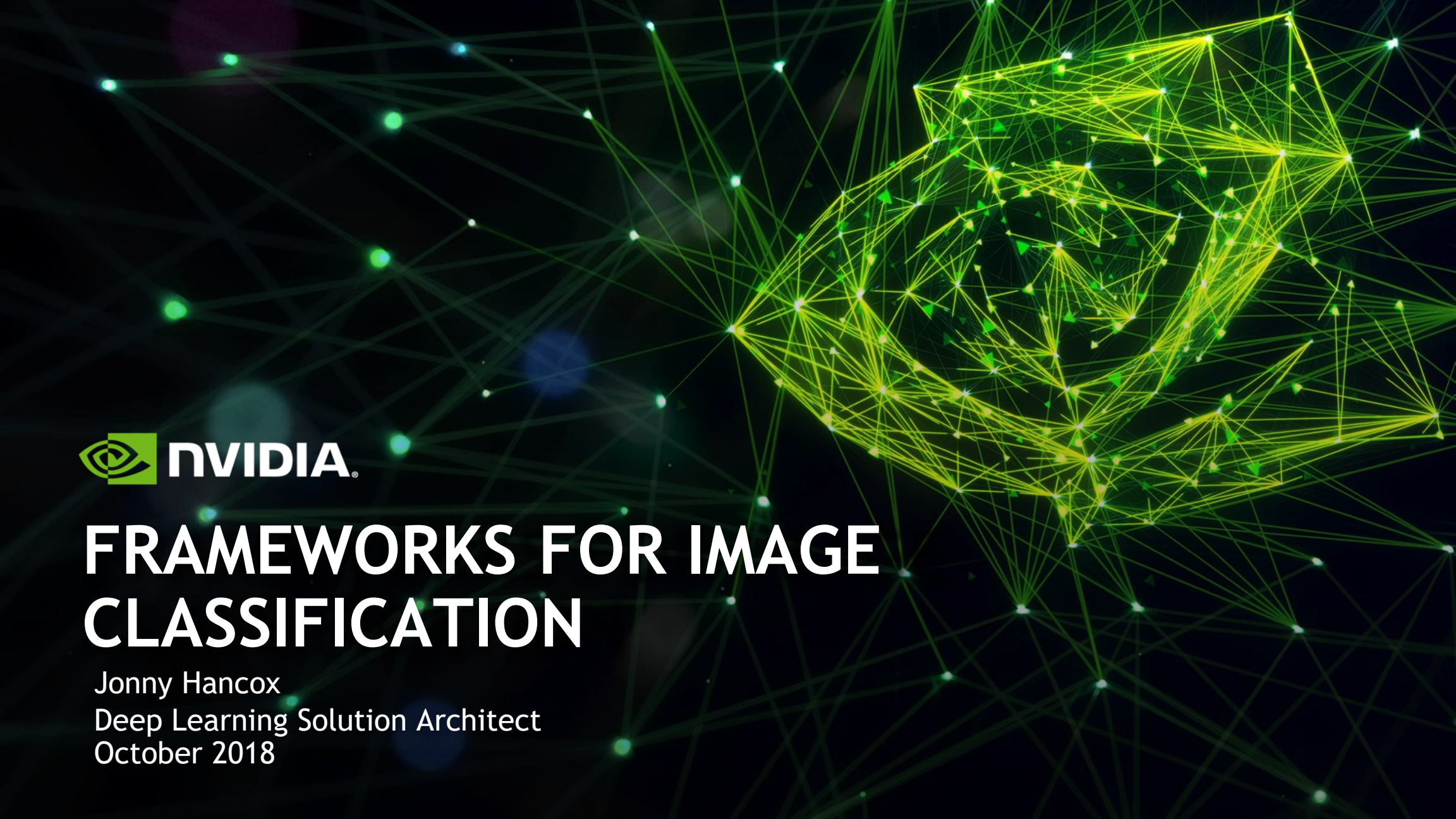


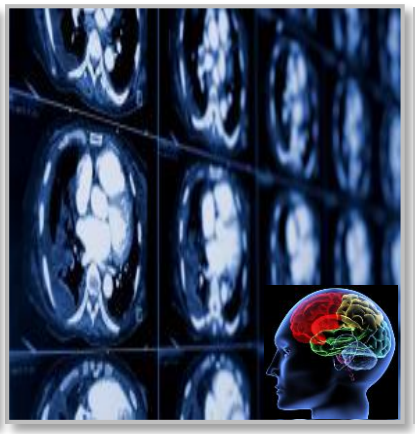
FRAMEWORKS FOR IMAGE CLASSIFICATION

Jonny Hancox
Deep Learning Solution Architect
October 2018

AGENDA

- What is a Deep Learning Framework?
- Overview of the field
- Some code examples
- Conclusions

DEEP LEARNING DRIVES INNOVATION

INTERNET SERVICES	HEALTHCARE	MEDIA & ENT.	SECURITY & DEFENSE	SELF DRIVING CARS
				
• 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

WHAT IS A DL FRAMEWORK?

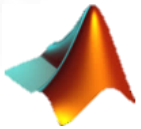
A software framework is:

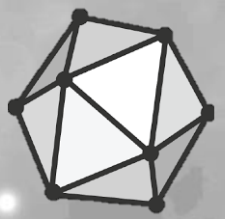
- a universal, reusable software platform used to develop applications, products and solutions
- an abstraction in which software providing generic functionality can be selectively changed by additional user-written code, thus providing application-specific software

A DL framework is therefore:

- A set of tools and libraries to enable a developer or data scientist to train and deploy DL solutions

DEEP LEARNING FRAMEWORKS



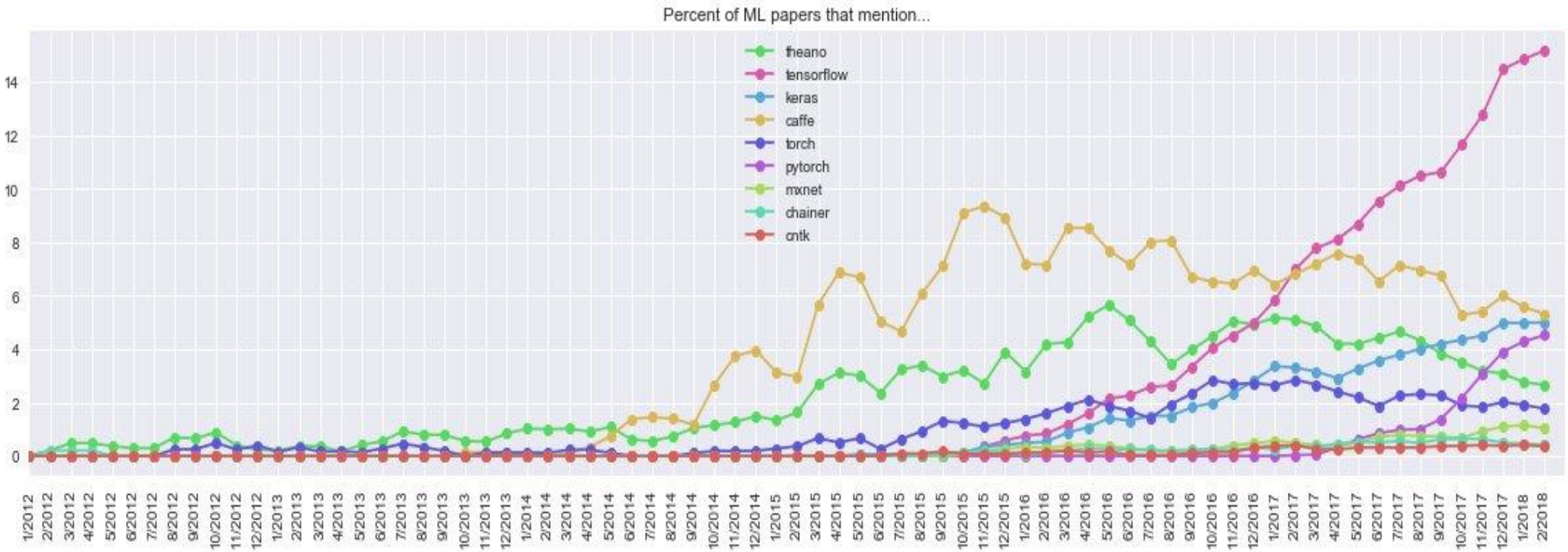


DEEP LEARNING FRAMEWORKS

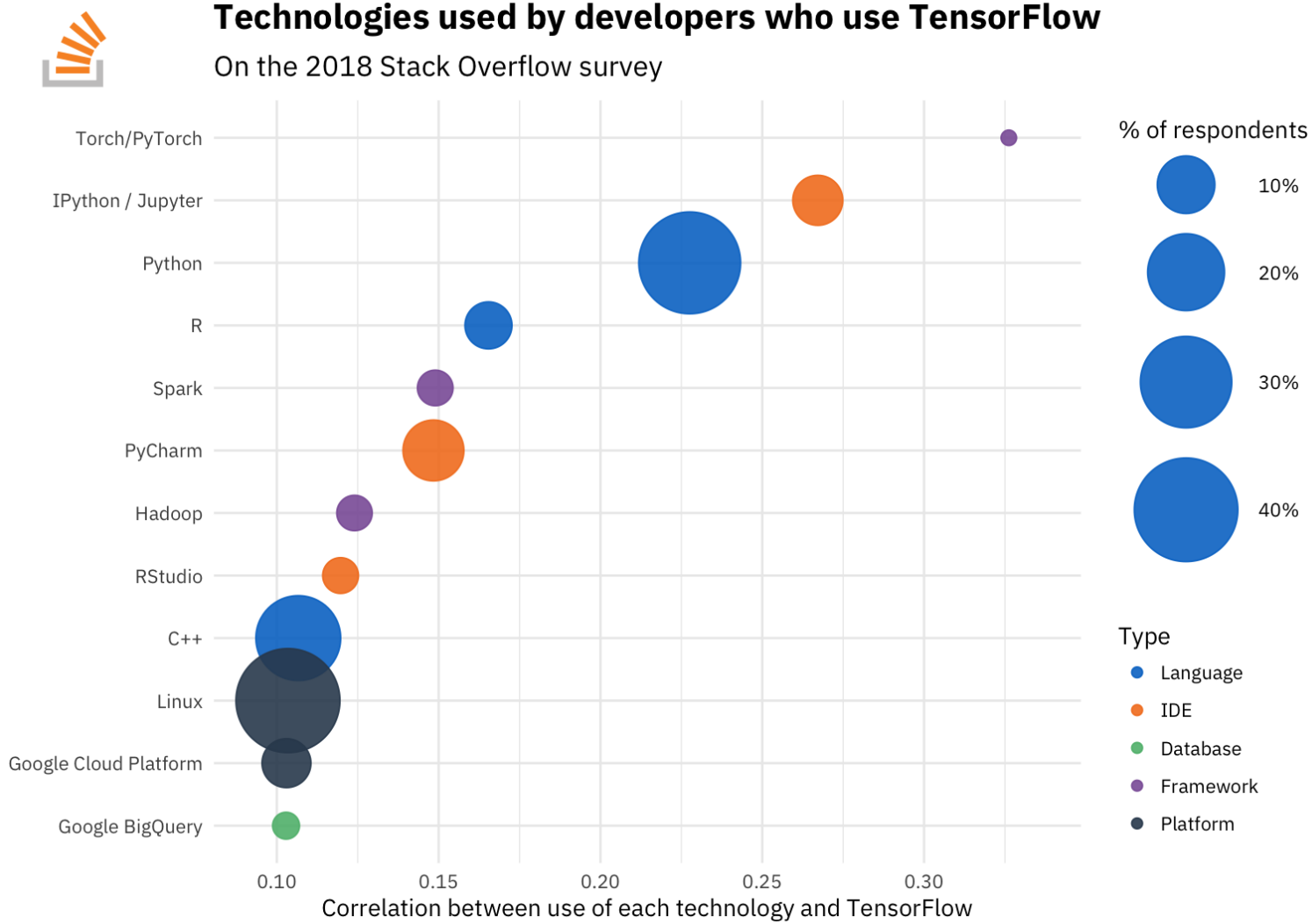
Some important attributes to consider:

- Licensing Model
- Open or Closed Source
- Platform support
- Language Written In
- API languages
- CUDA support
- Multi-GPU (Scalability)
- Fine Control vs Ease of Use/Productivity
- Community Support

DEEP LEARNING FRAMEWORKS



https://twitter.com/karpathy?lang=en



Source: Stack Overflow 2018 Developer Survey

THE DEEP LEARNING SOFTWARE STACK

GPU PROGRAMMING LANGUAGES

Numerical analytics	MATLAB, Mathematica, LabVIEW
Fortran	CUDA Fortran, OpenACC
C, C++	CUDA C++, OpenACC
Python	CUDA Python, PyCUDA
C#	Altimesh Hybridizer, Alea GPU

ACCELERATED DEEP LEARNING TRAINING STACK

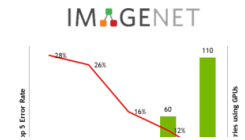


Image Classification

Object Detection

COMPUTER VISION

Voice Recognition

Language Translation

SPEECH AND AUDIO

Recommendation Engines

Sentiment Analysis

NATURAL LANGUAGE PROCESSING

TensorFlow

PYTORCH

torch

Caffe2

Caffe

mxnet

theano

Microsoft CNTK

Chainer

DL4J

Deeplearning4j

KERAS

MATLAB

MINERVA

OpenDeep

Purine

Pylearn2

DEEP LEARNING FRAMEWORKS

ACCELERATED DEEP LEARNING TRAINING STACK

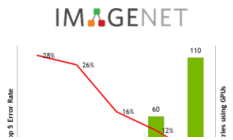


Image Classification

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DL SW Libraries: Tensor/Graph Execution Engines (AKA Frameworks)

ACCELERATED DEEP LEARNING TRAINING STACK

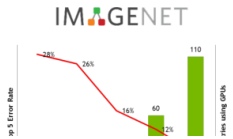

Image Classification

Object Detection

COMPUTER VISION

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SPEECH AND AUDIO

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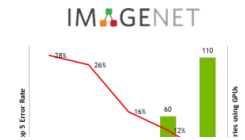
NATURAL LANGUAGE PROCESSING

Network description, Workflow, Hyper-parameter Sweep,
Experiment, Data and Job Management

DL SW Libraries: Tensor/Graph Execution Engines (AKA Frameworks)

Architecture Specific Optimization Layer

ACCELERATED DEEP LEARNING TRAINING STACK



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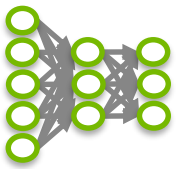


