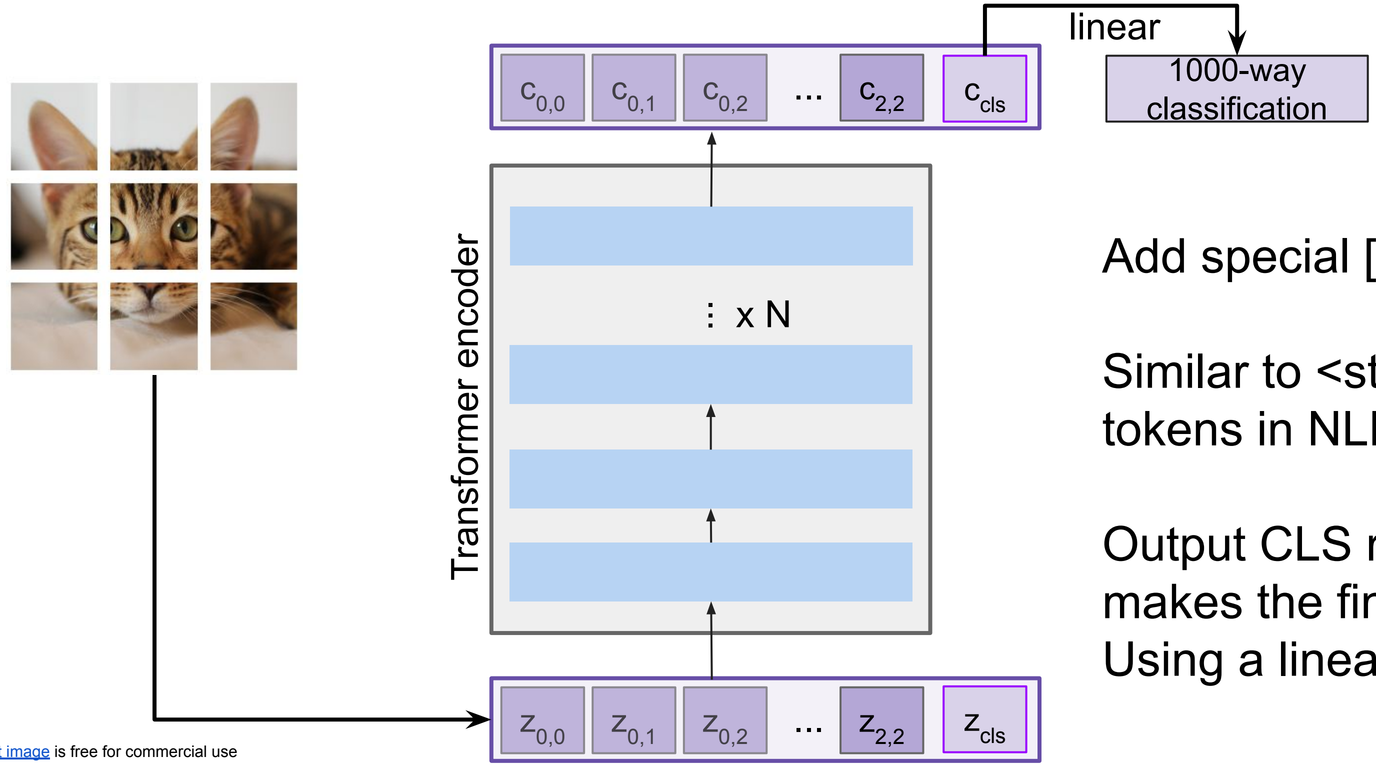
Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

How to turn the output to a class prediction?



Add special [CLS] token.

Similar to <start> and <end> tokens in NLP.

Output CLS representation makes the final prediction
Using a linear layer

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Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Common ViT architectures

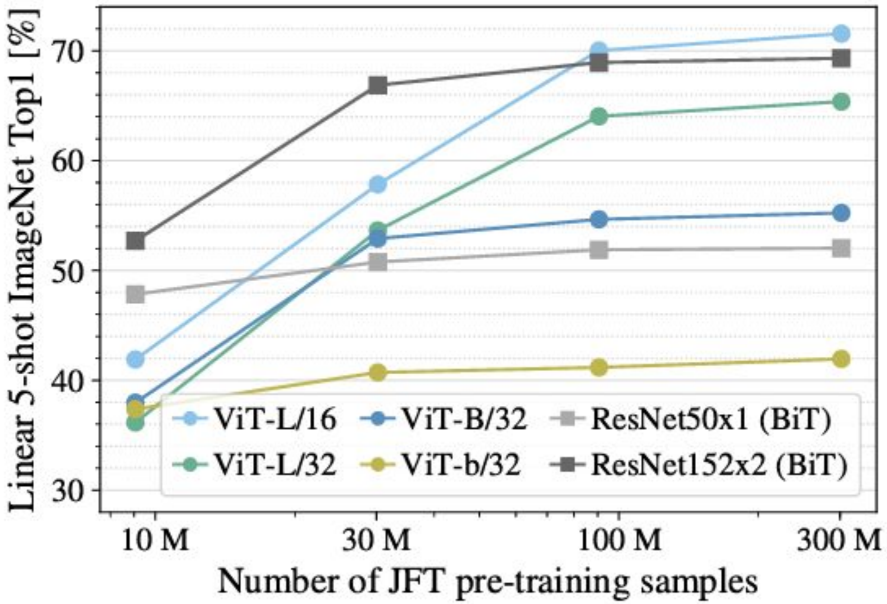
Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

