THE UNIVERSITY OF MELBOURNE

Deep Learning I

Semester 2, 2022

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Outline

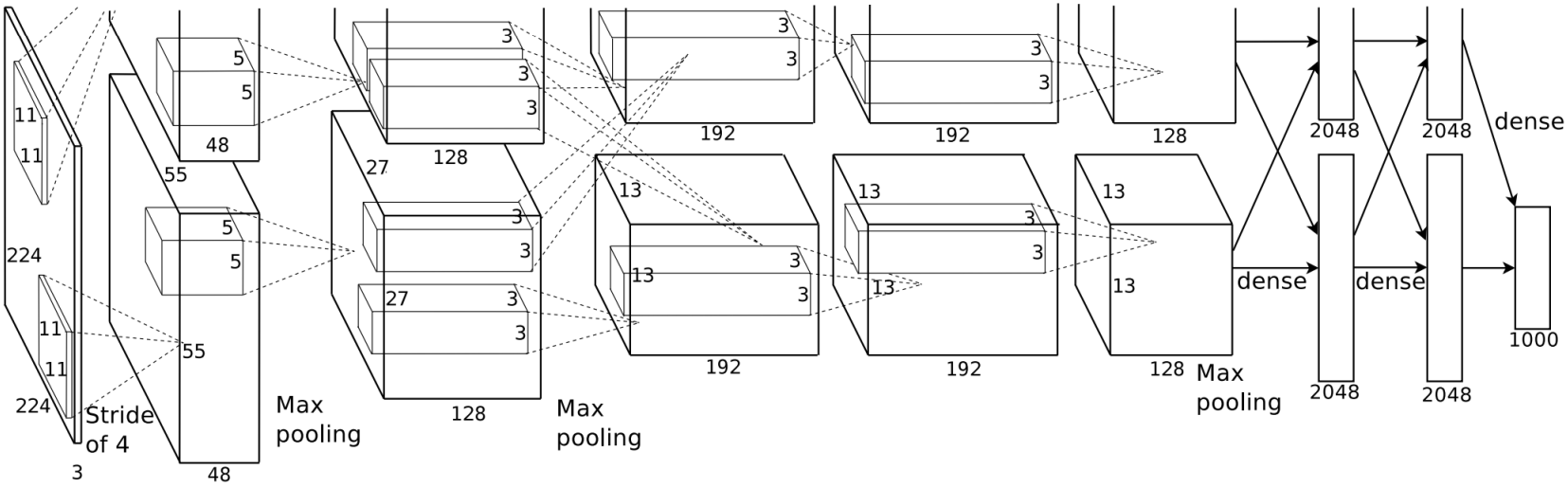
- Common architectures for ImageNet classification
- ImageNet classification results
- Transfer learning

Learning outcomes

- Explain the key differences between commonly-used architectures for ImageNet classification
- Evaluate image classification results
- Explain and implement transfer learning with networks pretrained on ImageNet

Common architectures

AlexNet

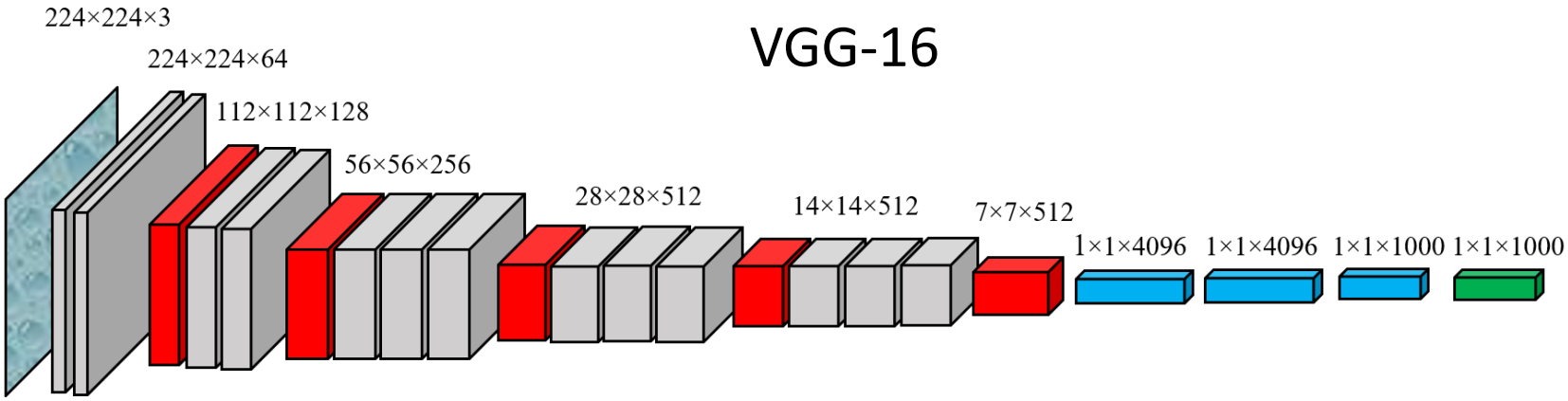


Krizhevsky, Sutskever, & Hinton (2012)

AlexNet innovations

- ReLU (Rectified Linear Unit) activation function – faster training
- Training on GPU – parallelisation allows faster training (actually required 2 GPUs at the time!)
- Overlapping max pooling regions, response normalisation after ReLU – small accuracy increase
- Data augmentation – reduces overfitting
- Dropout – reduces overfitting

VGG



VGG-16

Convolutional layer
Kernel size = 3 x 3 x channels

Max pooling

Fully-connected layer

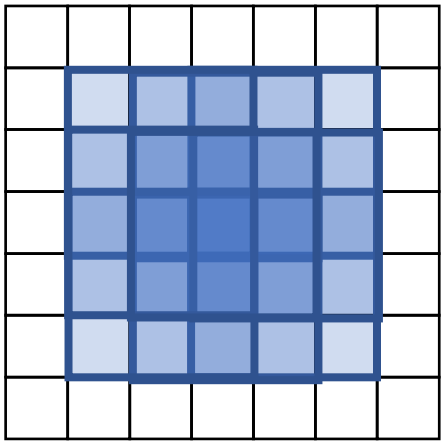
Softmax

Other VGG variations with more/fewer layers (e.g., VGG-19)

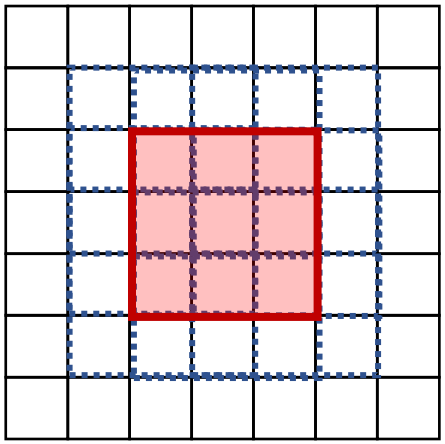
Simonyan & Zisserman (2014)

Stacked convolutional layers

- VGG stacks multiple 3 x 3 convolutional kernels to effectively make larger kernels:
  - Two 3 x 3 conv. layers = effective receptive field of 5 x 5
  - Three 3 x 3 conv. layers = effective receptive field of 7 x 7



Conv layer 1

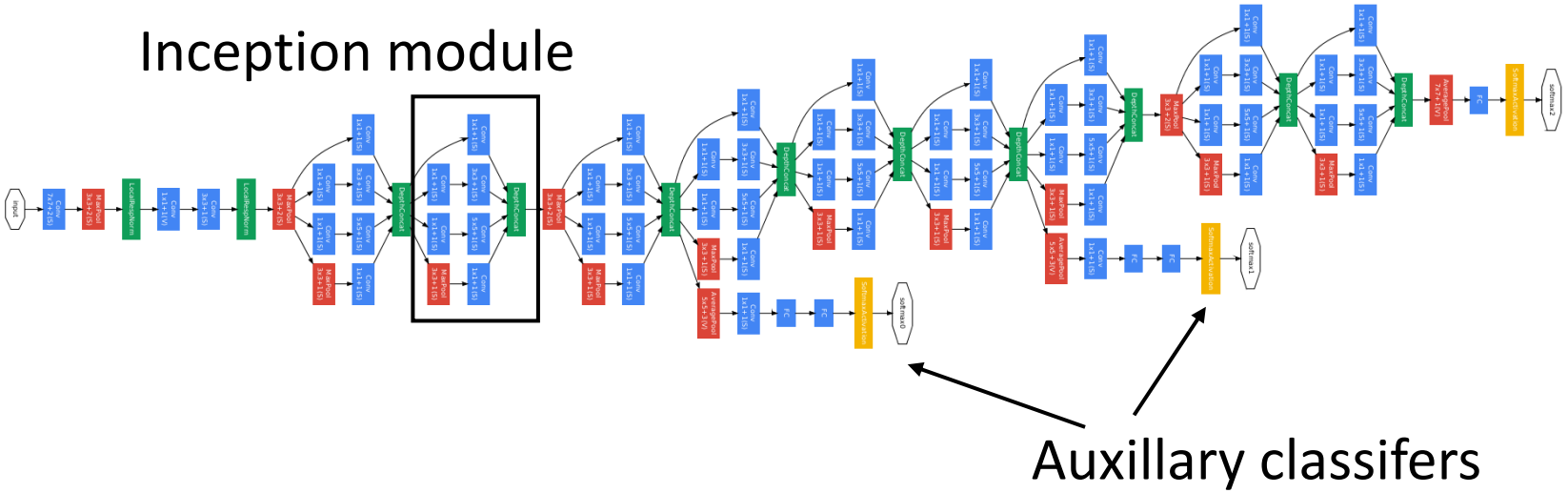


Conv layer 2

VGG innovations

- Stacked 3x3 convolutional layers
  - Learn more complex features thanks to additional non-linearities
  - Fewer parameters than 1 layer with the equivalent receptive field
- Doesn’t use AlexNet’s response normalisation – allows faster training with only very small accuracy drop

