

Convolutional neural nets

CISC 5800
Professor Daniel Leeds

Innovations in computer vision: Convolutional neural networks

- Introduced by Yann LeCun (IEEE 1988) for digit recognition
- Popularized by Alex Krizhevsky (NIPS 2012) for broad object recognition

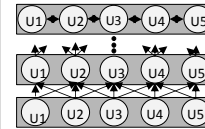
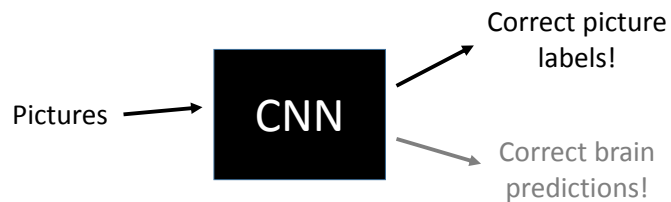


Image-Net: photos of >100K object classes
2012: best non conv-net 26% error rate

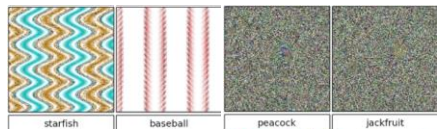
| Year | Group | Error |
|-----------|--------------|-------|
| 2012 | Krizhevsky | 15.3% |
| 2014 | VGG | 7.3% |
| 2014 | GoogLeNet | 6.7% |
| 200,000BC | Human Vision | 5.1% |

Top 5 - % data where top 5 most likely classes were NOT correct class ²

What are CNNs?



Limits: Fooling CNNs
Nguyen CVPR 2015

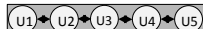




Why understand CNNs?


Insights on:

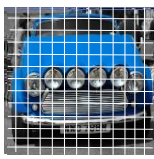
- Making better-performing models
- Making simpler models
- How the brain actually works

How do CNNs work?

Layer 8  Collection of "neurons" divided among k layers

Layer 2  Each neuron looks for one pattern 

Layer 1  Each neuron looks for same pattern at multiple locations in input



U1


| | | | |
|----|----|----|----|
| 10 | 1 | 40 | 0 |
| 0 | 3 | 65 | 15 |
| 0 | 12 | 12 | 0 |
| 0 | 5 | 15 | 0 |

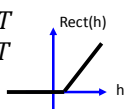
U2

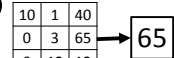
| | | | |
|---|----|----|----|
| 0 | 0 | 10 | 25 |
| 0 | 90 | 0 | 6 |
| 0 | 40 | 25 | 0 |
| 0 | 14 | 0 | 0 |


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Cascade of linear and non-linear computations

Summation $f(x) = \sum_i w_i x_i$ 

Rectification $g(y) = \begin{cases} 0 & y \leq T \\ y - T & y > T \end{cases}$ 

Max pool $h(z) = \max(z_1, \dots, z_n)$ 

Normalization $\tilde{r}_{x,y} = \frac{r_{x,y}}{(k + \alpha \sum_j r_{x,y}^j)^{\beta}}$ 

Layer 2

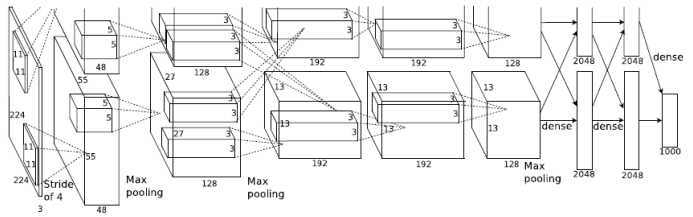
Norm
 Max pool
 Rectify
 Sum

Layer 1

Norm
 Max pool
 Rectify
 Sum

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Example full network – Krizhevsky NIPS 2012



Eight layers One, two, or four sub-layers

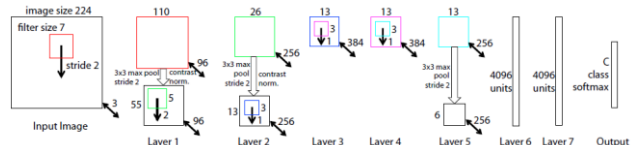
256 – 384 neurons per layer

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Convolution

Each neuron looks for same pattern at multiple locations in input

- How big a location (size)?
- How many locations (stride)?



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1D convolution

input

pattern

Check if 1-D pattern matches (multiply and add) at different windows of the input

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1D convolution

input

pattern

$0+0+0+1+0=1$
 $0+0+2+2=4$
 $0+1+4+1=6$
 $0+2+2+1=5$

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“Spectrogram” as image

- Speech, motion, stock-prices converted to frequency-over-time
- Learn 2D patterns from spectrograms

- Or learn wave-gram from wavelets

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Speech spectrum: convolution of sine waves

Shifting time windows, sine waves at each frequency

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Inflating data set

- Flip/rotate image



- Change lighting/contrast

