Lecture 3: Convolutional Neural Networks

How Do Computer Process an Image?

- For a computer, images, are just numbers
  - Grayscale images: 2D array
  - RGB images: 3D array

Tasks in Computer Vision

- **Regression**: output is continuous
- **Classification**: output is a class label (probability)

Learning Feature Representations

- Can we learn a hierarchy of features directly from data instead on "hand-engineering"?

Learning Visual Features Using NNs

Using a Fully Connected Neural Network

- Input: $x \in \mathbb{R}^n$, 2D image "unwrapped" into vector of pixel intensities
- Connect neural in hidden layer to all neurons in input layer
- We lose spatial information
- Lots and lots of parameters

Using Spatial Structure

- Input: $x \in \mathbb{R}^{n \times m}$, 2D image as array of pixel intensities
- Connect patches of input to neurons in hidden layer
  - Neuron only "sees" region of vaues
- Connect patch in input layer to single neuron in subsequent layer, use a sliding window to define these connections
- How does *weighting* come in?

Applying "Filters" to Learn Visual Features

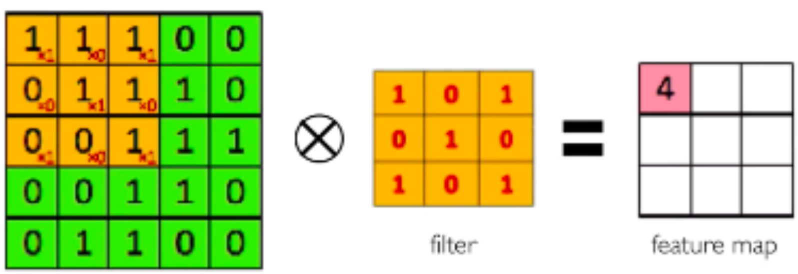
1. Apply a set of weights (filter) to extract **local features**
2. Use **multiple filters** to extract different features

3. Spatially **share** parameters of each filter (features that matter in one part of input should matter everywhere)

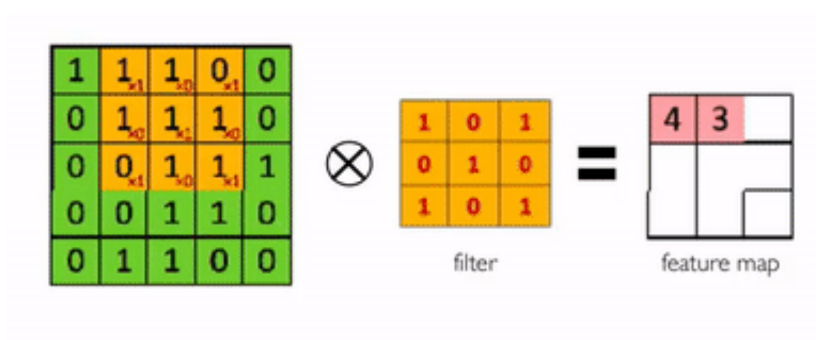
Feature Extraction With Convolution

- Filter of size 4×4, means 16 different weights
- Apply this filter to 4×4 patches in input
- Shift by 2 pixels for next patch
- This "patchy" operation = **convolution**
- Convolution is an element-wise product between patch of input matrix and a filter matrix, then add all outputs
    - Define input patch as P and filter as F, convolution is defined as $\text{sum}(P \otimes F)$
- What if we want to, say, compute convolution of 5×5 image and 3×3 filter?
    - We slide the 3×3 filter over the input image and perform convolution similarly

Step 1:



Steps 2-9:

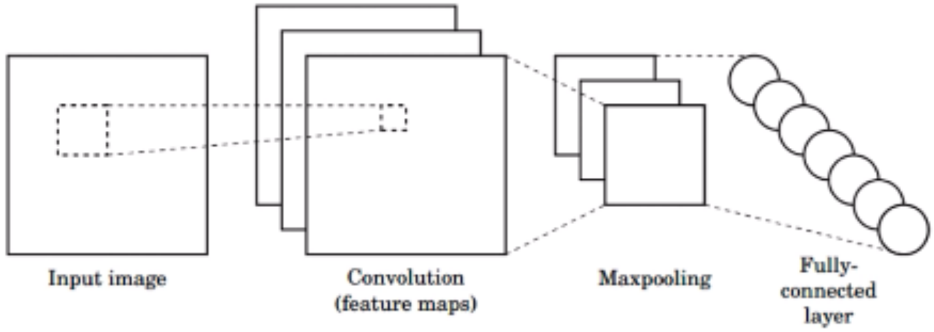


CNNs

CNNs for Classification

1. Convolution: Apply filters with learned weights to generate feature maps
2. Non-linearity: often ReLu
3. Pooling: Downsampling operation on each feature map

- Train model with image data, learn weights in convolutional layers.



