



- feature
(old school) hand-crafted feature : Hog feature , SIFT, color
self learning feature : CNN

CNN : Conv, pool, MLP

LECTURE II OBJECT RECOGNITION II

Punnarai Siricharoen, Ph.D.

OBJECTIVES

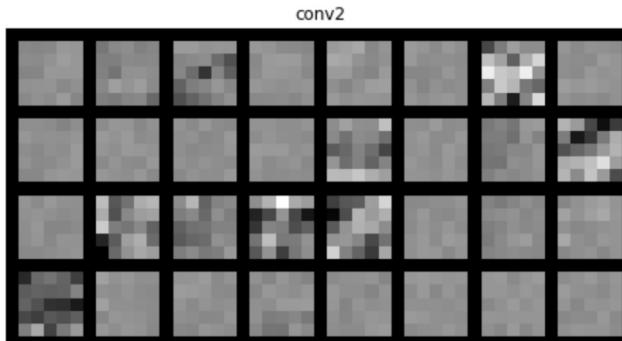
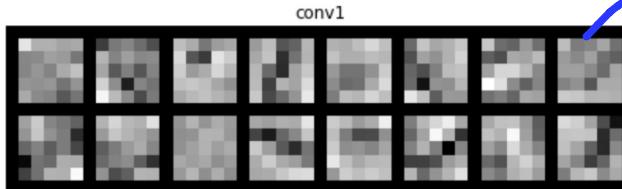
- Learn how to improving your model by augmentation techniques
- Learn the evolution of deep learning and how can you reuse the pre-trained model.

TODAY'S CONTENT

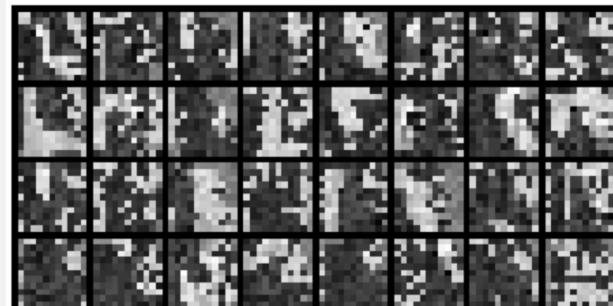
- Introduction
- Evaluation
- Recap - Image Transformation / Augmentation
- Visualizing filter and feature maps
- Evolution of Deep learning
- Transfer Learning

VISUALIZING FILTERS

filter in train layer 1



Conv3 (if added)



```
Net(  
    (conv1): Sequential(  
        (0): Conv2d(1, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    )  
    (conv2): Sequential(  
        (0): Conv2d(16, 32, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    )  
    (out): Linear(in_features=1568, out_features=10, bias=True)  
)
```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 16, 28, 28]	416
ReLU-2	[-1, 16, 28, 28]	0
MaxPool2d-3	[-1, 16, 14, 14]	0
Conv2d-4	[-1, 32, 14, 14]	12,832
ReLU-5	[-1, 32, 14, 14]	0
MaxPool2d-6	[-1, 32, 7, 7]	0
Linear-7	[-1, 10]	15,690

32 x 7 x 7

Total params: 28,938
Trainable params: 28,938
Non-trainable params: 0

Try to change kernel size?

VISUALIZING FEATURE MAPS

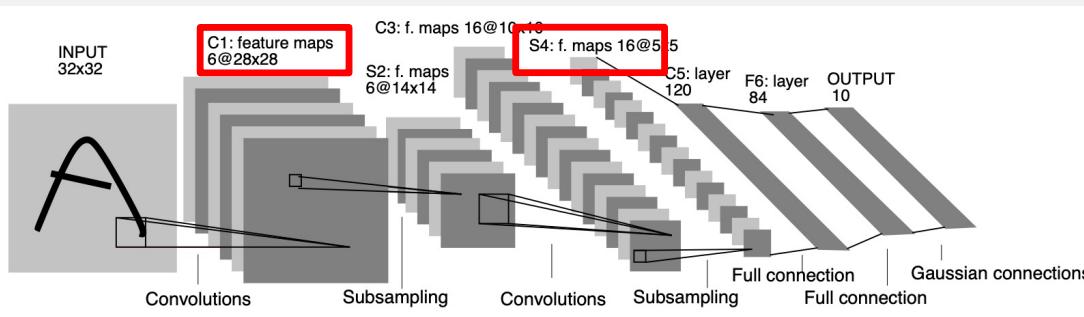
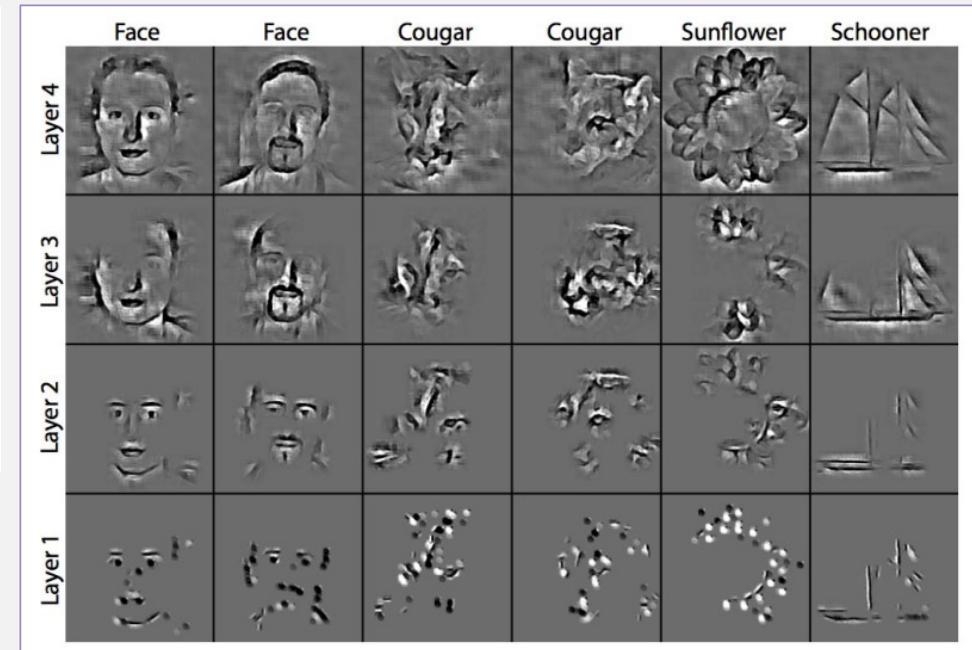
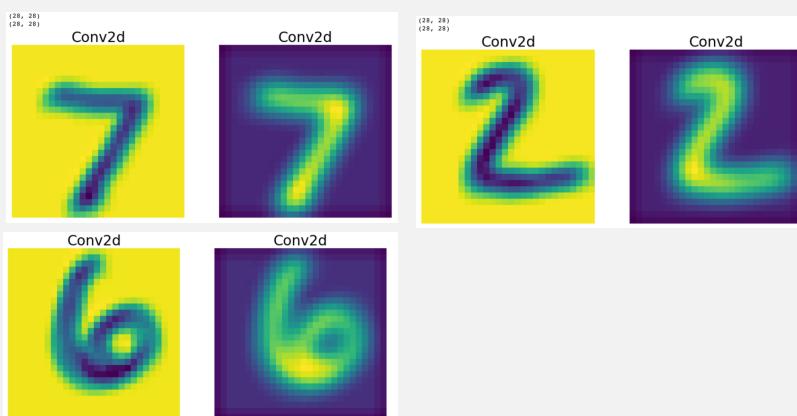


Fig. 1. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.



Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818–833). Springer International Publishing

TRANSFORMING AND AUGMENTING IMAGES

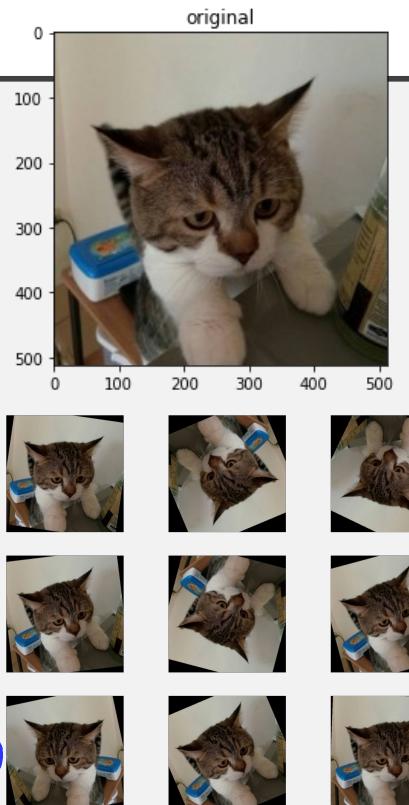
- **Pre-processing** – resize an image into the same size / convert an image into tensor type.

- **Image augmentation** - a technique that is used to artificially expand the dataset.
→ ដោយផ្តល់បច្ចុប្បន្ន data → more generalized

- This is helpful when we are given a dataset with very few data samples.
- In case of Deep Learning, this situation is bad as the model tends to over-fit when we train it on limited number of data samples.
- To improve the accuracy of Image Classification models
- Popular augmentation techniques - flip / scale / adding noise / rotation / crop / translation

សេចក្តី:

<https://pytorch.org/vision/stable/transforms.html>



ពេជ្របាយករណី

អង្គតា
អន្តោះ
អង្គន
(Gaussian, S&P)

នូវការបង្ការការងារ Medical : Augment នៅឯណ៍
ឱ្យការបង្ការការងារ

TRANSFORMING AND AUGMENTING IMAGES

- **Augmentation / Transformation in pytorch**

- Accept both PIL images and tensor images, although some transformations are PIL-only and some are tensor-only.

```
from PIL import Image
import numpy as np
im = Image.open("hopper.jpg")
a = np.asarray(im)
```

`Resize(size[, interpolation, max_size, ...])`

Resize the input image to the given size.

