## Grasping Deep Learning from Fundamentals

## to Applications

June 15, 2023

## Lecture 2 - Convolutional Neural Networks (CNNs)

Instructors: Yufei Huang, PhD; Arun Das, PhD

## AlphaFold Is The Most Important Achievement In AI - Ever

$37 \%$ of tech organizations use Al!
VB VentureBeat
Uber's self-driving AI predicts the trajectories of pedestrians, vehicles, and cyclists
In a paper, Uber researchers describe an autonomous vehicle perception
 system that reasons about the behavior of pedestrians, vehicles, and ...
= World Economic Forum
How Al and machine learning are helping to tackle COVID19
Organizations have been quick to apply Al and machine-learning in the fight to curb the pandemic - and here are some of the most exciting


Deepfake Generation: Forbes Article



Instance Segmentation

Results
tag Confidence
Negative
(1) 1

Classify Text


## The AI needs to see!

- Human vision is a complex phenomenon starting with the light rays entering through the cornea of the eye and the visual cortex making sense of the various signals it receives.
- However, computers speak only numbers. Hence, images are represented as numbers, usually in intensities ranging from 0 to 255 .


0215001110000099000 - 0 O 460157235255255177 95 61320029 - $101611923825524426524325024925522210310 \quad 0$ - $14170255255244254255253245255249253251124 \quad 1$ 29825522825525125421114111612221525123825549 $13217243255155 \quad 3322652 \quad 2 \quad 01013232255255 \quad 36$ $\begin{array}{lllllll}13217243255155 & 33226 & 52 & 2 & 0 & 10 & 132322552255 \\ 16229252254 & 49 & 12 & 0 & 0 & 7 & 7\end{array} 07023725223562$ $\begin{array}{llllllll}6141245255212 & 25 & 11 & 9 & 3 & 0115236243255137 & 0\end{array}$ - $8725225024821560 \quad 1 \quad 1121252255248144 \quad 6 \quad 0$ - 1311325525524525518218124525224220836019 $10 \quad 5117251255241255267255241162170070$ - O O 4 5825125524525425325512011010 - O \& 972552552552482522552442551821004 - $2220625224625124110024113255245255194 \quad 9 \quad 0$ $011125524225515824 \quad 0 \quad 0 \quad 6 \quad 3925523223056$ $0218251250137 \quad 711000226255250125 \quad 3$ $0173255255101 \quad 920 \quad 0 \quad 13 \quad 31318225124561 \quad 0$ $010725124125523058551911821724825325552 \quad 4$ - $181462502552472552552552452552402551290 \quad 5$ - O $231132152552502482552552582481181412 \quad 0$ - 06610581532332552521473700041



University of
Pittsburgh

## Challenges with learning images



## Problems:

- High dimensional input
- $150 \times 150$ pixels $\times 3$ $($ RGB $)=67,500$
- 2D correlations
- Operational invariance
, Scale, translation, etc


## Very hard to train with DNN!

Number of parameters $=3 \times(\mathrm{D} \times \mathrm{D})+\mathrm{D}$ To feed images to FCN (DNN), we can flatten the images.

For a $32 \times 32$ image, $D=1024$.

Number of parameters $=3 \times(1024 \times 1024)$
$+1024=\sim 3 \times 10^{6}$


## Convolutional neural networks (CNNs)



## Hierarchical Architecture of the mammalian visual cortex



- Ventral (recognition) pathway in the visual cortex has multiple stages Retina - LGN - V1 - V2 - V4 - PIT - AIT ....
- It's hierarchical
- There is local processing


## LeNet (1989)



A Full Convolutional Neural Network (LeNet)

## LeNet1 Demo from 1993

- Running on a 486 PC with an AT\&T DSP32C add-on board (20 Mflops!)


 answer: 384
$\begin{array}{llll}33 & 88 & 44\end{array}$ 3318814



## Why CNN now? A: ImageNet and GPU

- The ImageNet dataset [Fei-Fei et al. 2012]
- 1.5 million training samples
- 1000 categories

Flute
-NVIDIA Graphical Processing Units (GPU)

- Capable of 1 trillion operations/second


Backpac



Strawberry


Racket


## ImageNet large-scale visual recognition challenge (ILSVRC)

- The ImageNet dataset
-1.5 million training samples of size $224 \times 224 \times 3$
- 1000 fine-grained categories (breeds of dogs....)