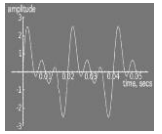
cuDNN

DEEP LEARNING

cuBLAS

cuSPARSE

cuFFT



MATH LIBRARIES

MULTI-GPU

ACCELERATED DEEP LEARNING TRAINING STACK

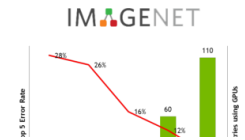


Image Classification

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Network description, Workflow, Hyper-parameter Sweep,
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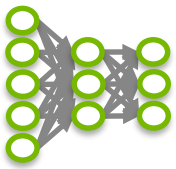
TensorFlow PYTORCH torch Caffe2 Caffe mxnet theano Microsoft CNTK Chainer DL4J Deeplearning4j K KERAS MATLAB OpenDeep Purine MINERVA Pylearn2

DEEP LEARNING FRAMEWORKS



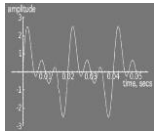
cuDNN

DEEP LEARNING

cuBLAS

cuSPARSE

cuFFT



MATH LIBRARIES

MULTI-GPU

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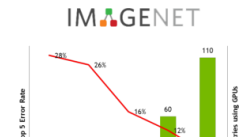

Image Classification

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Sentiment Analysis

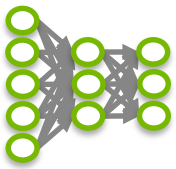
NATURAL LANGUAGE PROCESSING

Productivity Layer/Rapid experimentation: DIGITS, NVIDIA GPU Cloud

UI / JOB MANAGEMENT / DATASET VERSIONING/ VISUALIZATION

TensorFlow PYTORCH torch Caffe2 Caffe mxnet theano Microsoft CNTK Chainer DL4J Deeplearning4j K KERAS MATLAB OpenDeep Purine MINERVA Pylearn2

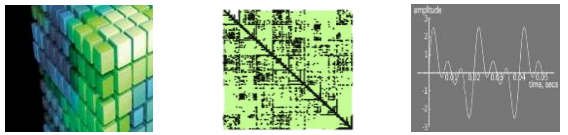
DEEP LEARNING FRAMEWORKS



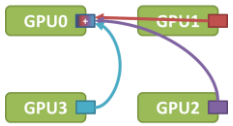
cuDNN

DEEP LEARNING

cuBLAS cuSPARSE cuFFT



MATH LIBRARIES



MULTI-GPU

DEEP LEARNING PERFORMANCE CONSIDERATIONS

- Preprocess data outside of main training loop
  - Training will be run for many epochs, and repeated often during model development
- Use high level support for data loading and multi-GPU parallelization if available
  - Many pitfalls that may hamper performance due to data loading or CPU bottlenecks
  - But: make sure the interface is actually meant for high performance / production.
    Example: TensorFlow feed_dict – bad performance but used in many examples
- Prefer versions of blocks / layers that is implemented on top of cuDNN if possible
- Prefer high level blocks if possible
  - Process all time steps of RNN using cuDNN based block instead of explicit loop

DEEP LEARNING PERFORMANCE CONSIDERATIONS

- All deep learning frameworks can achieve good (about equal) multi GPU performance and scaling
- But: Engineering effort differ significantly between frameworks and approaches
  - Trade-off between flexibility and low engineering effort
  - Monolithic frameworks offer less opportunity to “shoot oneself in the foot”
  - Many frameworks offer both high level interfaces and low level primitives for building any kind of multi GPU solution

NVIDIA cuDNN 7

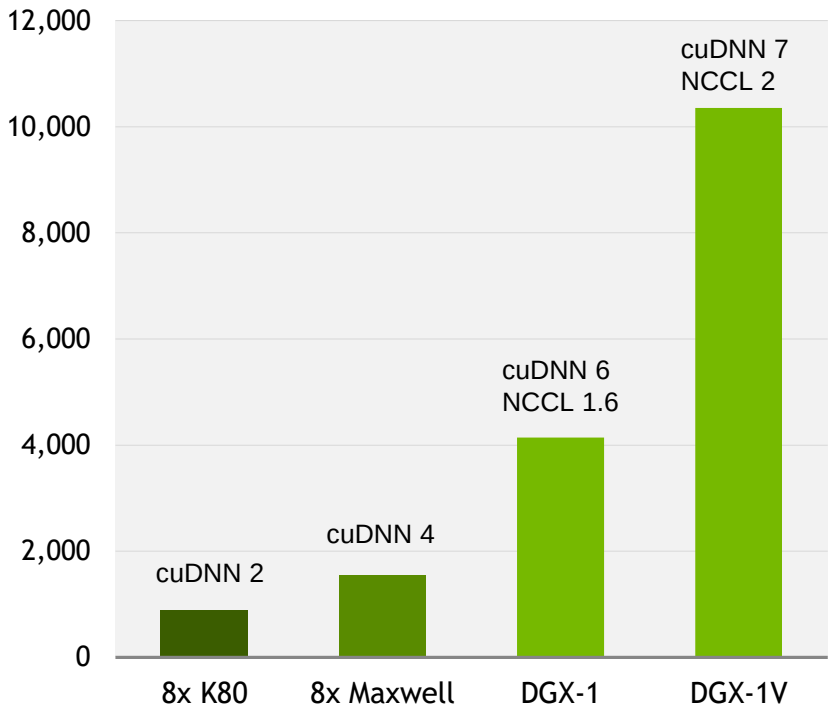
Deep Learning Primitives

High performance building blocks for deep learning frameworks

Drop-in acceleration for widely used deep learning frameworks such as Caffe2, Microsoft Cognitive Toolkit, PyTorch, Tensorflow, Theano and others

Accelerates industry vetted deep learning algorithms, such as convolutions, LSTM RNNs, fully connected, and pooling layers

Fast deep learning training performance tuned for NVIDIA GPUs



"NVIDIA has improved the speed of cuDNN with each release while extending the interface to more operations and devices at the same time."

— Evan Shelhamer, Lead Caffe Developer, UC Berkeley

developer.nvidia.com/cudnn

NVIDIA Collective Communications Library (NCCL) 2

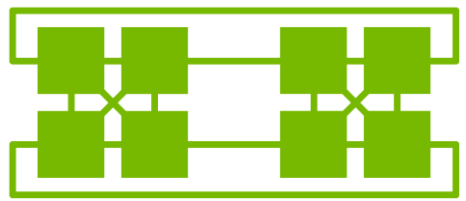
Multi-GPU and multi-node collective communication primitives

High-performance multi-GPU and multi-node collective communication primitives optimized for NVIDIA GPUs

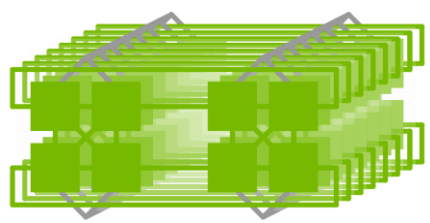
Fast routines for multi-GPU multi-node acceleration that maximizes inter-GPU bandwidth utilization

Easy to integrate and MPI compatible. Uses automatic topology detection to scale HPC and deep learning applications over PCIe and NVink

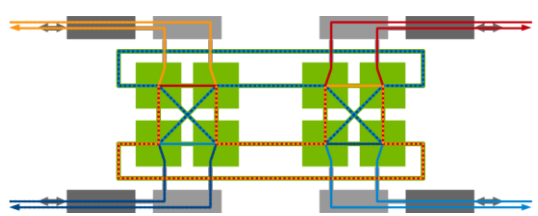
Accelerates leading deep learning frameworks such as Caffe2, Microsoft Cognitive Toolkit, MXNet, PyTorch and more



Multi-GPU:
NVLink
PCIe



Multi-Node:
InfiniBand verbs
IP Sockets



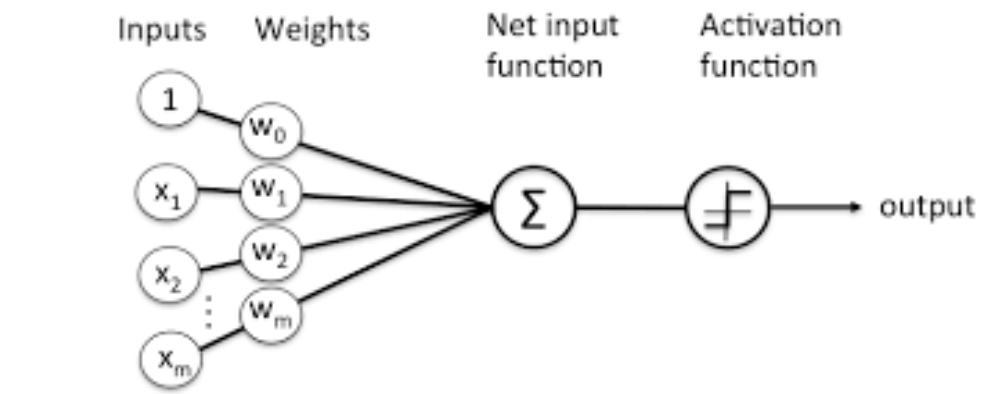
Automatic
Topology
Detection

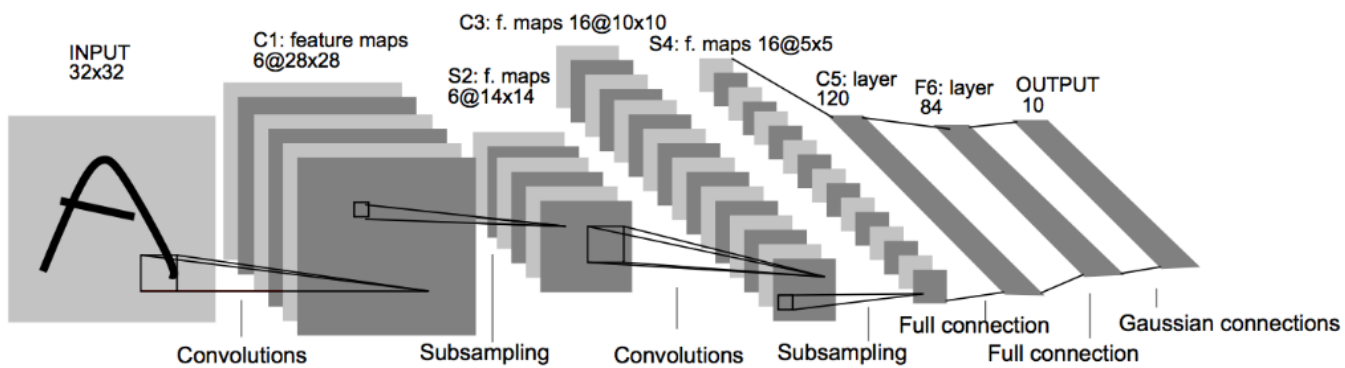
developer.nvidia.com/nccl

DL PLATFORMS

Many different platforms and styles of interface but one unifying set of concepts:

- Convolutions
- Pooling
- Activations
- Fully connected layers
- Back-propagation
- Etc.

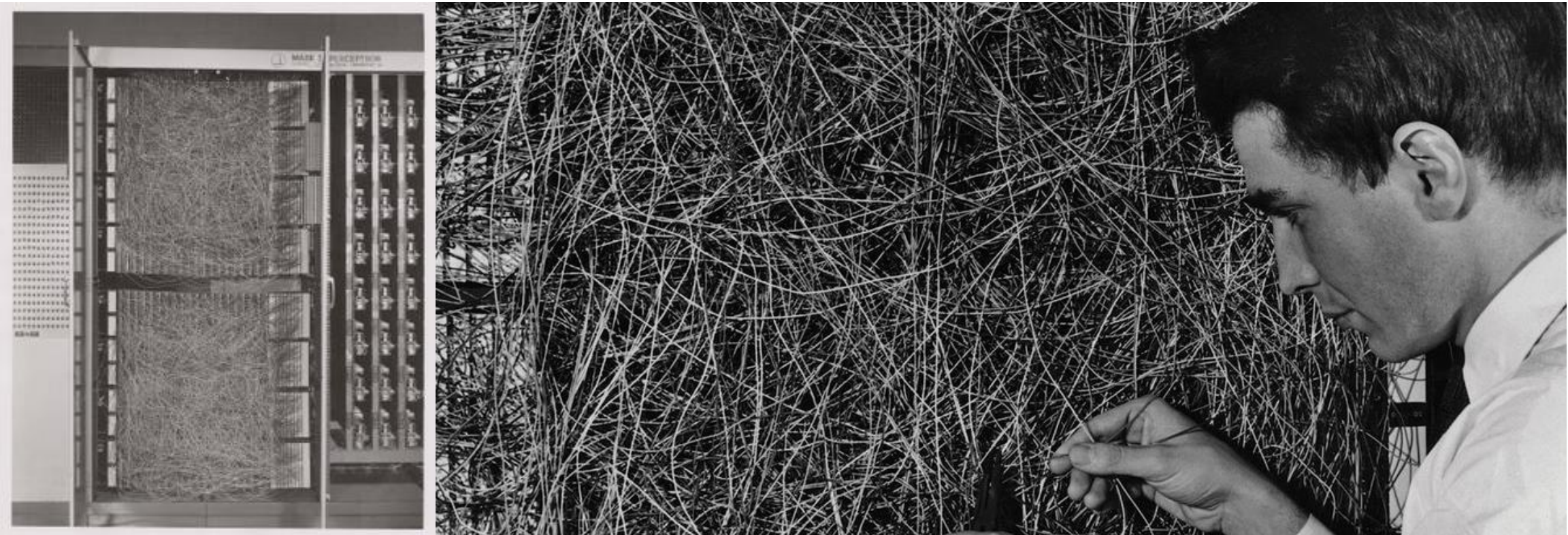




CNN called LeNet by Yann LeCun (1998)

THE PERCEPTRON

The fundamental unit of artificial neural networks



NVIDIA DIGITS

Interactive Deep Learning GPU Training System

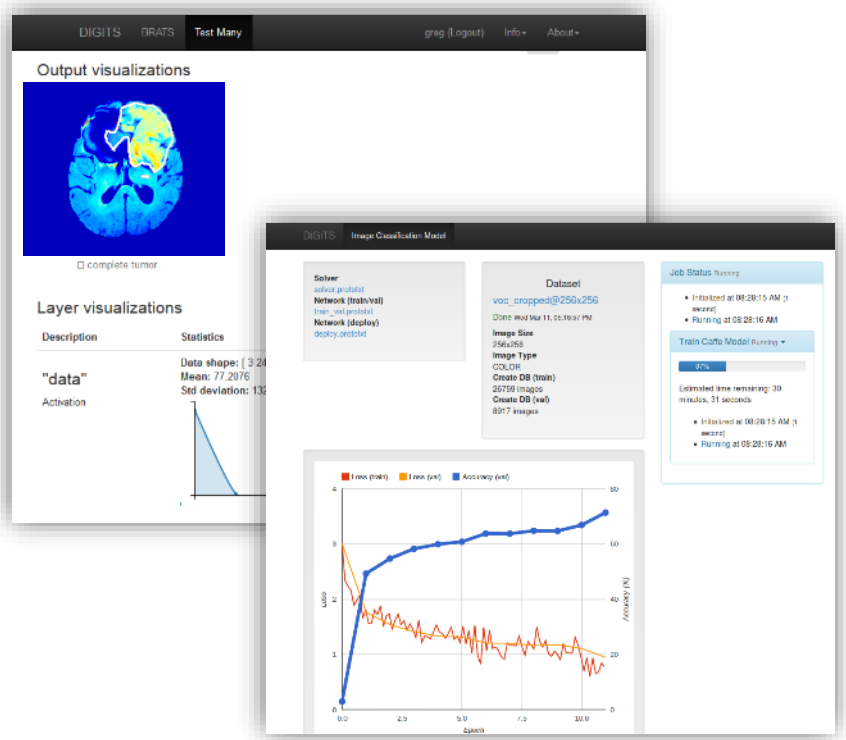
Interactive deep learning training application for engineers and data scientists