`RandomRotation(degrees[, interpolation, ...])`

Rotate the image by angle.

`RandomVerticalFlip([p])`

Vertically flip the given image randomly with a probability.

Conversion Transforms

`ToPILImage([mode])`

Convert a tensor or an ndarray to PIL Image.

`ToTensor()`

Convert a `PIL Image` or `numpy.ndarray` to tensor.

`PILToTensor()`

Convert a `PIL Image` to a tensor of the same type.

<https://pytorch.org/vision/stable/transforms.html>

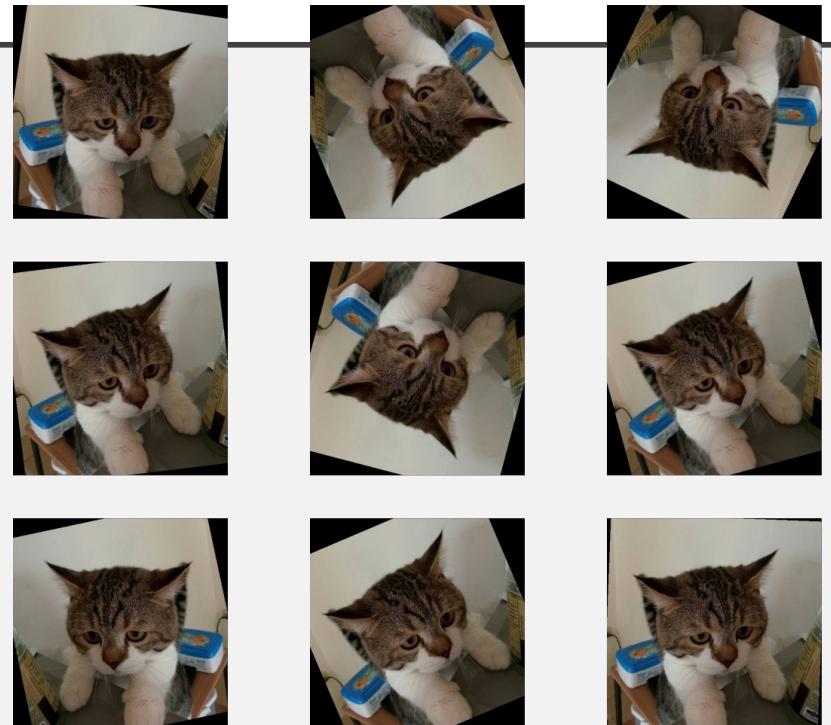
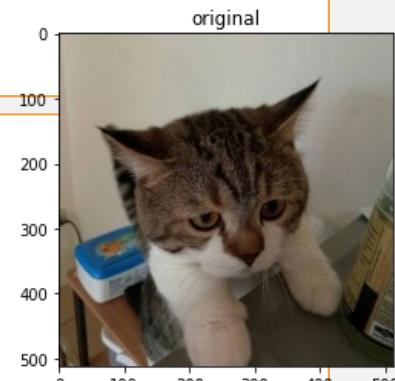
TRANSFORMING AND AUGMENTING IMAGES

```
data_transform = transforms.Compose([
    transforms.RandomHorizontalFlip(0.3),
    transforms.RandomVerticalFlip(0.3),
    transforms.RandomRotation((-30,30)),
    transforms.ToTensor(),
])
```

```
from PIL import Image
import numpy as np
im = Image.open("kitty.jpg")

figure(figsize=(18, 16), dpi=80)
for i in range(1,10):
    img_tr=data_transform(im).numpy()
    plt.subplot(3,3,i)
    plt.imshow(img_tr.transpose(1,2,0));
    plt.axis('off')

plt.show()
```



Use in the model

```
train_data = datasets.MNIST(
    root = 'data',
    train = True,
    transform = data_transform,
    download = True,
)
```

EXERCISE #1: AUGMENTATION WITH MNIST DATASET

- How are you going to augment the images for MNIST dataset?

EVOLUTION OF DEEP LEARNING

- The state-of-the-art **convolutional neural networks (CNNs or ConvNets)** is used for classification and regression.
- A pioneering 7-level convolutional network by LeCun et al in 1998, that classifies digits, was applied by several banks to recognize hand-written numbers on checks (cheques) digitized in 32x32 pixel greyscale input images.

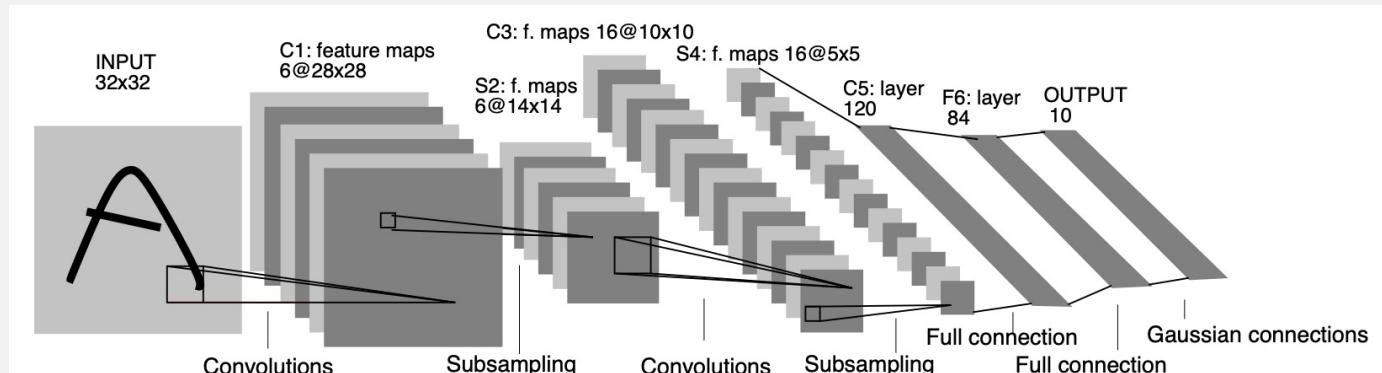


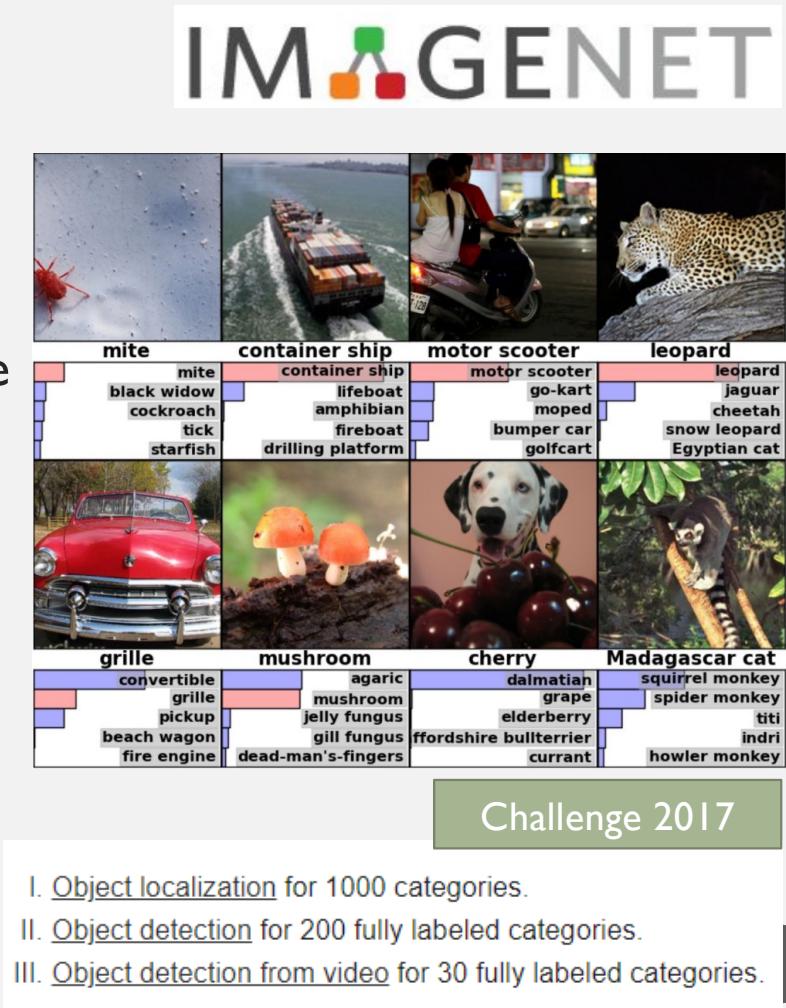
Fig. 1. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

1999 LeCun paper

EVOLUTION OF DEEP LEARNING

- **ImageNet** project is a **large** visual **database** for use in visual object recognition software research.
- More than **14 million images** have been hand-annotated by the project to indicate what objects are pictured
- In at least one million of the images, bounding boxes are also provided.
- ImageNet contains **more than 20,000 categories**
- The ImageNet project runs an annual software contest, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) – popular from 2012-2017

Referecne: <https://www.image-net.org>



EVOLUTION OF DEEP LEARNING

Top-5 សម្រាប់ប្រកបដោយ: អំពីរង់, ទូទៅ Top-1 error នឹងត្រួត 100:

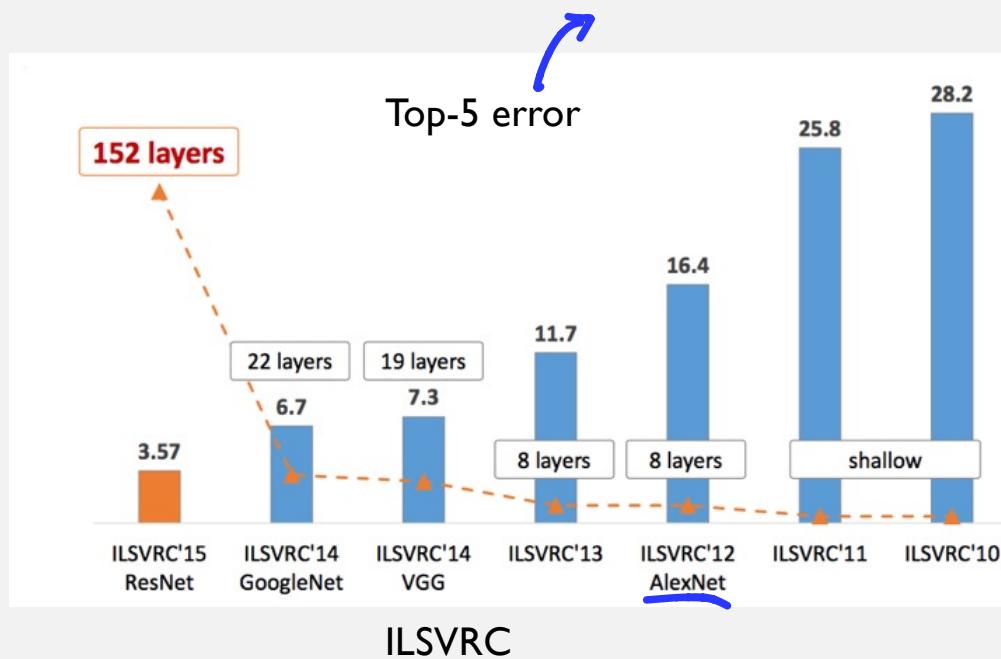
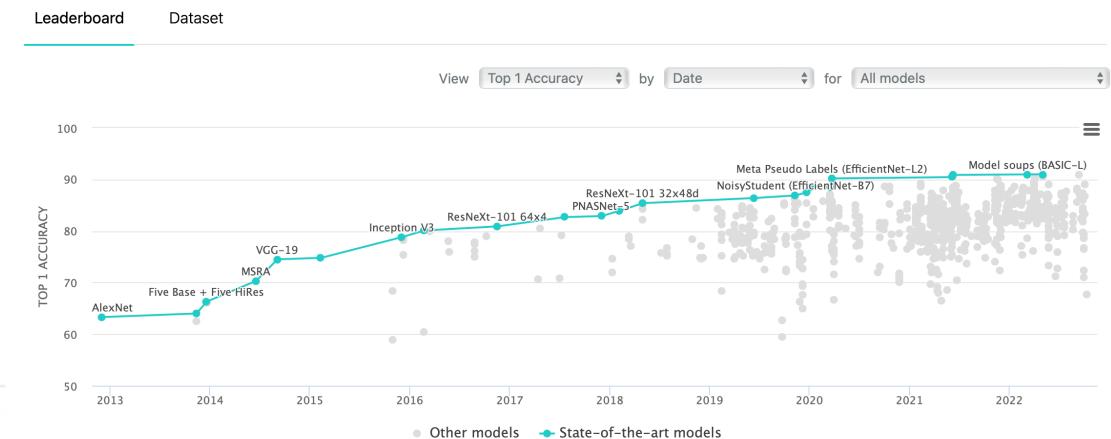


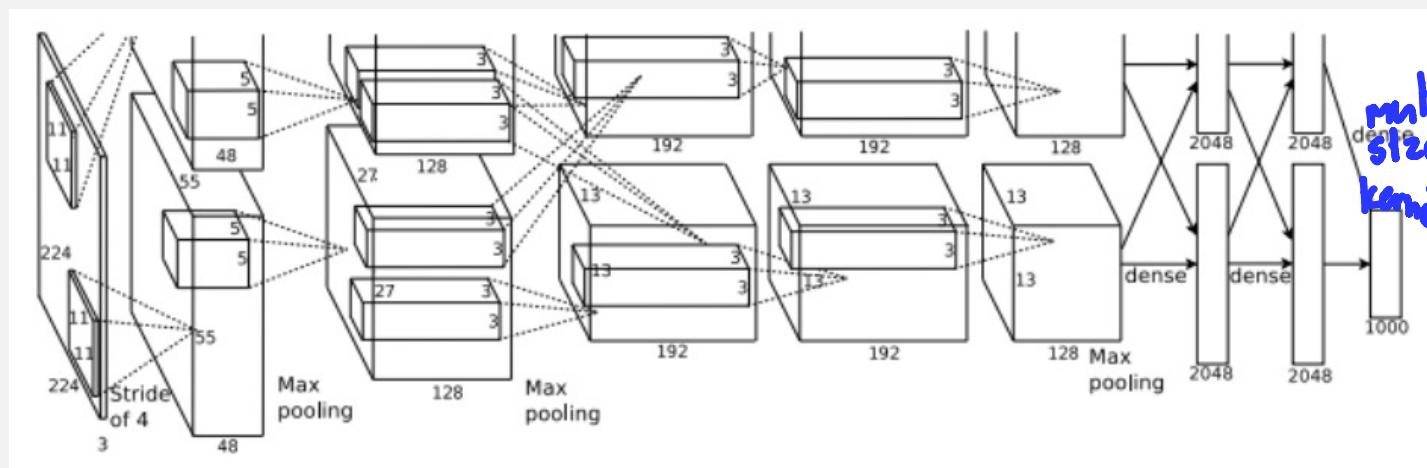
Image Classification on ImageNet



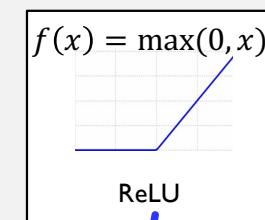
Paper with code

EVOLUTION OF DEEP LEARNING: ALEXNET (2012)

- In 2012, AlexNet, significantly outperformed all the prior competitors and won the challenge by reducing the top-5 error from 26% to 15.3%



Deeper than LeNet-5, with more filters per layer, and with stacked convolutional layers. It consisted of 11x11, 5x5, 3x3 convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum.



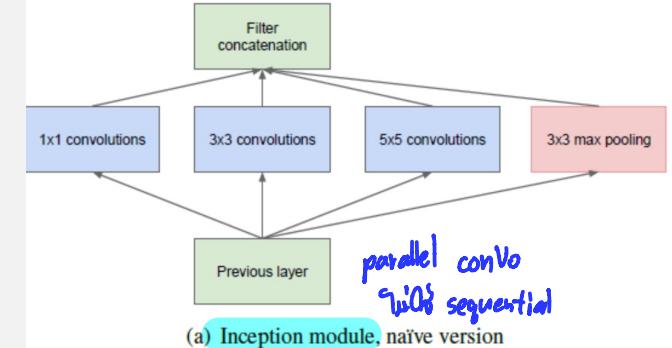
Alex net

<https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5>

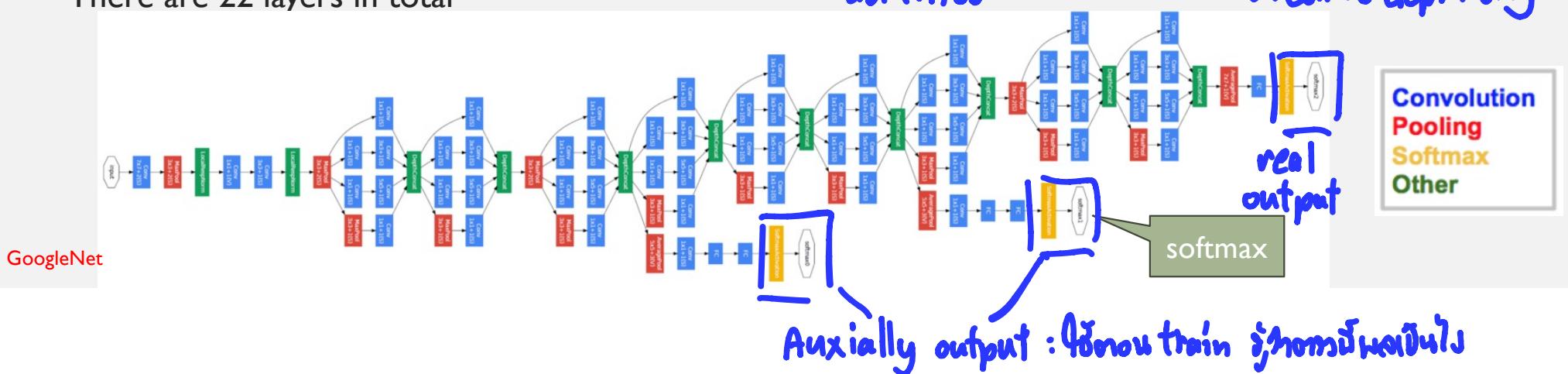
Quick to train!

EVOLUTION OF DEEP LEARNING: GOOGLENET/INCEPTION(2014)

- The winner of the ILSVRC 2014 competition was GoogleNet (a.k.a. Inception V1) from Google. It achieved a top-5 error rate of 6.67%!
- inception module**, is to have different sizes/types of convolutions for the same input and stacking all the outputs.
- Batch normalization, image distortions and RMSprop
- 1x1 Convolution at the middle of the network** - reduced the number of parameters from 60 million (AlexNet) to 4 million - help to reduce model size which can also somehow help to reduce the overfitting problem!!
- There are 22 layers in total



1x1 ConV \rightarrow depth w/ sed Convo
 ແກ້ວມີການສະແດງທີ່ໄສຂັ້ນທາງຕົວ
 1D ConVo depth only



EVOLUTION OF DEEP LEARNING: VGGNET (2014)

- The runner-up at the ILSVRC 2014 competition; developed by Simonyan and Zisserman (Oxford team)
- VGGNet consists of 16/19 convolutional layers and is very appealing because of its very uniform architecture.
- Similar to AlexNet, only 3x3 convolutions, but lots of filters. Trained on 4 GPUs for 2–3 weeks.

