Introduction to Deep Learning Methods and Their Scientific Applications

Yihui "Ray" Ren (yren@bnl.gov) Computational Science Initiative 08/06/2021

BNL Physics Department Summer Lecture series

- Memorable Moments of AI
 - Computer Vision
 - Natural Language Processing (NLP)
 - Control and Optimization
- What is Deep Learning
- Some examples

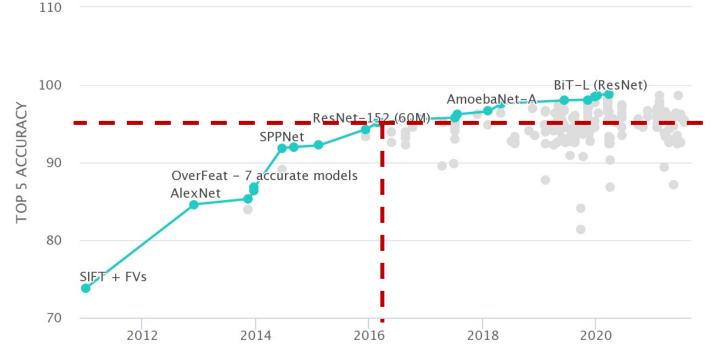
Feel free to ask questions at any moments!

ImageNet Large Scale Visual Recognition Challenge

Show affiliations

https://arxiv.org/pdf/1409.0575.pdf

Russakovsky, Olga; Deng, Jia; Su, Hao; Krause, Jonathan; Satheesh, Sanjeev; Ma, Sean; Huang, Zhiheng; Karpathy, Andrej; Khosla, Aditya; Bernstein, Michael; Berg, Alexander C.; Fei-Fei, Li



Classify each image into one of 1000 different classes!

"The human error was estimated to be 5.1%"



Other popular computer vision tasks

- Image Segmentation
- Instance Segmentation
- Object Detection
- Pose Estimation
- Face Recognition





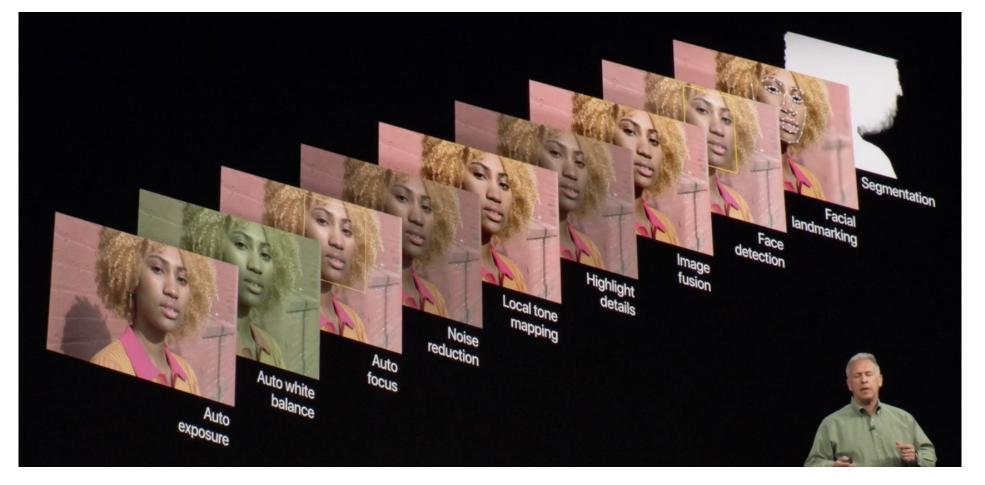
Image credit: https://ai.facebook.com/tools/detectron2/

How AI is changing photography

Cameras' biggest recent advancements have come from AI, not sensors and lenses

By Sam Byford | @345triangle | Jan 31, 2019, 8:00am EST

https://www.theverge.com/2019/1/31/18203363/ai-artificialintelligence-photography-google-photos-apple-huawei



End-to-end computation Photography.

Self-driving Cars

- Level 1 "hands-on"
- Level 2 "hands-off"
- Level 3 "eyes-off".
- Level 4 "minds-off"



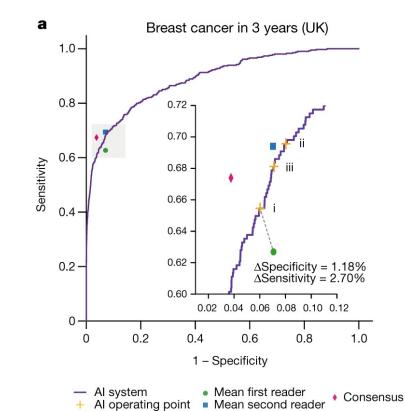
https://www.tesla.com/videos/autopilot-self-driving-hardware-neighborhood-long

International evaluation of an AI system for breast cancer screening

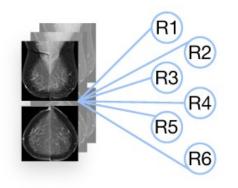
Scott Mayer McKinney 🗠, Marcin Sieniek, [...]Shravya Shetty 🗠

