



Introduction to Deep Learning

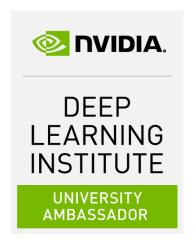
Dr. Alptekin Temizel Professor, Graduate School of Informatics, METU DLI Certified Instructor, DLI University Ambassador

GPU/Deep Learning Related Activities

- NVIDIA Professor Partnership Award July 2009
- •GPU Teaching Center December 2010
- GPU Research Center February 2012
- Deep Learning Institute (DLI) Certification and DLI University Ambassadorship- Aug. 2017



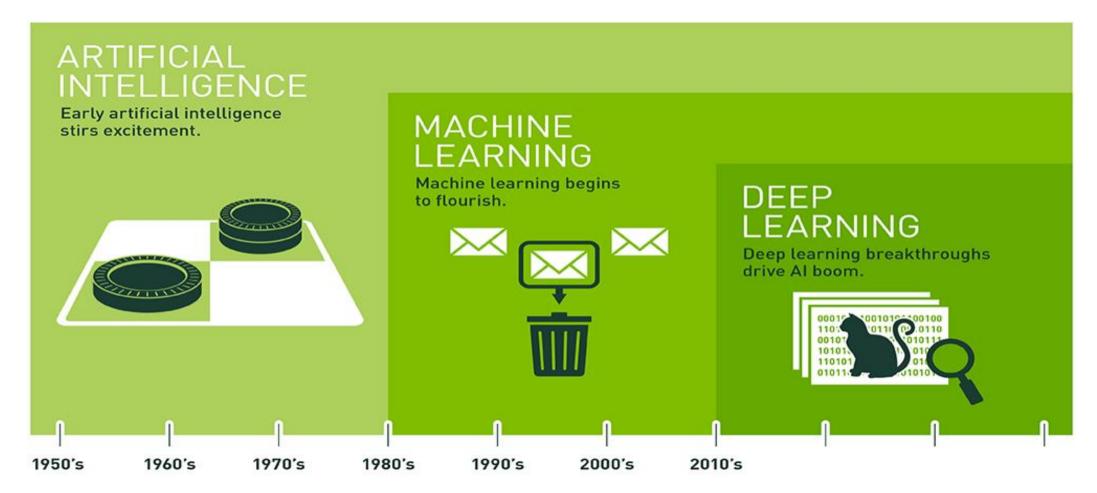








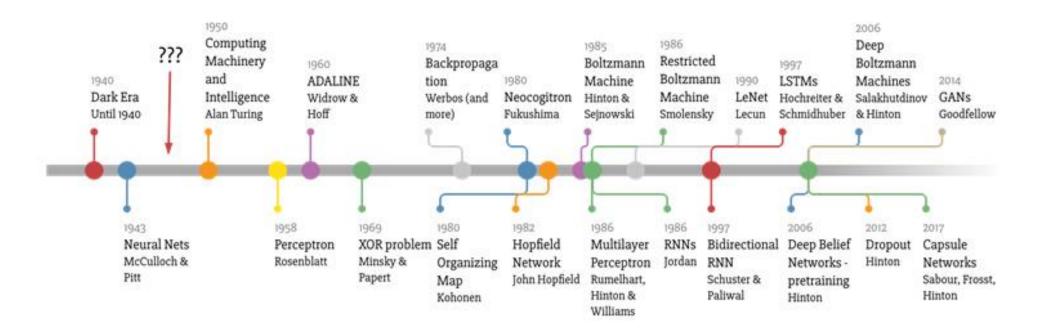
Definitions







Deep Learning Timeline



Made by Favio Vázquez





Deep Learning Across Industries

Internet Services

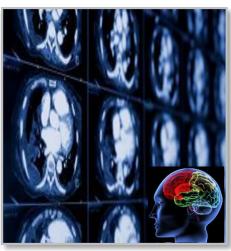




Security & Defense

Autonomous Machines











- > Image/Video classification
- > Speech recognition
- > Natural language processing
- > Cancer cell detection
- > Diabetic grading
- > Drug discovery

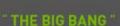
- > Video captioning
- ➤ Content based search
- > Real time translation
- > Face recognition
- > Video surveillance
- > Cyber security

- ➤ Pedestrian detection
- > Lane tracking
- > Recognize traffic signs





THE EXPANDING UNIVERSE OF MODERN AI



Big Data GPU Algorithms







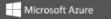




INVIDIA. CUDNN









api.ai

BLUERIVER

crop-yield optimization

clarifai

nervana

eCommerce & Medica

Morpho!