GoogLeNet (Inception)



Convolutional layer

Concatenate & normalise

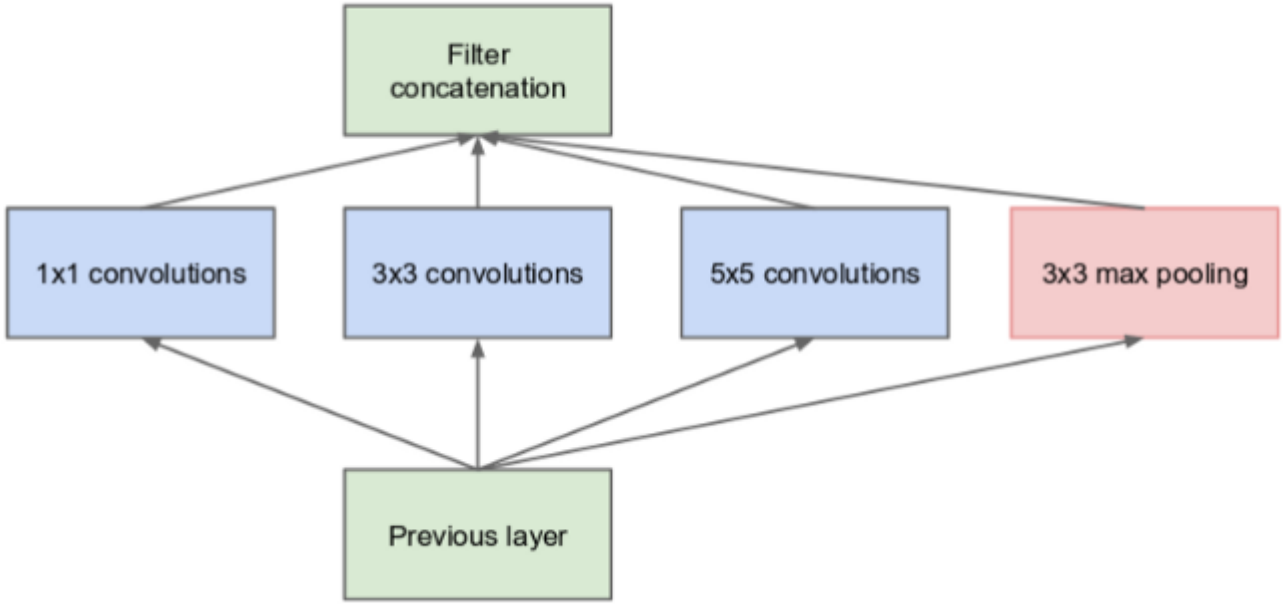
Max pooling

Softmax

Szegedy, et al. (2014)

Inception module

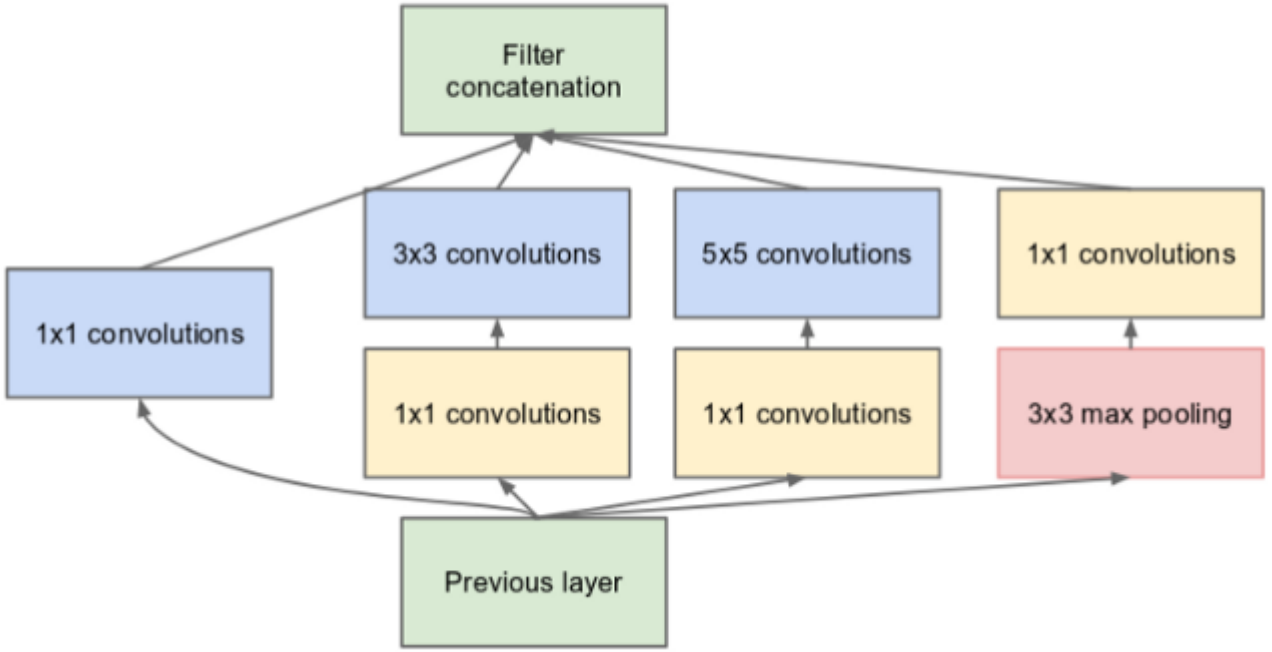
- Choosing the right kernel size in CNNs is difficult because objects/features can appear at any scale
- Solution: use multiple kernel sizes and concatenate



Szegedy, et al. (2014)

Inception module

- 1x1 convolutional layers reduce the number of channels (dimensionality reduction)



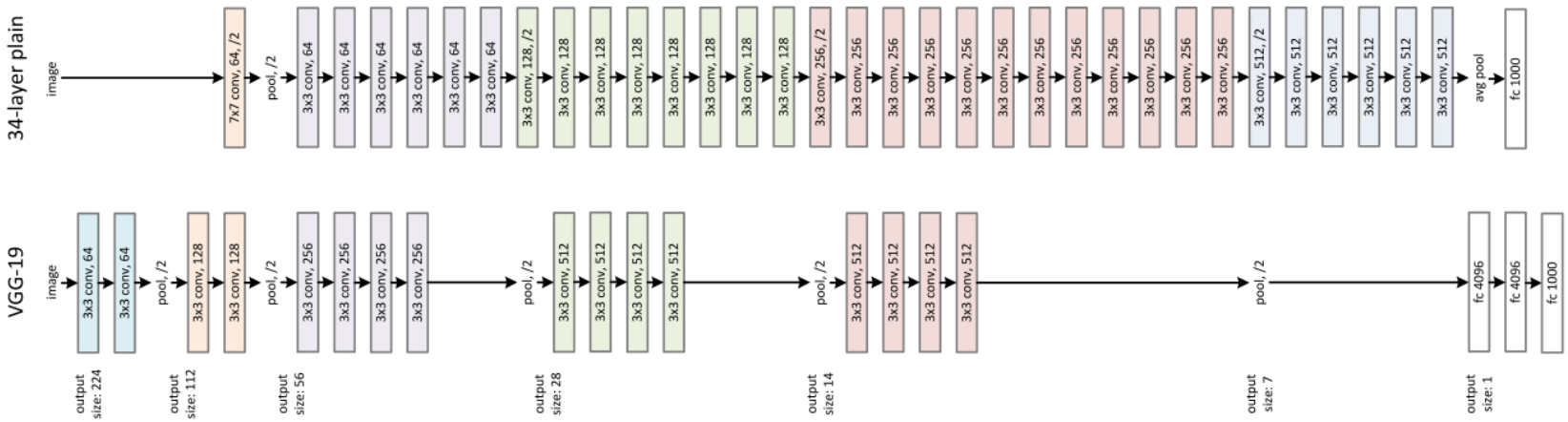
Szegedy, et al. (2014)

GoogLeNet innovations

- Inception module
  - Learns features at a variety of kernel sizes/scales
- Auxillary classifiers
  - Used during training only – classify images based on early layer representations and update parameters
  - Helps with vanishing gradient problem

ResNet: Background

- Will deeper neural networks will always give better performance?