Nature **577**, 89–94 (2020) Cite this article

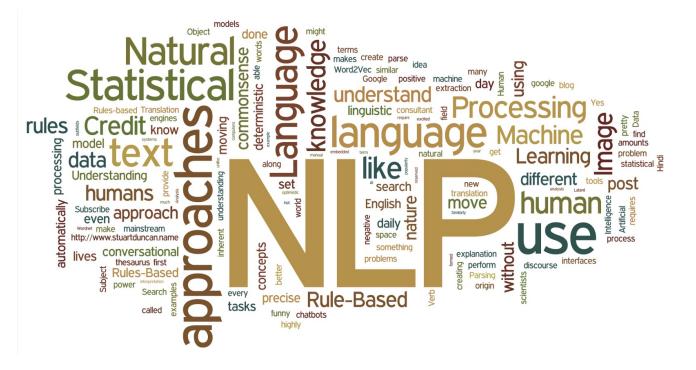
"In an independent study of six radiologists, <u>the Al system</u> <u>outperformed all of the human readers</u>: the area under the receiver operating characteristic curve (AUC-ROC) for the Al system was greater than the AUC-ROC for the average radiologist by an absolute margin of 11.5%."



Independently conducted reader study



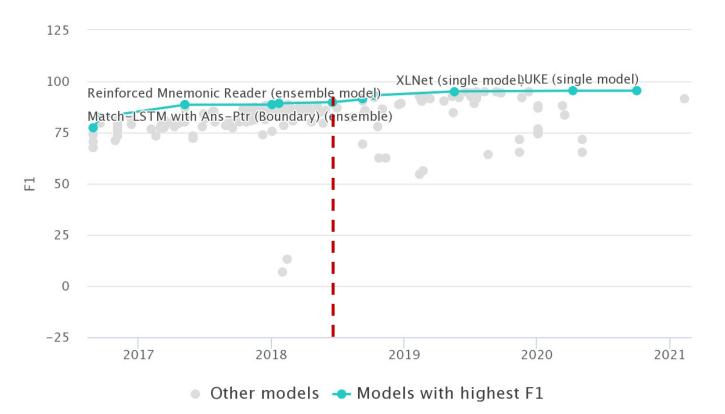
6 radiologists read 500 cases from US test set



Common NLP tasks:

- Machine Translation
- Question Answering
- Text Generation
- Named Entity Recognition
- Sentiment Analysis
- Text Summarization
- Speech Recognition

Question Answering



The resulting human performance score on the test set **is 91.2% F1**.

Passage Sentence

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity.

Question

What causes precipitation to fall?

Answer Candidate

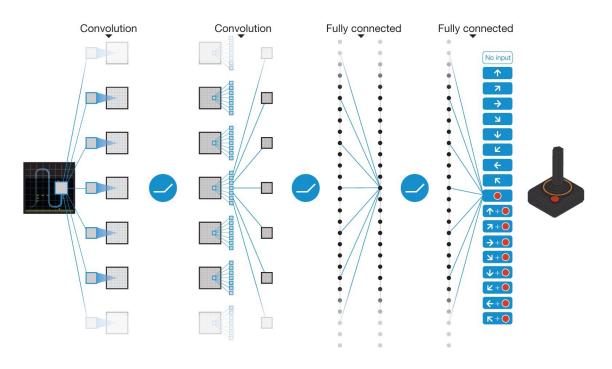


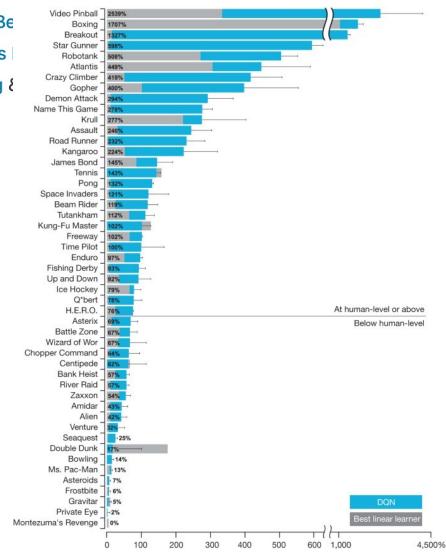
The Stanford Question Answering Dataset (SQuAD) https://rajpurkar.github.io/mlx/qa-and-squad/ Published: 25 February 2015

Human-level control through deep reinforcement learning

Volodymyr Mnih, Koray Kavukcuoglu 🗠, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Be Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg & Hassabis 🖂