YSADAKO

Waste Management

drive ai

SocialEves*

1,000+ AI START-UPS

\$5B IN FUNDING



AstraZeneca 2

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charles SCHWAB

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FANUC

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MERCK













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Ann. Phys. 17, 132-148

Gesichtpunkt A Einstein

Albert Einstein Institute of Advanced Studies, Princeton No verified email **Physics**

TITLE	CITED BY	YEAR
Can quantum-mechanical description of physical reality be considered complete? A Einstein, B Podolsky, N Rosen Physical review 47 (10), 777	17154	1935
Uber einen die Erzeugung und Verwandlung des Lichtes betreffenden heurischen	11080 *	1905

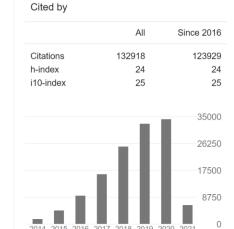




Alex Krizhevsky

Dessa Verified email at dessa.com Machine Learning

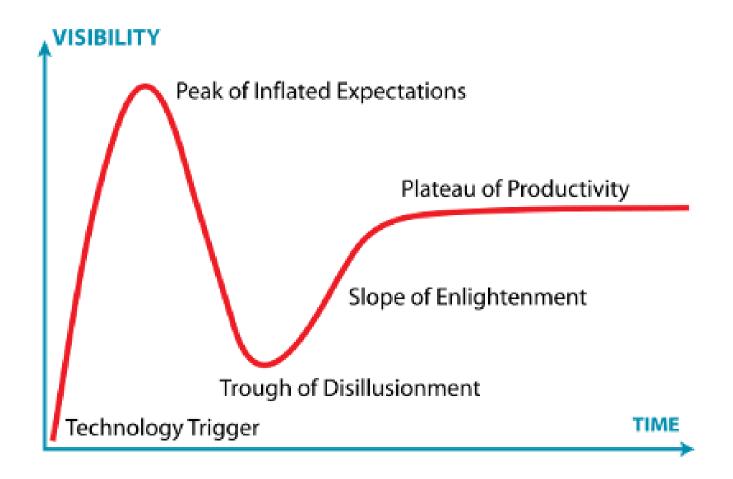
TITLE	CITED BY	YEAR
Imagenet classification with deep convolutional neural networks A Krizhevsky, I Sutskever, GE Hinton Advances in neural information processing systems 25, 1097-1105	82404	2012
Dropout: a simple way to prevent neural networks from overfitting N Srivastava, G Hinton, A Krizhevsky, I Sutskever, R Salakhutdinov The journal of machine learning research 15 (1), 1929-1958	26688	2014



Disclaimer: Number of citations is not a metric that could or should be used to compare the scientific quality or significance of the papers. This slide is only intended to demonstrate the **popularity** of deep learning.

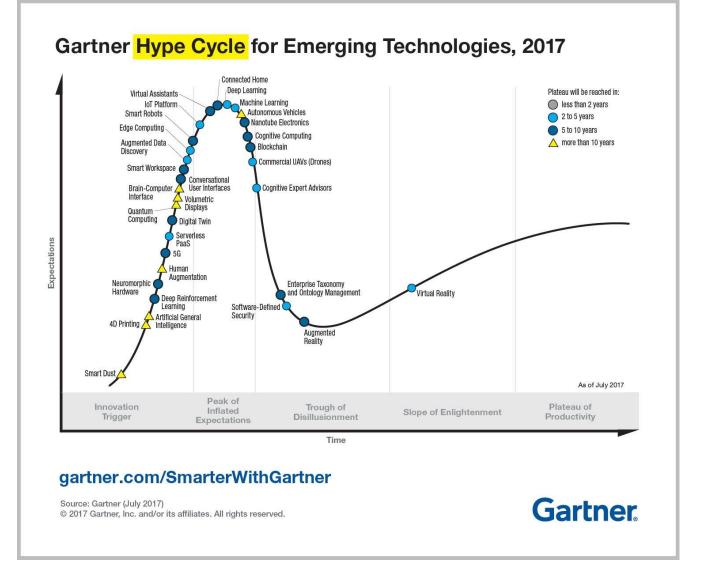








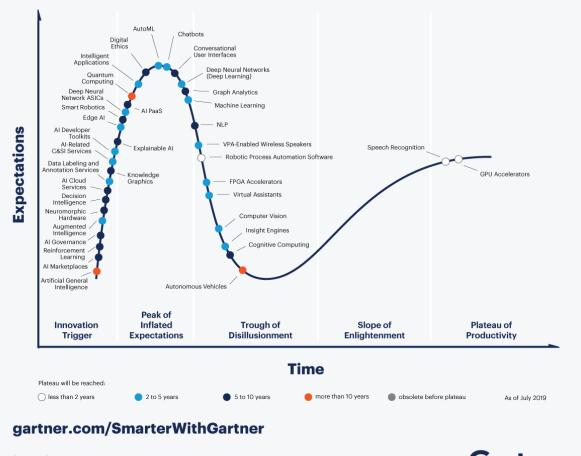








Gartner Hype Cycle for Artificial Intelligence, 2019

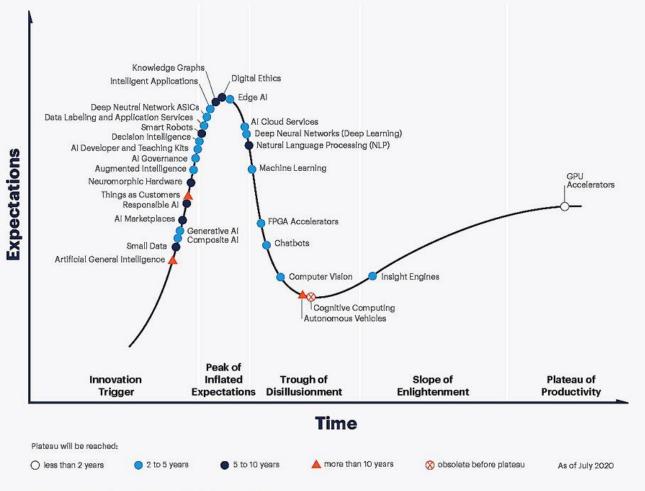


Gartner





Hype Cycle for Artificial Intelligence, 2020



gartner.com/SmarterWithGartner







What Deep Learning Is NOT!