Common patch sizes: 32, 16, 14…
Smaller patches results in larger more powerful models.

Nomenclature: ViT-B/32 means that its a ViT model that uses Base values for layers, hidden size, mlp vize, and head. /32 means the input image patches are 32x32.

Dosovitskiyet al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Comparing ResNets with ViTs



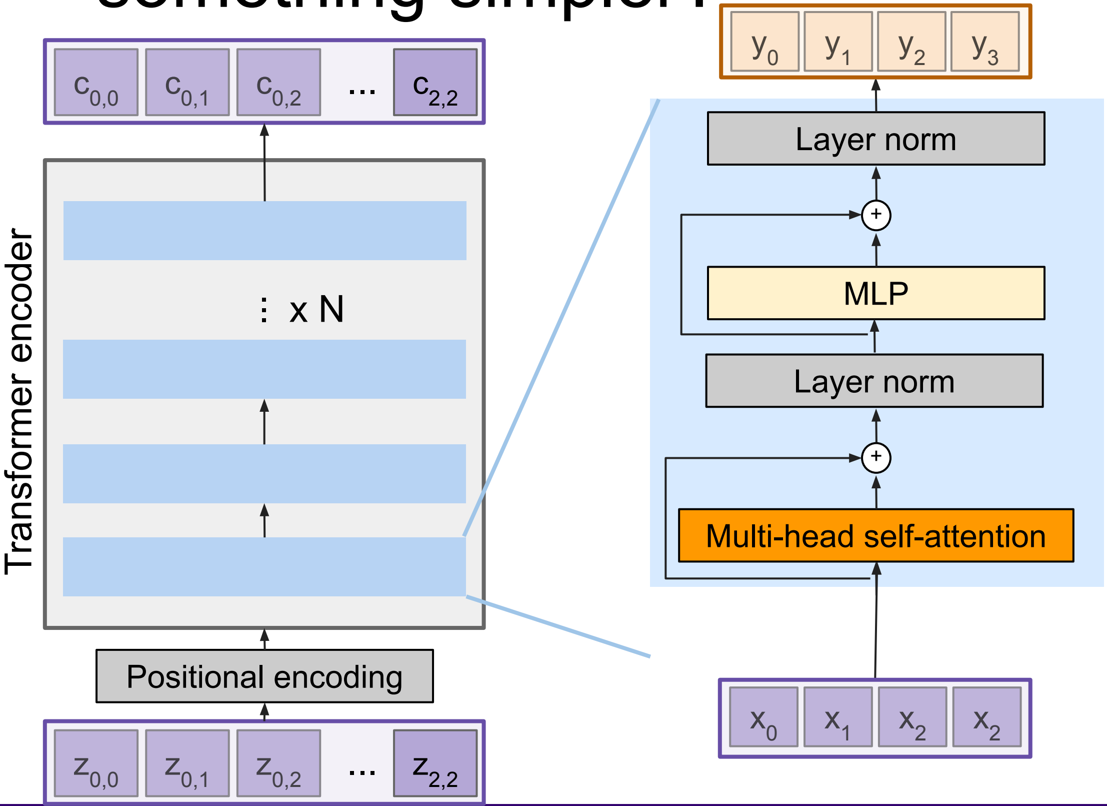
Models are initially trained on a large dataset called JFT-300M

And then the last linear layer is finetuned on ImageNet-1.5M

ViT performs worse when only 10M images are used from JFT. But ViT outperforms ResNets with larger training data (300M images from JFT).

Dosovitskiyet al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Self-attention is expensive… can we design something simpler?



Every self-attention is expensive. We want each input to “interact” with other tokens but can we simplify the operation a bit?