Nature 518, 529–533 (2015) Cite this article







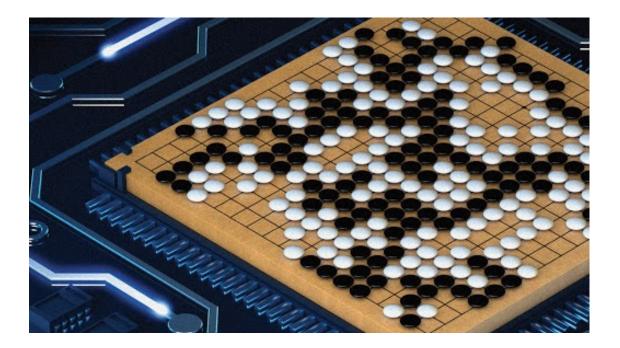
Published: 27 January 2016



Mastering the game of Go with deep neural networks and tree search

David Silver 🖂, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche,





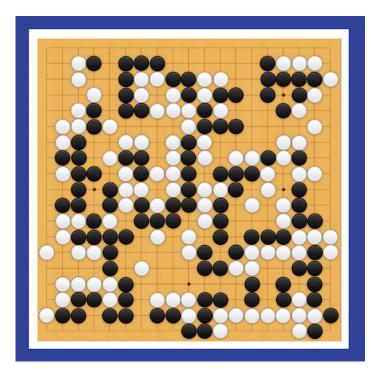
"AlphaGo's 4-1 victory in Seoul, South Korea, on March 2016"



Mastering the game of Go without human knowledge

David Silver 🗠, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez,





AlphaGo 3-0 Ke Jie world No. 1 ranking player Go player in a three-game Go match in May 2017.

'It will change everything': **DeepMind's AI makes gigantic leap** in solving protein structures

Google's deep-learning program for determining the 3D shapes of proteins stands to transform biology, say scientists.

Article Published: 15 July 2021

This is an unedited manuscript that has been accepted for publicatio



version of the manuscript as a service to our authors and readers. The manuscript will undergo copyediting typesetting and a proof review before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers apply.

https://www.nature.com/articles/s41586-021-03819-2

Highly accurate protein structure prediction with AlphaFold

John Jumper ⊡, Richard Evans, [...]Demis Hassabis ⊡

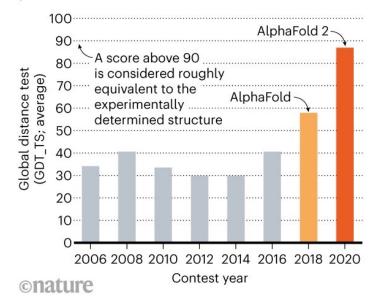
Nature (2021) Cite this article

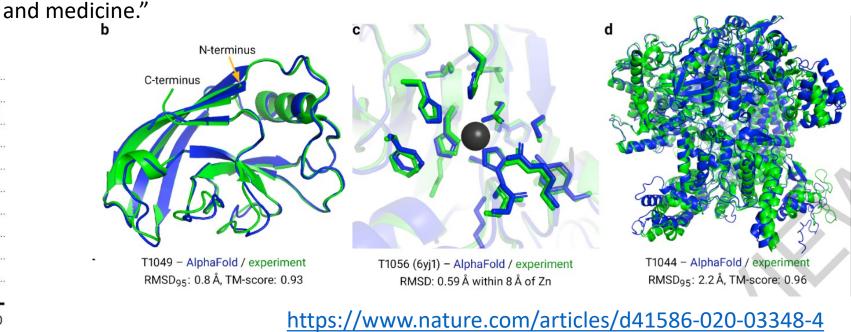
250k Accesses | 1 Citations | 2658 Altmetric | Metrics

"The ability to accurately predict protein structures from their amino-acid sequence would be a huge boon to life sciences

STRUCTURE SOLVER

DeepMind's AlphaFold 2 algorithm significantly outperformed other teams at the CASP14 proteinfolding contest - and its previous version's performance at the last CASP.



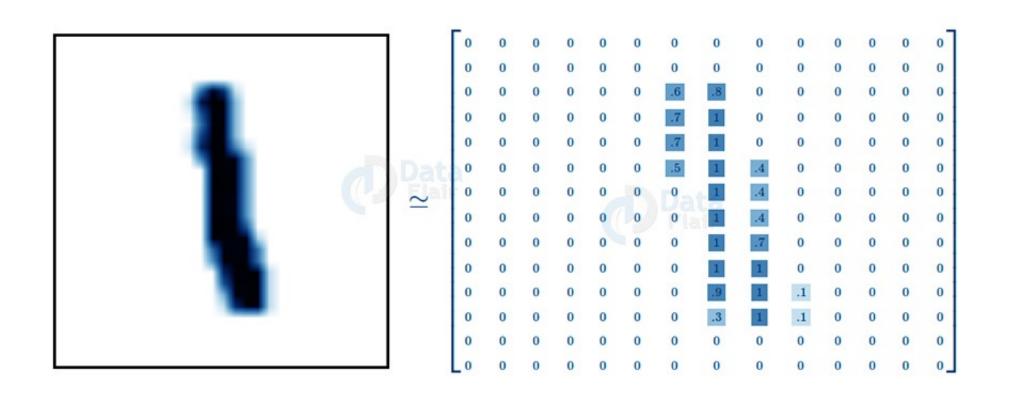


- Memorable Moments of Al
 - Computer Vision
 - Natural Language Processing (NLP)
 - Control and Optimization
- What is Deep Learning
 - Stochastic Gradient Descent & Backpropagation (90s)
 - Fast enough hardware & Big Data (recently)
- Some examples