- X Deep learning algorithms do not aim to accurately model the brain
- √ They are machine learning systems with some inspiration from neurons

- X Deep learning systems do not have "deep" thoughts (or any thoughts!)
- √ The architecture has many layers, implying a deep architecture

- X Deep learning systems do not try to compete with human learning
- ✓ They aim to solve **particular problems** using statistical machine learning techniques and for some particular problems they have better accuracy than humans











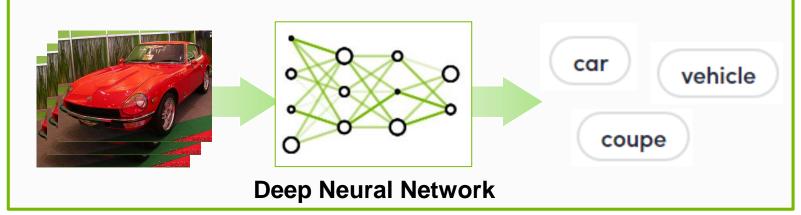
A New Computing Model

Algorithms that Learn from Examples



Traditional Approach

- > Requires domain experts
- > Time consuming
- Not scalable to new problems



Deep Learning Approach

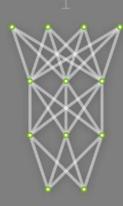
- ✓ Learn from data
- √ Easy to extend



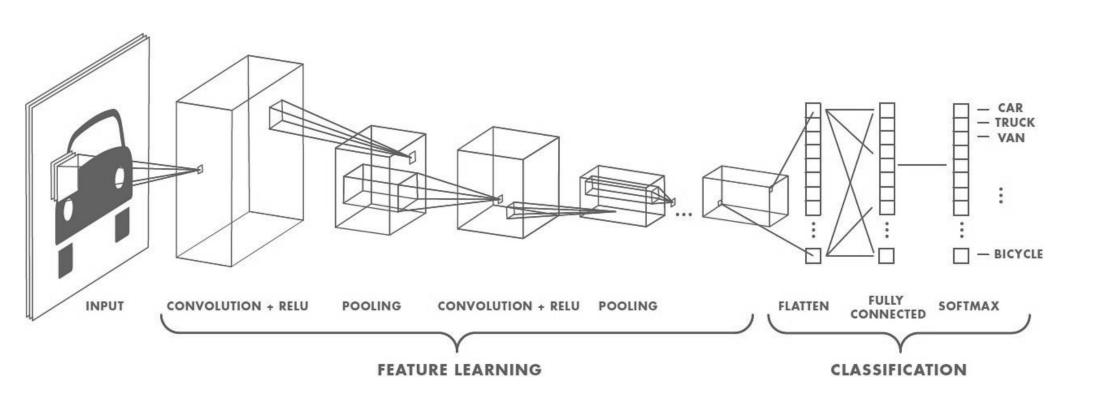


DEEP LEARNING

Untrained Ieural Network Model



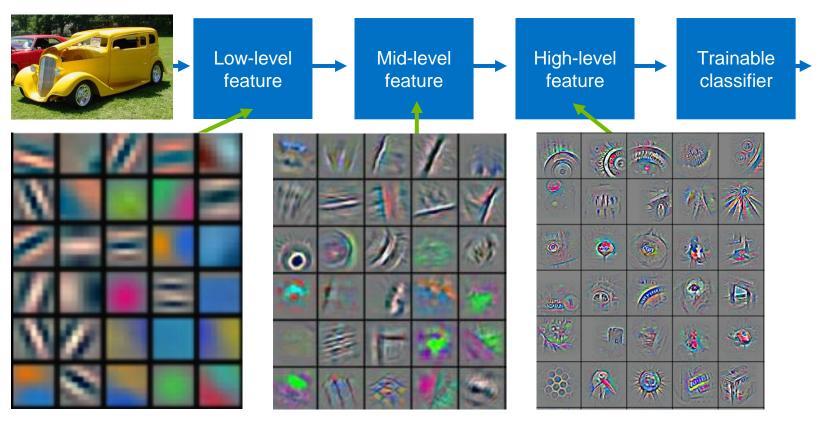
Deep Learning - Convolutional Networks







Deep Learning - Convolutional Networks



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]





Have Daan in Franch?