State space models offer a potential solution but it hasn’t been adopted yet (out of scope for this course)

Vaswani et al, “Attention is all you need”, NeurIPS 2017

Main takeaways

AlexNet showed that you can use CNNs to train Computer Vision models.
ZFNet, **VGG** shows that bigger networks work better
GoogLeNet is one of the first to focus on efficiency using 1x1 bottleneck convolutions and global avg pool instead of FC layers
ResNet showed us how to train extremely deep networks

- Limited only by GPU & memory!
- Showed diminishing returns as networks got bigger

After ResNet: CNNs were better than the human metric and focus shifted to Efficient networks:

- Lots of tiny networks aimed at mobile devices: **MobileNet**, **ShuffleNet**

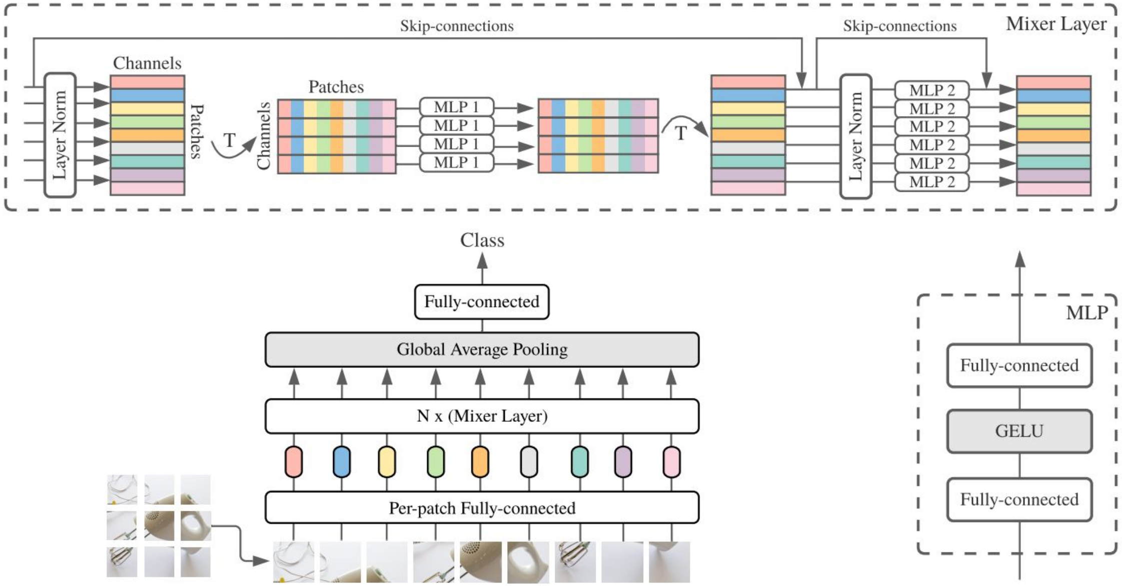
Neural Architecture Search can now automate architecture design
ViT is the current favorite architecture but requires a lot of compute and data
State space models have presented an alternative to transformers but they haven't taken off.

Summary: Modern Architectures

- **ResNet-50** and **ViT** currently good defaults to use
- Next time: Structure prediction