Remixed from: http://introtodeeplearning.com/

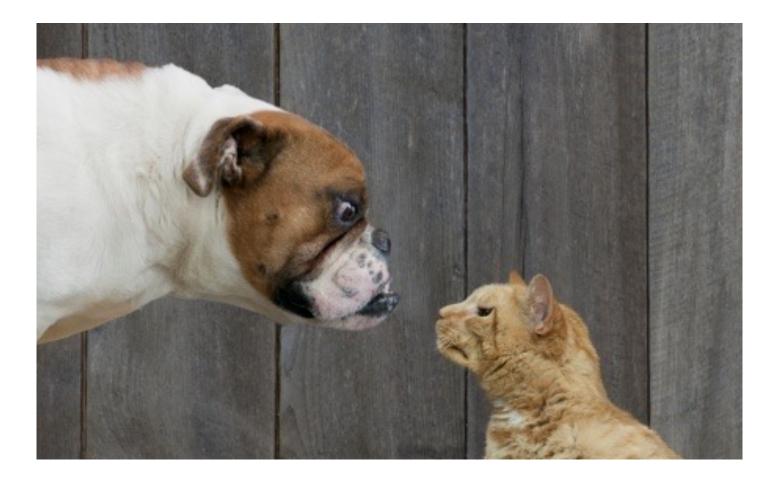
MIT 6.5191 Introduction to Deep Learning

MIT's introductory course on deep learning methods with applications in computer vision, and more!



How can we teach a computer this is a "one"?

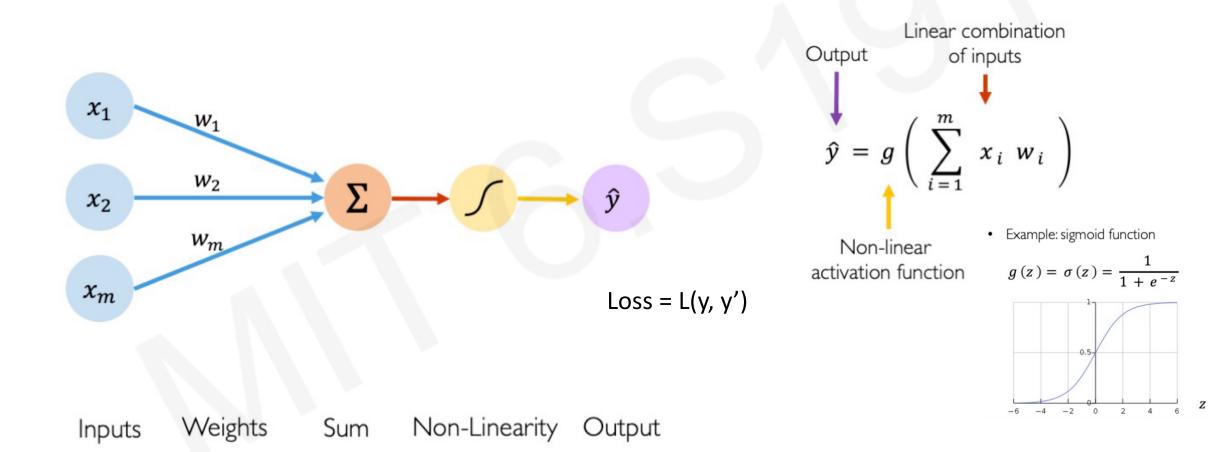
Image credit: https://data-flair.training/blogs/tensorflow-mnist-dataset/

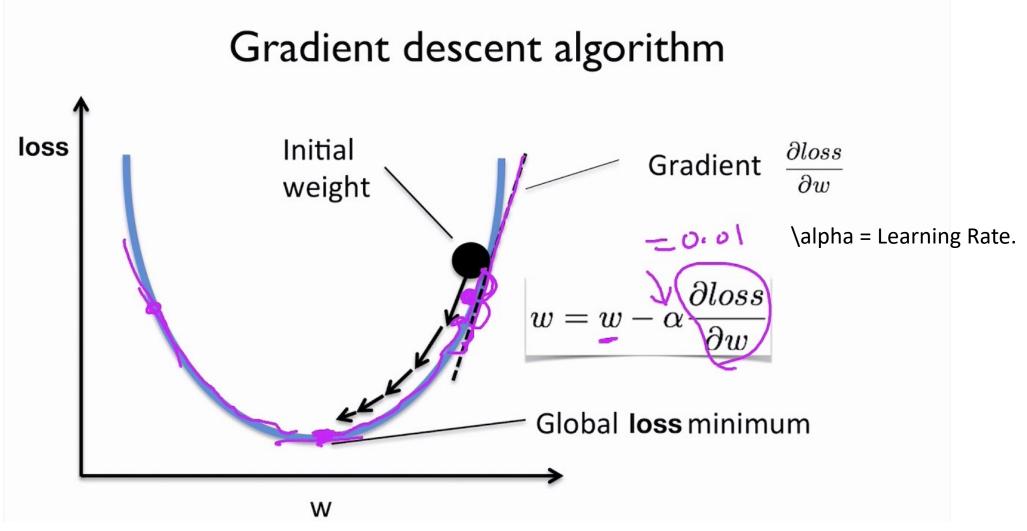


How about cat vs dog?