Simplify deep neural network training with an interactive interface to train and validate, and visualize results

Built-in workflows for image classification, object detection and image segmentation

Improve model accuracy with pre-trained models from the DIGITS Model Store

Faster time to solution with multi-GPU acceleration

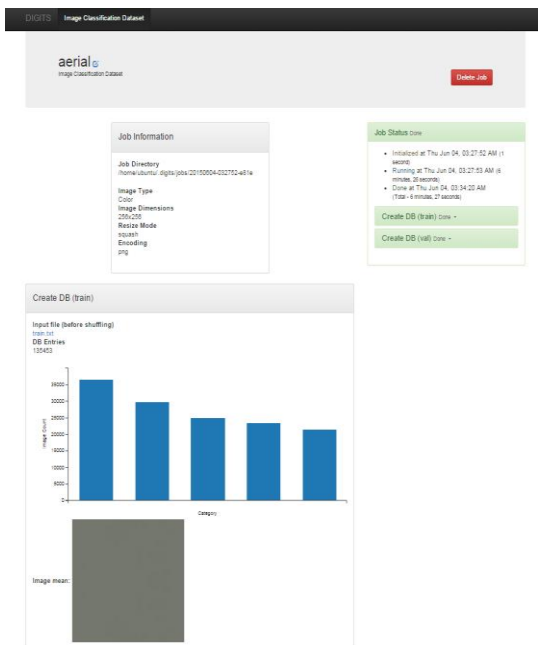


developer.nvidia.com/digits

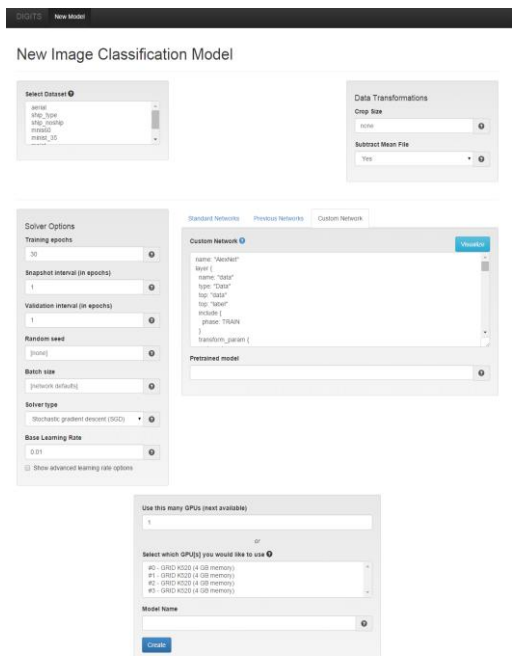
NVIDIA DIGITS

Interactive Deep Learning GPU Training System

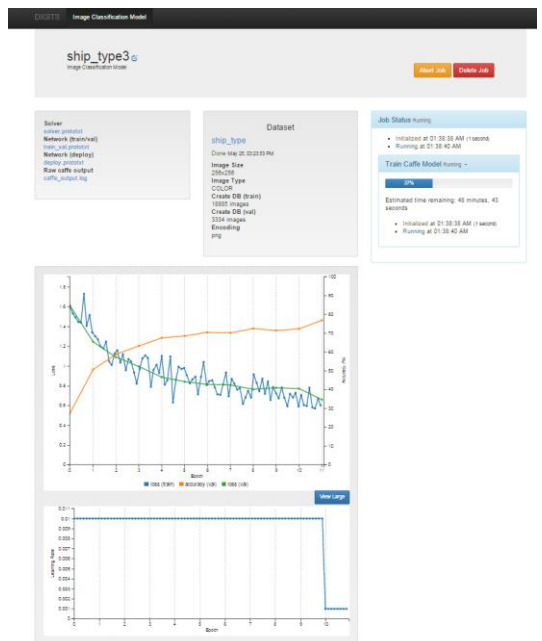
Process Data



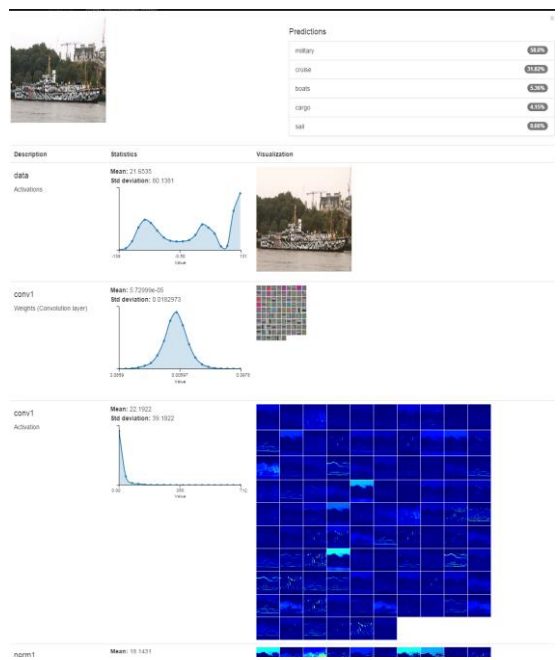
Configure DNN



Monitor Progress



Visualization



DL FRAMEWORKS - KERAS

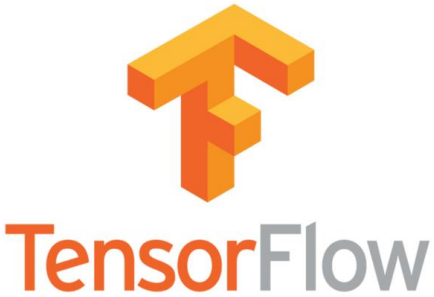
Enables fast experimentation with DNNs

- Supports multiple backends, including Tflow, CNTK, Theano
- Contains many commonly used layers types
- Features many tools to simplify working with text and images
- Keras can create deployments for iOS Andriod and the JVM
- Supports multi-GPU training

```
model = Sequential()
model.add(Conv2D(64, (3, 3), activation='relu'))
```

DL FRAMEWORKS - TENSORFLOW

Powerful, popular and well-maintained

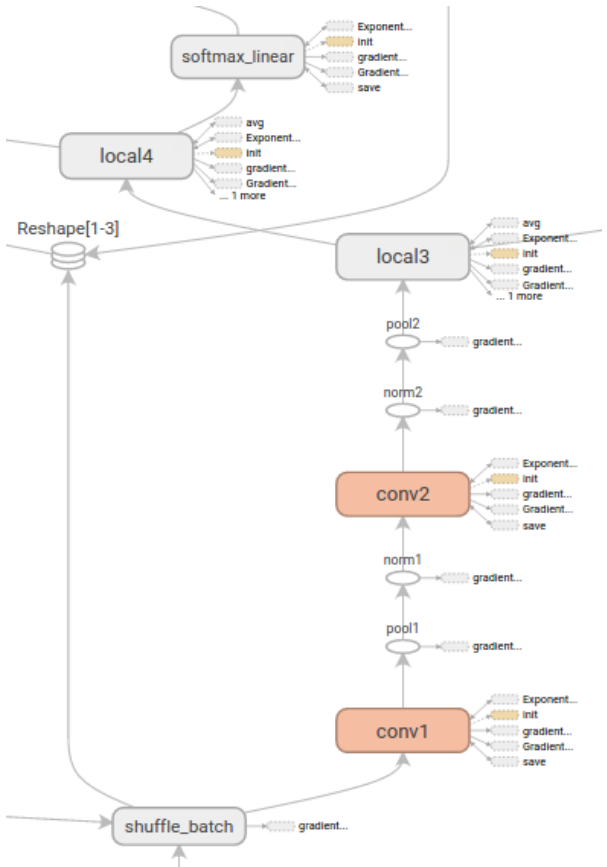


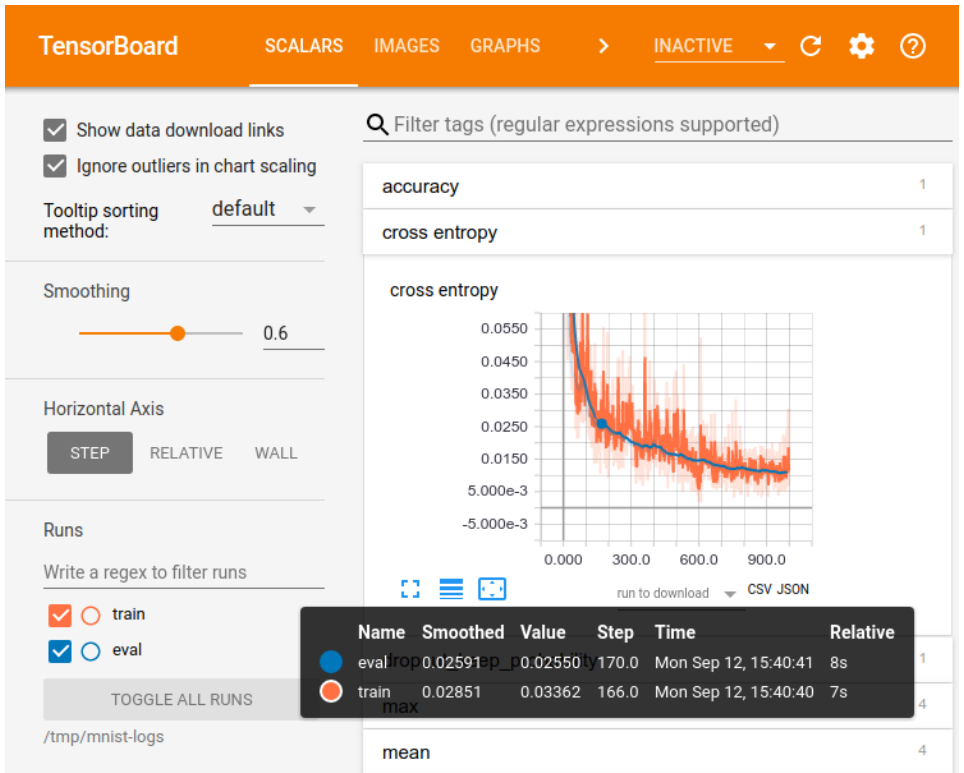
- Supports huge variety of DNN features
- Includes Tensorboard GUI for layer and output visualisation
- Many popular third-party integrations
- Python & C++ APIs
- Custom layers can be created
- Uses a declarative syntax for efficient graph execution

```
conv1 = tf.nn.conv2d(_X, _weights['wc1']
        , strides=[1, 1, 1, 1], padding='SAME')
conv1 = tf.nn.bias_add(conv1 ,_biases['bc1'])
```

DL FRAMEWORKS - TENSORFLOW

Tensorboard – useful GUI





DL FRAMEWORKS - PYTORCH

Increasingly popular and easy to use

Primarily developed by Facebook

Good GPU Acceleration

Ideal for Python users (Pythonic implementation)

Dynamic computation graphs

Tensor usage similar to Numpy

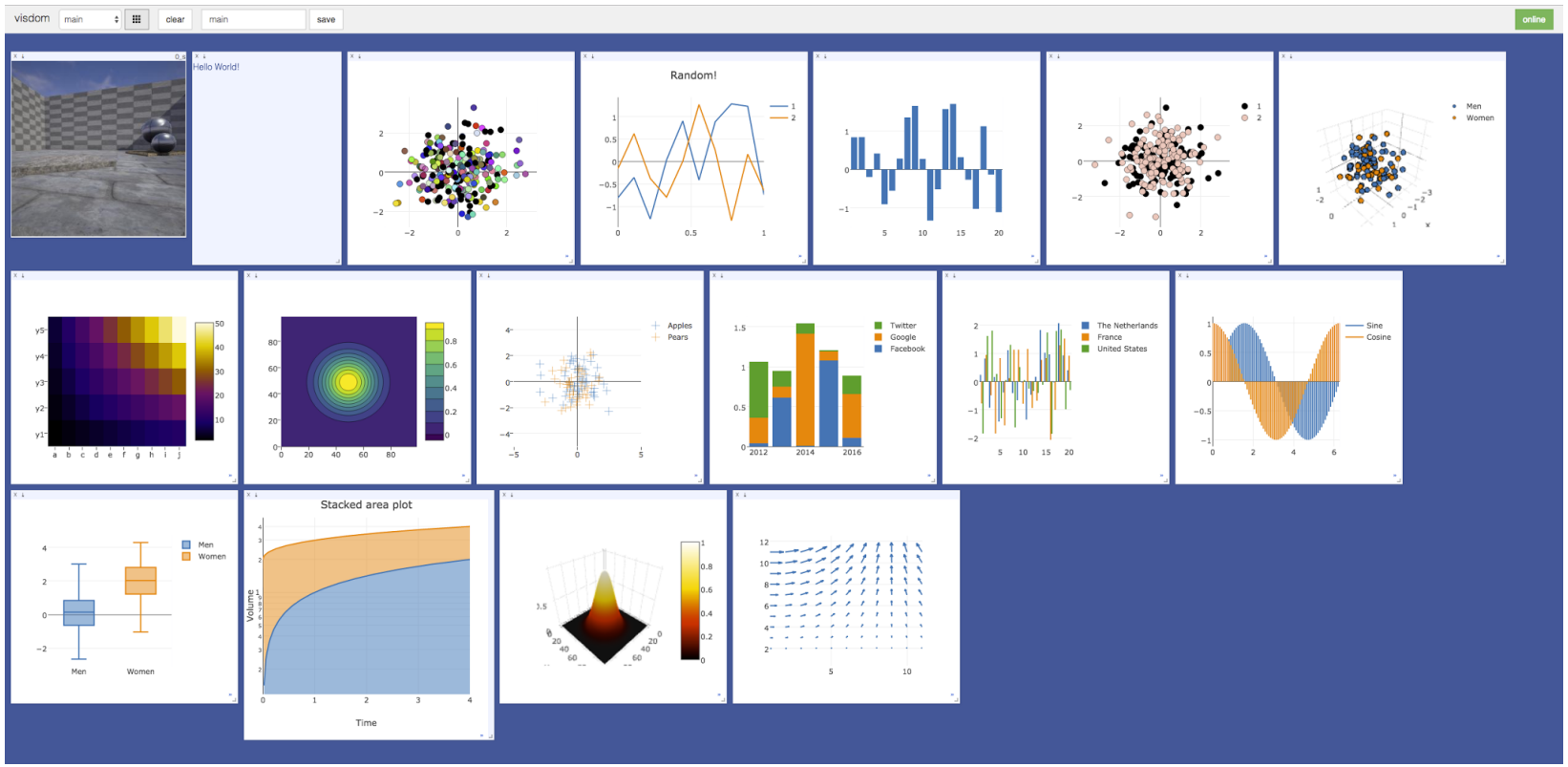
More suited to training than deployment

```
model = torch.nn.Sequential(
Torch.nn.add(Conv2D(64, (3, 3), activation='relu'))
)
```