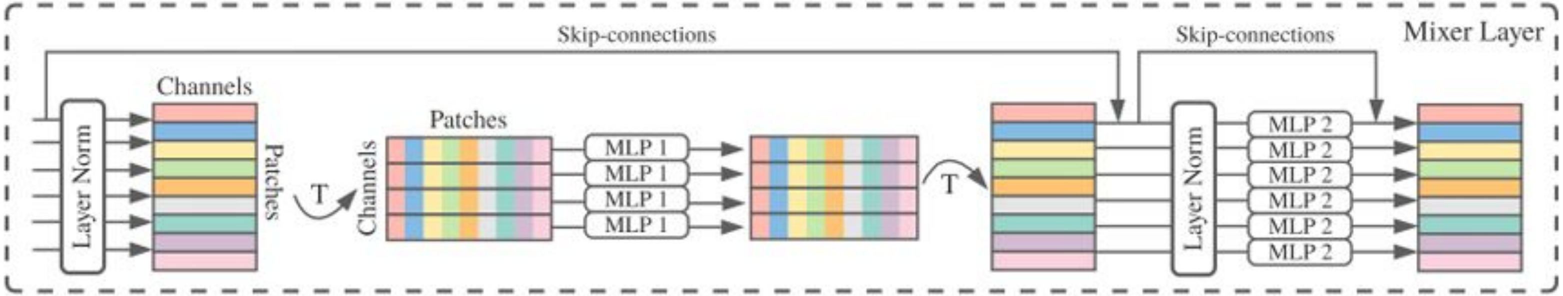
Next time: Structured Prediction

MLP-Mixer: an all-MLP architecture



Tolstikhinet al, “MLP-Mixer: An all-MLP architecture for vision”, NeurIPS2021

MLP-Mixer: an all-MLP architecture



Input: N x C
N patches with
C channels each

MLP 1: C -> C,
apply to each of the
N patches

MLP 2: N -> N,
apply to each of the
C patches

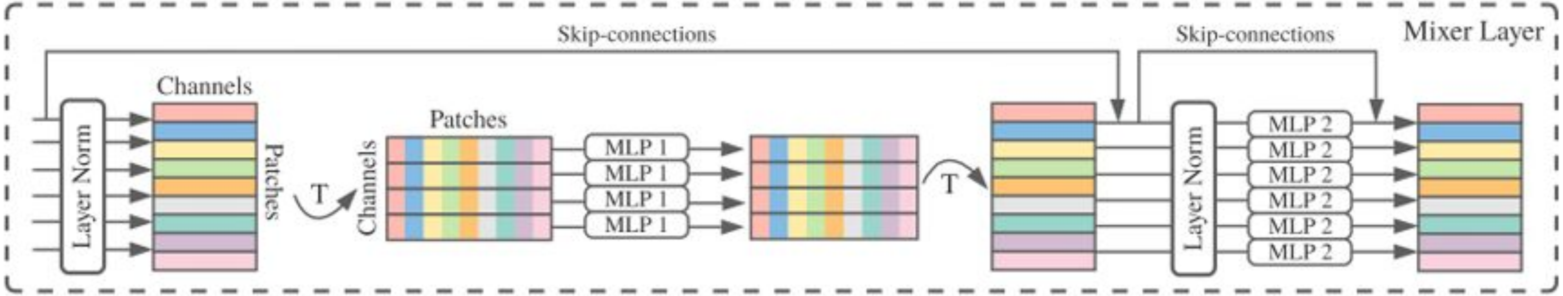
Tolstikhinet al, “MLP-Mixer: An all-MLP architecture for vision”, NeurIPS2021

MLP-Mixer: The MLPs are sort of like **convs**

Cool idea; but hasn't taken off yet.

Equivalent to
Conv(1x1, C->C, stride=1)

Equivalent to
Conv($N^{1/2}$ x $N^{1/2}$, C->C, groups=C)



Input: N x C
N patches with
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MLP 1: C -> C,
apply to each of the
N patches

MLP 2: N -> N,
apply to each of the
C patches

Tolstikhinet al, "MLP-Mixer: An all-MLP architecture for vision", NeurIPS2021

MLP-Mixer: Many concurrent and followups

Touvronet al, “ResMLP: Feedforward Networks for Image Classification with Data-Efficient Training”, arXiv2021, https://arxiv.org/abs/2105.03404

Tolstikhinet al, “MLP-Mixer: An all-MLP architecture for vision”, NeurIPS2021, https://arxiv.org/abs/2105.01601

Liu et al, “Pay Attention to MLPs”, NeurIPS2021, https://arxiv.org/abs/2105.08050

Yu et al, “S2-MLP: Spatial-Shift MLP Architecture for Vision”, WACV 2022, https://arxiv.org/abs/2106.07477

Chen et al, “CycleMLP: AMLP-like Architecture for Dense Prediction”, ICLR 2022, https://arxiv.org/abs/2107.10224

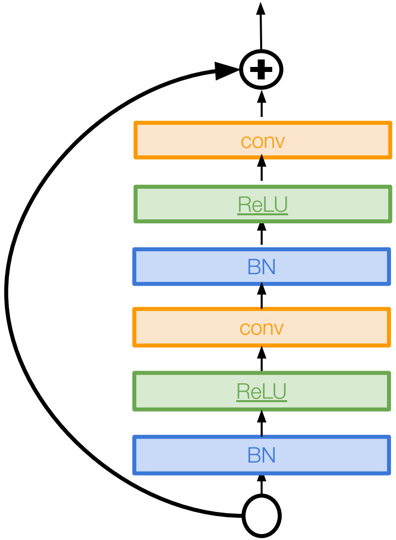
But research has continued since ImageNet

(Will go over following slides if time,
Otherwise skip to the summary slides in the end.)