Image credit: https://www.kaggle.com/c/dogs-vs-cats

The Perceptron: Forward Propagation

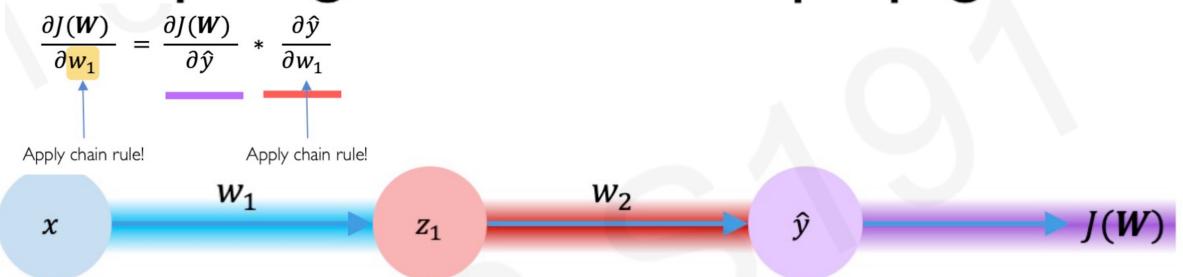


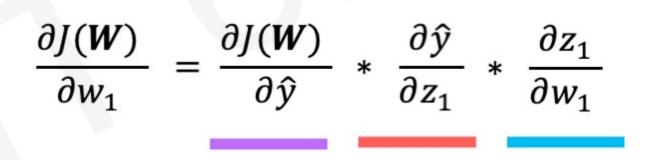


HKUSTCode: https://github.com/hunkim/PyTorchZeroToAll Slides: http://bit.ly/PyTorchZeroAll

Computing Gradients: Backpropagation w_1 W_2 Ŷ (W)x z_1 $\partial J(W)$ $\partial J(W)$ дŷ ∂W_2 $\partial \hat{v}$ ∂W_2

Computing Gradients: Backpropagation

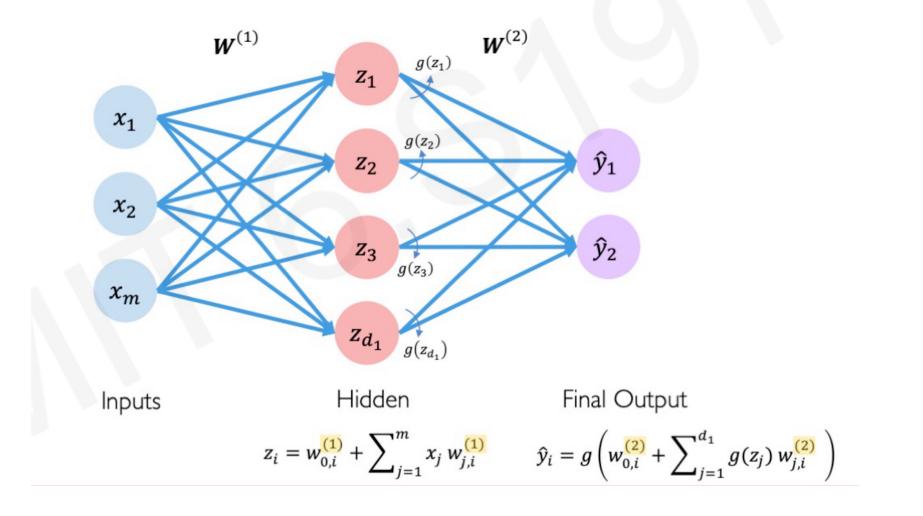




We need to do this for ALL weights in the network.

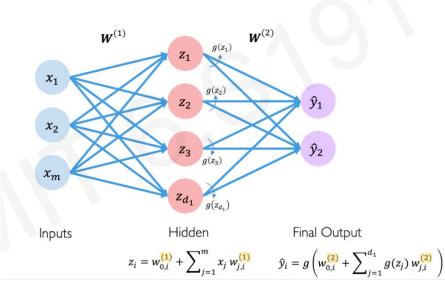
Single Layer Neural Network

Make it wider



Multilayer Perceptron (MLP)