DL FRAMEWORKS - PYTORCH

PYTORCH

Visdom is Pytorch's equivalent to TensorBoard



DL FRAMEWORKS – CAFFE2

Great performance and flexibility

- Primarily developed by Facebook
- Good GPU Acceleration
- Python & C++ APIs
- Support multi-GPU and multi-node execution
- Being merged with PyTorch

```
conv1 = brew.conv(model, data, 'conv1', 1, 20, 5)
    pool1 = brew.max_pool(model, conv1, 'pool1', kernel=2, stride=2)
    conv2 = brew.conv(model, pool1, 'conv2', 20, 50, 5)
```

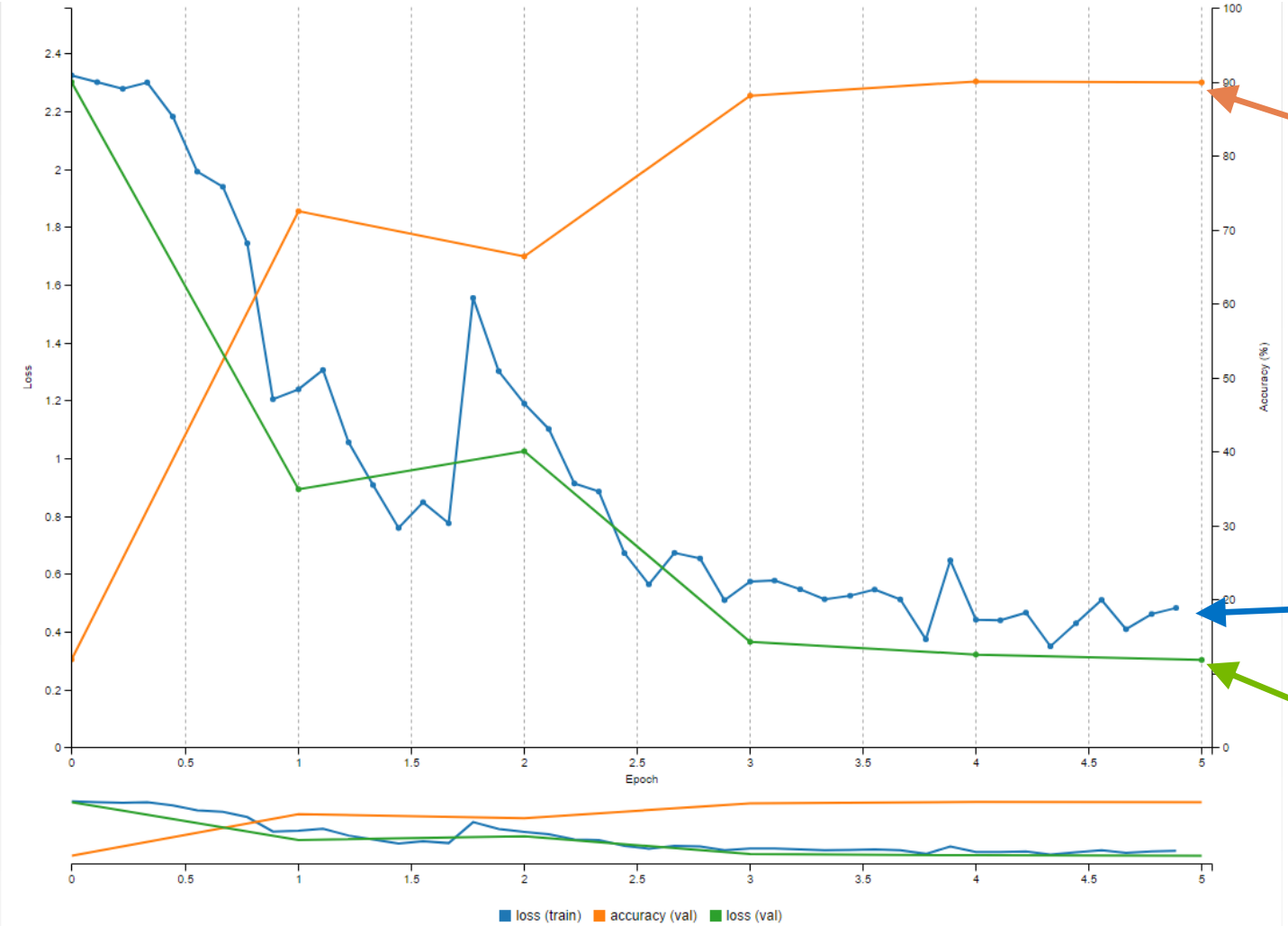
DL FRAMEWORKS – MS COGNITIVE TOOLKIT

Great performance and flexibility

- Created by MS Speech researchers (formerly CNTK)
- Open-sourced since Jan 2016
- Multiple language support (C#, R, Python, C++)
- Supports multi-GPU, multi-node execution and Spark
- Composes computational graphs from NNs
- Lower precision support
- Fast execution!

```
import cntk as C
input_dim = 784
num_output_classes = 10
feature = C.input_variable(input_dim)
label = C.input_variable(num_output_classes)
```

EVALUATE THE MODEL



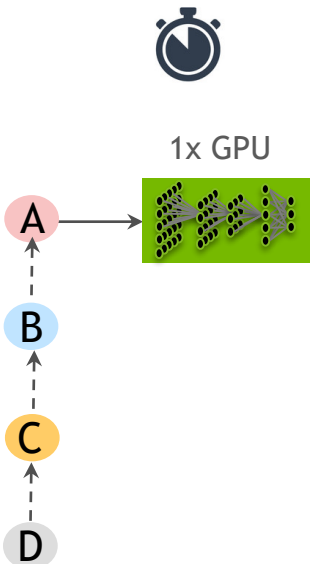
Accuracy obtained from validation dataset

Loss function (Training)

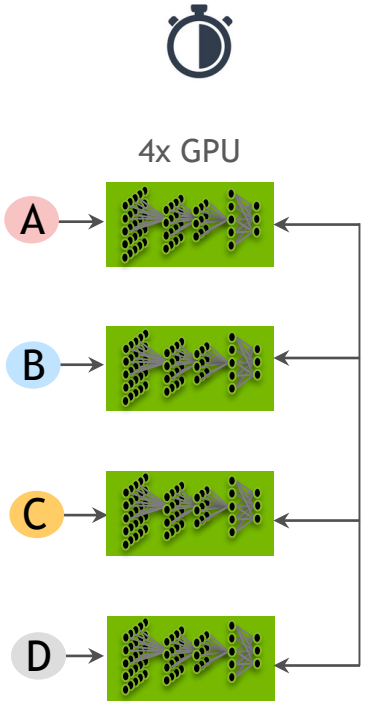
Loss function (Validation)

DISTRIBUTED DEEP LEARNING

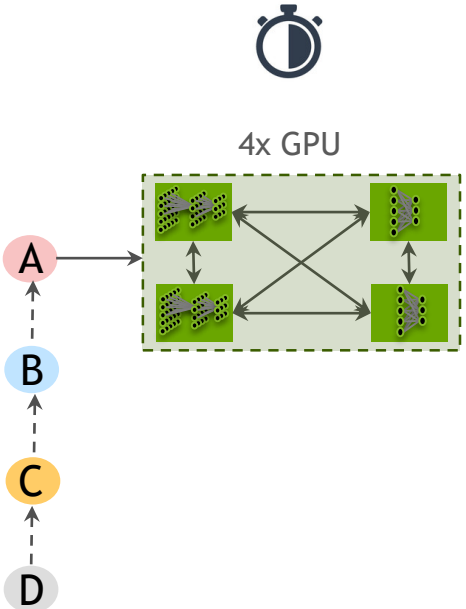
SINGLE GPU



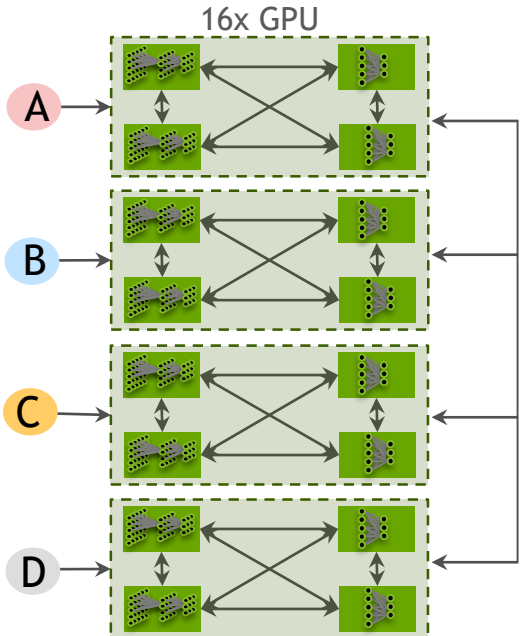
DATA PARALLEL



MODEL PARALLEL



DATA AND MODEL PARALLEL

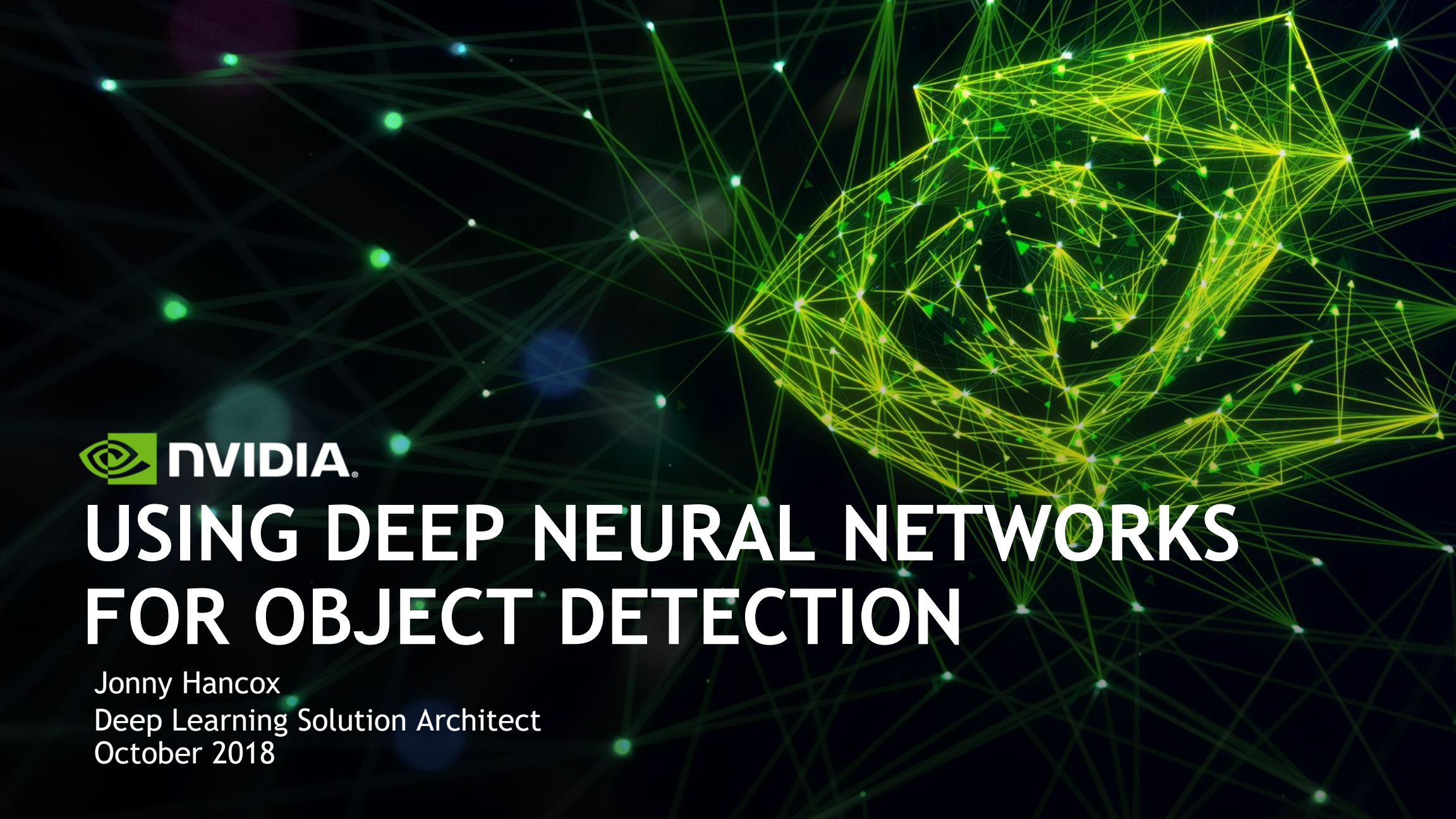


Data & Model Parallel training yields increasingly faster time-to-solution

CONCLUSIONS

- There are many frameworks out there
- Most support the same operations
- There is no ‘best’ framework
- The right choice for you is dependent on several factors
- All the main frameworks support GPUs


