Deep Computer Vision

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January 28, 2020
Impact: Facial Detection & Recognition
Impact: Medicine, Biology, Healthcare

A. HEALTHY

B. DISEASED

Hemorrhages
Impact: Self-Driving Cars
What Computers “See”
Images are Numbers
Images are Numbers
Images are Numbers

What the computer sees

An image is just a matrix of numbers [0,255],
i.e., $1080 \times 1080 \times 3$ for an RGB image
Tasks in Computer Vision

- **Regression**: output variable takes continuous value
- **Classification**: output variable takes class label. Can produce probability of belonging to a particular class
High Level Feature Detection

Let’s identify key features in each image category

- Nose, Eyes, Mouth
- Wheels, License Plate, Headlights
- Door, Windows, Steps
Manual Feature Extraction

Domain knowledge
Define features
Detect features to classify

Problems?
Manual Feature Extraction

Domain knowledge

Define features

Detect features to classify

Viewpoint variation
Scale variation
Deformation
Occlusion

Illumination conditions
Background clutter
Intra-class variation

6.5191 Introduction to Deep Learning
introdeeplearning.com MITDeepLearning
Manual Feature Extraction

- Domain knowledge
- Define features
- Detect features to classify

- Viewpoint variation
- Scale variation
- Deformation
- Occlusion

- Illumination conditions
- Background clutter
- Intra-class variation
Learning Feature Representations

Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

- **Low level features**: Edges, dark spots
- **Mid level features**: Eyes, ears, nose
- **High level features**: Facial structure
Learning Visual Features
Fully Connected Neural Network
Fully Connected Neural Network

Input:
- 2D image
- Vector of pixel values

Fully Connected:
- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!
Fully Connected Neural Network

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How can we use spatial structure in the input to inform the architecture of the network?
Using Spatial Structure

**Input:** 2D image. Array of pixel values

**Idea:** connect patches of input to neurons in hidden layer. Neuron connected to region of input. Only “sees” these values.
Using Spatial Structure

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?*
Applying Filters to Extract Features

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
   (features that matter in one part of the input should matter elsewhere)
Feature Extraction with Convolution

- 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
Feature Extraction and Convolution
A Case Study
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
Filters to Detect X Features

filters
The Convolution Operation

\[ \begin{pmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{pmatrix} \times \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = 1 \]

element wise multiply

add outputs

\[ \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} = 9 \]
The Convolution Operation

Suppose we want to compute the convolution of a 5x5 image and a 3x3 filter:

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs…
The Convolution Operation

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We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:

\[
\begin{array}{ccc}
1 & 1 & 1 \\
1 & 1 & 0 \\
0 & 1 & 1 \\
0 & 1 & 1 \\
0 & 1 & 1 \\
0 & 1 & 0 \\
\end{array}
\times
\begin{array}{ccc}
1 & 1 \\
1 & 0 \\
0 & 0 \\
1 & 1 \\
1 & 1 \\
1 & 0 \\
\end{array}
= \begin{array}{ccc}
4 & 3 & 4 \\
2 & 4 & 3 \\
1 & 0 & 1 \\
\end{array}
\]
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:

```
1 1 1 0 0
0 1 1 1 0
0 0 1 1 1
0 0 1 1 0
0 1 1 0 0
```

```
1 0 1
0 1 0
1 0 1
```

```
4 3 4
2 4 3
2
```

filter = feature map
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:
The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:
Producing Feature Maps

Original
Sharpen
Edge Detect
“Strong” Edge Detect
Feature Extraction with 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
Convolutional Neural Networks (CNNs)
1. **Convolution**: Apply filters to generate feature maps.

2. **Non-linearity**: Often ReLU.

3. **Pooling**: Downsampling operation on each feature map.

**Train model with image data.**
Learn weights of filters in convolutional layers.
Convolutional Layers: Local Connectivity

For a neuron in hidden layer:
- Take inputs from patch
- Compute weighted sum
- Apply bias
Convolutional Layers: Local Connectivity

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4x4 filter: matrix of weights \( w_{ij} \)

\[
\sum_{i=1}^{4} \sum_{j=1}^{4} w_{ij} x_{i+p,j+q} + b
\]

1) applying a window of weights
2) computing linear combinations
3) activating with non-linear function
CNNs: Spatial Arrangement of Output Volume

Layer Dimensions: $h \times w \times d$

where $h$ and $w$ are spatial dimensions
$d$ (depth) = number of filters

Stride:
Filter step size

Receptive Field:
Locations in input image that a node is path connected to

```python
import tensorflow as tf
tf.keras.layers.Conv2D( filters=d, kernel_size=(h,w), strides=s )
```
Introducing Non-Linearity

- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**

\[ g(z) = \max(0, z) \]
Pooling

max pool with 2x2 filters and stride 2

1) Reduced dimensionality
2) Spatial invariance

How else can we downsample and preserve spatial invariance?
Representation Learning in Deep CNNs

Low level features
- Edges, dark spots
  - Conv Layer 1

Mid level features
- Eyes, ears, nose
  - Conv Layer 2

High level features
- Facial structure
  - Conv Layer 3
CNNs for Classification: Feature Learning

1. Learn features in input image through convolution
2. Introduce non-linearity through activation function (real-world data is non-linear)
3. Reduce dimensionality and preserve spatial invariance with pooling
CNNs for Classification: Class Probabilities

- CONV and POOL layers output high-level features of input
- Fully connected layer uses these features for classifying input image
- Express output as **probability** of image belonging to a particular class

\[
\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}
\]
import tensorflow as tf

def generate_model():
    model = tf.keras.Sequential([
        # first convolutional layer
        tf.keras.layers.Conv2D(32, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # second convolutional layer
        tf.keras.layers.Conv2D(64, filter_size=3, activation='relu'),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),

        # fully connected classifier
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(1024, activation='relu'),
        tf.keras.layers.Dense(10, activation='softmax')  # 10 outputs
    ])
    return model
An Architecture for Many Applications
An Architecture for Many Applications

Detection
Semantic segmentation
End-to-end robotic control
Detection: Breast Cancer Screening

International evaluation of an AI system for breast cancer screening

b. Breast cancer in 2 years (USA)

- AI
- MD Readers

c. Breast cancer in 1 year (USA)

- AI
- MD Readers

CNN-based system outperformed expert radiologists at detecting breast cancer from mammograms

Breast cancer case missed by radiologist but detected by AI
Semantic Segmentation: Fully Convolutional Networks

FCN: Fully Convolutional Network. Network designed with all convolutional layers, with **downsampling** and **upsampling** operations.

- **Input:** $3 \times H \times W$
- **Low-res:** $D_3 \times H/4 \times W/4$
- **Med-res:** $D_2 \times H/4 \times W/4$
- **High-res:** $D_1 \times H/2 \times W/2$
- **Predictions:** $H \times W$

```python
tf.keras.layers.Conv2DTranspose
```
Semantic Segmentation: Biomedical Image Analysis

Brain Tumors
Dong+ MIUA 2017.

Malaria Infection
Self-Driving Cars: Navigation from Visual Perception

Raw Perception $I$
(ex. camera)

Coarse Maps $M$
(ex. GPS)

Possible Control Commands
End-to-End Framework for Autonomous Navigation

Entire model is trained end-to-end **without any human labelling or annotations**
Deep Learning for Computer Vision: Impact
Deep Learning for Computer Vision: Summary

**Foundations**
- Why computer vision?
- Representing images
- Convolutions for feature extraction

**CNNs**
- CNN architecture
- Application to classification
- ImageNet

**Applications**
- Segmentation, image captioning, control
- Security, medicine, robotics