Single Layer Neural Network



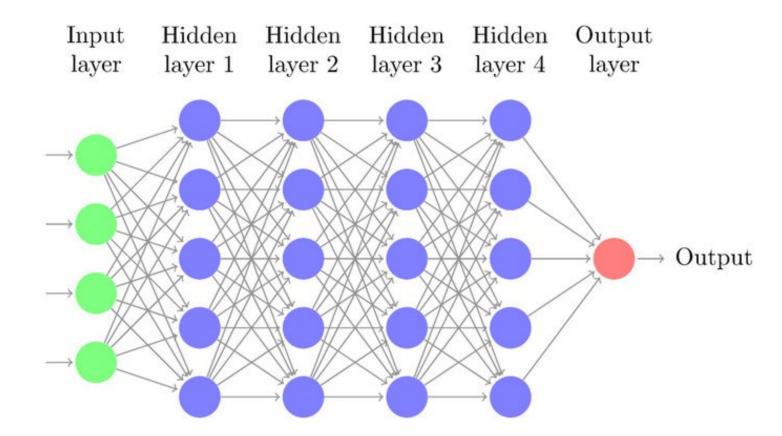
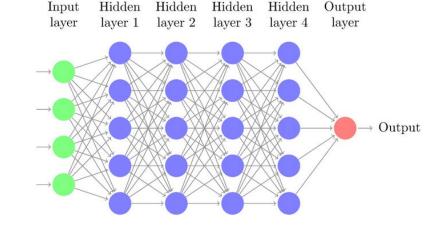
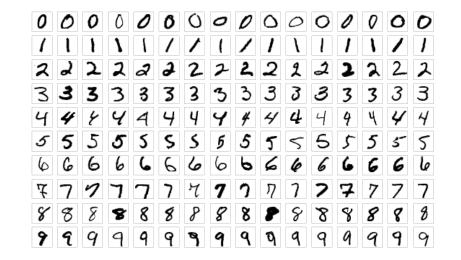


Image credit: https://www.researchgate.net/figure/Multi-Layer-Perceptron-MLP-diagram-with-four-hidden-layers-and-a-collection-of-single_fig1_334609713

However, there are two major problems of MLP when handling image data.

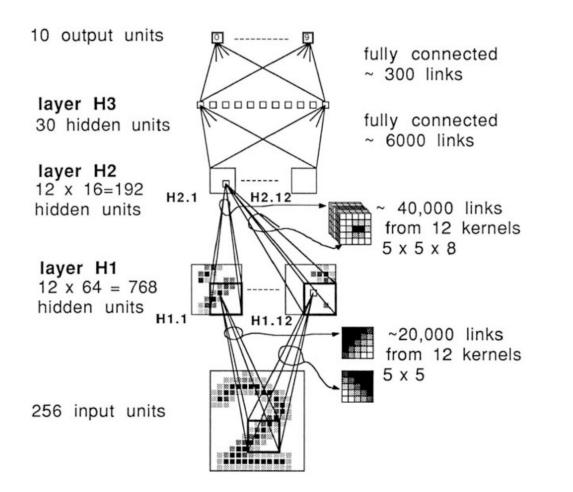
- 1. <u>Parameter efficiency.</u> Each layer is a large matrix of dimension `input_dim X output_dim`. (i.e. think about image size of 1000x1000)
- 2. <u>Does not handle "shift-invariance" of images.</u> If we shift the digital "1" several pixels away, the model has to learn it as a "new" instance.

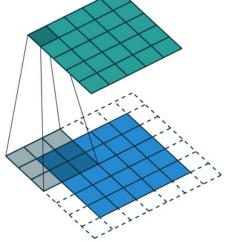




https://github.com/vdumoulin/conv_arithmetic

Convolutional Neural Networks (CNN)



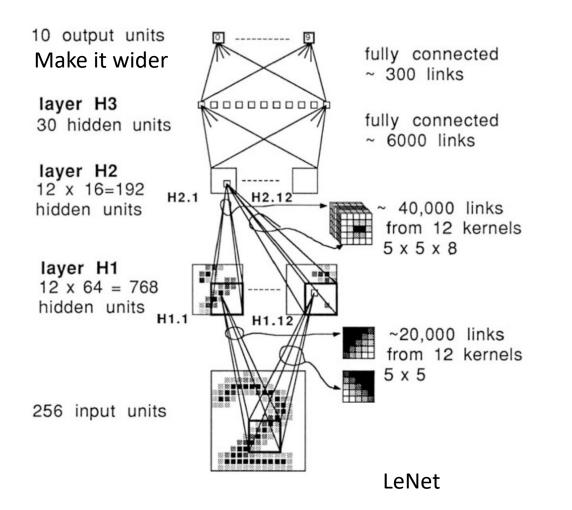


Backpropagation Applied to Handwritten Zip Code Recognition

Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, L. D. Jackel
Author and Article Information
Neural Computation (1989) 1 (4): 541–551.
https://doi.org/10.1162/neco.1989.1.4.541
Article history C

- 1. <u>Parameter efficiency.</u> "Kernels" are reused at all locations. Parameters won't grow with input image dimension.
- 2. <u>Handles "shift-invariance" of images.</u> Any location containing "signal" will activate the kernel.

Convolutional Neural Networks (CNN)



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for. We used an off-the-shelf board that contains 256 kbytes of local memory and an AT&T DSP-32C general purpose DSP with a peak performance of 12.5 million multiply add operations per second on 32 bit floating point numbers (25 MFLOPS). The DSP operates as a coproces-

Big Data for benchmarking

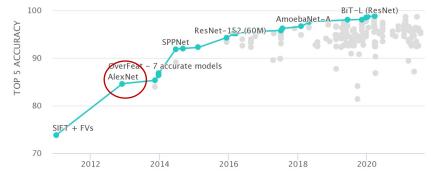
AlexNet: implemented in CUDA and utilized GPU.