NVIDIA
Thank you!
QUESTIONS?
jhancox@nvidia.com



USING DEEP NEURAL NETWORKS FOR OBJECT DETECTION

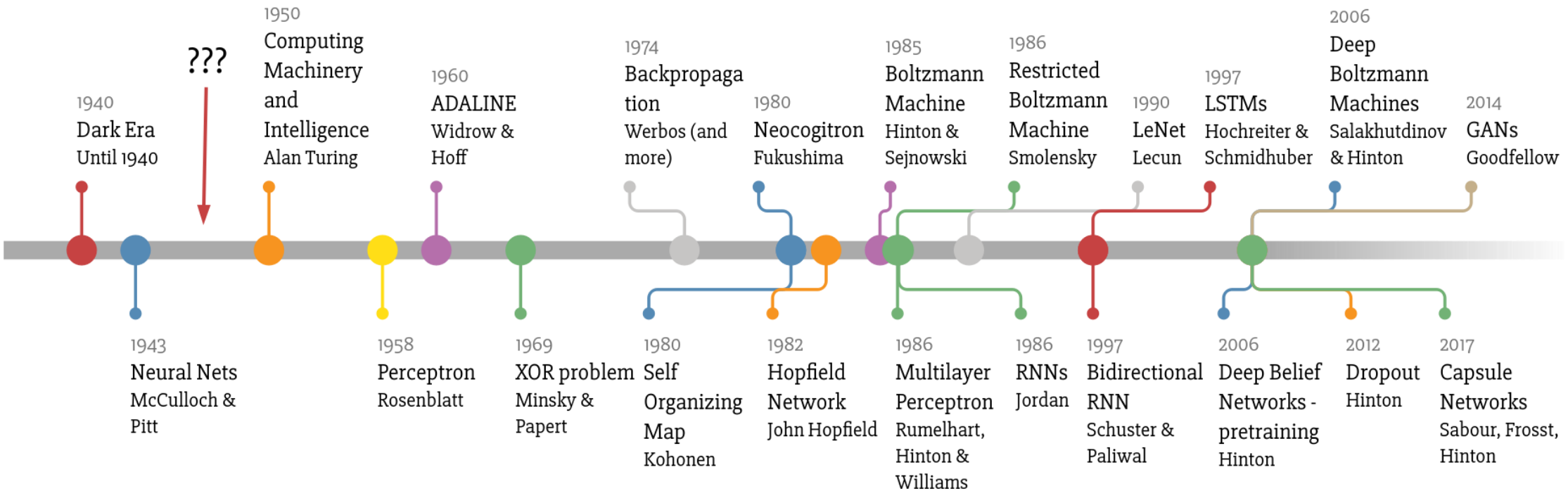
Jonny Hancox
Deep Learning Solution Architect
October 2018

HOW DL CAN BE APPLIED

INPUTS	BUSINESS QUESTION	AI/DL TASK	EXAMPLE OUTPUTS HEALTHCARE	EXAMPLE OUTPUTS RETAIL	EXAMPLE OUTPUTS FINANCE
 Text Data  Images  Video  Audio	**Is "it" present or not?**	Detection	Cancer Detection	Targeted ads	Cybersecurity
	What type of thing is "it"?	Classification	Image Classification	Basket Analysis	Credit Scoring
	To what extent is "it" present?	Segmentation	Tumor Size/Shape Analysis	Build 360° Customer View	Credit Risk Analysis
	What is the likely outcome?	Prediction	Survivability Prediction	Sentiment & behavior recognition	Fraud Detection
	What will satisfy the objective?	Recommendations	Therapy Recommendation	Recommendation Engine	Algorithmic Trading
	What is the speaker saying?	Natural Language Processing	Expert diagnosis	Virtual personal assistants	Robo Advisors

NEURAL NETS

Some (recent) history



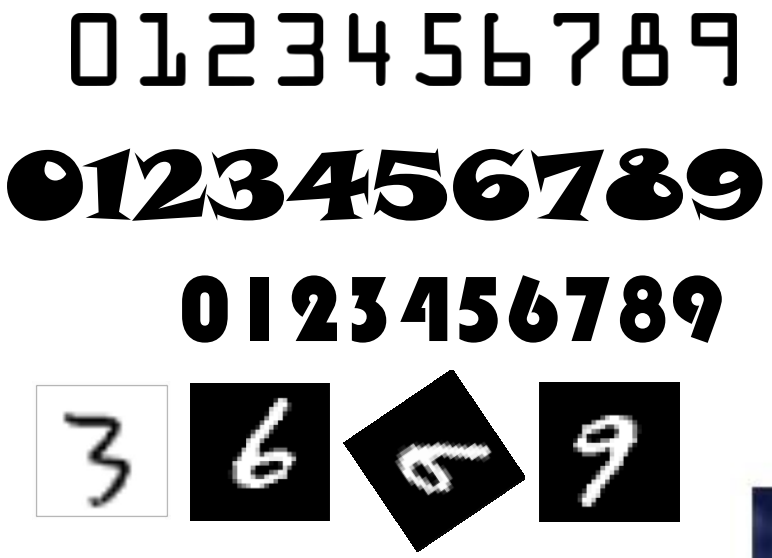
Made by Favio Vázquez

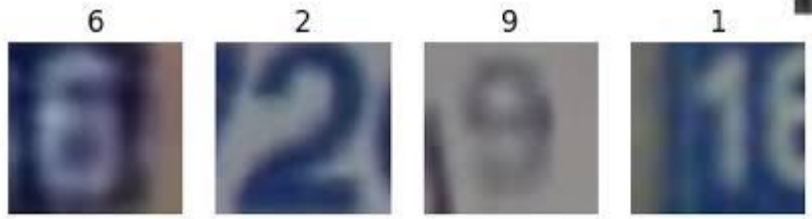
https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

RECOGNIZING DIGITS

The canonical image classification problem

We have 10 digits – how do we recognise them and distinguish between them?



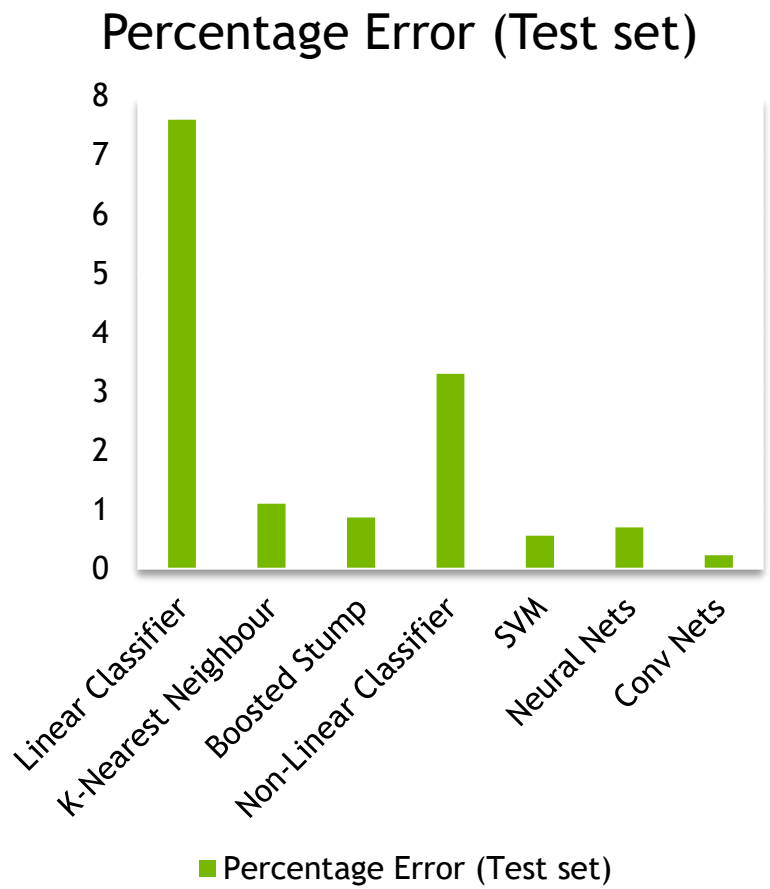


RECOGNIZING DIGITS

The MNIST Database of handwritten digits

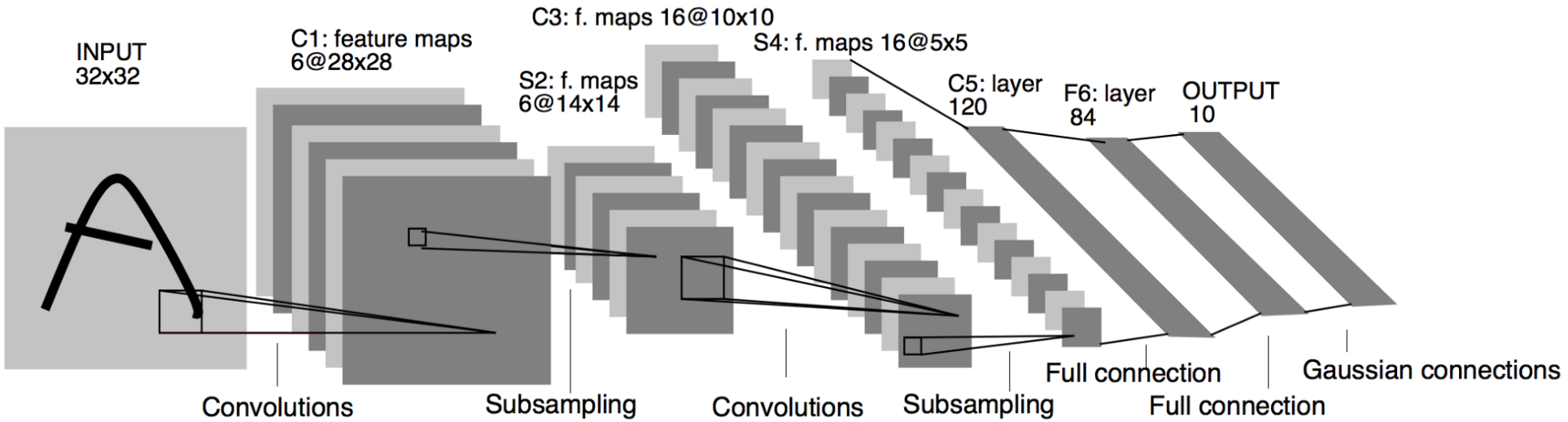
Yann LeCun Courant Institute, NYU
Corinna Cortes Google Labs, New York
Christopher J.C. Burges Microsoft Research, Redmond

- A training set of 60,000 examples
- test set of 10,000 examples
- The digits have been size-normalised and centred



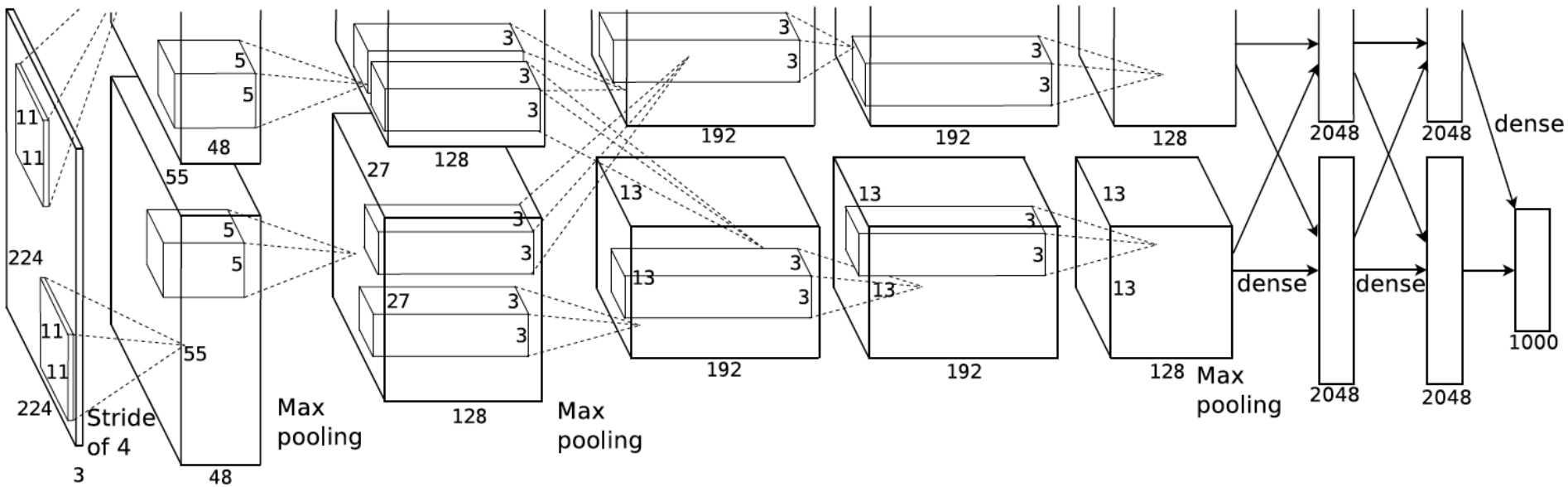
RECOGNIZING DIGITS

The LeNet-5 architecture as per Yann Lecun's original paper (1998)



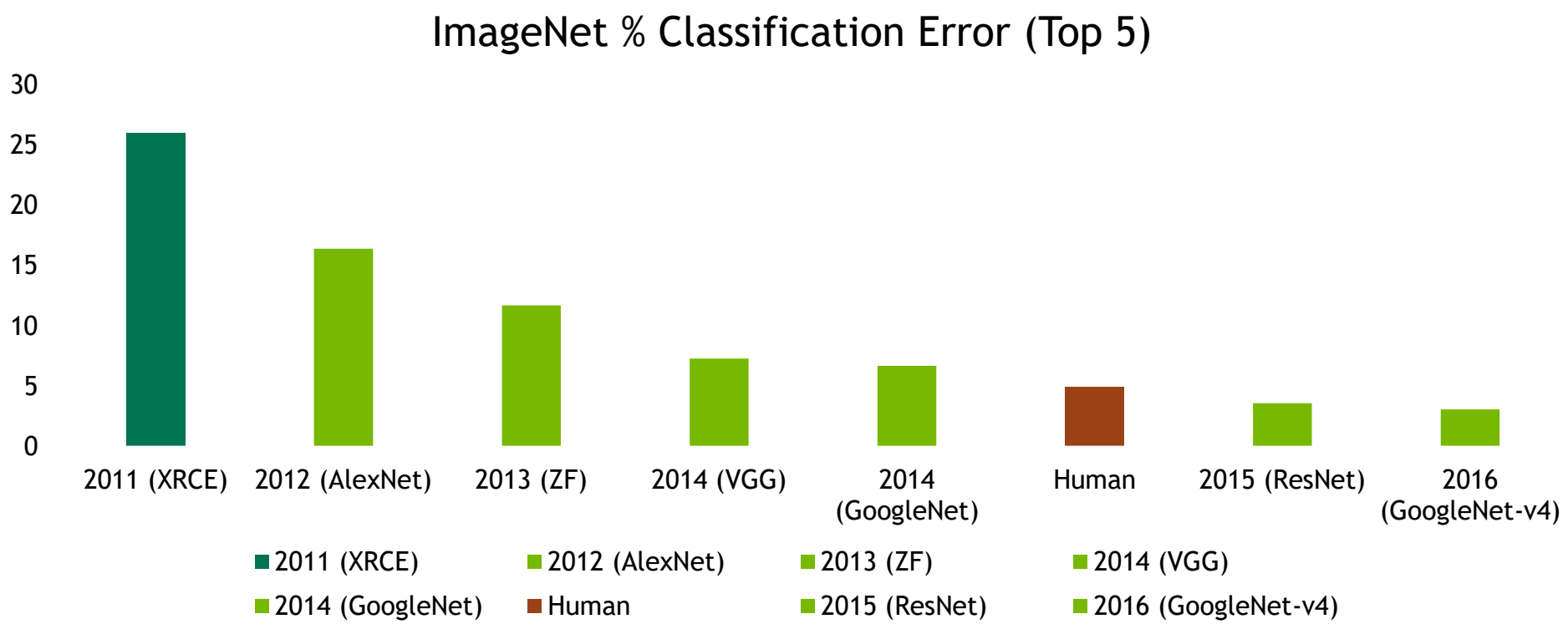
CLASSIFYING INTERNET IMAGES

The AlexNet architecture that won ImageNet (2012)