Simple, ไม่มีอะไรผิดปกติ
กล้วยๆมาก

VGGNet consists of
138 million parameters



EVOLUTION OF DEEP LEARNING: RESNET (2015)

- Residual learning is adopted to every few stacked layers. The operation $F + x$ is performed by a shortcut connection and element-wise addition.
- batch normalization (BN) is implemented right after each convolution and before activation.
- Such skip connections are also known as gated units or gated recurrent units and have a strong similarity to recent successful elements applied in RNNs.
- easier to optimize and achieves a top-5 error rate of 3.57% which beats human-level performance on this dataset.

Resnet

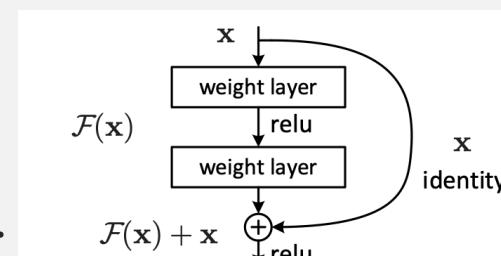


Figure 2. Residual learning: a building block.

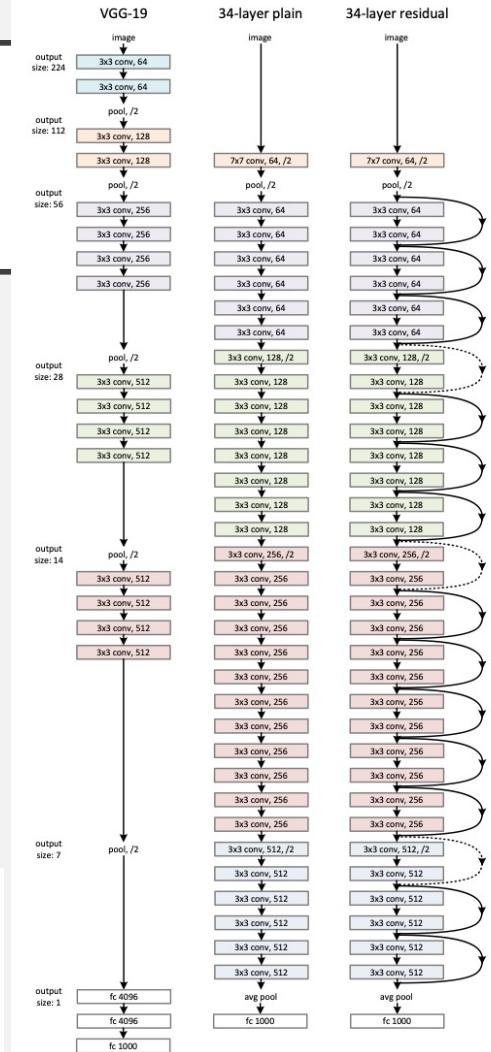
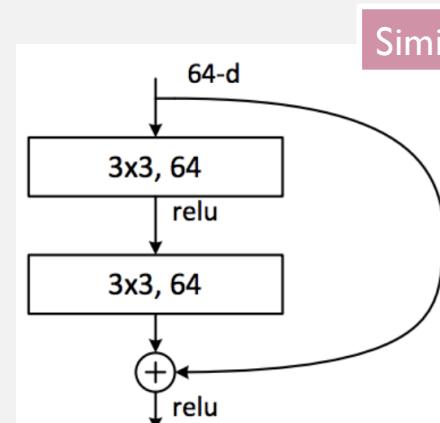
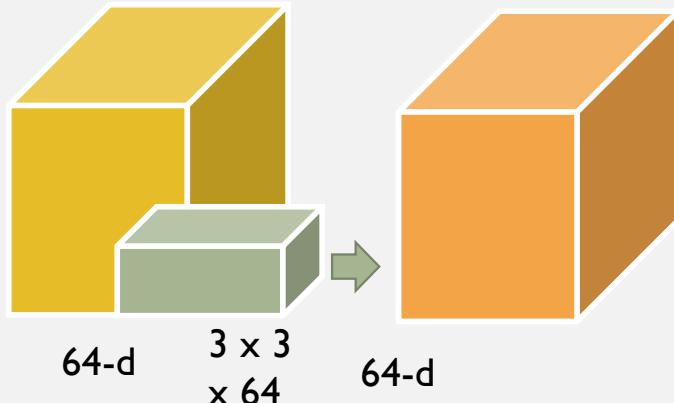


Figure 3. Example network architectures for ImageNet. Left: the VGG-19 model [40] (19.6 billion FLOPs) as a reference. Middle: a plain network with 34 parameter layers (3.6 billion FLOPs). Right: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. Table 1 shows more details and other variants.

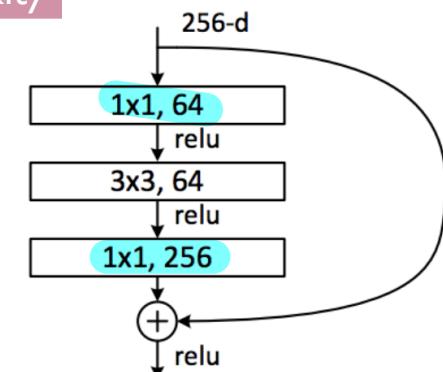
ఇంజనీరింగ్, ఆఫీస్

EVOLUTION OF DEEP LEARNING: RESNET (2015)

- A BottleNeck block is very similar to a BasicBlock in the figure below. Where the 1x1 layers are responsible for reducing and then increasing (restoring) dimensions, leaving the 3x3 layer a bottleneck with smaller input/output dimensions.



Similar complexity



Convolution -> $256 \times 64 + 64 \times 3 \times 3 \times 64 + 64 \times 256 = 69,632$ params (excluding bias)

Convolution -> $64 \times 3 \times 3 \times 64 \times 2 = 73,728$ params (excluding bias)

Figure 1: Basic block on the left. BottleNeck on the right.

Params ດូសត្រូវ depth នៅ 4 នាក់

EVOLUTION OF DEEP LEARNING: RESNET (2015)

- Performance of the Bottleneck

With bottleneck

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112			7×7, 64, stride 2		
conv2_x	56×56	$\left[\begin{array}{l} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$
conv3_x	28×28	$\left[\begin{array}{l} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 8$
conv4_x	14×14	$\left[\begin{array}{l} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array} \right] \times 6$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 6$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 23$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 36$
conv5_x	7×7	$\left[\begin{array}{l} 3 \times 3, 512 \\ 3 \times 3, 512 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 512 \\ 3 \times 3, 512 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Param
ಗಳನ್ನು

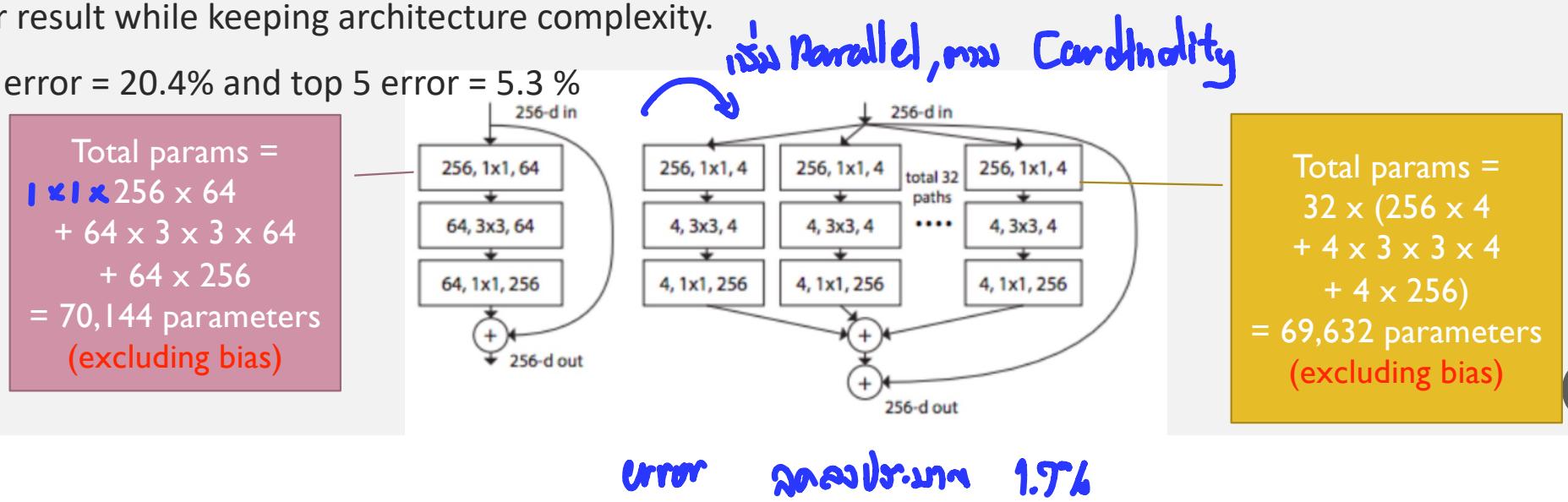
model	top-1 err.	top-5 err.
VGG-16 [40]	28.07	9.33
GoogLeNet [43]	-	9.15
PReLU-net [12]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	21.43	5.71

Table 3. Error rates (%), 10-crop testing) on ImageNet validation. VGG-16 is based on our test. ResNet-50/101/152 are of option that only uses projections for increasing dimensions.

