Convolutional Neural Networks

Devashish Khatwani May 2018



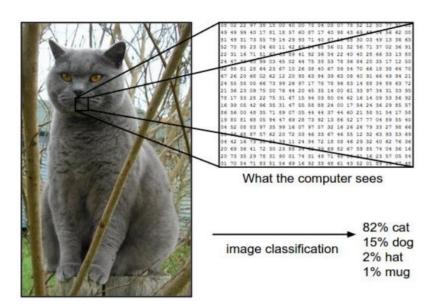








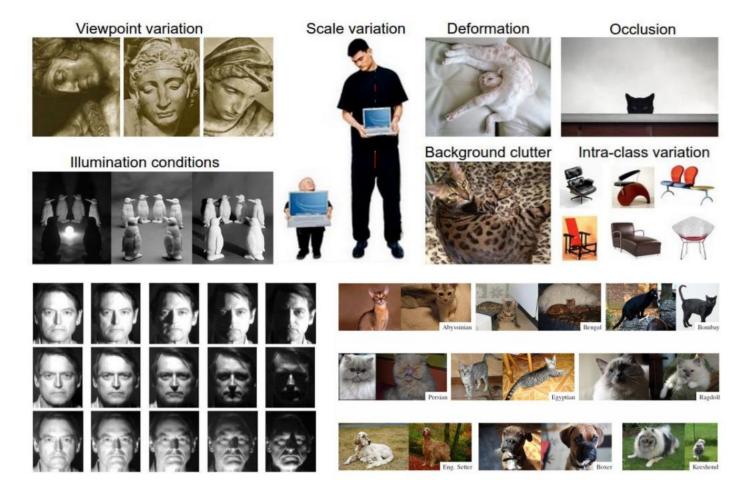
Images are numbers!



So it should be easy to classify images?

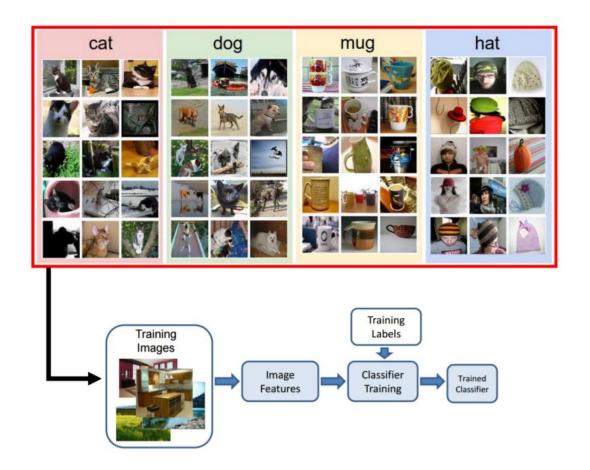


Computer Vision is hard!





Computer Vision Machine Learning pipeline





Some famous Computer Vision datasets



MNIST: handwritten digits



CIFAR-10(0): tiny images



ImageNet: WordNet hierarchy

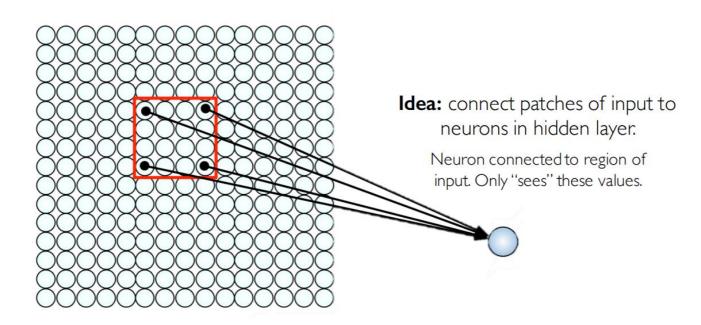


Places: natural scenes



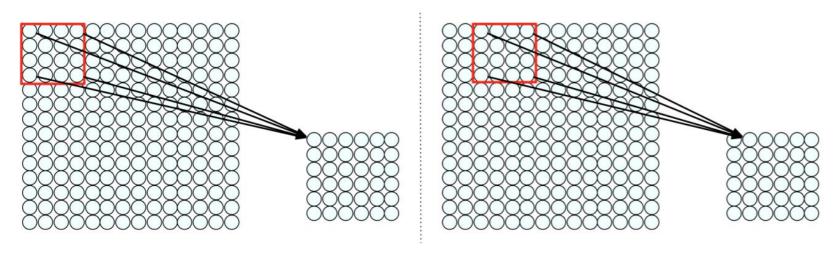
Use Spatial structure of data in an image

Input: 2D image. Array of pixel values





Use Spatial structure of data in an image



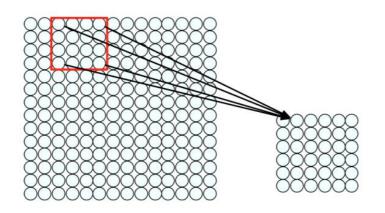
Connect patch in input layer to a single neuron in subsequent layer.