Identity Mappings in Deep Residual Networks

[He et al. 2016]

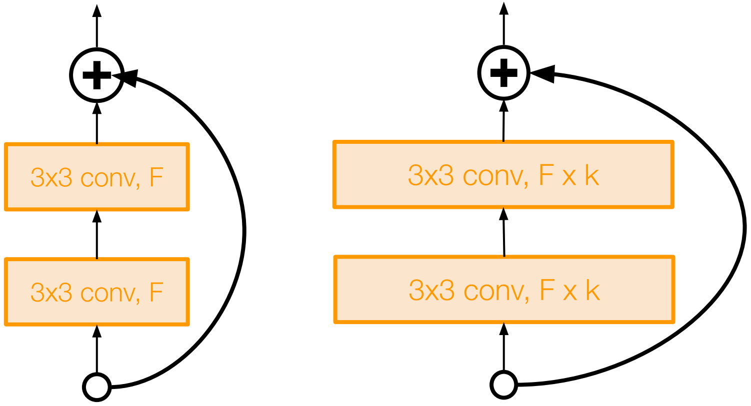
- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network
- Gives better performance



Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- User wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)

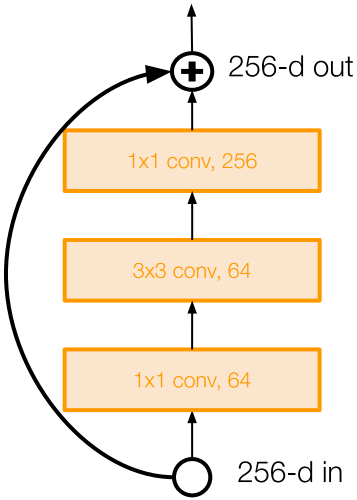


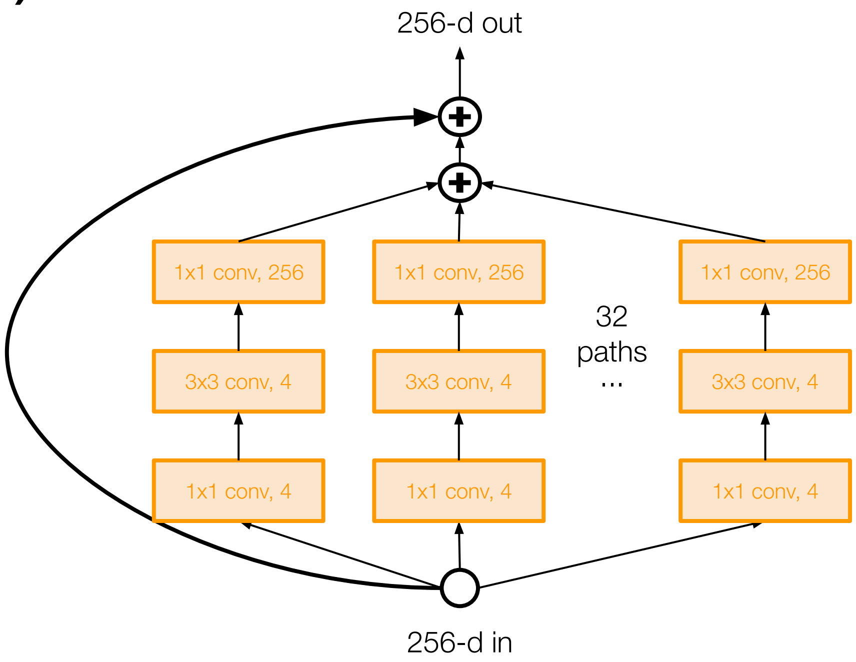
Basic residual block   Wide residual block

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways ("cardinality")
- Parallel pathways similar in spirit to Inception module



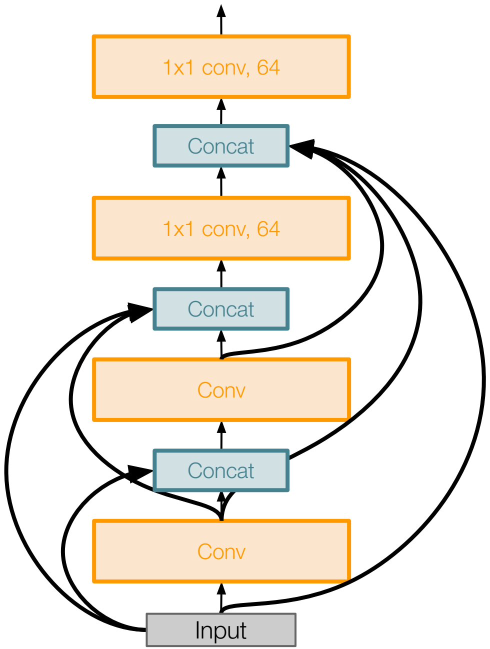


Other ideas...