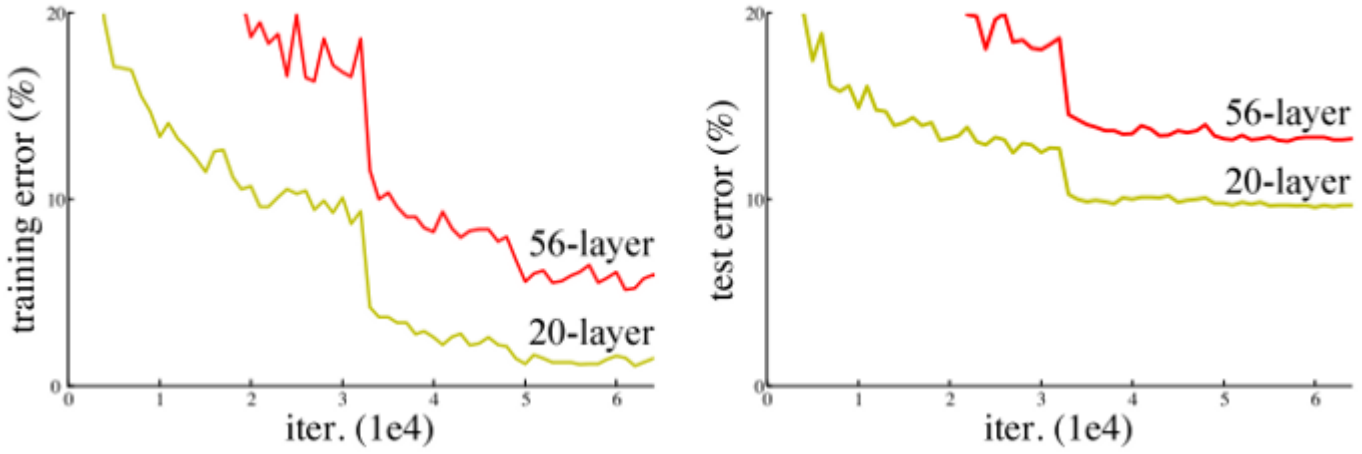


He, Zhang, Ren, & Sun (2016)

ResNet: Background

- No, performance saturates and then decreases
- Not due to overfitting – performance is worse on the training set

CIFAR-10 classification



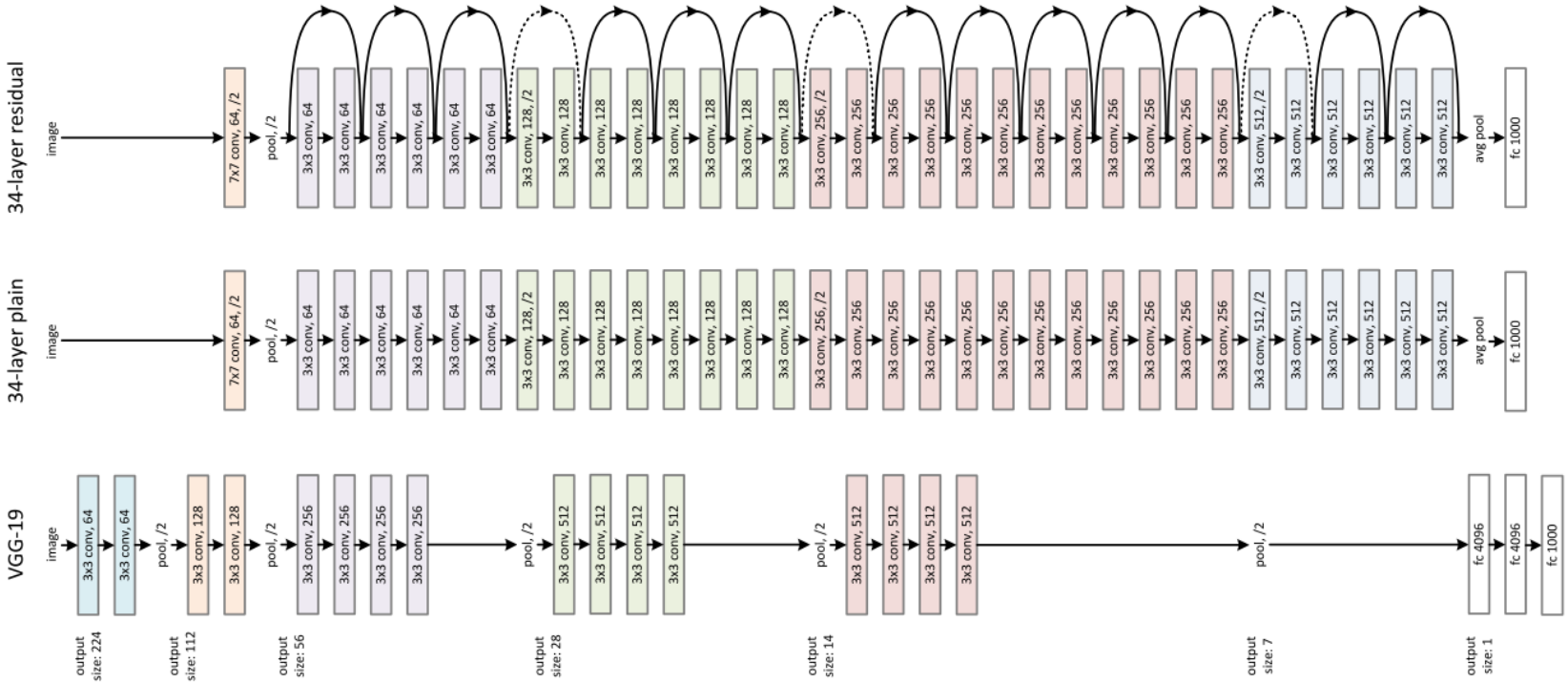
He, Zhang, Ren, & Sun (2016)

ResNet: Background

- It should be possible to learn parameters in the deep network that would allow it to act like the small network
  - For example, some conv. layers learn identity kernels, while others learn the shallow network's kernels
- However, deep CNNs cannot learn this solution (at least, not within a reasonable training time)

ResNet

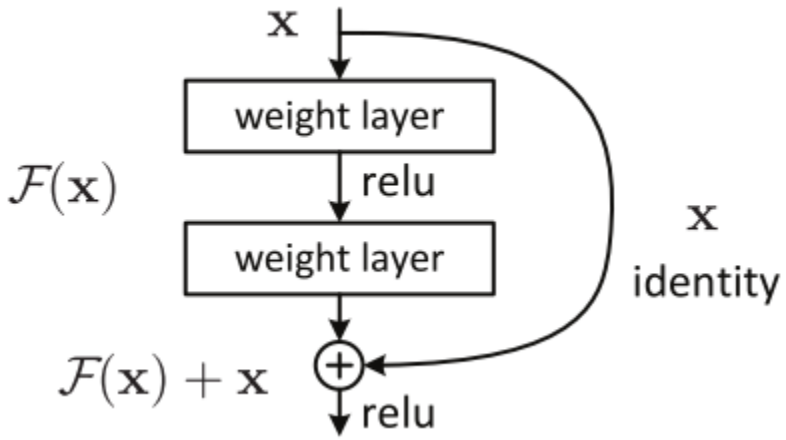
- Solution: Add “shortcut connections” that skip some layers



He, Zhang, Ren, & Sun (2016)

Residual learning

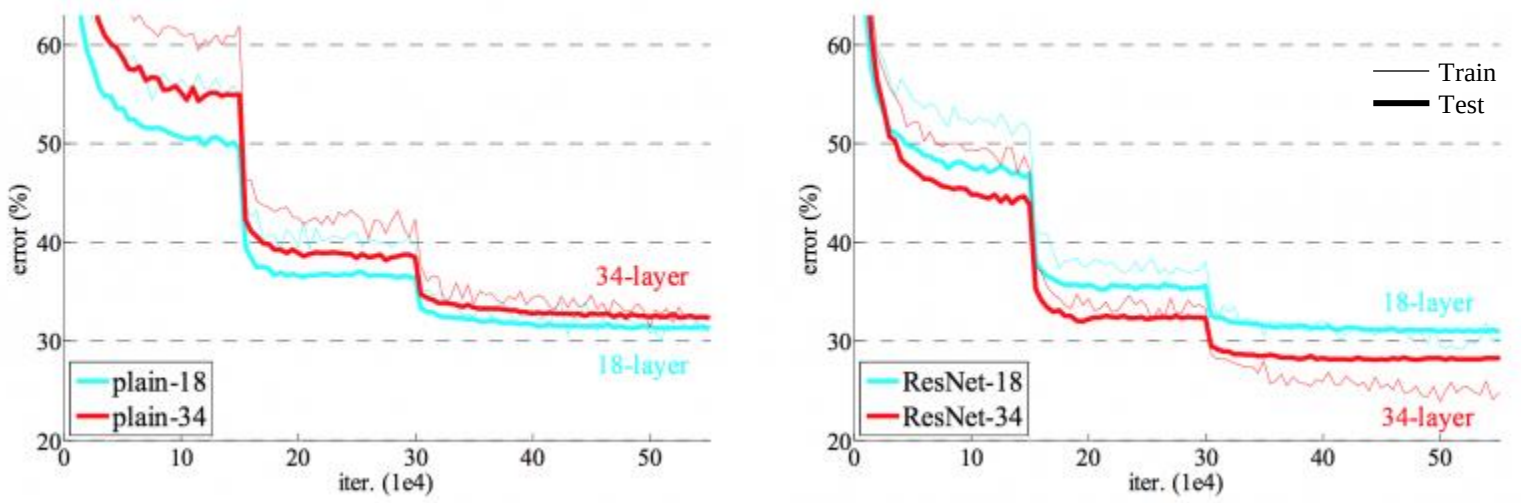
- Reformulate the learning problem:
  - Traditional network: input x, output $\mathcal{H}(x)$, which is the feature representation of x
  - Residual network: input x, learn $\mathcal{H}(x) - x$, which is then added to x to get $\mathcal{H}(x)$
- Makes it easier to learn identity mapping



He, Zhang, Ren, & Sun (2016)

