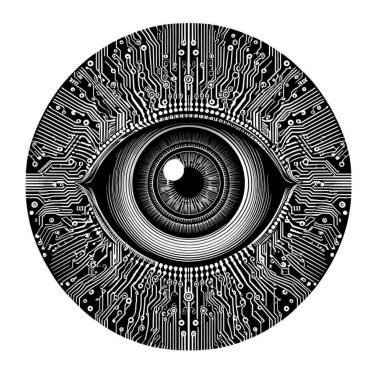


# **Pooling in Neural Networks**



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## **Learning goals**

• Explore image downsampling and reduction of network parameters with mean, max, and global pooling

### Architecture of a convolutional network with pooling

```
nn.Sequential(
           nn.Conv2d(3, 16, kernel_size=5, stride=1, padding=2),
                                                                              airplane
           nn.ReLU(),
                                                                              automobile
           nn.MaxPool2d(kernel_size=2, stride=2),
                                                                              bird
           nn.Conv2d(16, 32, kernel_size=5, stride=1, padding=2),
                                                                              cat
           nn.ReLU(),
                                                                              deer
           nn.MaxPool2d(kernel_size=2, stride=2),
                                                                              dog
           nn.Flatten(),
                                                                              frog
           nn.Linear(32 * 8 * 8, 120),
                                                                              horse
           nn.ReLU(),
           nn.Linear(120, 84),
                                                                              ship
           nn.ReLU(),
                                                                              truck
           nn.Linear(84, 10), # 10 classes, we are working with CIFAR 10
                                                                                         The CIFAR-10 dataset
                                                                          - TRUCK
                                                                          - VAN
```

- BICYCLE

FULLY SOFTMAX

CLASSIFICATION

FEATURE LEARNING

# **Max Pooling**

### Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2 pool size

100	184	
12	45	

Input Image Shape: 224x224



Max Pooled Image (4x4 Kernel) Shape: 56x56



# **Mean Pooling**

### Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2 pool size

36	80
12	15

Input Image Shape: 224x224

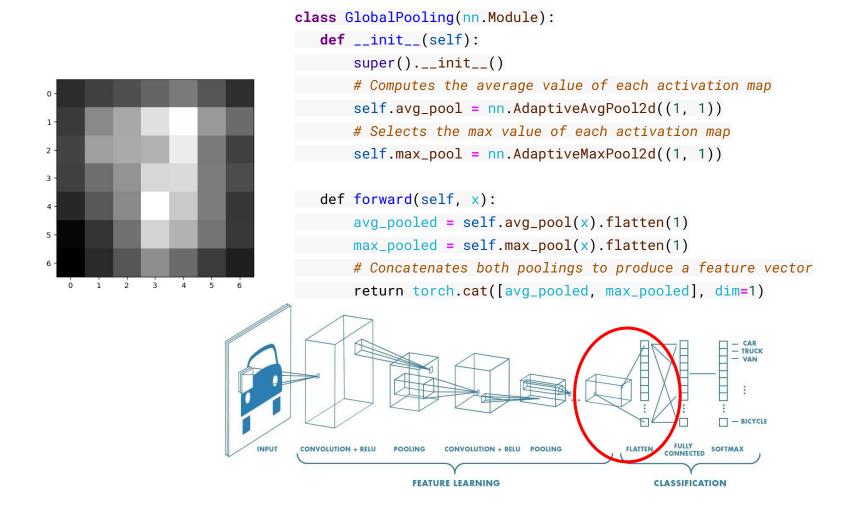


Mean Pooled Image (2x2 Kernel) Shape: 112x112



### Global pooling aka adaptive pooling

import torch.nn as nn



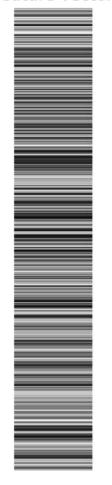
#### Feature vector



## Using global pooling to reduce parameters

```
import torch
import torch.nn as nn
model = nn.Sequential(
   nn.Conv2d(3, 16, kernel size=5, stride=1, padding=2),
   nn.ReLU(),
   nn.MaxPool2d(kernel size=2, stride=2),
   nn.Conv2d(16, 32, kernel size=5, stride=1, padding=2),
   nn.ReLU(),
   nn.MaxPool2d(kernel_size=2, stride=2),
   GlobalPooling(), # This replaces the Flatten layer
   nn.Linear(64, 120),
   nn.ReLU(),
   nn.Linear(120, 84),
   nn.ReLU(),
   nn.Linear(84, 10)
                                                   FEATURE LEARNING
                                                                                 CLASSIFICATION
```

#### Feature vector





## **Summary**

#### Pooling is a way to compress information

- Pooling allows us to do lossy compression while retaining important visual features
- Convolutions with stride > 1 achieve a similar effect at the cost of a higher number of parameters

### Global pooling is an alternative to flattening activation maps

 We can create feature vectors (aka embeddings) using the global mean and/or max pooling operations



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### Further reading and references

#### A guide to convolution arithmetic for deep learning

https://arxiv.org/abs/1603.07285

#### **Network in network (1x1 convolutions)**

https://arxiv.org/abs/1312.4400

#### Hypercolumns for object segmentation and fine-grained localization

 https://openaccess.thecvf.com/content\_cvpr\_2015/papers/Hariharan\_Hypercolumns\_for\_ Object\_2015\_CVPR\_paper.pdf



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