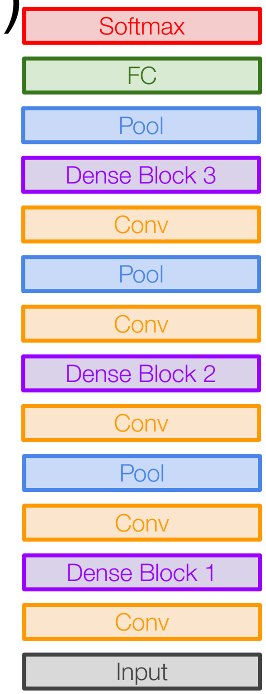
Densely Connected Convolutional Networks (DenseNet)

[Huang et al. 2017]

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse
- Showed that shallow 50-layer network can outperform deeper 152 layer ResNet



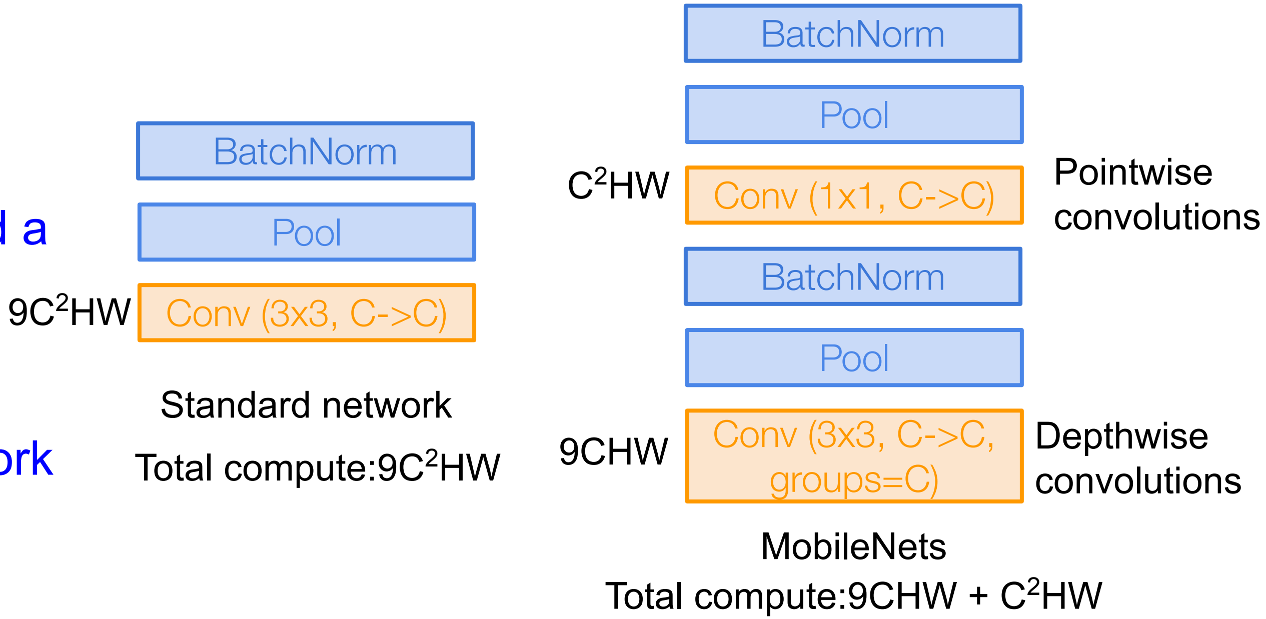
Dense Block



Efficient networks...

MobileNets: Efficient Convolutional Neural Networks for Mobile Applications *[Howard et al. 2017]*

- Depthwise separable convolutions replace standard convolutions by factorizing them into a depthwise convolution and a 1x1 convolution
- Much more efficient, with little loss in accuracy
- Follow-up MobileNetV2 work in 2018 (Sandler et al.)
- ShuffleNet: Zhang et al, CVPR 2018

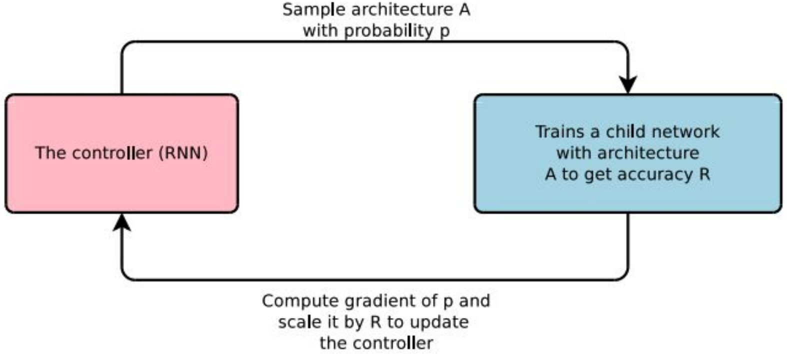


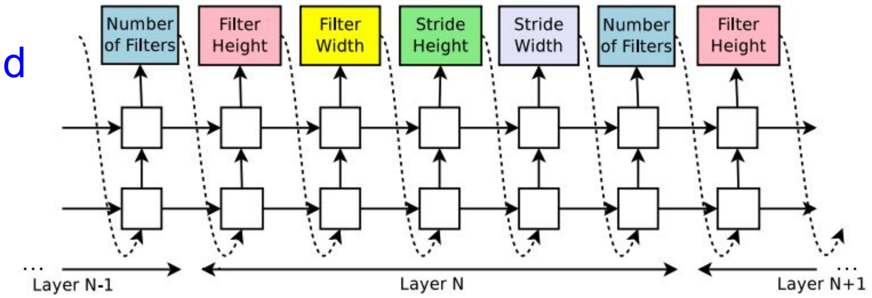
Learning to search for network architectures...