ResNet innovations

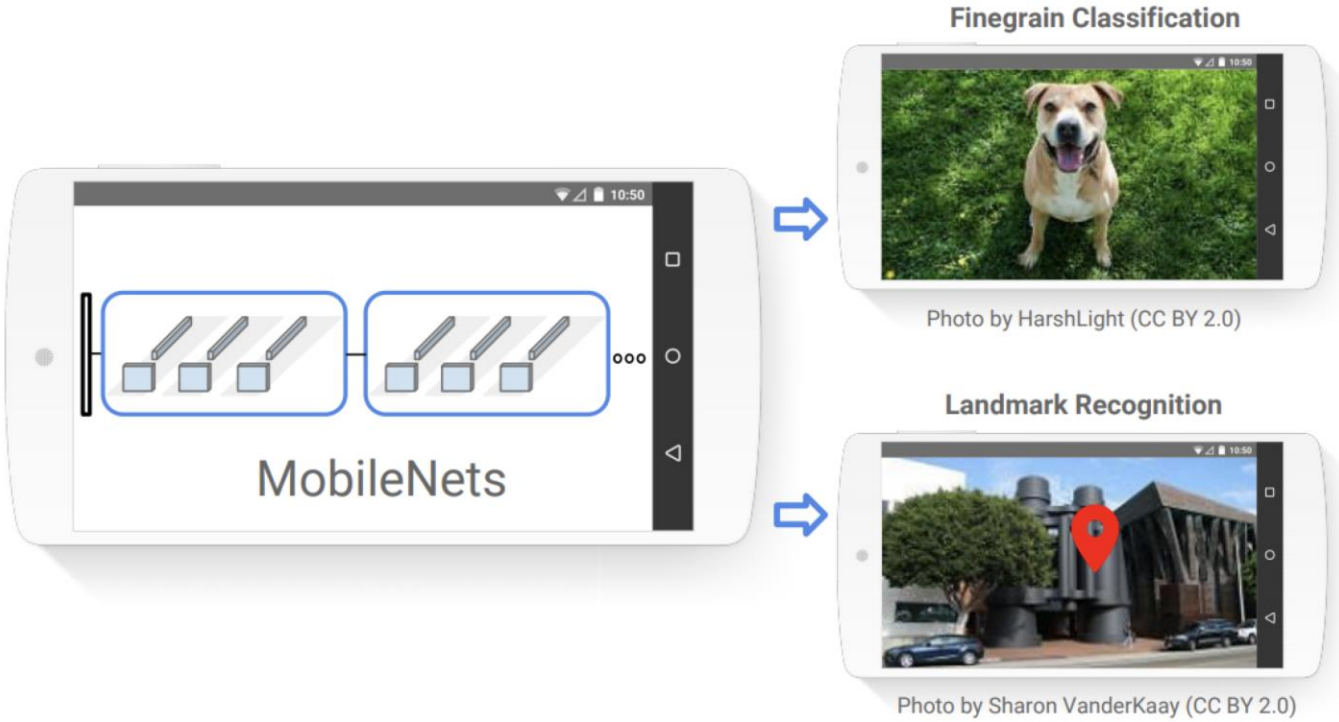
- Residual block
  - Simplifies the learning problem by making it easier for networks to learn identity mapping
  - Allows deeper networks to improve accuracy



He, Zhang, Ren, & Sun (2016)

MobileNets

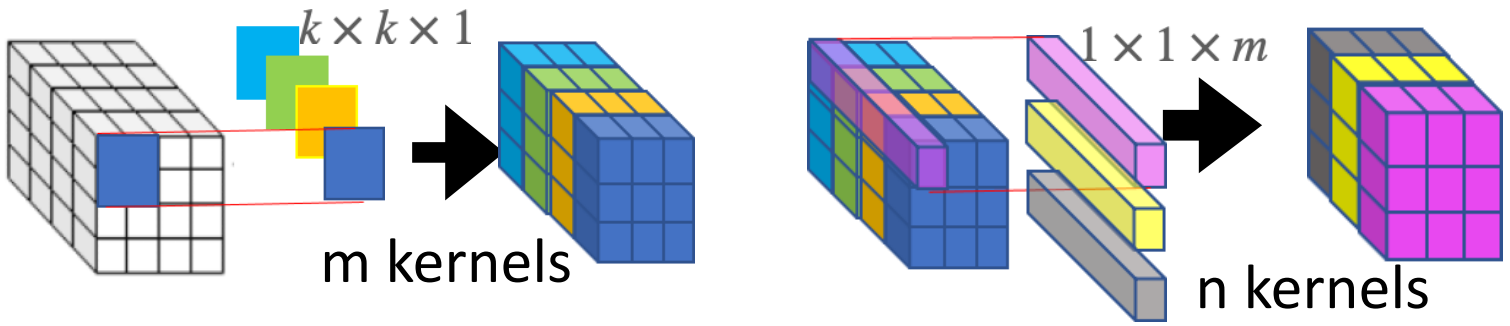
- Lightweight architecture for mobile apps



Howard, et al. (2017)

MobileNets

- Separable filters
  - Recall that filtering with a 2D filter is equivalent to filtering with two orthogonal 1D filters
  - Similarly, filtering with a 3D filter is equivalent to filtering with a 2D filter and an orthogonal 1D filter
- MobileNets uses depthwise-separable filters – 2D filters in x,y and 1D filters over channels



MobileNets innovations

- Depthwise separable convolution
  - Fewer parameters and less computation
  - Limits what kernels the model can learn – not all kernels are separable
- Smaller and faster than other architectures
  - Lower accuracy than VGG, ResNet, etc.
  - But better suited for real-time applications, phones

Summary

- Common architectures for ImageNet classification:
  - AlexNet
  - VGG
  - GoogLeNet / Inception
  - ResNet
  - MobileNet
- Choice of architecture depends on your application
  - Runtime, memory, processing power

Classification results

ImageNet classification

- 1000 object classes
- Model output = a probability distribution (from softmax) over 1000 class labels
- Top-1 accuracy
  - For each test image, model is correct if the most likely class == ground truth class
- Top-5 accuracy
  - For each test image, model is correct if any of the 5 most likely classes == ground truth class

Classification performance

ImageNet classification

Russakovsky et al. (2014):

"With a sufficient amount of training, a human annotator is still able to outperform the GoogLeNet result… by approximately 1.7%."

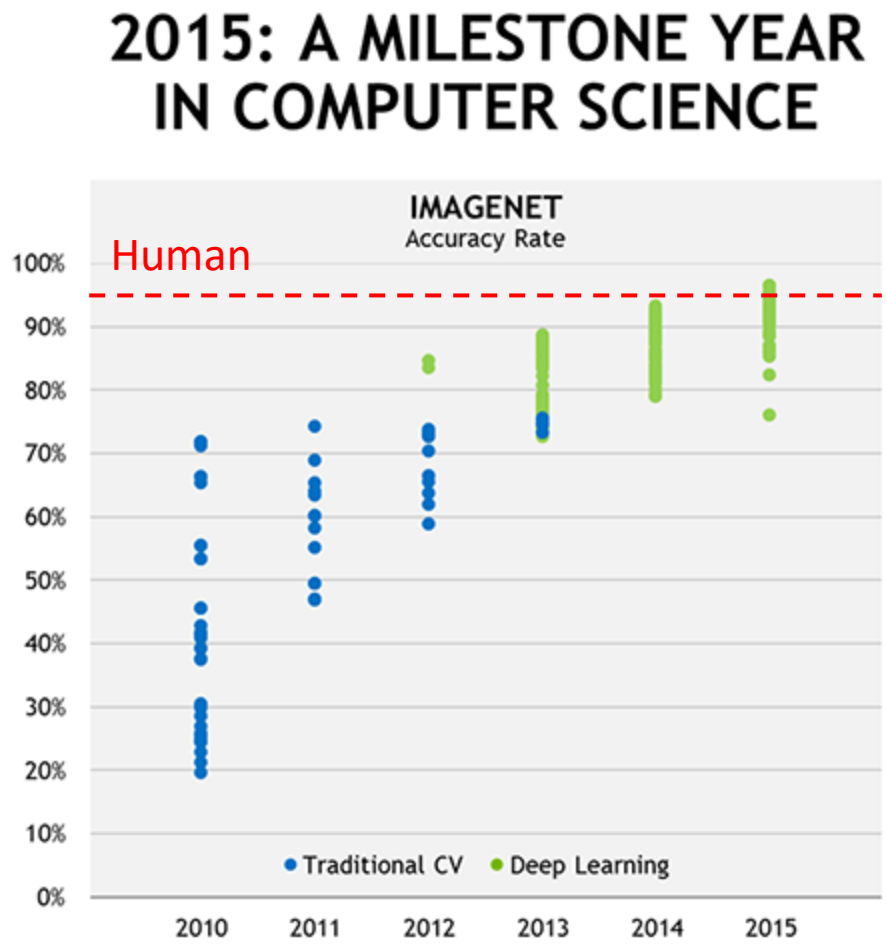
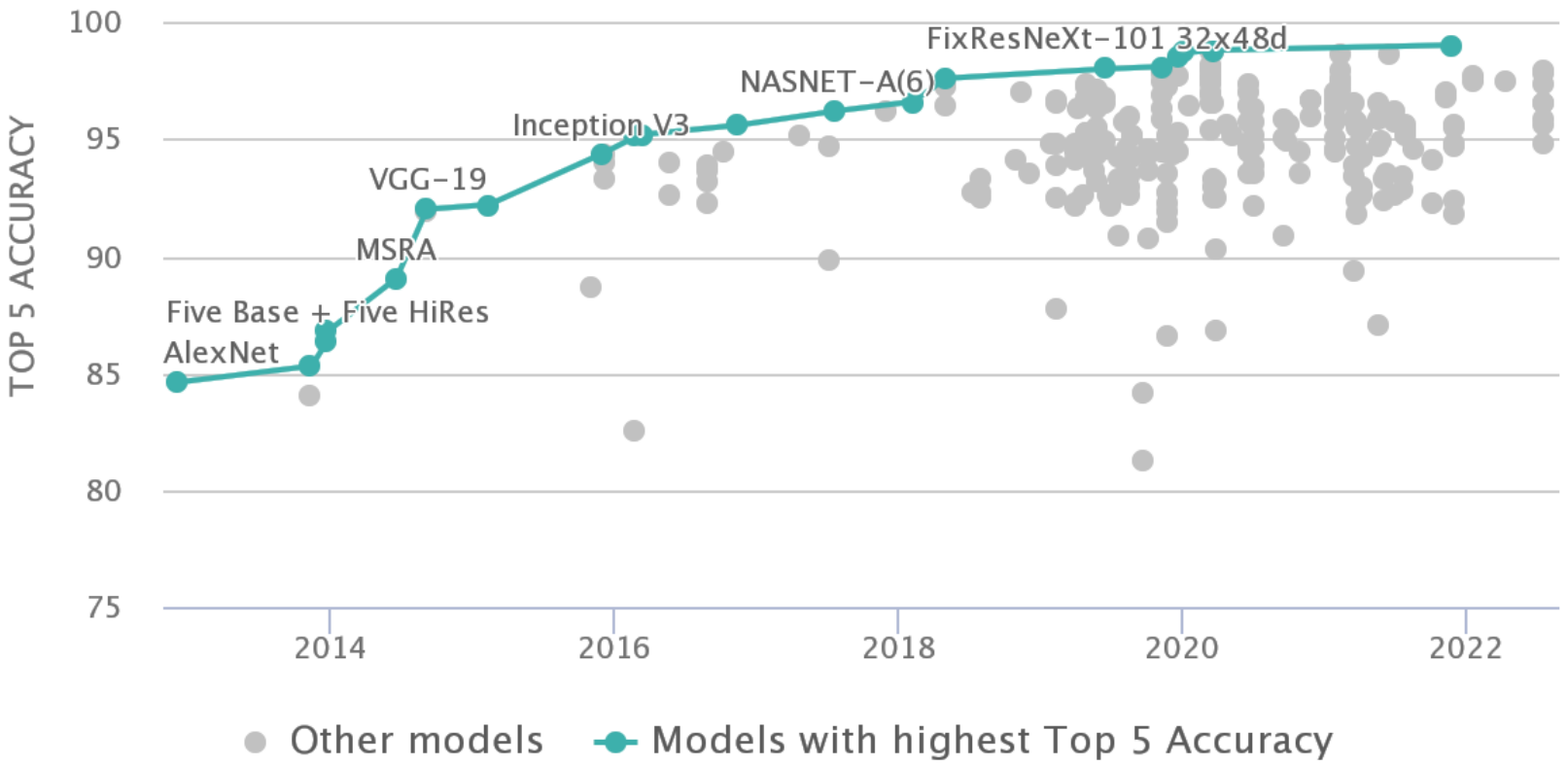