CLASSIFYING INTERNET IMAGES

Alex Krishevsky's 'AlexNet' spawned a new generation of DNNs

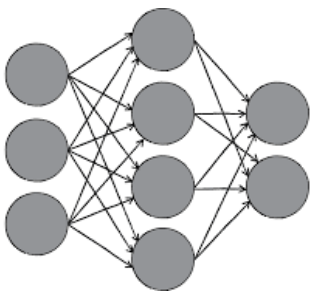


TRAINING A DNN

The three fundamental ingredients are the same for images or any other data

DATA

NETWORK



FEEDBACK

TRAINING A DNN

Classification, Segmentation & Detection

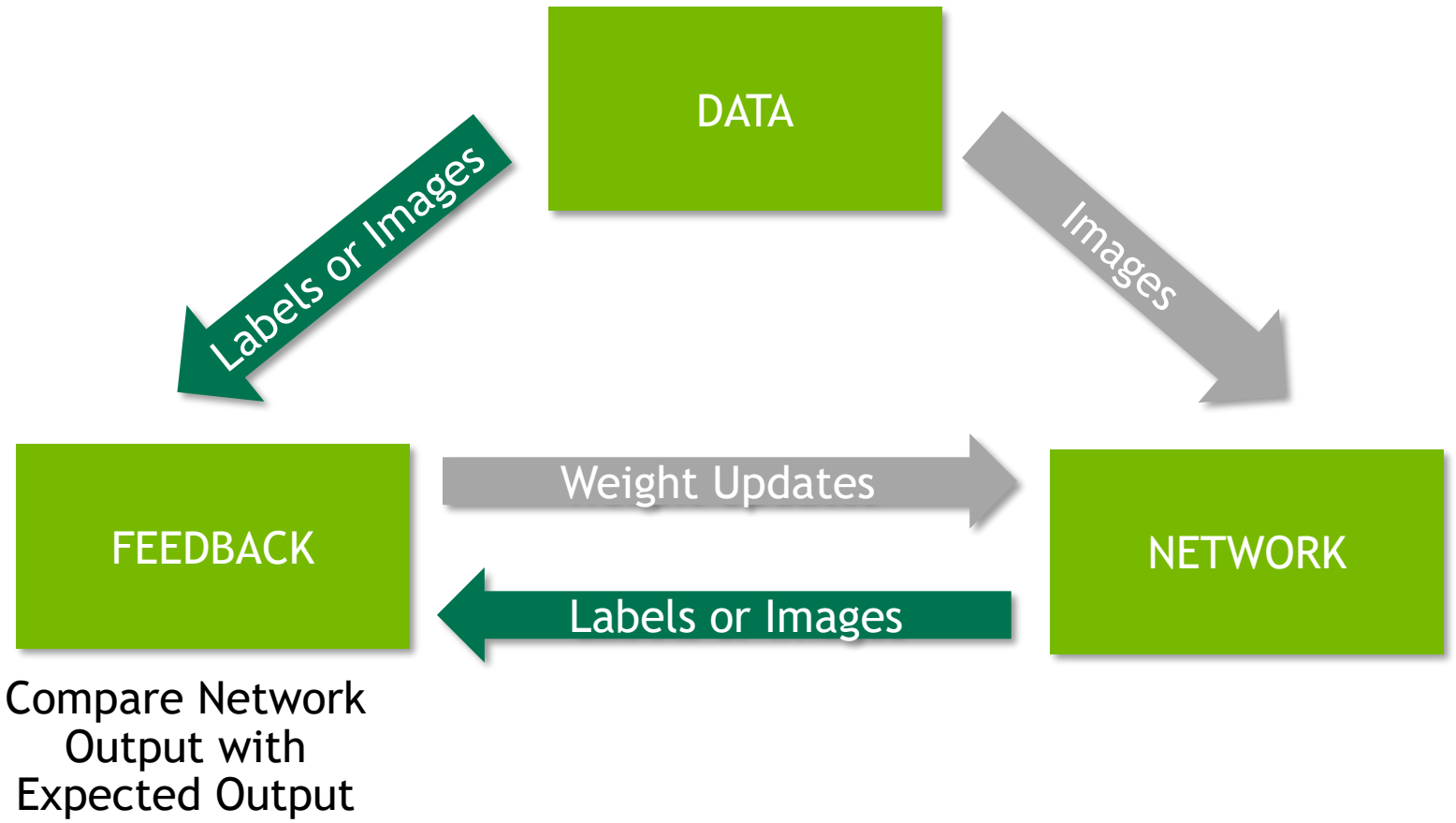
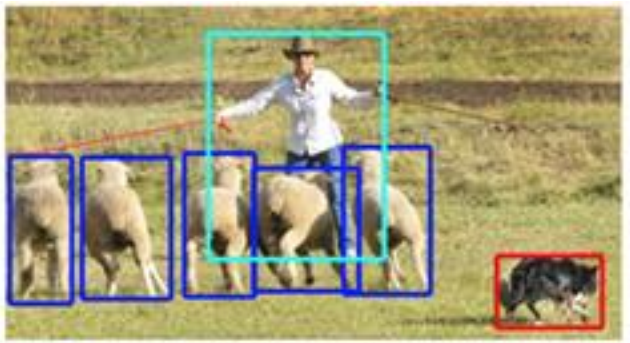


IMAGE DNN OUTPUTS

Classification, Detection & Segmentation require different levels of sophistication

(a) classification

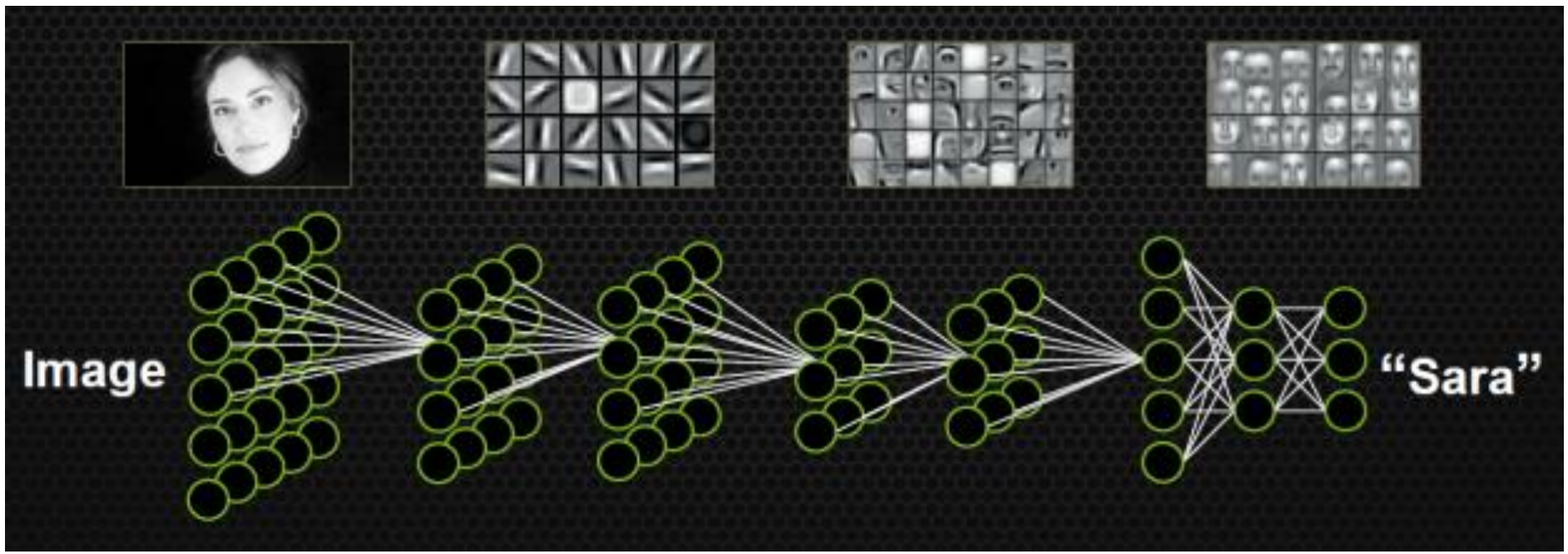


(b) detection

(c) segmentation

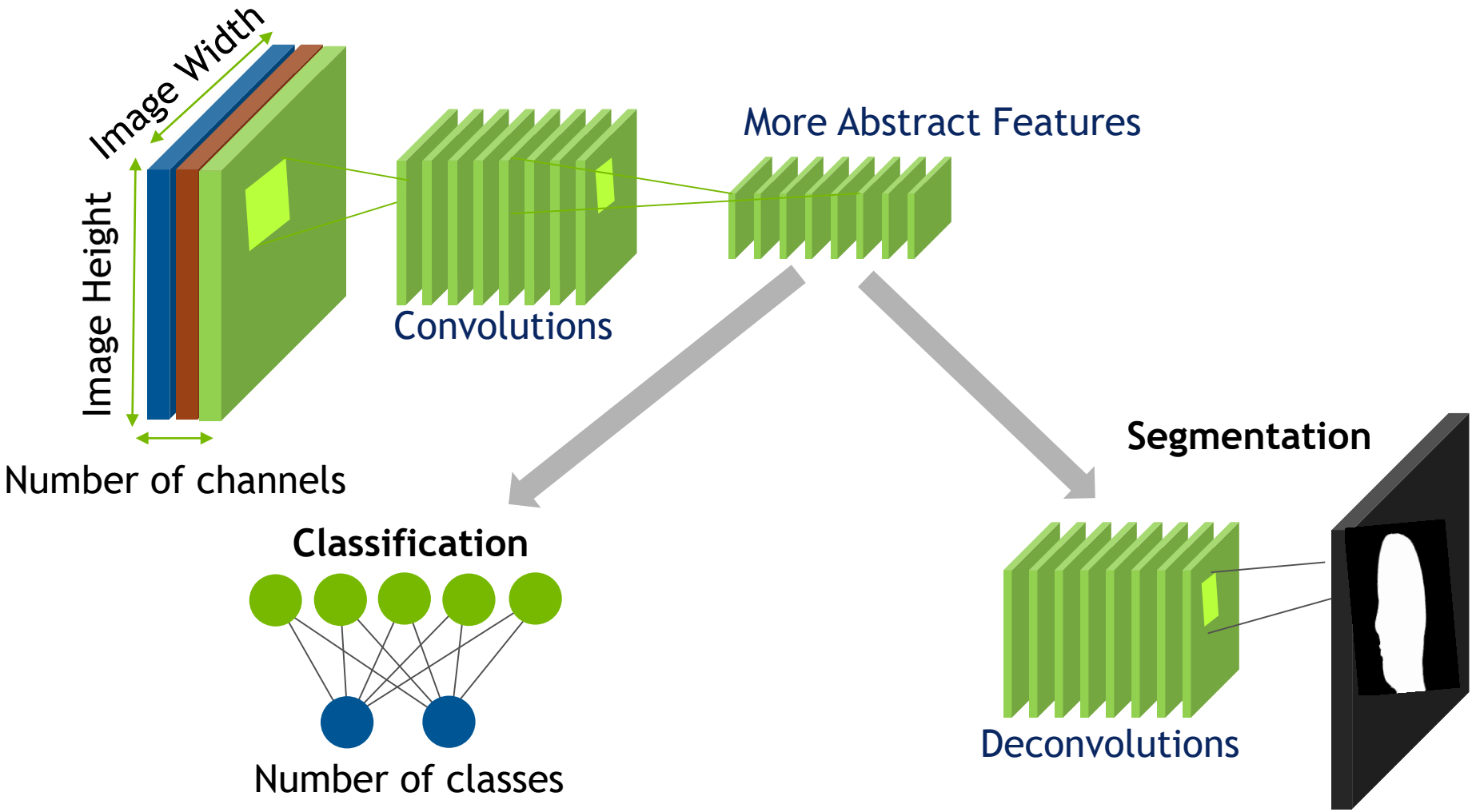
NETWORKS FOR IMAGES

Convolutions are the essential component, the rest depends on the task



NETWORKS FOR IMAGES

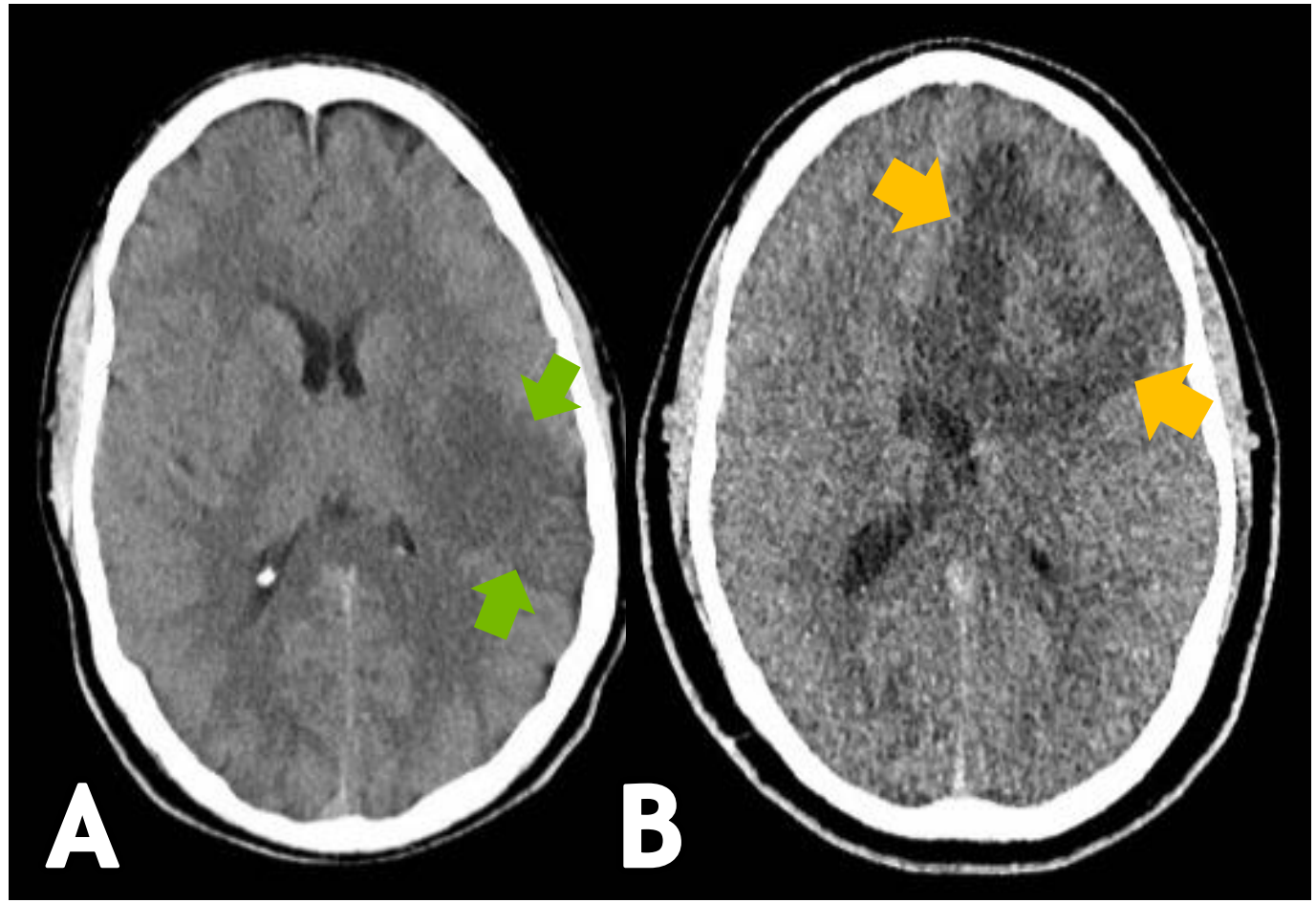
Convolutions are the essential component, the rest depends on the task



AI SPEEDS TIME TO CRITICAL CARE

The phrase “Time is Brain” means every minute counts after a stroke. A typical patient loses almost 2 million neurons per minute in which a stroke is untreated. Immediate treatment minimizes brain damage.