Neural Architecture Search with Reinforcement Learning (NAS)

[Zoph et al. 2016]

- “Controller” network that learns to design a good network architecture (output a string corresponding to network design)
- Iterate:
  1) Sample an architecture from search space
  2) Train the architecture to get a “reward” R corresponding to accuracy
  3) Compute gradient of sample probability, and scale by R to perform controller parameter update (i.e. increase likelihood of good architecture being sampled, decrease likelihood of bad architecture)



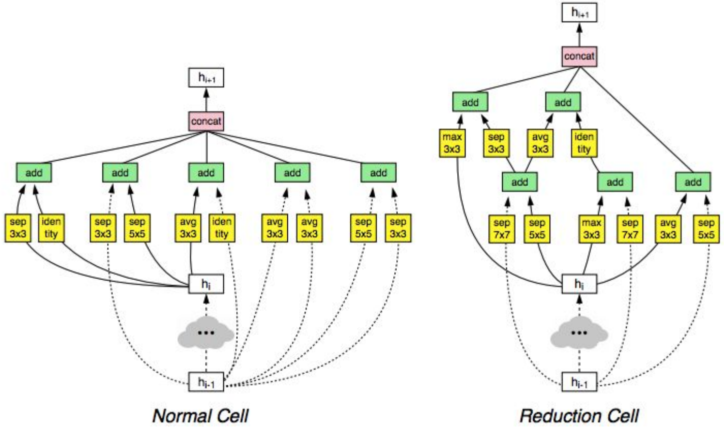


Learning to search for network architectures...

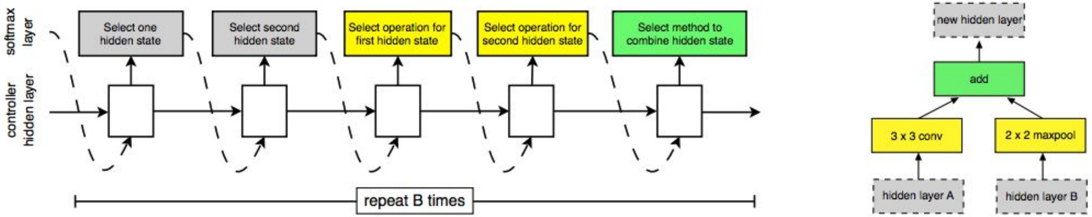
Learning Transferable Architectures for Scalable Image Recognition

[Zoph et al. 2017]

- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a search space of building blocks ("cells") that can be flexibly stacked
- NASNet: Use NAS to find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet



- Many follow-up works in this space e.g. AmoebaNet (Real et al. 2019) and ENAS (Pham, Guan et al. 2018)



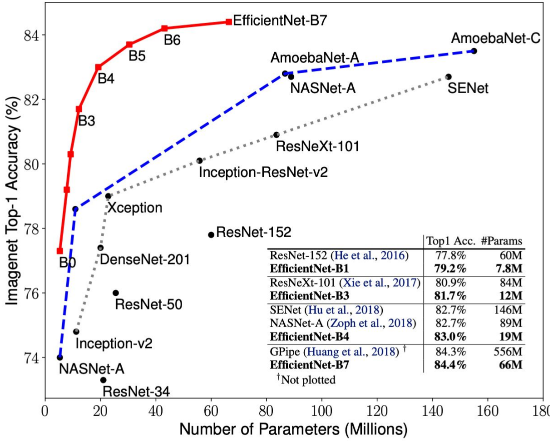
But sometimes smart heuristic is better than NAS ...