Image: https://blogs.nvidia.com/wp-content/uploads/2016/01/2-milestone-web1.gif

Classification performance



https://paperswithcode.com/sota/image-classification-on-imagenet

Common architectures

CNN Architecture	Layers	Top-5 error
AlexNet	8	16.4%
VGG-19	19	7.3%
GoogleNet	22	6.7%
ResNet	152	3.57%

Classification errors

ImageNet Classification Failures (GoogLeNet 2014)

ruler

pencil box
rubber eraser
ballpoint pen

king crab

pizza
strawberry
orange

sidewinder

maze
gar
valley

saltshaker

pill bottle
water bottle
lotion

reel

stethoscope
whistle
ice lolly

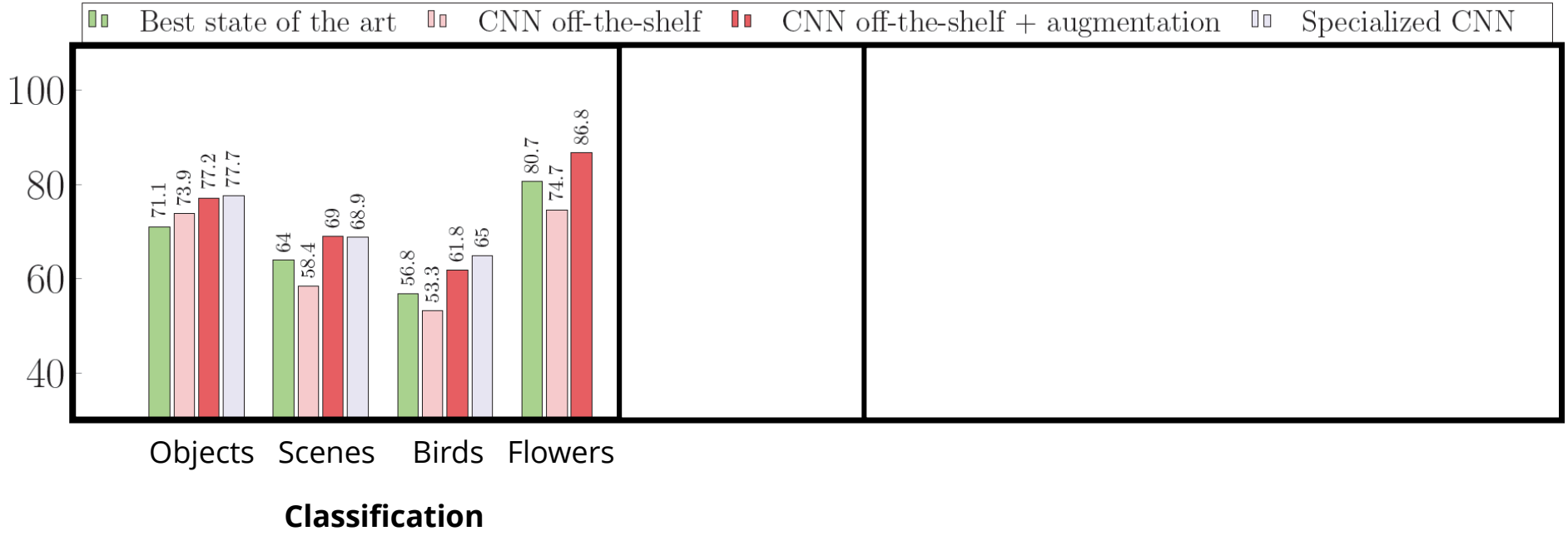
hatchet

vase
pitcher
coffeepot

Russakovsky et al. (2014)

Generalisation

- Features from neural networks are good representations for a range of tasks



Razavian et al. (2014)

Summary

- CNNs are the state-of-the-art for image classification, exceeding human performance on ImageNet
- CNN classification errors are often understandable (odd views, small objects), which suggests they learn reasonable features for this task