AlexNet (2012)

5 convolutional layers 3 fully-connected layers





AlexNet (2012) VGG-M (2013) VGG-D (2013)





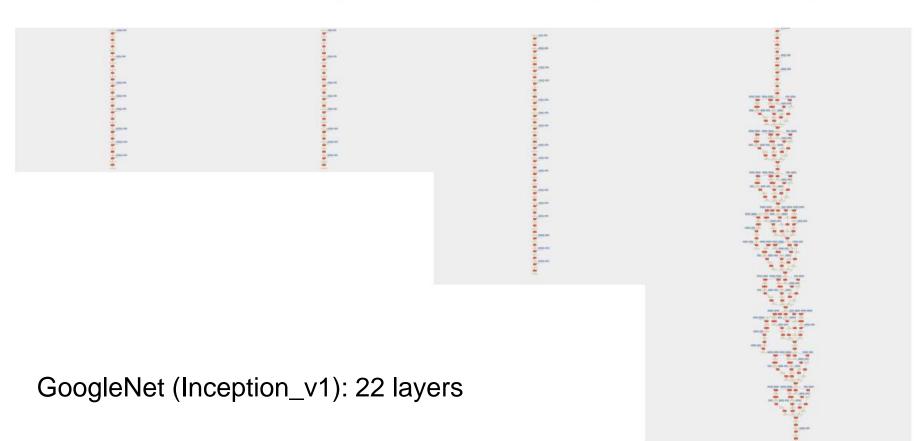


- AlexNet:5 convolutional layers,
- VGG-D: 16 layers
- VGG-E: 19 layers
- VGG-E Top-5 error rate: 7.3%
- To reduce the number of parameters in such very deep networks, they used smaller 3x3 filters in all convolutional layers





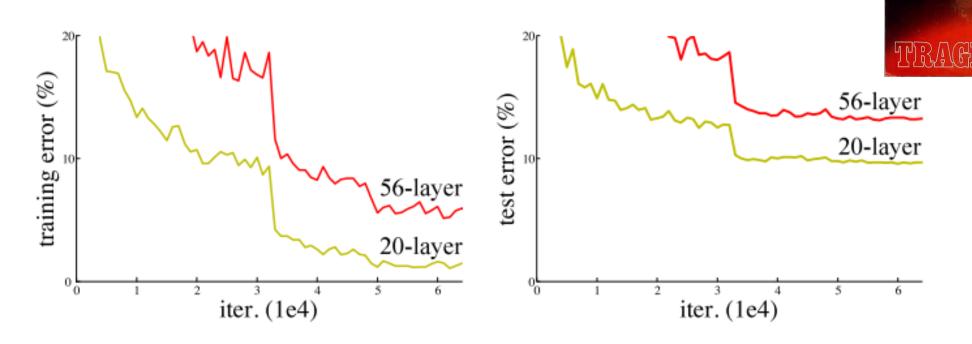
AlexNet (2012) VGG-M (2013) VGG-VD-16 (2014) GoogLeNet (2014)









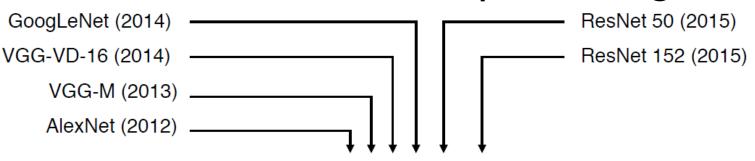


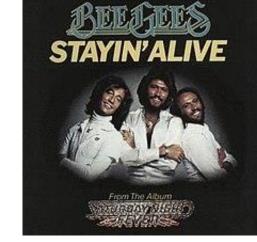
Increasing network depth leads to worse performance!

Vanishing gradients problem: gradients do not propagate through so many layers (they become smaller and smaller) to the earlier layers









16 convolutional layers

50 convolutional layers

152 convolutional layers

Krizhevsky, I. Sutskever, and G. E. Hinton. ImageNet classification with deep convolutional neural networks. In Proc. NIPS, 2012.

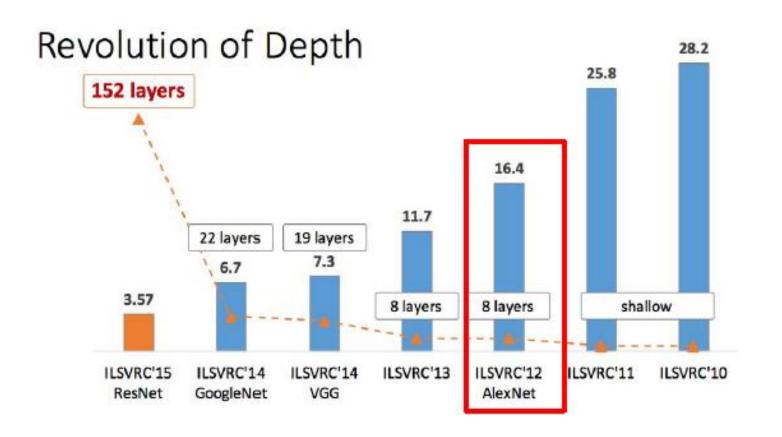
C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. *Going deeper with convolutions*. In Proc. CVPR, 2015.

K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition*. In Proc. ICLR, 2015.