Use a sliding window to define connections.

How can we weight the patch to detect particular features?



Use Spatial structure of data in an image



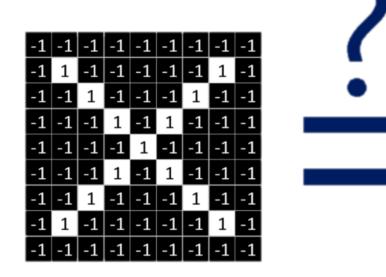
- Filter of size 4x4 : 16 different weights
- Apply this same filter to 4x4 patches in input
- Shift by 2 pixels for next patch

This "patchy" operation is **convolution**

- 1) Apply a set of weights a filter to extract **local features**
 - 2) Use **multiple filters** to extract different features
 - 3) **Spatially share** parameters of each filter



X or X?



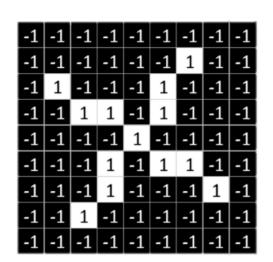
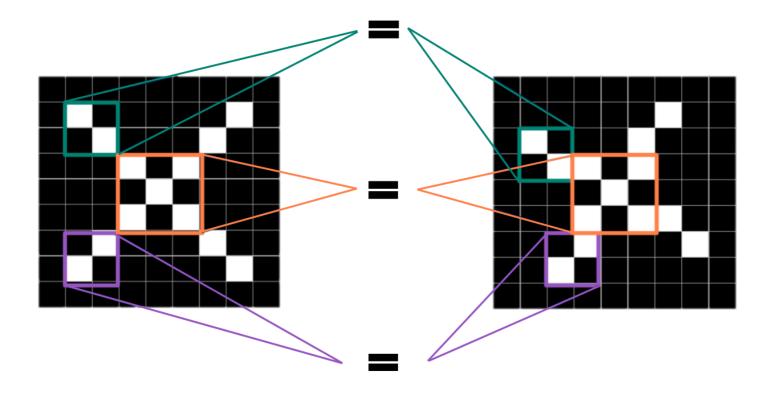


Image is represented as matrix of pixel values... and computers are literal! We want to be able to classify an X as an X even if it's shifted, shrunk, rotated, deformed.



Features of X





Convolution Operation

0	1	2
2	2	0
0	1	2



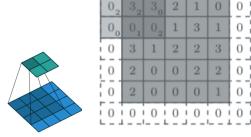
Kernel or Filter (3X3)

30	3,	22	1	0
02	02	10	3	1
30	1,	22	2	3
2	0	0	2	2
2	0	0	0	1





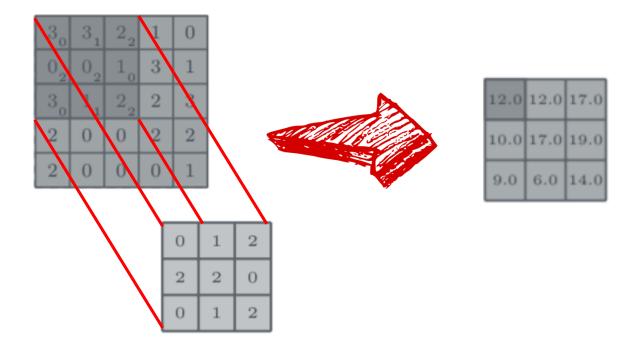
Stride of One





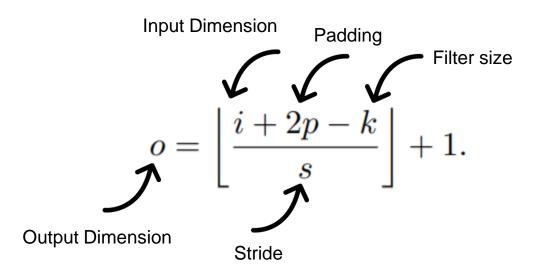
Padding of One

Convolution Operation Contd.





Relationship between input and output dimensions





Convolution Operation Contd.