Transfer learning

Image recognition: Pixels

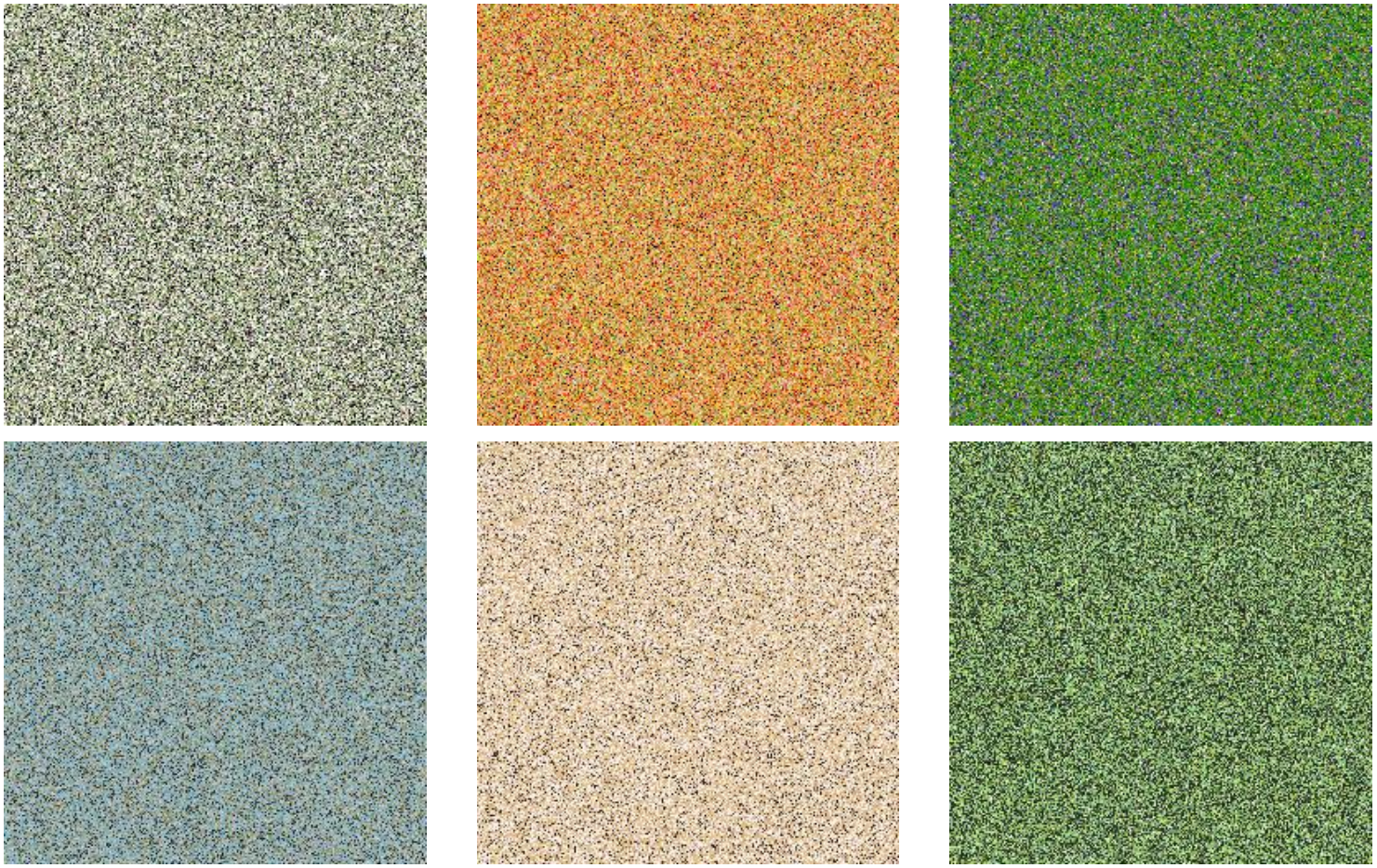


Image recognition: Pixels

- Pixels are a poor space for classification
  - High-dimensional space: 256 x 256 x 3 image = 196,608 attributes
  - Irrelevant transformations (translation, lighting change, scale change, rotation, etc.) cause large changes in pixel values

Image recognition: Features

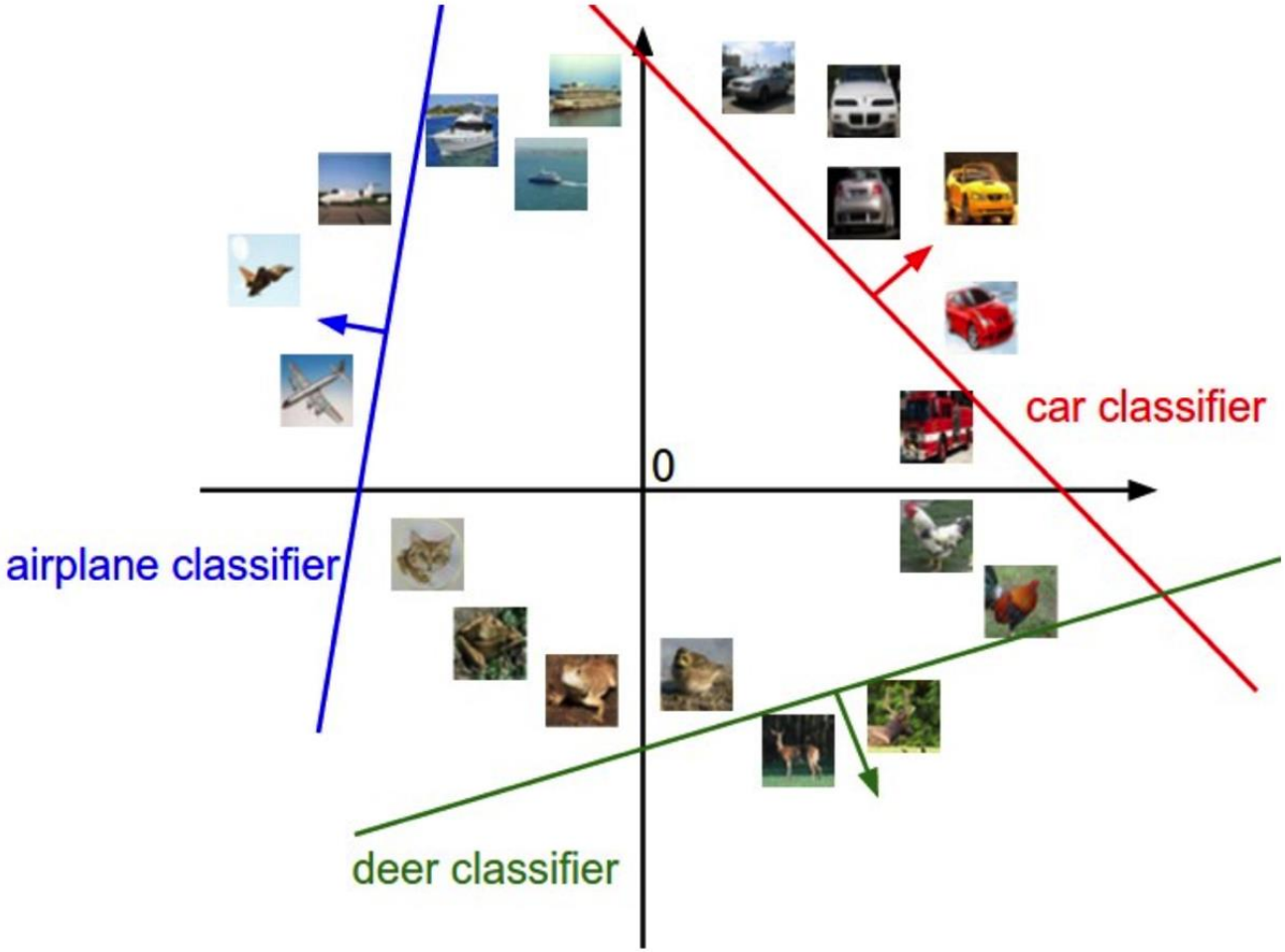


Image recognition: Features

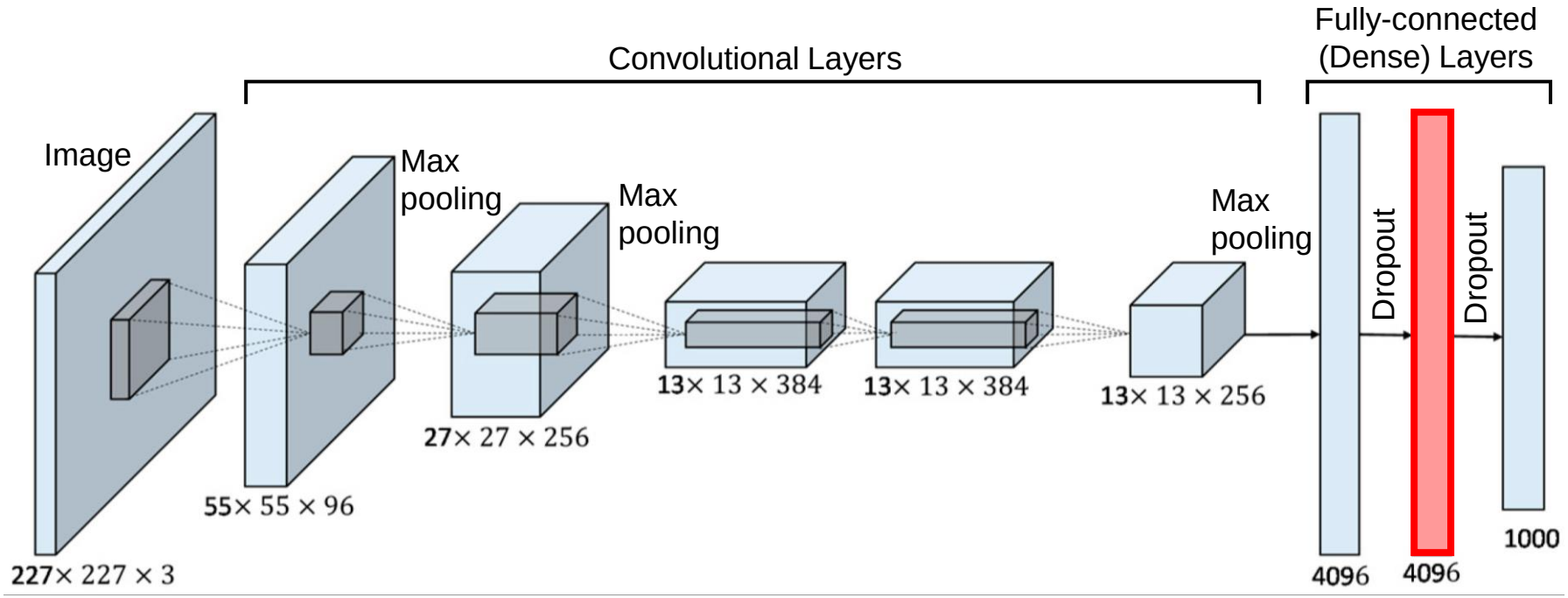
- A good feature space for image recognition:
  - Is lower-dimensional – e.g., 1000s of values per image
  - Projects images from the same class into a similar part of the space (images with the same class label have similar features)

Using pretrained networks

- CNNs convert images from pixels to high-level features that are good for classification (feature embedding)
- These high-level features give good performance on a range of computer vision tasks
- Transfer learning – use features from a CNN trained on a large-scale task (e.g., ImageNet classification) as input for another task, with minimal retraining

Transfer learning

"AlexNet": Krizhevsky, Sutskever, & Hinton (2012)