EfficientNet: Smart Compound Scaling

[Tan and Le. 2019]

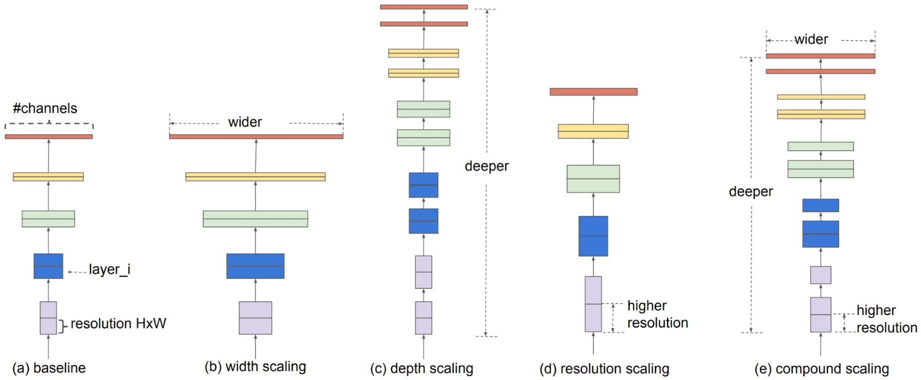
- Increase network capacity by scaling width, depth, and resolution, while balancing accuracy and efficiency.
- Search for optimal set of compound scaling factors given a compute budget (target memory & flops).
- Scale up using smart heuristic rules

$$
\begin{aligned}
\text{depth: } & d = \alpha^{\phi} \\
\text{width: } & w = \beta^{\phi} \\
\text{resolution: } & r = \gamma^{\phi} \\
\text{s.t. } & \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\
& \alpha \geq 1, \beta \geq 1, \gamma \geq 1
\end{aligned}
$$

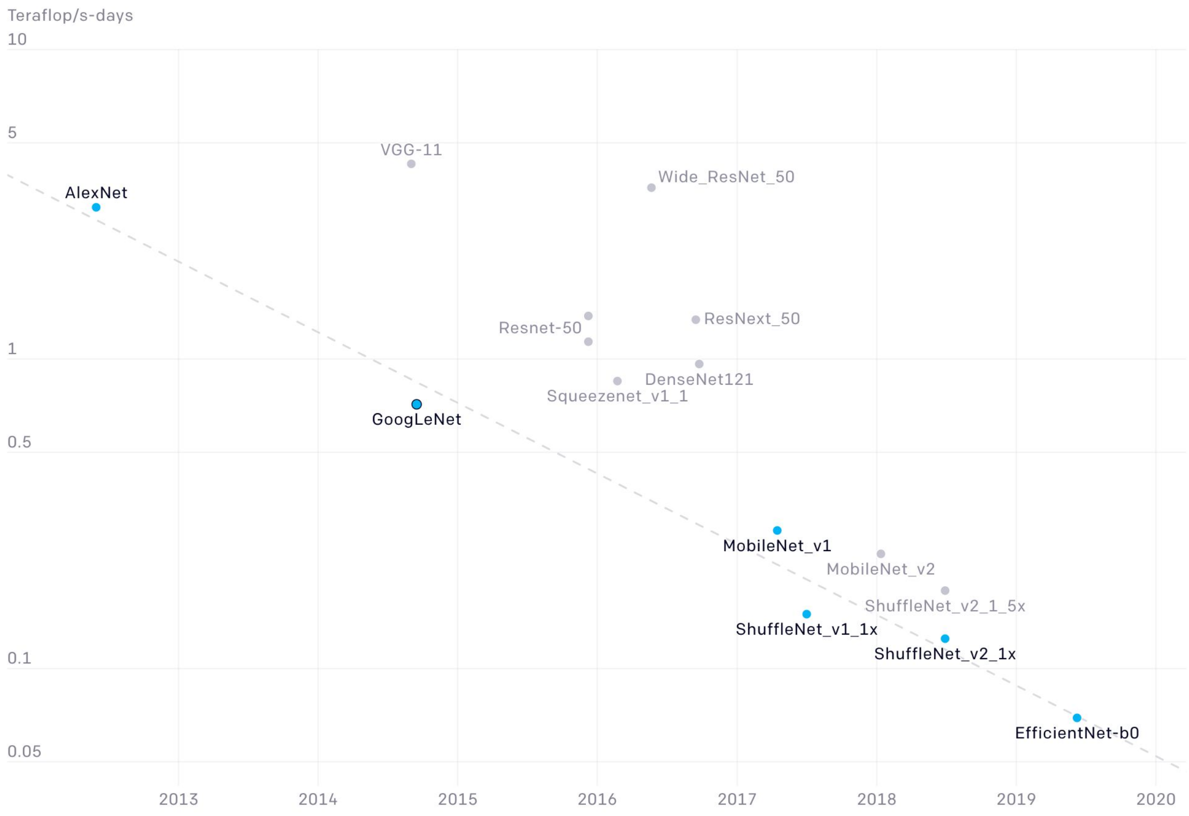


	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.2%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.7%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**83.0%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**66M**

†Not plotted



Efficient networks...



https://openai.com/blog/ai-and-efficiency/

Summary: Modern Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet
- Vit
- MLP-Mixer

Also....

- SENet
- Wide ResNet
- ResNeXT
- DenseNet
- MobileNets
- NASNet