Filter?
Stride?
Padding?

30	3,	22	1	0
02	02	10	3	1
30	1,	22	2	3
2	0	0	2	2
2	0	0	0	1

12.0 12.0 17.0 10.0 17.0 19.0 9.0 6.0 14.0			
	12.0	12.0	17.0
9.0 6.0 14.0	10.0	17.0	19.0
0.00	9.0	6.0	14.0

3	30	2,	12	0
0	02	12	30	1
3	10	2,	22	3
2	0	0	2	2
2	0	0	0	1

_	_	_
12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0





Filter = 3x3 Stride = 1 Padding = 0

3	3	2	1	0
00	0,	12	3	1
32	12	20	2	3
20	0,	02	2	2
2	0	0	0	1

12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0

3	3	2	1	0
0	00	1,	32	1
3	12	22	20	3
2	00	0,	22	2
2	0	0	0	1



3	3	2	1	0
0	0	10	3,	1_2
3	1	2	22	30
2	0	00		_
2	0	0	0	1

12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0



3	3	2	1	0
0	0	1	3	1
30	1,	22	2	3
22	02	00	2	2
20	0,	02	0	1

12.0	12.0	17.0	
10.0	17.0	19.0	
9.0	6.0	14.0	

3	3	2	1	0
0	0	1	3	1
3	10	2,	22	3
2	02	02	20	2
2	00	0,	02	1

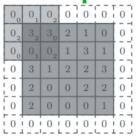
12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0

3	3	2	1	0
0	0	1	3	1
3	1	20	2,	32
2	0	02	22	20
2	0	00	0,	1,

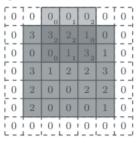
12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0

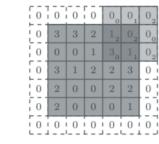
Convolution Operation Contd.

Filter? Stride? Padding?











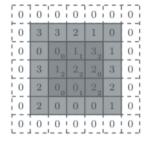
0 !

Filter = 3x3

Stride = 1

Padding = 1		0	0	0	0	0	0
	0	3	3	2	1	0	0
	00	0,	02	1	3	1	0 ¦
	02	32	10	2	2	3	0
	00	2,	02	0	2	2	0 ¦
	0	2	0	0	0	1	0
	0	0	0	0	0	0	0

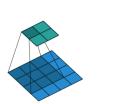






0	0		0	0	0	
0	3	3	2	1	0	0
0	0	0	1		1,	02
0	3	1	2	22	32	00
0	2	0	0	20	2,	02
0	2	0	0	0	1	0
0	0	0	0	0	0	0

6.0	14.0	17.0
14.0	12.0	12.0
8.0	10.0	17.0



0	0	0				0
	3	3	2	1	0	0
0	0	0	1	3	1	0
0	3	1	2	2	3	0
00	2,	02	0	2	2	0
02	22	00	0	0	1	0
00	0,	02	0	0	0	0



0	0			0	0	
[0]	3	3	2	1	0	0
0	0	0	1	3	1	0 ¦
	3	1	2	2	3	0
0	2		0,	22	2	0 ¦
0	2		02	00	1	0
0	0	00	0,	02	0	0]

C-1-0---------

6.0	14.0	17.0
14.0	12.0	12.0
8.0		17.0

0		0	0	0		
0	3	3	2	1	0	0 }
0	0	0	1	3	1	0
0	3	1	2	2	3	0
0	2	0	0	20	2,	02
0	2	0	0		12	00
0	0	0	0	00	0,	02



Relationship between Filter Channels, Input Channels and Output Channels

Filter = 3x3 Stride = 1 Padding = 0 Input Channels = 2 Filter Channels = 3 Output Channels = 3

Filter 1 Filter 2 Filter 3





Pooling Operation

Average Pooling

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

_	_		
1.7	1.7	1.7	
1.0	1.2	1.8	
1.1	0.8	1.3	

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

1.7	1.7	1.7
1.0	1.2	1.8
1.1	0.8	1.3







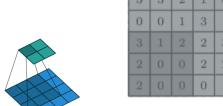




1.7	1.7	1.7
1.0	1.2	1.8
1.1	0.8	1.3







1.7	1.7	1.7	
1.0	1.2	1.8	
1.1	0.8	1.3	

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

1.7	1.7	1.7
1.0	1.2	1.8
1.1	0.8	1.3

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Pooling Operation Contd.