Pittsburgh

## CNN ingredients

## - Convolutional filters

- local connectivity
- parameter sharing
-Pooling/subsampling hidden units



## Convolution filters



| $1_{x_{1}}$ | $1_{x 0}$ | $1_{x 1}$ | 0 | 0 |
| :--- | :--- | :--- | :--- | :--- |
| $0_{x 0}$ | $1_{x 1}$ | $1_{x 0}$ | 1 | 0 |
| $0_{x 1}$ | $0_{x 0}$ | $1_{x 1}$ | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |



Convolved Feature

8 feature maps.
Size of feature map -> parameters we set for the kernel.

(height, width, channels)

| $1_{x_{1}}$ | $1_{x 0}$ | $1_{x_{1}}$ | 0 | 0 |
| :--- | :--- | :--- | :--- | :--- |
| $0_{x 0}$ | $1_{x 1}$ | $1_{x 0}$ | 1 | 0 |
| $0_{x 1}$ | $0_{x 0}$ | $1_{x 1}$ | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

Image

Convolved Feature

5


5

Kernet of Conv-Layer


Output of Conv Layer

Feature Map

tf.keras.layers.Conv2D(filters=2, kernel_size=(4,2), padding='same', activation='relu', input_shape=(5,5,1)),

| $* 1$ | $* 2$ |
| :--- | :--- |
| $* 3$ | $* 4$ |
| $* 5$ | $* 6$ |
| $* 7$ | $* 8$ |


tf.keras.layers.Conv2D(filters=2, kernel_size=2, padding='same', activation='relu')



University of
Pittsburgh

## Pooling



Example of Max Pooling.

## Padding

Input

| $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ |
| :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 2 |
| 0 | 3 | 4 | 5 |
| 0 | 0 | 7 | 8 |
| 0 | 0 | 0 | 0 |
|  | 0 | 0 |  |
|  | 0 |  |  |

Kernel


## Strides



Strides $=1$


Stride is how much we move the kernels forward at each step during the convolution operation. When the stride is 1 then we move the filters one pixel at a time. When the stride is 2 then the filters jump 2 pixels at a time as we slide them around. This will produce smaller output volumes spatially.

## Data augmentation

- Goal: introduce scale and rotational invariance
- How? Generate artificial images



## Different CNNs

- AlexNet
- VGGNet
- Inception model
- ResNet


Inception module

ILSVRC 2014 winner (6.7\% top 5 error)

## ResNet (He et al, 2015)

## ILSVRC 2015 winner ( $3.6 \%$ top 5 error)

## - 1st places in all five main tracks

- ImageNet Classification: "Ultra-deep" (quote Yann) 152-layer nets
- ImageNet Detection: 16\% better than 2nd
- ImageNet Localization: 27\% better than 2nd
- COCO Detection: $11 \%$ better than 2nd
- COCO Segmentation: $12 \%$ better than 2nd


## 152 layers!!!

### 25.5M parameters

| method | top-1 err. | top-5 err. |
| :--- | :---: | :---: |
| VGG [41] (ILSVRC' 14) | - | $8.43^{\dagger}$ |
| GoogLeNet [44] (ILSVRC' 14) | - | 7.89 |
| VGG [41] (v5) | 24.4 | 7.1 |
| PReLU-net [13] | 21.59 | 5.71 |
| BN-inception [16] | 21.99 | 5.81 |
| ResNet-34 B | 21.84 | 5.71 |
| ResNet-34 C | 21.53 | 5.60 |
| ResNet-50 | 20.74 | 5.25 |
| ResNet-101 | 19.87 | 4.60 |
| ResNet-152 | $\mathbf{1 9 . 3 8}$ | $\mathbf{4 . 4 9}$ |





## ResNet (He et al, 2015)

## ILSVRC 2015 winner (3.6\% top 5 error)



## ResNet (He et al, 2015)



Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
\{kahe, v-xiangz, v-shren, jiansun\} @ microsoft.com


Why does it work?

- The "identity" path preserve the gradient!


## Results of 2017



## Deep learning modules

## Dense layers



## Convolutional layer <br> Residual layer



Attention layer


## Prediction layers



## Building a convolution neural network (CNN)



## Supervised deep learning models




Transformer
RNN (LSTM, GRU)


Pittsburgh


Graph CNN

ResNet


## Unsupervised deep learning models



Generative Adversarial Network (GAN)