So 34 → Resnet50
with Resnet34

EVOLUTION OF DEEP LEARNING: RESNEXT (2017)

- A combination of splitting, transforming, and aggregating.
 - **Splitting**: the input is split into a few lower-dimensional embeddings
 - **Transforming**: the low-dimensional representation is transformed
 - **Aggregating**: the transformations in all embeddings are aggregated by summation.
- Cardinality is the size of the set of transformations. Refer to the following figure, the architecture includes 32 same topology blocks so the value of cardinality is 32. Because of using the same topology, fewer parameters are required while more layers are added into this architecture. Increasing cardinality lead to better result while keeping architecture complexity.
- Top 1 error = 20.4% and top 5 error = 5.3 %



EVOLUTION OF DEEP LEARNING: RESNEXT (2017)

Total params =
 256×64
 $+ 64 \times 3 \times 3 \times 64$
 $+ 64 \times 256$
 $= 70,144$ parameters
 (excluding bias)

983,040 parameters

3,932,160
parameters

stage	output	ResNet-50	ResNeXt-50 (32×4d)
conv1	112×112	7×7, 64, stride 2	7×7, 64, stride 2
conv2	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	3×3 max pool, stride 2 $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128, C=32 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3	28×28	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256, C=32 \\ 1\times1, 512 \end{bmatrix} \times 4$
conv4	14×14	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512, C=32 \\ 1\times1, 1024 \end{bmatrix} \times 6$
conv5	7×7	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 1024 \\ 3\times3, 1024, C=32 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	global average pool 1000-d fc, softmax	global average pool 1000-d fc, softmax
# params.		25.5×10^6	25.0×10^6
FLOPs		4.1×10^9	4.2×10^9

Total params =
 $32 \times (256 \times 4$
 $+ 4 \times 3 \times 3 \times 4$
 $+ 4 \times 256)$
 $= 69,632$ parameters
 (excluding bias)

614,400 parameters

3,440,640
parameters

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EVOLUTION OF DEEP LEARNING: EFFICIENTNET (2020)

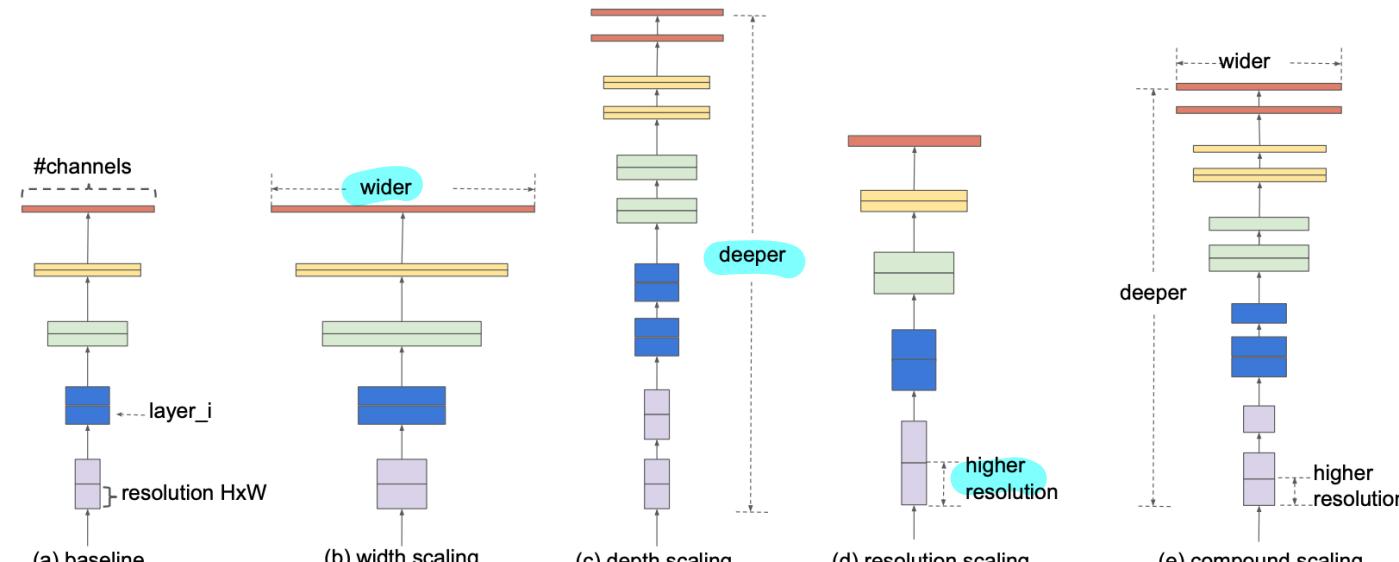


Figure 2. Model Scaling. (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

- A compound scaling method, which use a compound coefficient ϕ to uniformly scales network width, depth, and resolution in a principled way
- EfficientNet-B0 is the baseline scaled up to EfficientNet-B7

Table 8. ImageNet Validation vs. Test Top-1/5 Accuracy.

	B0	B1	B2	B3	B4	B5	B6	B7
Val top1	77.11	79.13	80.07	81.59	82.89	83.60	83.95	84.26
Test top1	77.23	79.17	80.16	81.72	82.94	83.69	84.04	84.33
Val top5	93.35	94.47	94.90	95.67	96.37	96.71	96.76	96.97
Test top5	93.45	94.43	94.98	95.70	96.27	96.64	96.86	96.94

4.04%

EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)

CNN uses image *man text*

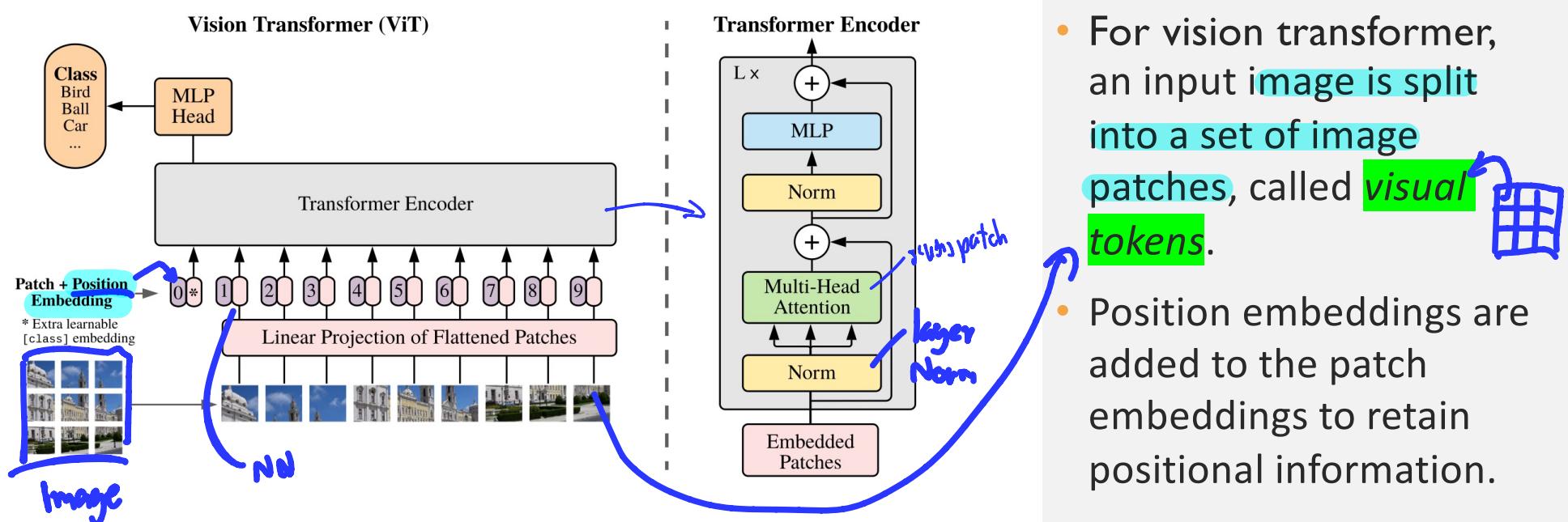
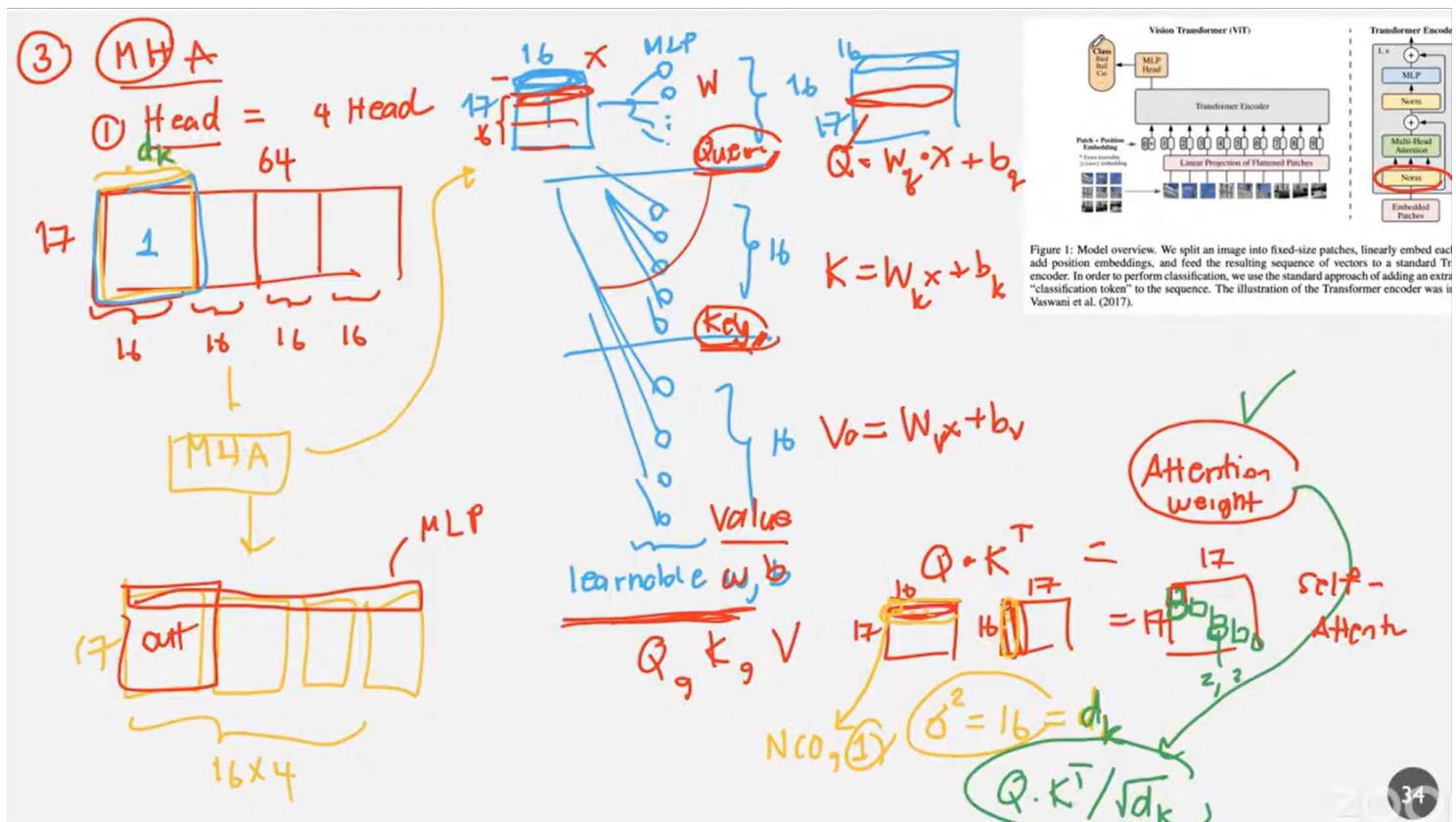
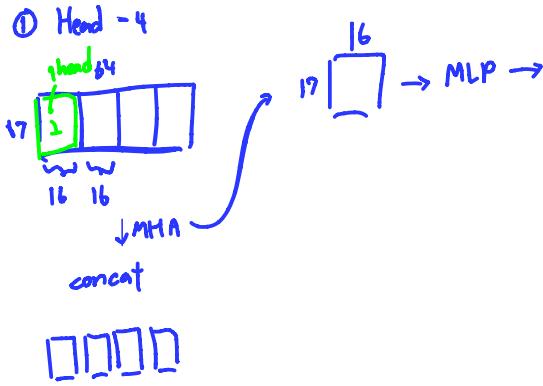