K. He, X. Zhang, S. Ren, and J. Sun. *Deep residual learning for image recognition*. In Proc. CVPR, 2016.



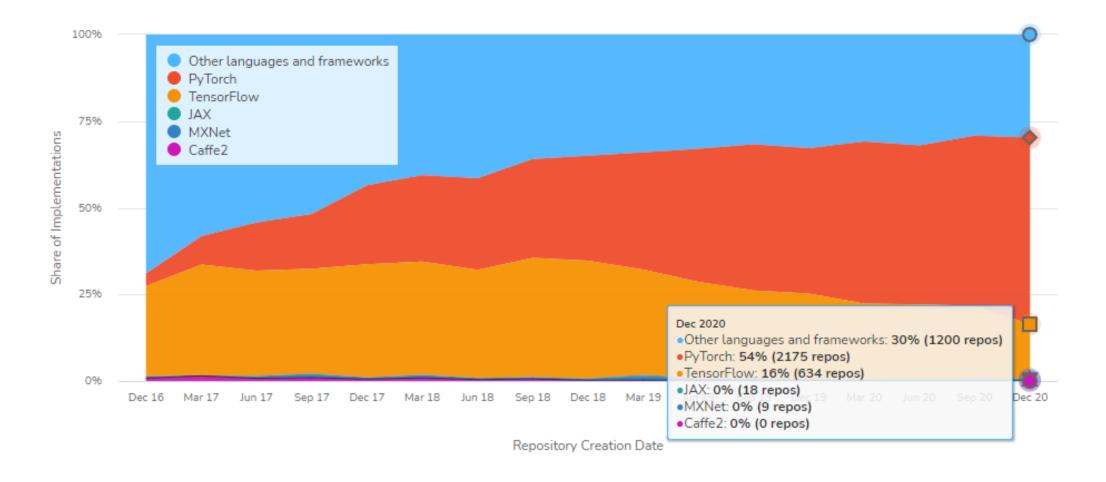








Deep Learning Software - Training

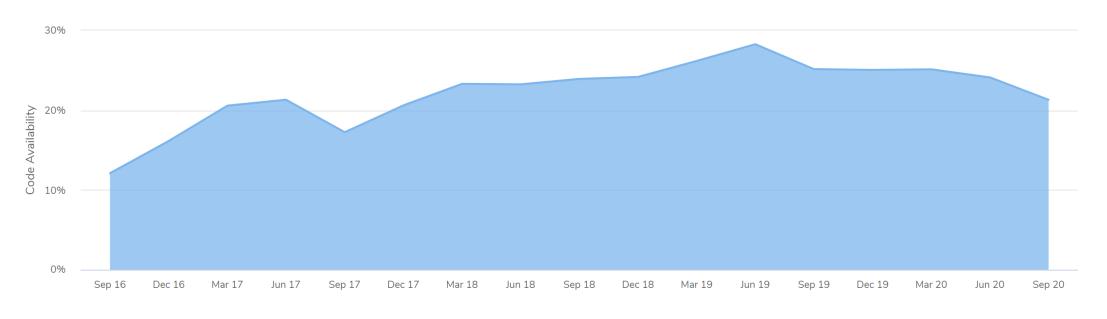






Deep Learning Software - Training

Percentage of published papers that have at least one code implementation



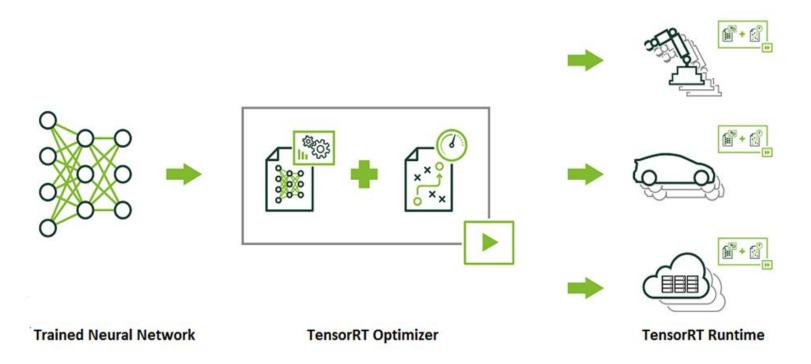
Paper Publication Date





Deep Learning Software - Inference

TensorRT
Inference engine for production deployment of deep learning applications





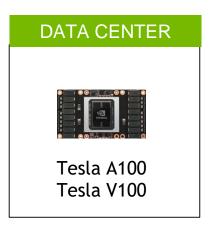


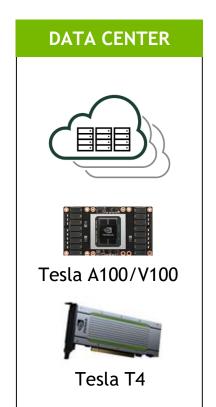
Deep Learning Hardware

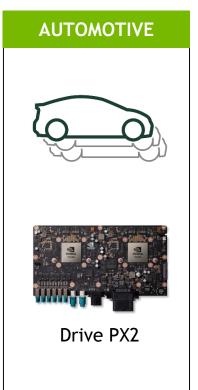
TRAINING INFERENCE

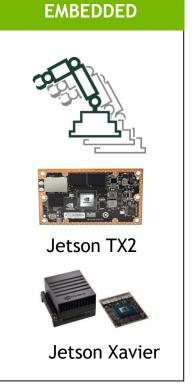


















Deep Learning Hardware



NVIDIA® DGX™-2, the first 2 petaFLOPS system that combines 16 fully interconnected GPUs