60K parameters	61M parameters		
LeNet	AlexNet		
Image: 28 (height) × 28 (width) × 1 (channel)	Image: 224 (height) × 224 (width) × 3 (channels)		
Convolution with 5×5 kernel+2padding:28×28×6	Convolution with 11×11 kernel+4 stride: 54×54×96		
sigmoid	√ ReLu		
Pool with 2×2 average kernel+2 stride:14×14×6	Pool with 3×3 max. kernel+2 stride: 26×26×96		
\checkmark			
Convolution with 5×5 kernel (no pad):10×10×16	Convolution with 5×5 kernel+2 pad:26×26×256		
sigmoid	√ ReLu		
Pool with 2×2 average kernel+2 stride: 5×5×16	Pool with 3×3 max.kernel+2stride:12×12×256		
$\sqrt{flatten}$	\downarrow		
Dense: 120 fully connected neurons	Convolution with 3×3 kernel+1 pad:12×12×384		
sigmoid	V ReLu		
Dense: 84 fully connected neurons	Convolution with 3×3 kernel+1 pad:12×12×384		
🗸 sigmoid	V ReLu		
Dense: 10 fully connected neurons	Convolution with 3×3 kernel+1 pad:12×12×256		
\checkmark	√ ReLu		
Output: 1 of 10 classes	Pool with 3×3 max.kernel+2stride:5×5×256		
	√ flatten		
	Dense: 4096 fully connected neurons		
	√ ReLu, dropout p=0.5		
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	√ ReLu, dropout p=0.5		
	Dense: 1000 fully connected neurons		
	\checkmark		
	Output: 1 of 1000 classes		

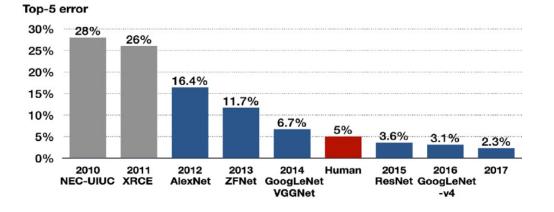
Image credit:

https://en.wikipedia.org/wiki/AlexNet#/media/File:Comparison_image_neural_networks.svg





110



Big Data for benchmarking

AlexNet: implemented in CUDA and utilized GPU.



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"Our network takes between five and six days to train on two GTX 580 3GB GPUs"

GTX 580: 1.581 TFLOPS Each.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems* 25 (2012): 1097-1105.

Image credit:

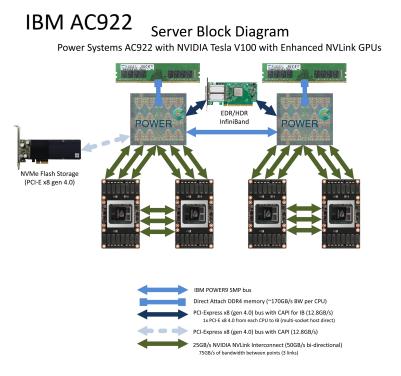
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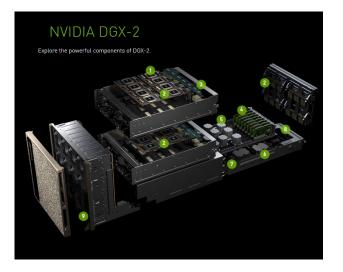
Most modern High-performance computing (HPC) are powered by GPUs.



https://www.top500.org/

	Accelerator/Co-Processor	Count	System Share (%)
1	NVIDIA Tesla V100	80	16
2	NVIDIA A100	15	3
3	NVIDIA Tesla V100 SXM2	12	2.4
4	NVIDIA Tesla P100	8	1.6
5	NVIDIA A100 SXM4 40 GB	5	1
6	NVIDIA A100 40GB	4	0.8
7	NVIDIA Volta GV100	4	0.8
8	NVIDIA Tesla K40	3	0.6
9	NVIDIA A100 80GB	2	0.4
10	Matrix-2000	1	0.2
11	NVIDIA 2050	1	0.2
12	NVIDIA Tesla K40m	1	0.2
13	NVIDIA Tesla K40/Intel Xeon Phi 7120P	1	0.2
14	NVIDIA Tesla P100 NVLink	1	0.2
15	Preferred Networks MN-Core	1	0.2
16	Nvidia Volta V100	1	0.2
17	NVIDIA Tesla K80	1	0.2
18	Intel Xeon Phi 31S1P	1	0.2
19	Deep Computing Processor	1	0.2
20	AMD Vega 20	1	0.2
21	Intel Xeon Phi 5110P	1	0.2
22	NVIDIA Tesla K20x	1	0.2