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

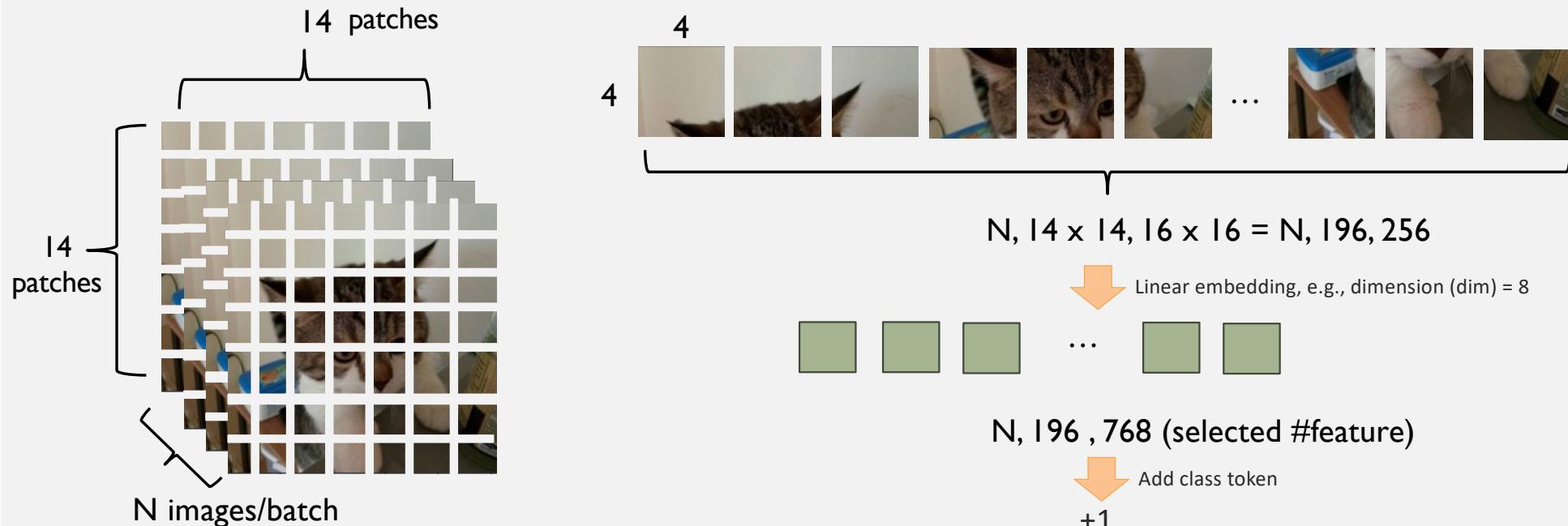
Attention is all you need, Vaswani A. et al. (2021)
class token : learnable, introduced for classification

Multi-head Attention



EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)

- Linear embedding of flattened patches and adding class token



Attention is all you need, Vaswani A., et al. (2021)

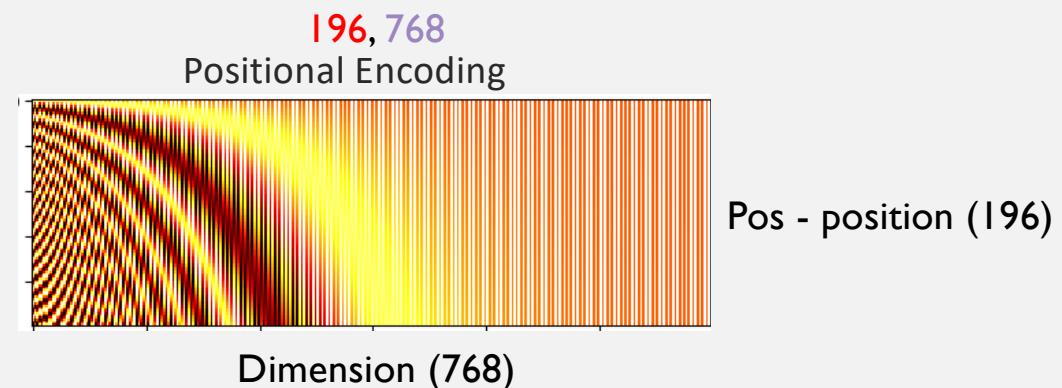
EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)

- Positional embedding – model knows where each patch would be placed.



$$PE_{pos,j} = \begin{cases} \sin(pos/10000^{2*j/dim}), & j \text{ even} \\ \sin(pos/10000^{2*j-1/dim}), & j \text{ odd} \end{cases}$$

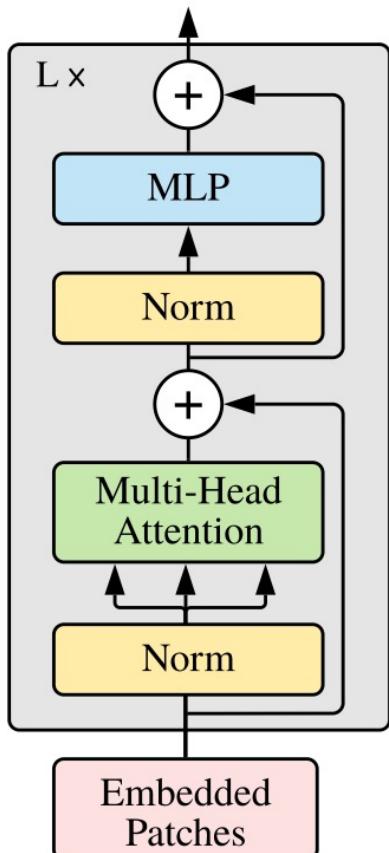
in learnable position



e.g., our dim = 768, have 196 different positional encoding values for each sequence (patch). It would allow the model to easily learn to attend by relative positions.

EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)

Transformer Encoder



Transformer Encoder

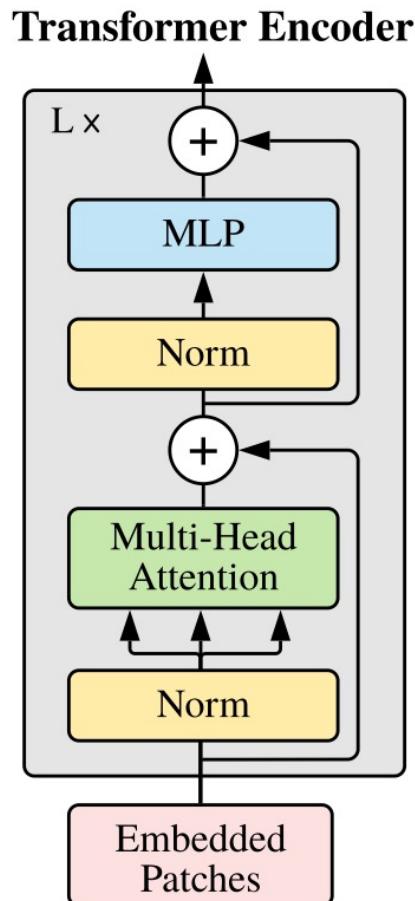
- There are multiple blocks in the ViT encoder ($L \times$)
- Each block consists of three major processing elements:
 1. **Layer Norm** - Applies Layer Normalization over a mini-batch of inputs across all features and keeps the training process on track and let model adapt to the variations among the training images.
bias 2 m

$$y = \frac{x - \mu}{\sqrt{\sigma + \epsilon}} * \gamma + \beta$$

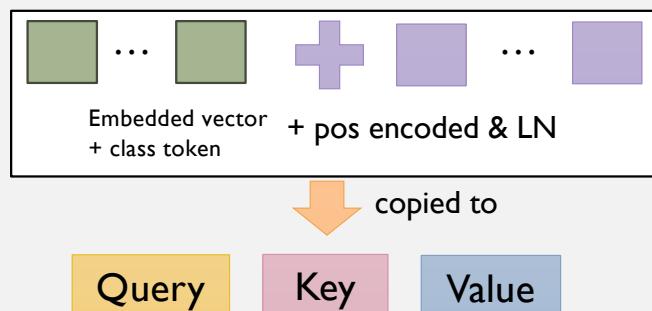
The mean (μ) and standard-deviation (σ) are calculated over the last dimension. γ and β are learnable parameters.