Edge Al-NVIDIA Jetson Xavier

Jetson AGX Xavier	
GPU	512-core Volta GPU with Tensor Cores
CPU	8-core ARM v8.2 64-bit CPU, 8MB L2 + 4MB L3
Memory	16GB 256-Bit LPDDR4x 137GB/s
Storage	32GB eMMC 5.1
DL Accelerator	(2x) NVDLA Engines*
Vision Accelerator	7-way VLIW Vision Processor*
Encoder/Decoder	(2x) 4Kp60 HEVC/(2x) 4Kp60 12-Bit Support
Size	105 mm x 105 mm

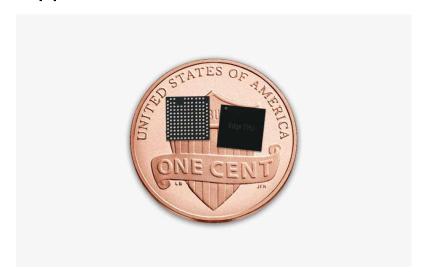






Edge AI- Google TPU

- Edge TPU: a small ASIC designed by Google that provides high performance ML inferencing for low-power devices.
- It can execute state-of-the-art mobile vision models such as MobileNet V2 at 100+ fps, in a power efficient manner.
- Supports Tensorflow Lite





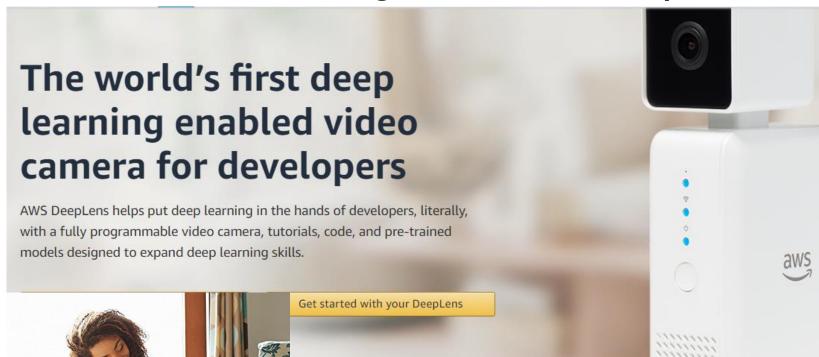
Two Edge TPU chips on the head of a US penny

USB Accelerator with Edge TPU





Edge AI- AWS Deeplens



AWS DeepLens - Deep learning enabled video camera for developers

by Amazon Web Services



27 customer reviews | 27 answered questions

Price: \$249.00 & FREE Shipping. Details



Recognize more than 30 kinds of actions such as brushing teeth, applying lipstick, and playing guitar.







Edge AI- Mobile Nets



Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M. and Adam, H., 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*.





Deep Learning to Keep Cats from Pooping on Lawn!







Deep Learning to Keep Cats from Pooping on Lawn!



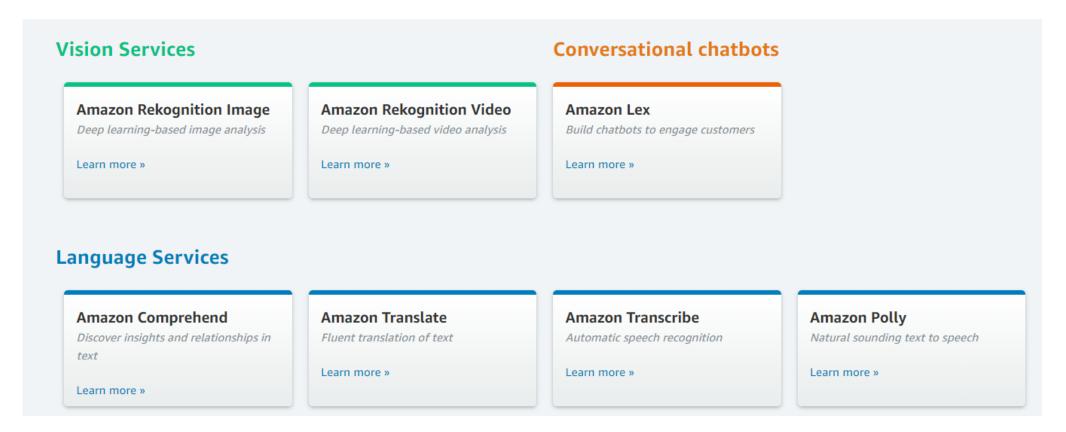






Al PaaS- Amazon AWS

Al Platform as a Service (Al PaaS): Al services provided by cloud vendors.



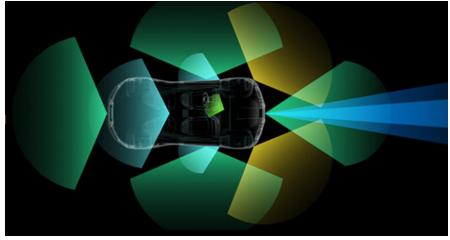




Deep Learning for Autonomous Driving

NVIDIA DRIVE systems can fuse data from multiple cameras, as well as lidar, radar, and ultrasonic sensors.

This allows algorithms to accurately understand the full 360-degree environment around the car to produce a robust representation, including static and dynamic objects.