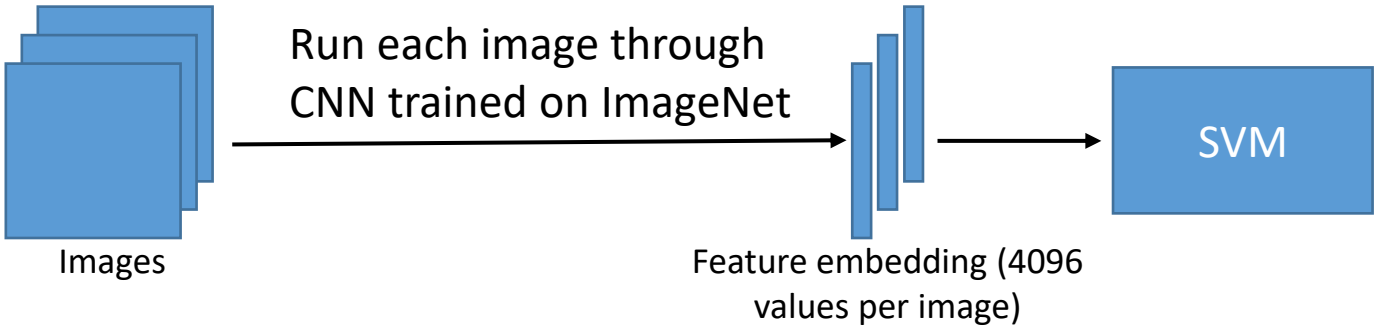


Embedding of an input = the network's response to the input at some layer

Image: Han, Zhong, Cao, & Zhang (2017)

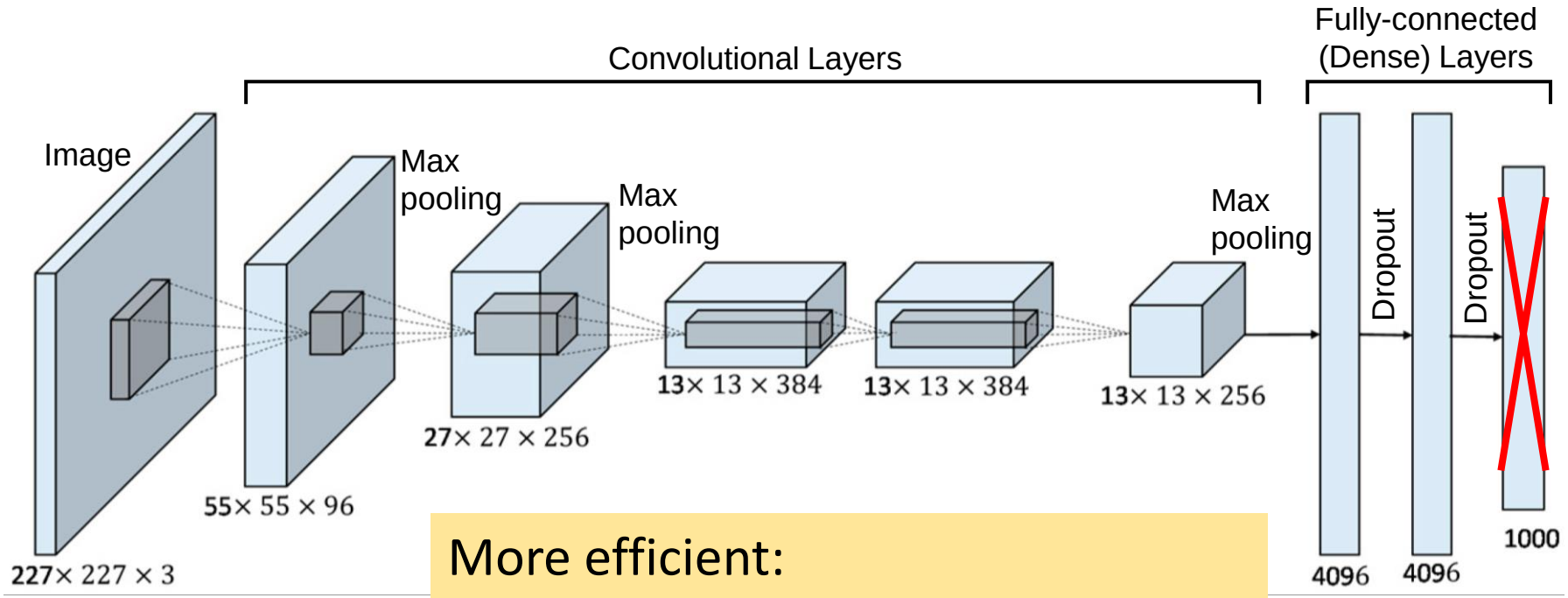
Transfer learning

- Extract the representation from a late layer of a CNN trained on ImageNet
  - E.g., for each image take the activations from the 4096 neurons that feed into the 1000-way ImageNet classification
- Use the neurons' activations as the attributes for a classifier of your choice (e.g., SVM, K-NN etc.)



Transfer learning

"AlexNet": Krizhevsky, Sutskever, & Hinton (2012)

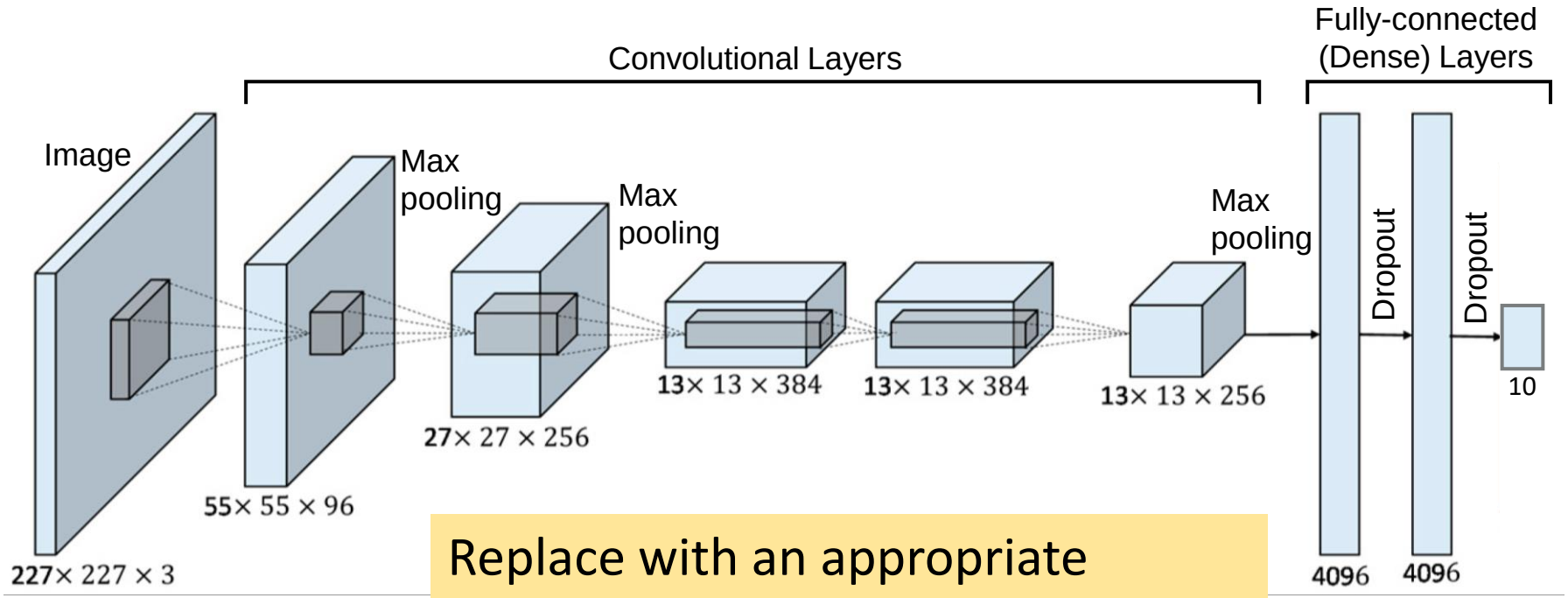


More efficient:
Remove the output layer of a CNN trained on ImageNet

Image: Han, Zhong, Cao, & Zhang (2017)

Transfer learning

"AlexNet": Krizhevsky, Sutskever, & Hinton (2012)