Max Pooling

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0



3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



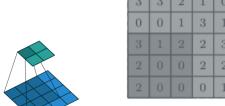


3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0





3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0



3.0	3.0	3.0	
3.0	3.0	3.0	
3.0	2.0	3.0	

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

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Pooling Operation Contd.

Max Pooling

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

3.0	3.0	3.0	
3.0	3.0	3.0	
3.0	2.0	3.0	



3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1





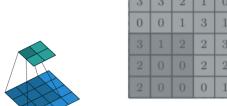
3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0











3.0	3.0	3.0	
3.0	3.0	3.0	
3.0	2.0	3.0	

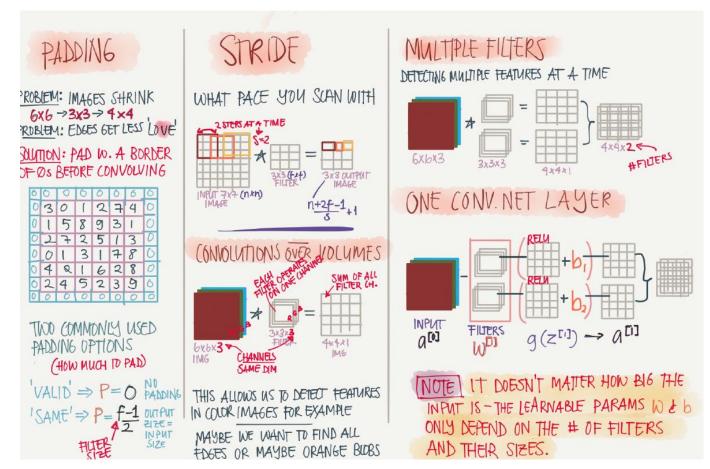
3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

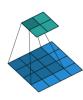
3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

Putting it all together

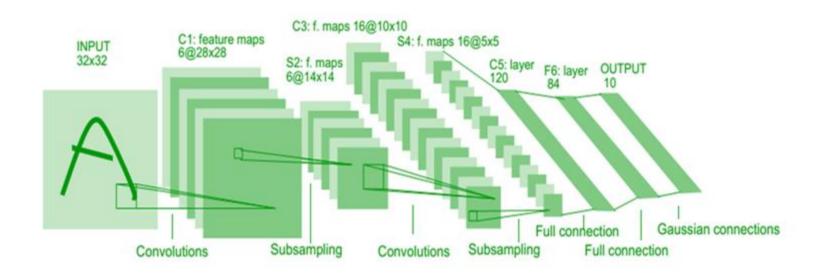


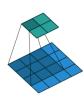


MNIST Classifier using Pytorch

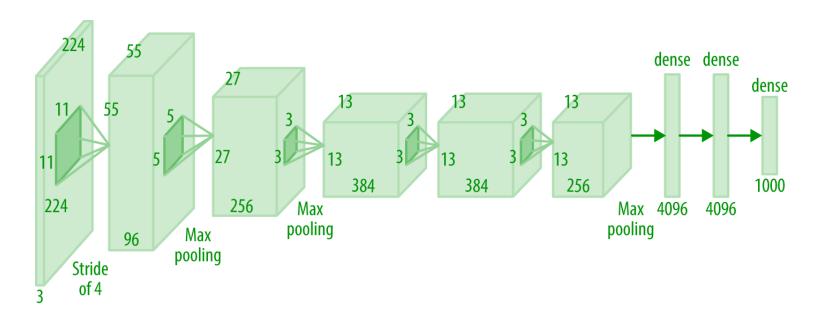


Commonly used CNN Architectures LeNet



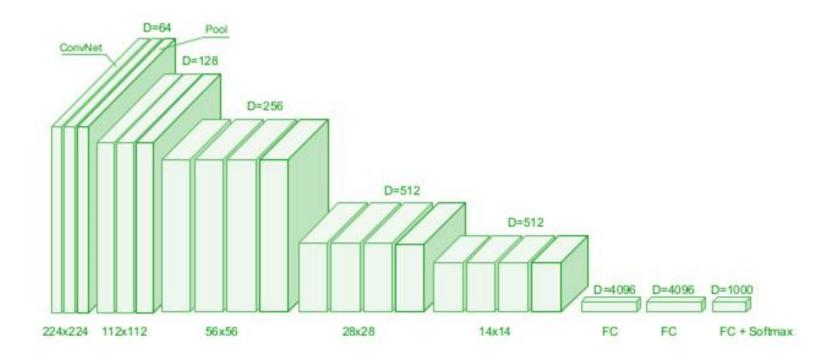


Commonly used CNN Architectures AlexNet





Commonly used CNN Architectures VGG16





What comes after VGG16?