Deep Learning Project Checklist

- 1. What problem are you solving, what are the DL tasks?
- 2. What data do you have/need, and how is it labeled?
- 3. Which deep learning framework & tools will you use?
- 4. What already trained models are available?
- 5. On what platform(s) will you train and deploy?





What Problem Are You Solving?

Defining the AI/DL Tasks

INPUTS	QUESTION	AI/DL TASK	EXAMPLE OUTPUTS
Text Data Images Video Audio	ls "it" <u>present</u> or not?	Detection	Cancer Detection
	What <u>type</u> of thing is "it"?	Classification	Tumor Identification
	To what <u>extent</u> is "it" present?	Segmentation	Tumor Size/Shape Analysis
	What is the likely outcome?	Prediction	Survivability Prediction
	What will likely satisfy the objective?	Recommendation	Therapy Recommendation





What Problem Are You Solving?

Can be a combination or chain of AI tasks to achieve more sophisticated outputs. Some examples:

Family photo: face detection followed by facial recognition (classification).

Translation: speech to text (**classification**) followed by translation (**prediction**) and then speech synthesis (**prediction**).

Google Maps: business type detection, open hours sign detection & hours recognition, published via Google Maps.





Generative Adversarial Networks (GAN)



JFT-300M dataset

512x512 3 channel resolution 300 million images 18000 classes Google's internal dataset, not public Brock, A., Donahue, J. and Simonyan, K., 2018. Large scale GAN training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096.





Generative Adversarial Networks (GAN)

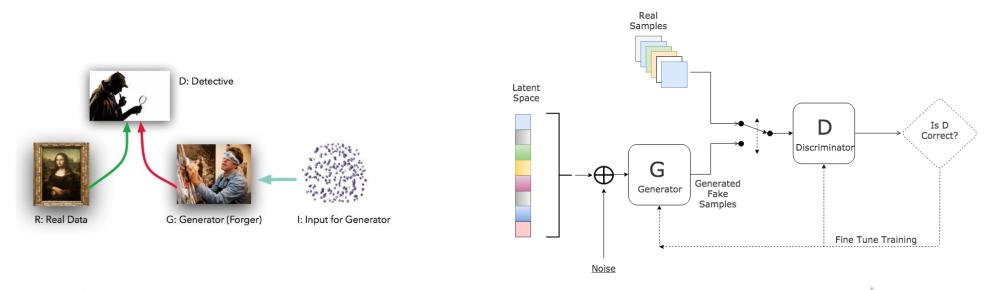
https://www.youtube.com/watch?v=kSLJriaOumA





Generative Adversarial Networks (GAN)

- An adversarial process for estimating generative models
- Consists of 2 simultaneously trained models
 - a generative model **G**
 - a discriminator model D
- The generative model G takes random noise as input and generates data candidates
- Discriminator model D tries to distinguish which is real data

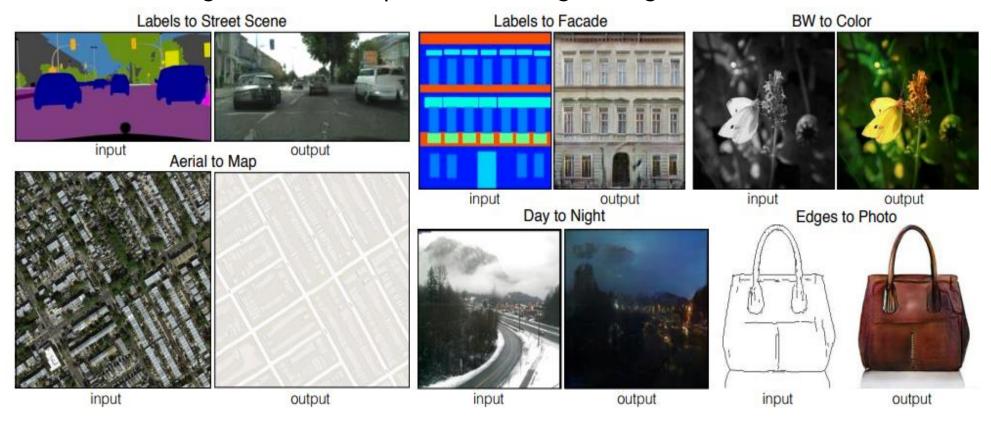






GAN Applications

pix2pix A general purpose solution to image-to-image translation Conditional GAN: generates an output from an image with given condition

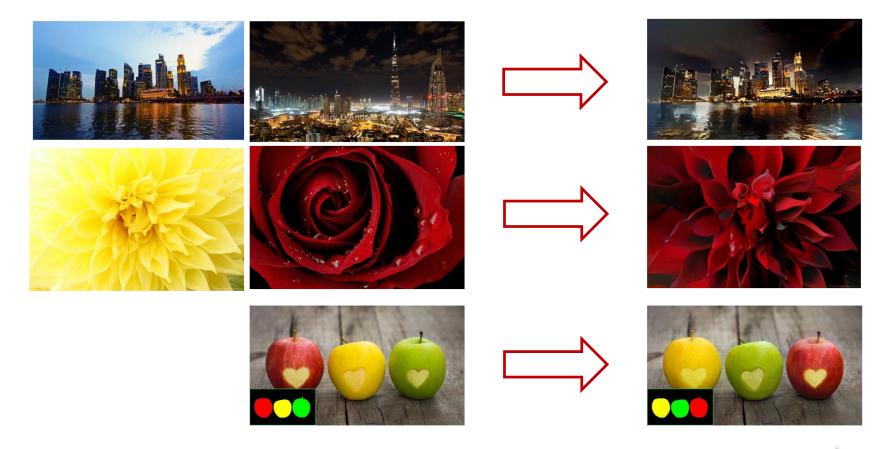






GAN Applications

Style transfer for scene images of cities and wide area Time of the day, weather, season and artistic edit.