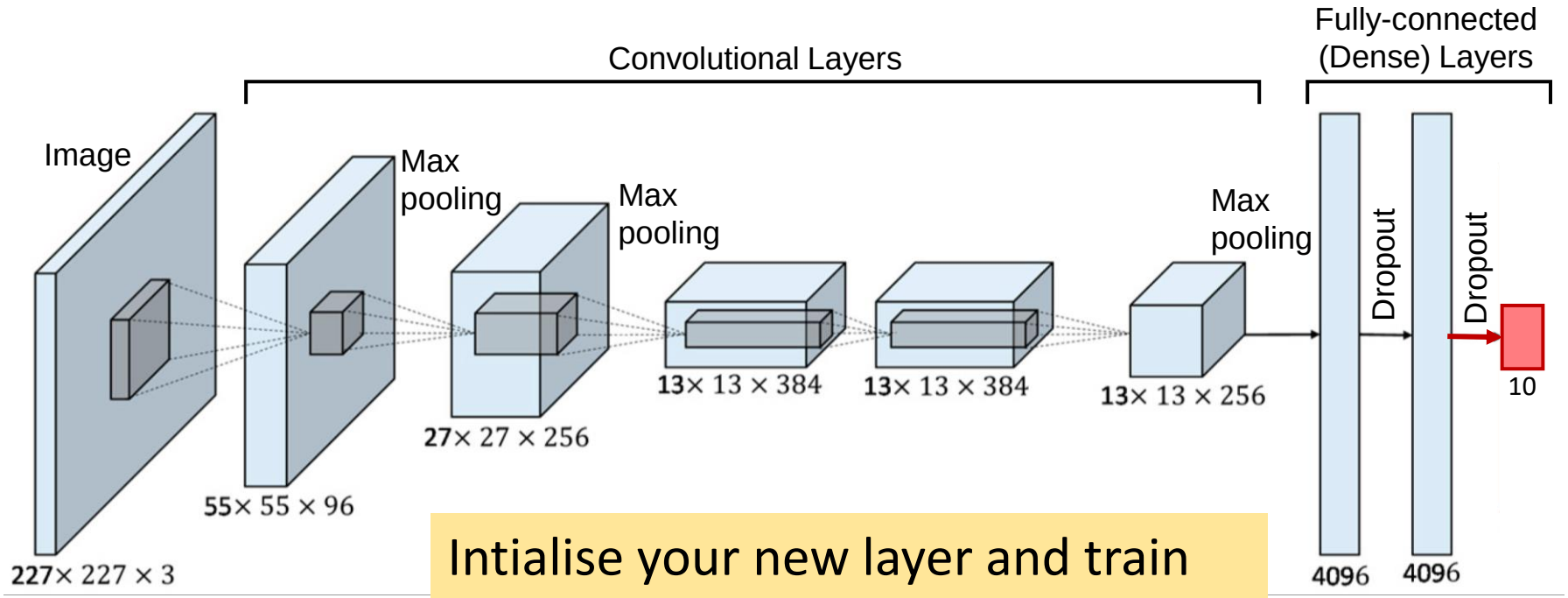


Replace with an appropriate output layer for your task

Image: Han, Zhong, Cao, & Zhang (2017)

Transfer learning

"AlexNet": Krizhevsky, Sutskever, & Hinton (2012)

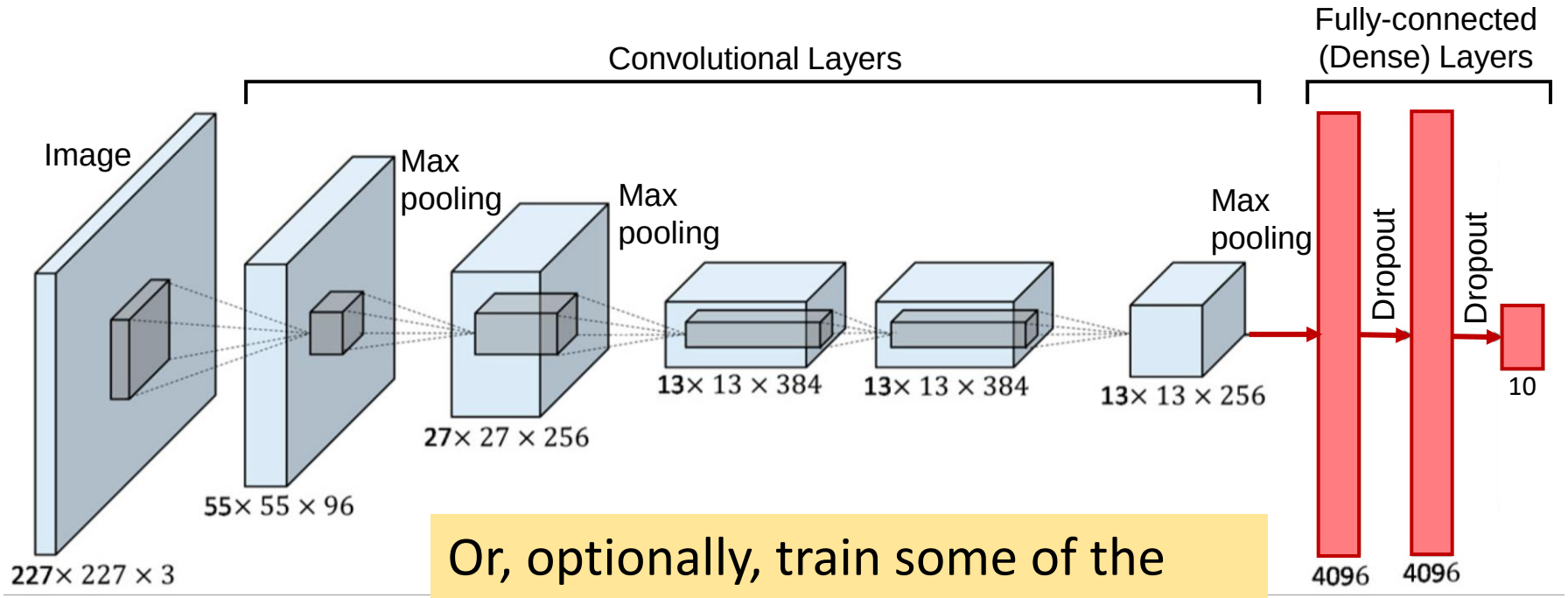


Intialise your new layer and train *only* this layer; freeze all other network parameters

Image: Han, Zhong, Cao, & Zhang (2017)

Transfer learning

"AlexNet": Krizhevsky, Sutskever, & Hinton (2012)



Or, optionally, train some of the later layers but freeze earlier layers

Image: Han, Zhong, Cao, & Zhang (2017)

Retraining layers

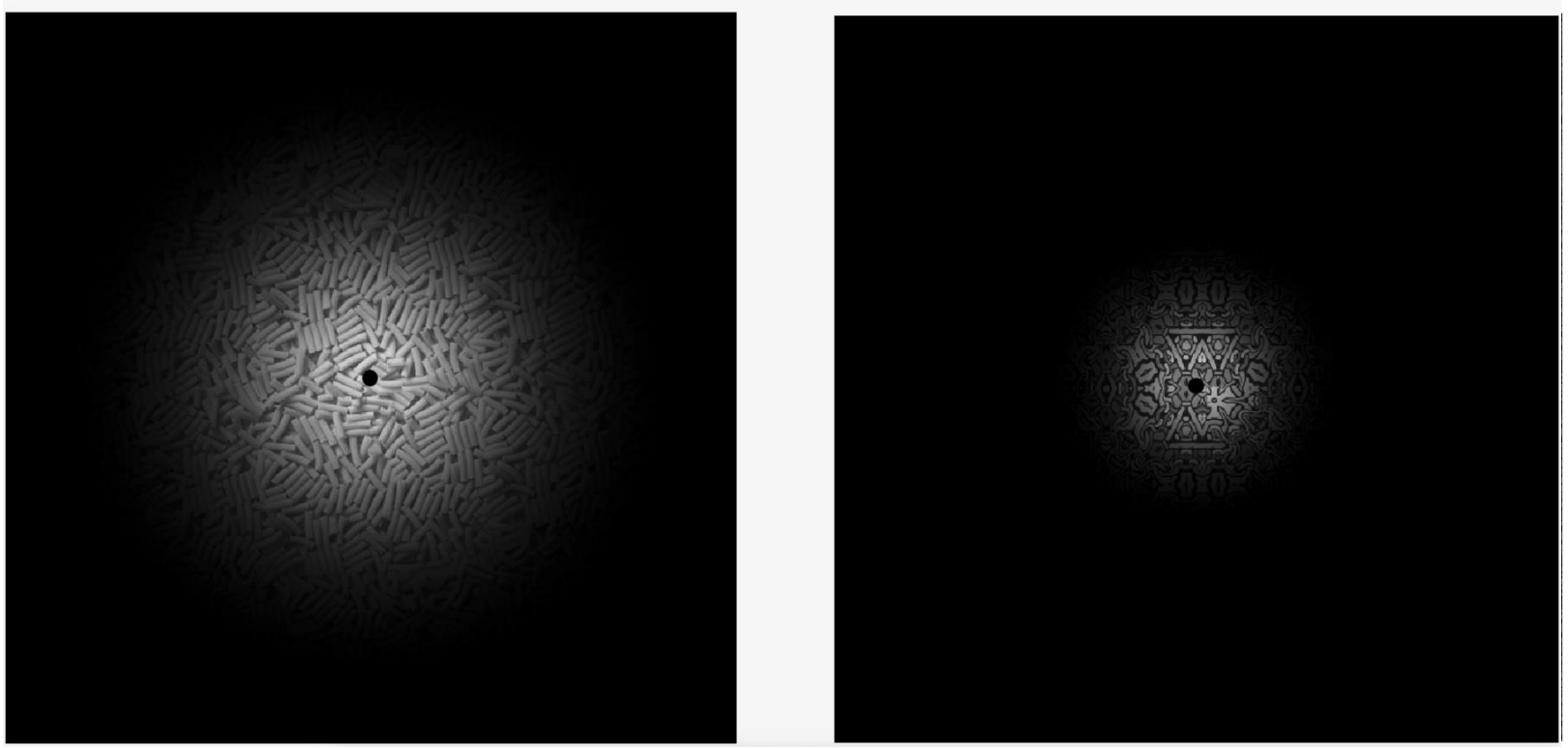
- **Finetuning** = retraining layers of a pretrained CNN
- How many layers to fine tune depends on dataset size and how similar it is to ImageNet
  - More dissimilar datasets may need more retraining of lower layers
  - If dataset size is limited, training lower layers may just lead to overfitting

Summary

- ImageNet-trained CNNs produce state-of-the-art performance on image recognition tasks
- It's common to use CNNs pretrained on ImageNet for a variety of computer vision tasks, either as-is ("off the shelf" feature embedding) or with some finetuning

Example: Pretrained features

Known target object  pasted at an unknown location



Rashidi, Ehinger, Turpin, & Kulik (2020); demo by Shima Rashidi