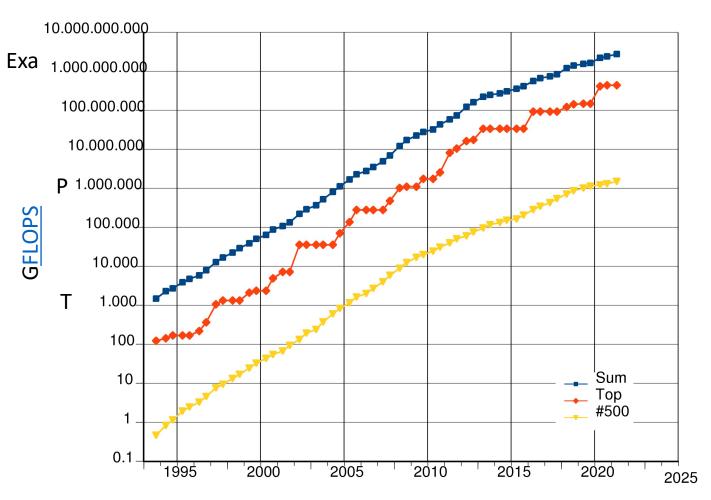




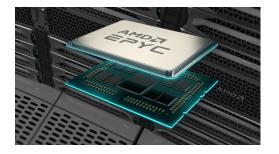
"the world's first <u>2 petaFLOPS</u> system integrating 16 NVIDIA V100 Tensor Core GPUs for large-scale AI projects" -- NVIDIA

For example, IBM AC922 has 4 (or 6 GPUs) per node. NVIDIA DGX2 has 16 GPUs per node, and DGX1 has 8 GPUs per node.

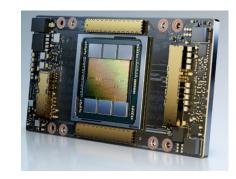
Comparing most advanced CPU and GPU



supercomputer performance



AMD EPYC 7763 (64-cores) FP32: 3.58 TFLOPS



NVIDIA A100 GPU (6912 CUDA cores) FP32: 19.5 TFLOPS Tensor Float 32 (TF32): 156 TFLOPS

Image credit: https://en.wikipedia.org/wiki/TOP500#/media/File:Supercomputers-history.svg https://www.amd.com/en/products/cpu/amd-epyc-7763 https://www.nvidia.com/en-us/data-center/a100/ However...

- Coding GPU in C/C++ with CUDA is difficult.
- Manually code forward and backward passes, and differentiation using chain rule is tedious.

- Coding GPU used to be difficult (C/C++ with CUDA).
- Manually code forward and backward pass, and differentiation using chain rule is tedious.

Modern Deep Learning libraries made these very easy! Mostly Python-based: PyTorch, TensorFlow, JAX and so on.

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
```

```
def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(-1, 16 * 5 * 5)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x
```

net = Net()
print(net)







Algorithm

- I. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
- 2. Loop until convergence:
- 3. Pick batch of *B* data points

4. Compute gradient,
$$\frac{\partial J(W)}{\partial W} = \frac{1}{B} \sum_{k=1}^{B} \frac{\partial J_k(W)}{\partial W}$$

5. Update weights,
$$W \leftarrow W - \eta \frac{\partial J(W)}{\partial W}$$

6. Return weights

Initialize the loss function
loss_fn = nn.CrossEntropyLoss()

#Initialize optimizer

optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

```
for batch, (X, y) in enumerate(dataloader):
    # Compute prediction and loss
    pred = model(X)
    loss = loss_fn(pred, y)
```

```
# Backpropagation
optimizer.zero_grad()
loss.backward()
optimizer.step()
```

To move model or data to GPU, simply <u>`model = model.cuda()`</u>

https://pytorch.org/tutorials/beginner/basics/optimization_tutorial.html

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- Manually code forward and backward pass, and differentiation using chain rule is tedious.

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https://huggingface.co/

Some higher-level deep learning libraries can get an inference job done in three lines of code!

```
>>> from transformers import pipeline
>>> classifier = pipeline('sentiment-analysis')
>>> classifier('We are very happy to show you the @ Transformers library.')
[{'label': 'POSITIVE', 'score': 0.9997795224189758}]
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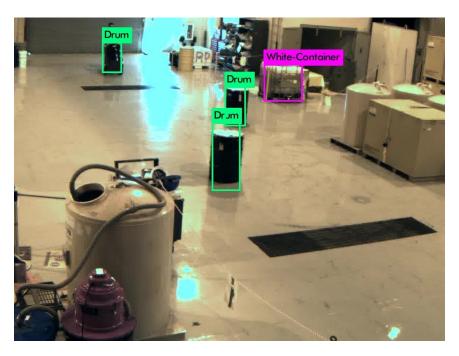
It's the best time to learn and practice deep learning!

- Memorable Moments
- What is Deep Learning
- Some examples
 - Object Detection for NNSA / IAEA
 - Neural Fingerprints for COVID drug screening
 - Bayesian Neural Nets for climate prediction
 - Auto-encoder for sPHENIX Data Compression
 - Bridge the gap between simulation and experiments, GAN!
 - Software hardware Co-design: deploying AI at edge.

Supervised Deep Learning Software for Surveillance Cameras

• Use computer vision (deep learning) algorithms to assist IAEA inspectors reviewing surveillance footage more efficiently.





2019 Joule Awards by NA-241 SG Tech National Nuclear Security Administration (NNSA)

Jihwan Park, Yuewei Lin, Shinjae Yoo, Yonggang Cui

Thank you!

- Please Contact me if you are interested in AI/ML SULI projects!
- yren@bnl.gov