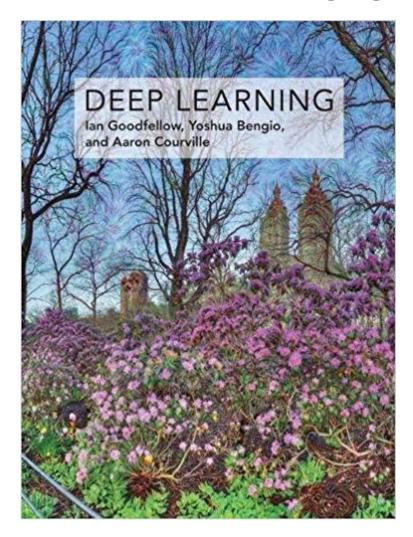
Conclusions

- Mature tools, availability of pre-trained models, easy access to GPUs in training and hardware integration for a complete solution makes it easy to develop "intelligent" applications
 - Makes the entry barriers low not just for you but for everyone!
 - Domain expertise makes a big difference!
- Being an AI expert and releasing AI enabled technologies are very "hot"; but
 - All experts are expected to have an in-depth understanding and experience in both theory and practice (and a track record)
 - Al enabled technologies are expected to satisfy "inflated" expectations of the users





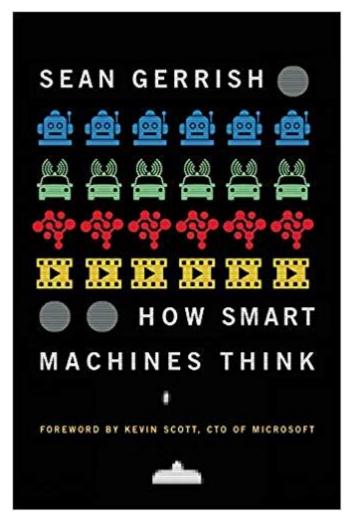
Reference Book



Deep Learning

Ian Goodfellow, Yoshua Bengio, Aaron Courville

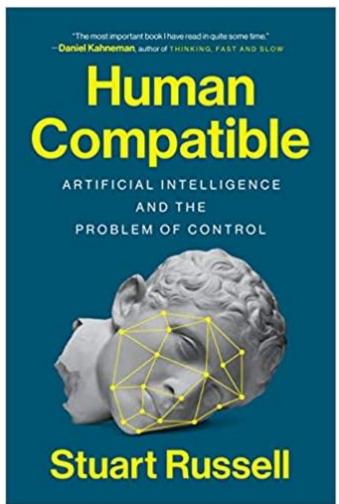
Reading Material



How Smart Machines Think (The MIT Press) Hardcover - 6 Nov 2018

Sean Gerrish, Kevin Scott

Reading Material



Human Compatible: Artificial Intelligence and the Problem of Control

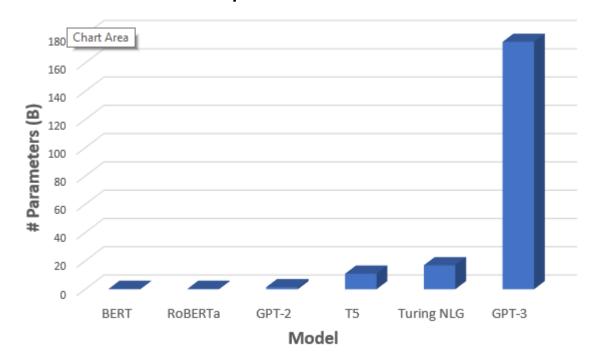
8 Oct 2019

Stuart Russell

Deep Learning in NLP

Pre-trained language models trained on huge text corpus (in an unsupervised way) are later fine-tuned on specific tasks such as translation, question answering using much smaller task specific datasets.

GPT-3 is a task agnostic model, which needs limited examples to do well and achieve close to state of the art performance on a number of NLP tasks





Deep Learning in NLP







IS 784 Deep Learning for Text Analytics

Natural language processing (NLP) concepts and NLP applications, deep learning methods for NLP, evaluation techniques, word embedding, Long-Short-Term Memory (LSTM) models, transformer models.

In addition, other application areas using the models initially proposed for NLP tasks will also be taught.



New Course Coming Next Semester!

MMI 7XX Machine Learning Systems Design and Deployment

Machine Learning (ML) Production Pipeline

Machine Learning Systems Design

Data Engineering

Model Development and Training

Scaling Up Training

Model Evaluation

Experiment Tracking and Versioning

Deployment

Deployment Platforms and Frameworks

TinyML

Integrating ML into Business

Future ML Systems