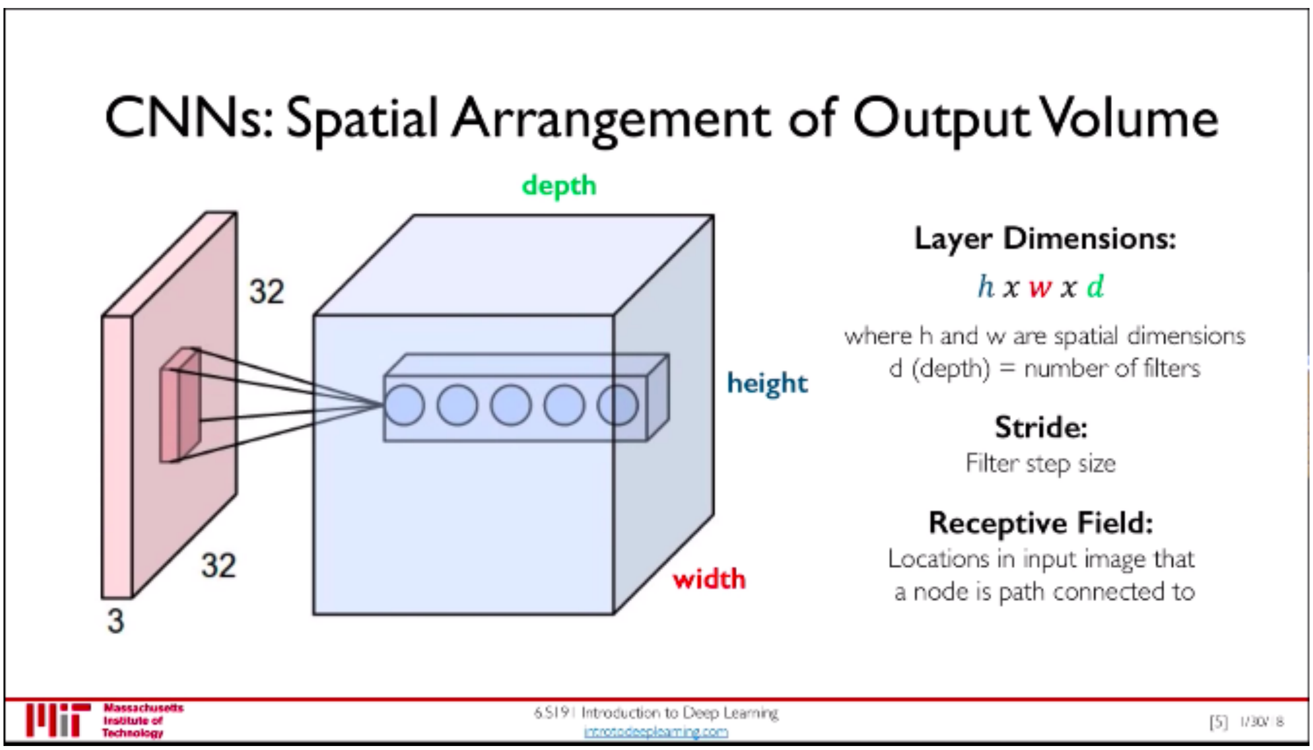
- For a neuron in hidden layer:
  - Takes inputs from patch that the neuron "sees"
  - Compute weighted sum, apply bias
- For 4×4 filter, convolution is defined as:

for neuron (p, q) in hidden layer:

$\sum_{i=1}^{4} \sum_{j=1}^{4} \theta_{ij} x_{i+p,j+q} + b$

where θ_{ij} is a matrix of weights

Spatial Arrangement of Output Volume



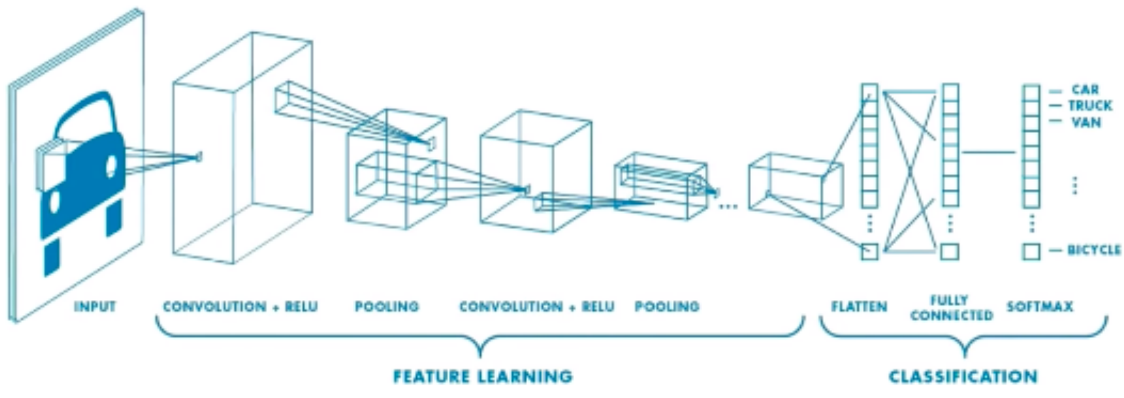
Introducing Non-Linearity

- Apply after every convolution operation
- Usually use ReLU

Pooling

- Downsampling but preserving spatial invariance
- Maxpooling: find "max" value in chunk

CNN Image Classification Pipeline



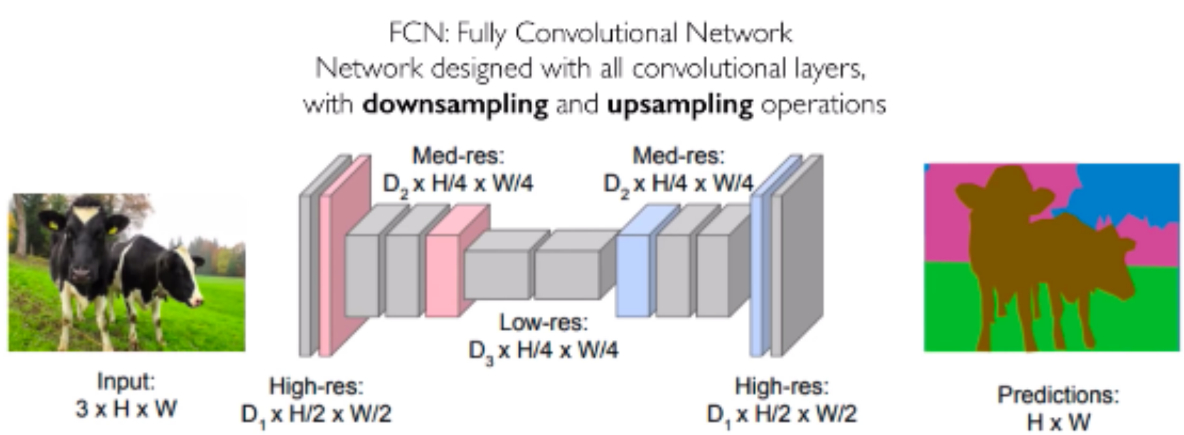
- Use cross-entropy loss in backprop

Beyond Classification

- Semantic segmentation: segment an image into multiple categories
- Object detection: detect objects in image
- Image captioning: generate captions of image

Semantic Segmentation with FCNs

- Fully Convolutional Network
- Downsampling to upsampling



Object Detection With R-CNNs

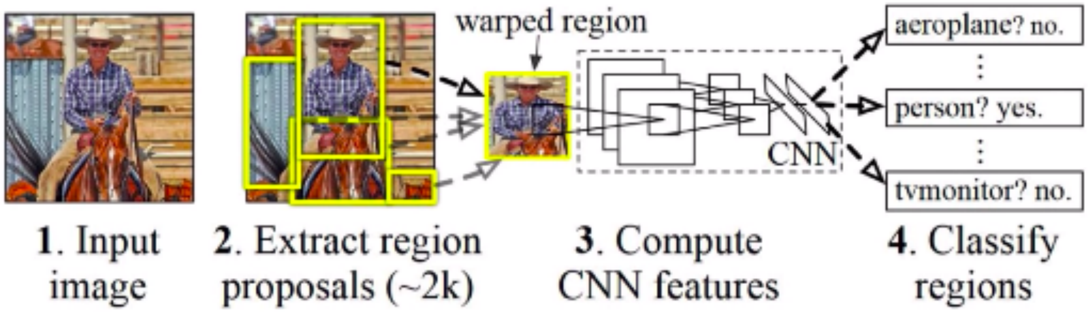


Image Captioning Using RNNs