Just adding more layer doesn't work!

- Vanishing Gradient
- Solvers are not able to get to an identity mapping

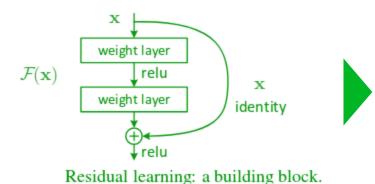


Need a better way of propagating information within the network

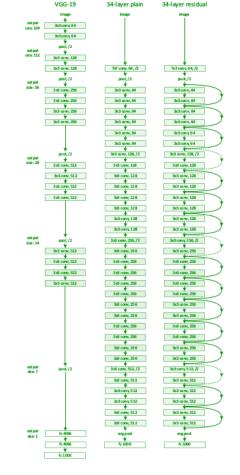
- Residual connections
- Highway networks
- Dense connections



Commonly used CNN Architectures Resnet50

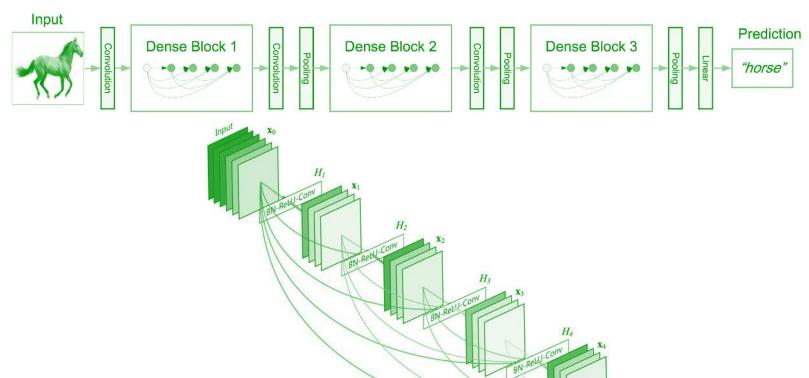






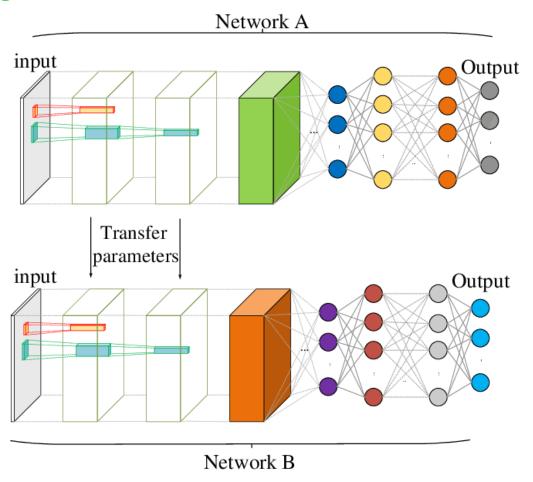


Commonly used CNN Architectures Densenet





Transfer Learning





```
from __future__ import print_function, division

import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import numpy as np
import torchvision
from torchvision import datasets, models, transforms
import matplotlib.pyplot as plt
import time
import os
import copy

plt.ion() # interactive mode
```



Transforms are common image transforms. They can be chained together using **Compose**

Data loader. Combines a dataset and a sampler, and provides single- or multi-process iterators over the dataset.



Define a function to train the model

Load the data into the model for training

```
def train_model(model, criterion, optimizer, scheduler, num_epochs=25)
    since = time.time()
    best model wts = copy.deepcopy(model.state dict())
    best acc = 0.0
    for epoch in range(num epochs):
        print('Epoch {}/{}'.format(epoch, num epochs - 1))
        print('-' * 10)
        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            if phase == 'train':
                scheduler.step()
                model.train() # Set model to training mode
            else:
                model.eval() # Set model to evaluate mode
            running_loss = 0.0
            running corrects = 0
            # Iterate over data.
            for inputs, labels in dataloaders[phase]:
                inputs = inputs
                labels = labels
                # zero the parameter gradients
```

optimizer.zero_grad()



Train step

```
# forward
# track history if only in train
with torch.set_grad_enabled(phase == 'train'):
    outputs = model(inputs)
    '''
    Returns the maximum value of each row of the input tensor in the given dim
    The second return value is the index location of each maximum value found
    '''
    _, preds = torch.max(outputs, 1)
    loss = criterion(outputs, labels)

# backward + optimize only if in training phase
    if phase == 'train':
        loss.backward()
        optimizer.step()
```