Attention is all you need, Vaswani A., et al. (2021)

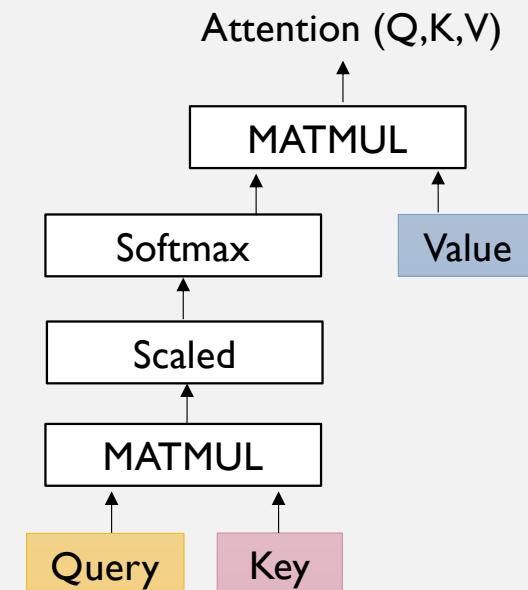
EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)



2. Multi-head Attention Network (MSA) - a network responsible for generation of attention maps from the given embedded visual tokens. These attention maps help network focus on most important regions in the image such as object(s).



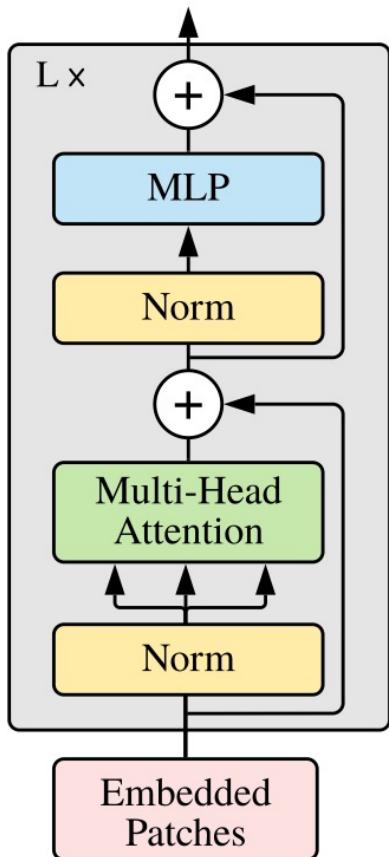
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{\dim}}\right) \cdot V$$



Attention is all you need, Vaswani A., et al. (2021)

EVOLUTION OF DEEP LEARNING: VISION TRANSFORMER (2021)

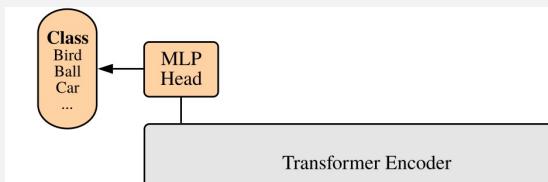
Transformer Encoder



3. Residual Connection – add the original input to the result of some computation

- **Multi-Layer Perceptrons (MLP)**

- Encoder blocks – composed of A two-layer classification network with GELU (*Gaussian Error Linear Unit*) at the end.



- Classification MLP block, also termed as *MLP head* (only the class token) is used as an output of the transformer. An application of *softmax* on this output can provide classification labels (i.e. if the application is Image Classification).

$N, 768 \times n\text{Head}$ $N, 10$
for 10-class
MLP

Original use of ViT:

- <https://github.com/lucidrains/vit-pytorch?tab=readme-ov-file#vision-transformer---pytorch>

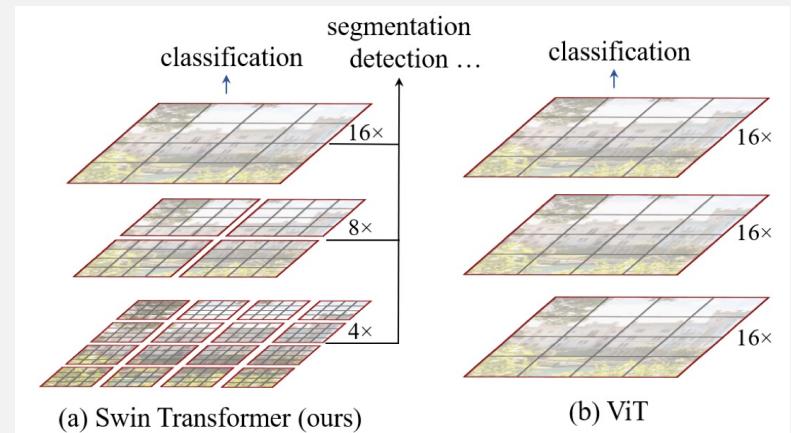
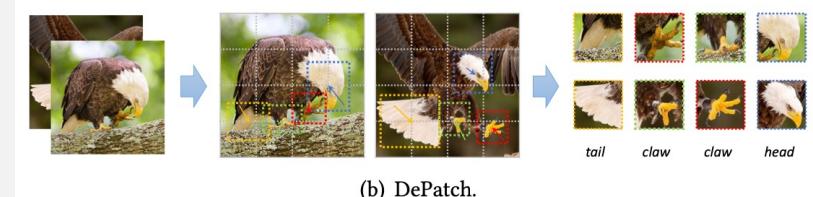
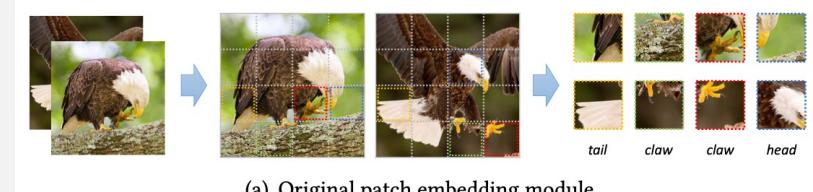
ViT from scratch

- Simplified version <https://github.com/tintn/vision-transformer-from-scratch>
 - <https://colab.research.google.com/drive/1FrOmq3G-xLYkc08sYV43xBY6ZOOF-LaA>
- <https://medium.com/@briannpulfer/vision-transformers-from-scratch-pytorch-a-step-by-step-guide-96c3313c2e0c>

VARIANTS OF VITS

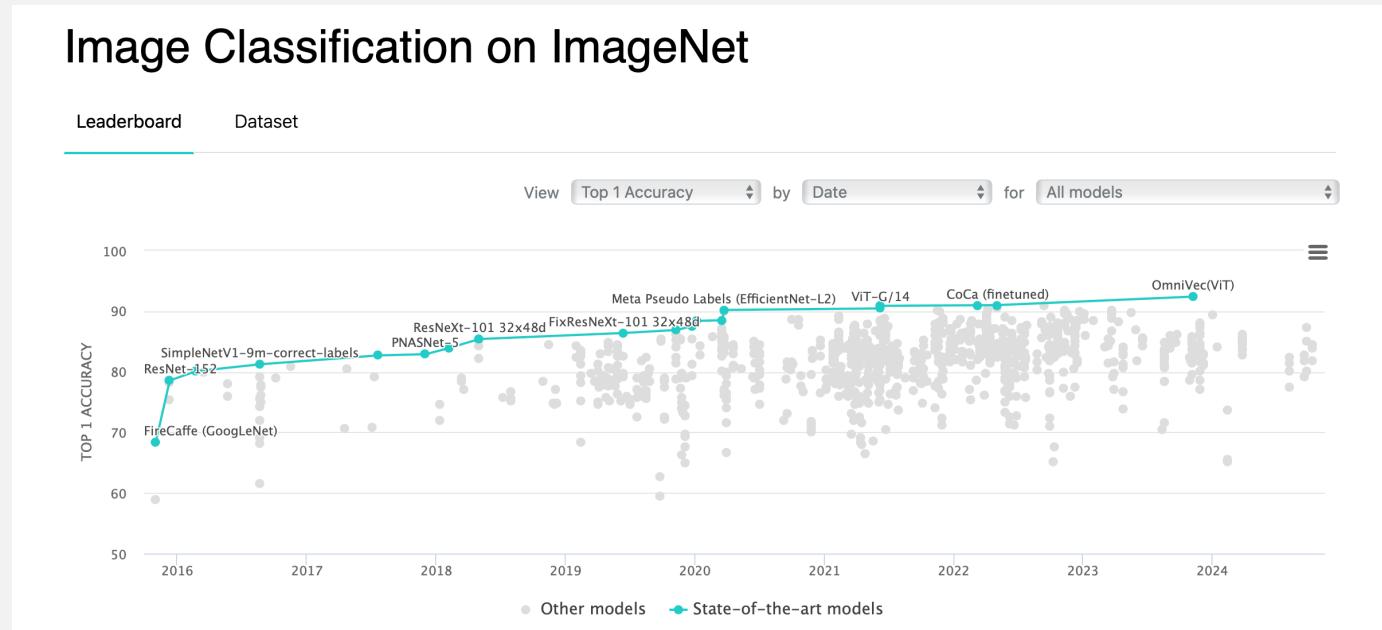
- **Deformable Patch-based Transformer (DPT)** – instead of using fixed-size patch embedding, DPT learns to adaptively split the images into patches with different positions and scales.
- **Swin Transformer: Hierarchical Vision Transformer using Shifted Windows** - the shifted windowing scheme brings greater efficiency by limiting self-attention computation to non-overlapping local windows while also allowing for **cross-window connection**.