To help Radiologists diagnose the most urgent cases and enhance critical care, the OSU Department of Radiology used GPU-accelerated deep learning to develop an Automated Critical Test-Findings Identification and Online Notification System (ACTIONS). With GPUs, ACTIONS was trained in minutes vs. days. It identifies in seconds the most urgent cases of stroke, hydrocephalus, hemorrhage, and large tumors with an accuracy rate of 81% (stroke) and 91% (hydrocephalus, hemorrhage, large tumors), speeding time to critical care.



Examples of head CT examinations containing critical findings.

A) A patient with a recent stroke involving the left cerebral hemisphere (green arrows).
B) A patient with a large left frontal tumor compressing adjacent structures (orange arrows).

http://pubs.rsna.org/doi/pdf/10.1148/radiol.2017162664

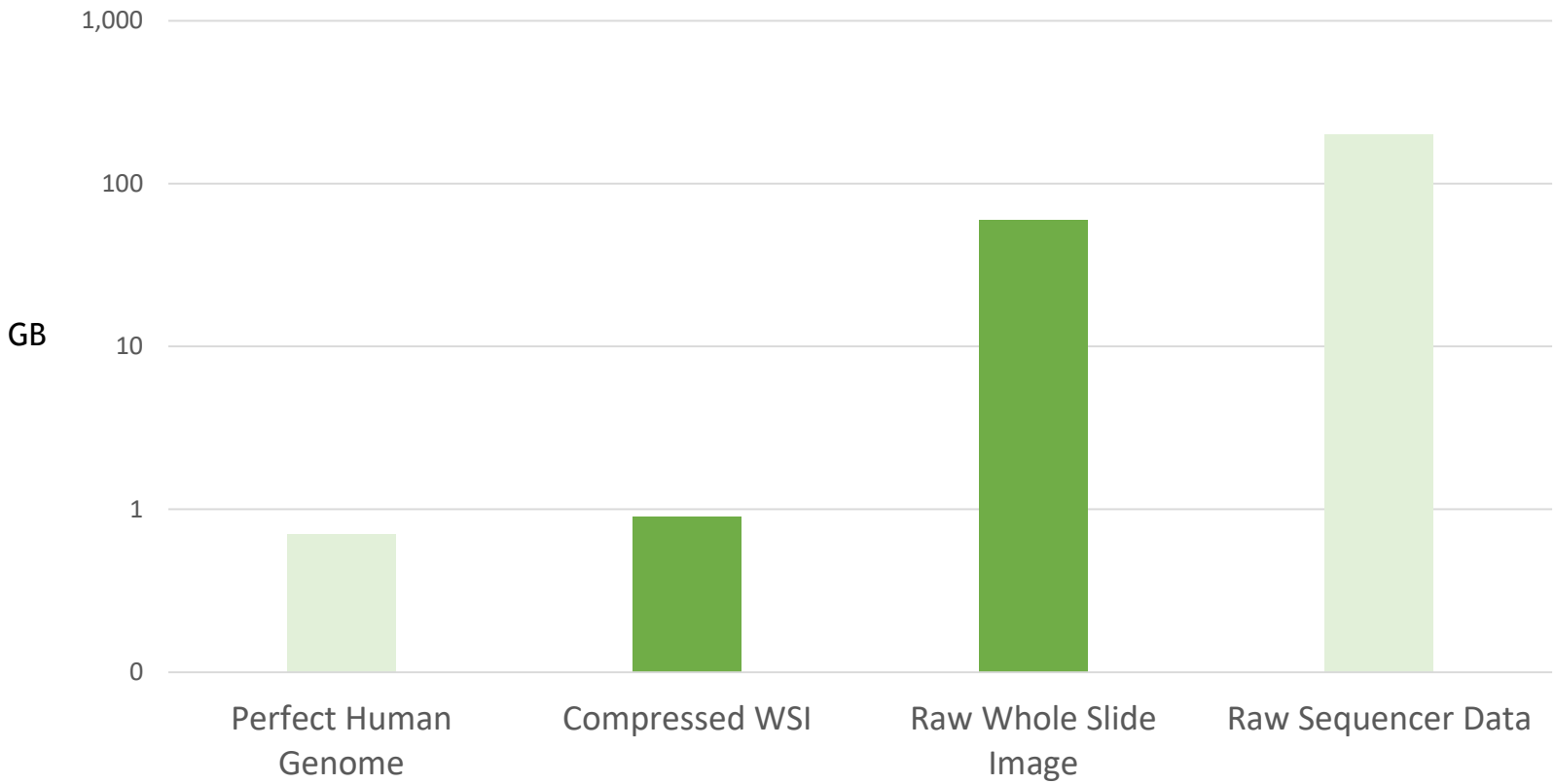
CHALLENGES IN DIGITAL PATHOLOGY

Although other modalities have their own data challenges, Whole Slide Images present a number of problems

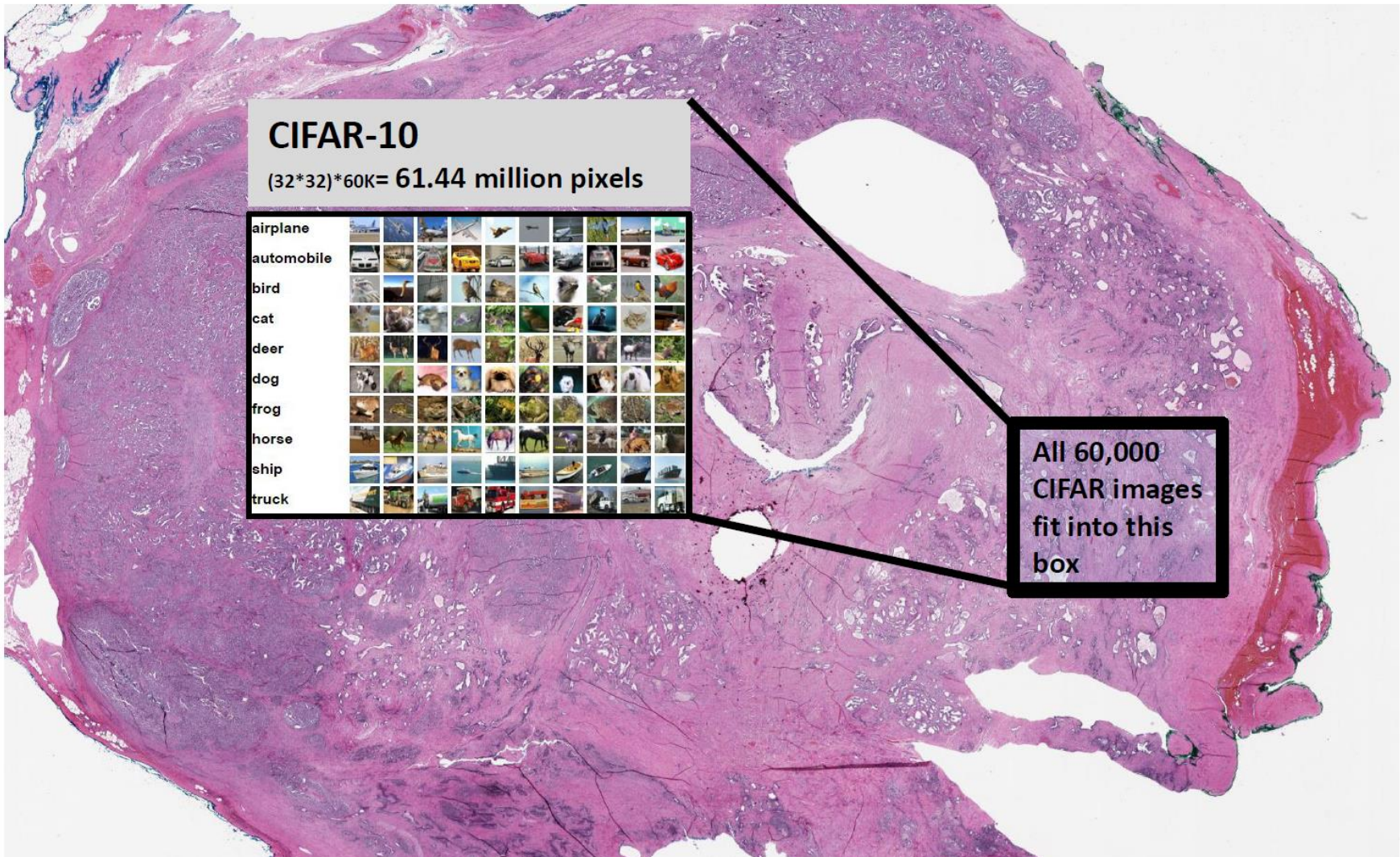
- VERY LARGE IMAGES
- Abnormalities may be limited to tiny islands in an ocean of ‘normal’ tissue
- Labels often only apply to whole image
- Limited public datasets and even fewer labelled ones
- A lot of background, which is not needed
- Only experts can identify abnormalities
- Subjective criteria used to classify – lots of inter (and intra) pathologist variability
- Lack of enthusiasm to digitise from many more ‘senior’ pathologists

DATA SIZES

Genomics vs. Digital Pathology

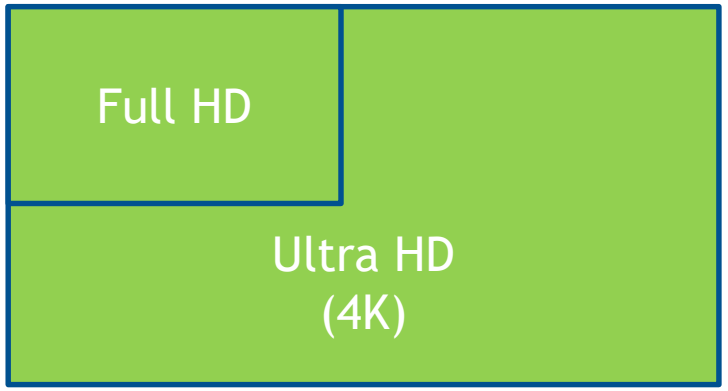


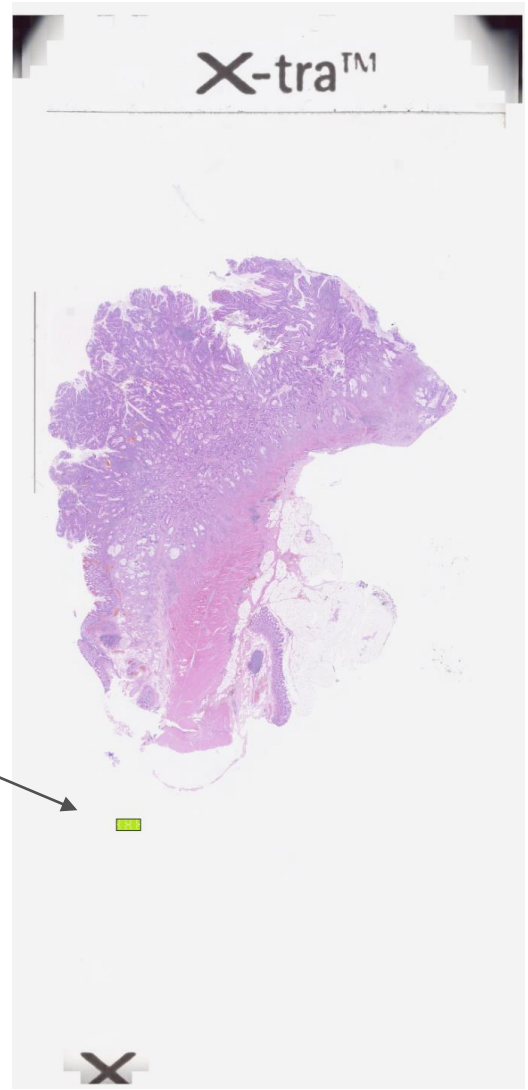
1 Whole Slide
= 100,000 x 60,000
= **6 billion pixels**