Chen Z., et al. (2021) DPT: Deformable Patch-based Transformer for Visual Recognition
Liu Z., et al. (2021) Swin Transformer: Hierarchical Vision Transformer using Shifted Windows



VARIANTS OF VITS

- https://paperswithcode.com/sota/image-classification-on-imagenet?tag_filter=171



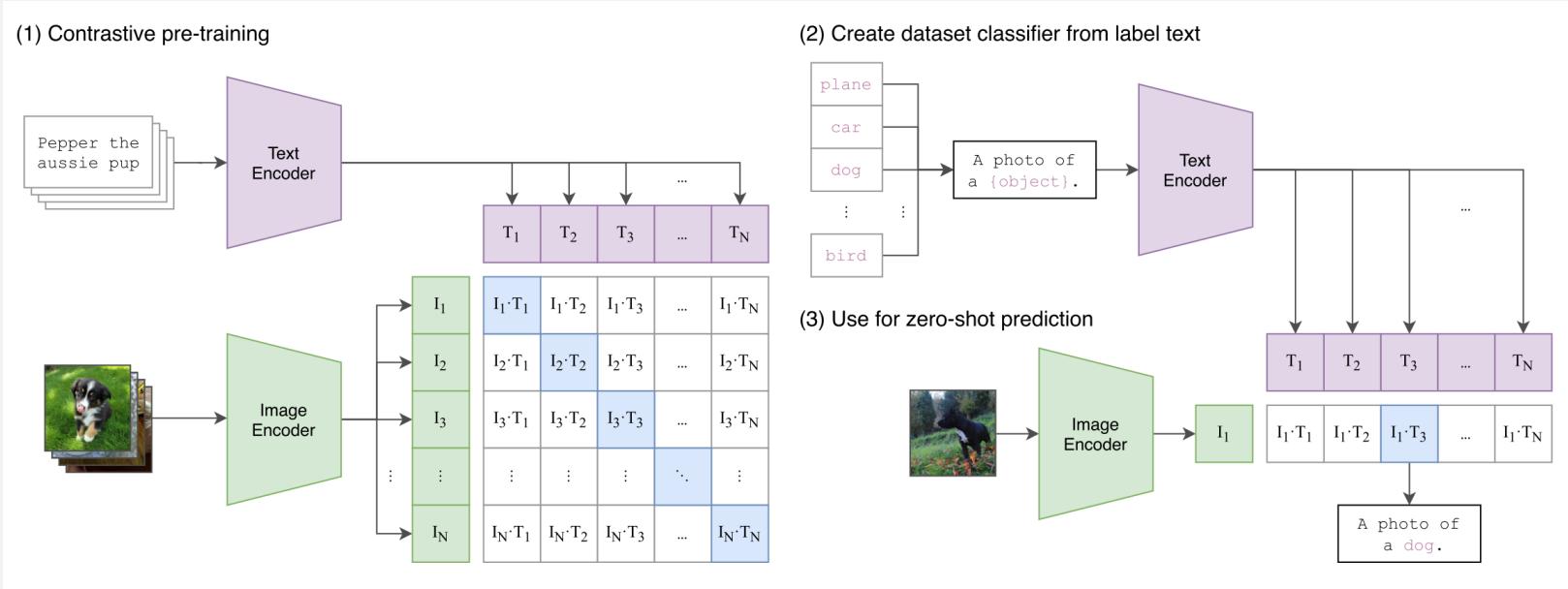
CLIP: CONTRASTIVE LANGUAGE-IMAGE PRETRAINING

- Traditional vision models are trained on fixed label sets and struggle to generalize to new categories.
- Approach: Train an image encoder + a text encoder jointly on 400 million (image, caption) pairs using a contrastive objective: match correct image–text pairs, distinguish incorrect ones.
- Zero-Shot Transfer: At test time, given an image and a set of text prompts (e.g., “a photo of a {label}”), the model computes similarities in embedding space and picks the best text match—allowing classification on new tasks without re-training.
- Results: Achieves performance competitive with supervised models across ~30 different vision benchmarks, e.g. it matches a ResNet-50 on ImageNet zero-shot despite not using the 1.28 M ImageNet labels.
- Implication: Natural language supervision scales vision models beyond fixed label sets, enabling broader generality and transferability.

A. Radford et al., “Learning Transferable Visual Models From Natural Language Supervision,” 2021. [Online]. Available: <https://github.com/OpenAI/CLIP>.

- <https://colab.research.google.com/drive/10eHIQkcpn4-Sc06hOiY36XQnyMn0A7DC?usp=sharing>

CLIP: CONTRASTIVE LANGUAGE–IMAGE PRETRAINING



CLIP Workflow

A. Radford et al., “Learning Transferable Visual Models From Natural Language Supervision,” 2021. [Online]. Available: <https://github.com/OpenAI/CLIP>.

- <https://colab.research.google.com/drive/10eHIQkcpn4-Sc06hOiY36XQnyMn0A7DC?usp=sharing>

TRANSFER LEARNING

- In practice, very few people train an entire Convolutional Network from scratch (with random initialization), because it is relatively rare to have a dataset of sufficient size.
- Instead, it is common to pretrain a ConvNet on a very large dataset (e.g. ImageNet, which contains 1.2 million images with 1000 categories), and then use the ConvNet either as an initialization or a fixed feature extractor for the task of interest.
- Three major Transfer Learning scenarios:
 1. ConvNet as fixed feature extractor
 2. Fine-tuning the ConvNet
 3. Pretrained models

TRANSFER LEARNING

1. ConvNet as fixed feature extractor

- Take a ConvNet pretrained on ImageNet, remove the last fully-connected layer
- Train a linear classifier (e.g. Linear SVM or Softmax classifier) for the new dataset.

2. Fine-tuning the ConvNet

- not only replace and retrain the classifier on top of the ConvNet on the new dataset, but to also fine-tune the weights of the pretrained network.
- It is possible to fine-tune all the layers, or to keep some of the earlier layers fixed (overfitting concerns)
- The observation that the earlier features of a ConvNet contain more generic features (e.g. edge detectors or color blob detectors)

3. Pretrained models

- Modern ConvNets take 2-3 weeks to train across multiple GPUs on ImageNet. The release of the final ConvNet checkpoints of many researcher can be beneficial for fine-tuning your model.

References: <https://cs231n.github.io/transfer-learning/>

TRANSFER LEARNING

When and how to fine-tune?

- New dataset is small and similar to original dataset.
- New dataset is large and similar to the original dataset.
- New dataset is small but very different from the original dataset.
- New dataset is large and very different from the original dataset.

The best idea might be to train a linear classifier on the CNN

More confidence that wont be overfit. Try to fine-tune through the full network.

best to only train a linear classifier.
- The top networks contains dataset-specific features
- work better to train the SVM classifier from activations somewhere earlier in the network.

- To train a ConvNet from scratch.
- Still beneficial to initialize with weights from a pretrained mode

References: <https://cs231n.github.io/transfer-learning/>

EXALPLE #2: TRANSFER LEARNING

The screenshot shows a web browser displaying the PyTorch documentation at pytorch.org/vision/stable/models.html. The page is titled "Classification". On the left, there is a sidebar with navigation links for various PyTorch modules and libraries. The main content area contains a list of classification models available with or without pre-trained weights.

Sidebar Navigation:

- Transforming and augmenting images
- Models and pre-trained weights (selected)
- Datasets
- Utils
- Operators
- Reading/Writing images and videos
- Feature extraction for model inspection
- Examples and training references
- Example gallery
- Training references
- PyTorch Libraries
- PyTorch
- torchaudio
- torchtext
- torchvision
- TorchElastic
- TorchServe
- PyTorch on XLA Devices

Main Content: Classification

The following classification models are available, with or without pre-trained weights:

- AlexNet
- ConvNeXt
- DenseNet
- EfficientNet
- EfficientNetV2
- GoogLeNet
- Inception V3
- MaxVit
- MNASNet
- MobileNet V2
- MobileNet V3
- RegNet
- ResNet
- ResNeXt
- ShuffleNet V2
- SqueezeNet
- SwinTransformer
- VGG
- VisionTransformer
- Wide ResNet

<https://pytorch.org/vision/stable/models.html>

EXALPLE #2: TRANSFER LEARNING

- **Fine-tuning the model** - Load a pretrained model and reset final fully connected layer.

```
model_ft = models.resnet18(pretrained=True)
num_ftrs = model_ft.fc.in_features
# Here the size of each output sample is set to 2.
# Alternatively, it can be generalized to nn.Linear(num_ftrs, len(class_names)).
model_ft.fc = nn.Linear(num_ftrs, 2)
```

```
model_ft = model_ft.to(device)

criterion = nn.CrossEntropyLoss()

# Observe that all parameters are being optimized
optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.001, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)
```

EXALPLE #2: TRANSFER LEARNING

- **ConvNet as fixed feature extractor** - freeze all the network except the final layer. We need to set `requires_grad = False` to freeze the parameters so that the gradients are not computed in `backward()`.

```
model_conv = torchvision.models.resnet18(pretrained=True)
for param in model_conv.parameters():
    param.requires_grad = False

# Parameters of newly constructed modules have requires_grad=True by default
num_ftrs = model_conv.fc.in_features
model_conv.fc = nn.Linear(num_ftrs, 2)

model_conv = model_conv.to(device)

criterion = nn.CrossEntropyLoss()

# Observe that only parameters of final layer are being optimized as
# opposed to before.
optimizer_conv = optim.SGD(model_conv.fc.parameters(), lr=0.001, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_conv, step_size=7, gamma=0.1)
```

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- DL Evolution: <https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5>
- Transformer: <https://medium.com/mlearning-ai/vision-transformers-from-scratch-pytorch-a-step-by-step-guide-96c3313c2e0c>
- Additional reading
 - Basic ML - <https://www.coursera.org/learn/machine-learning>
 - Convolutional neural networks & Object detection -
<https://www.coursera.org/lecture/convolutional-neural-networks/object-detection-VgyWR>

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