Fuchs Lab @ MSKCC + Weill Cornel lhttp://thomasfuchslab.org/

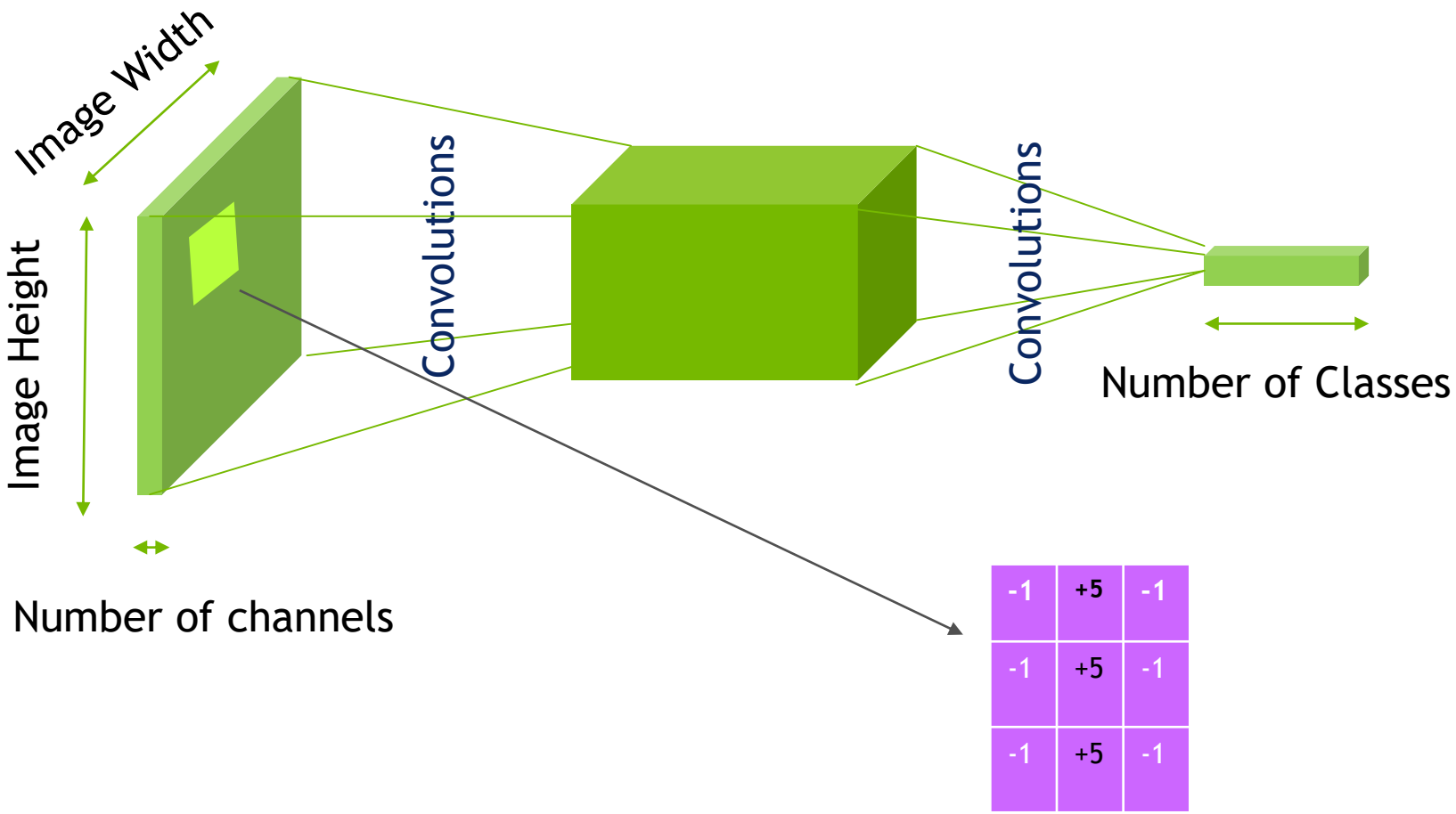
SIZE MATTERS





CONVOLUTIONAL NEURAL NETS

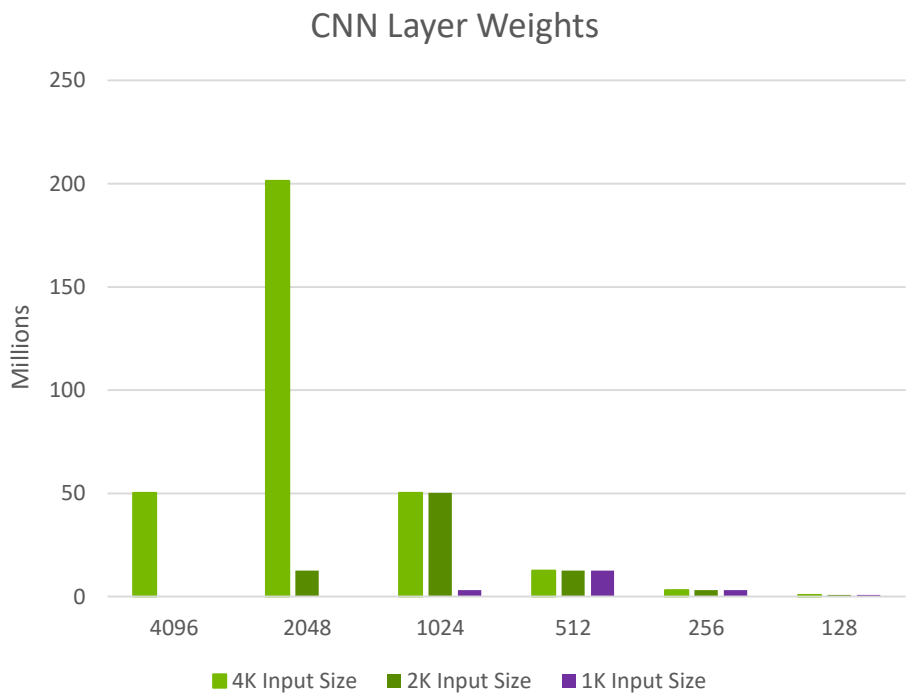
Why large images are problematic



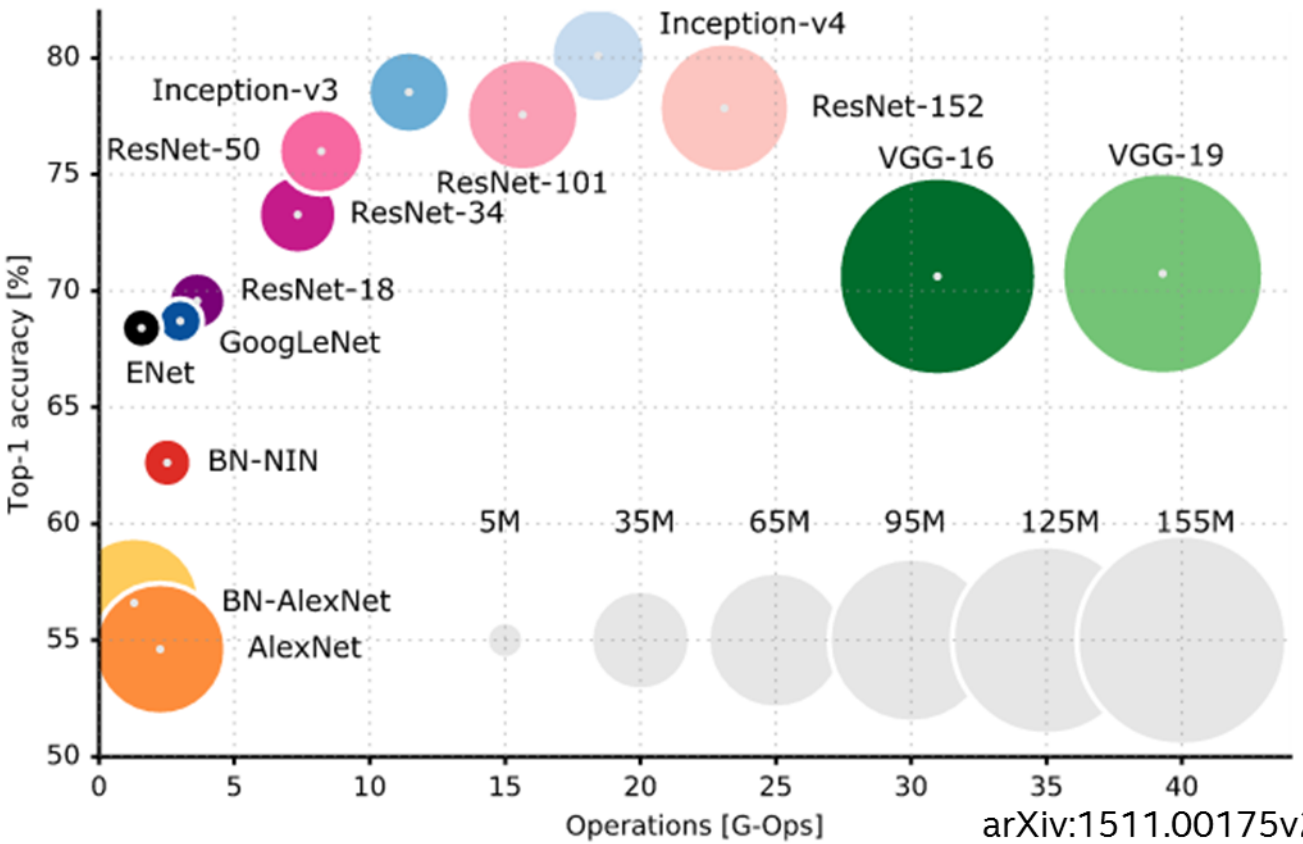
CONVOLUTIONAL NEURAL NETS

Adding convolution layers to ingest larger images increases memory exponentially

Input Size	Channels	Weights
4096	3	50M
2048	48	200M
1024	48	50M
512	48	12M
256	48	3M
128	48	790K



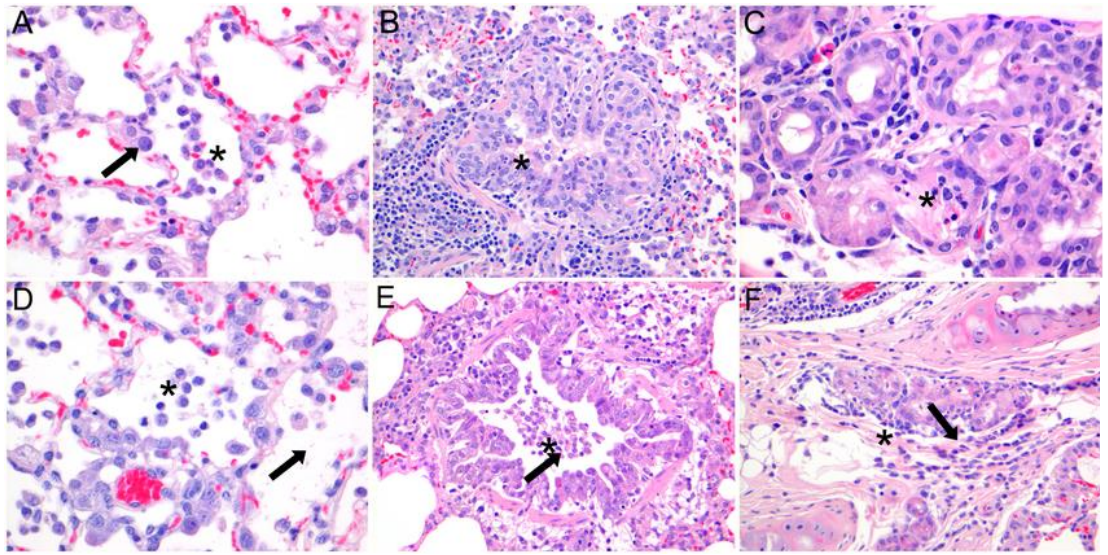
MODEL COMPLEXITY



arXiv:1511.00175v2 [cs.CV] 8 Jan 2016

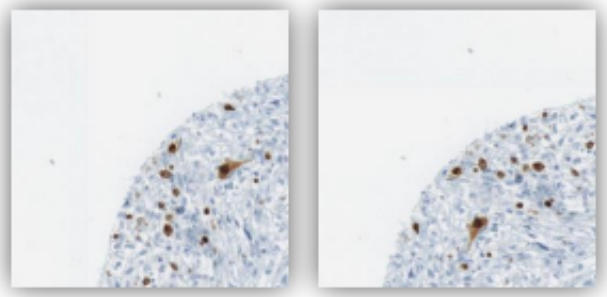
DOWN-SAMPLING

Down-sampling produces a significant loss of micro-features @ 40k to 512 pixels



EXPERT VARIABILITY

50 nuclei were repeated flipped and rotated to test the intra pathologist variability.

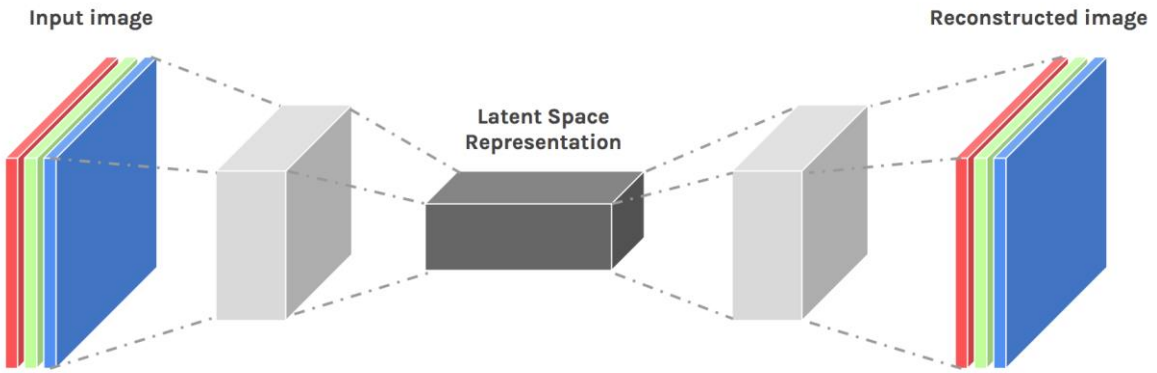


Original Flipped & Rotated

53/250
mismatches

Baseline: Intra-Pathologists classification uncertainty of ~**20%**

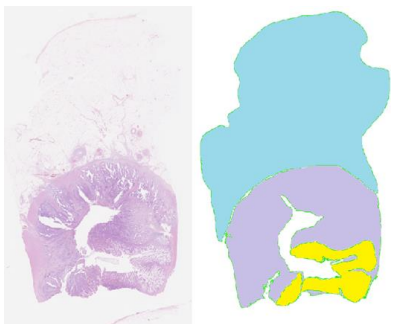
SEMI-SUPERVISED DEEP LEARNING TO DETECT ABNORMALITIES

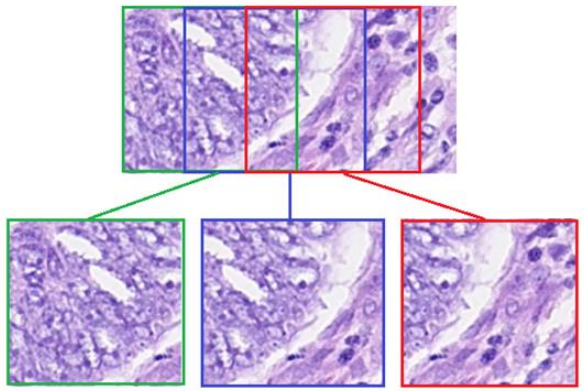


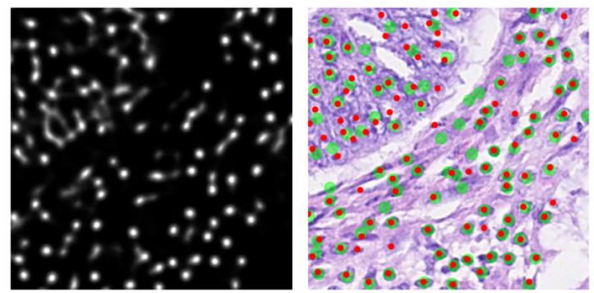
https://becominghuman.ai/understanding-autoencoders-unsupervised-learning-technique-82fb3fbaec2

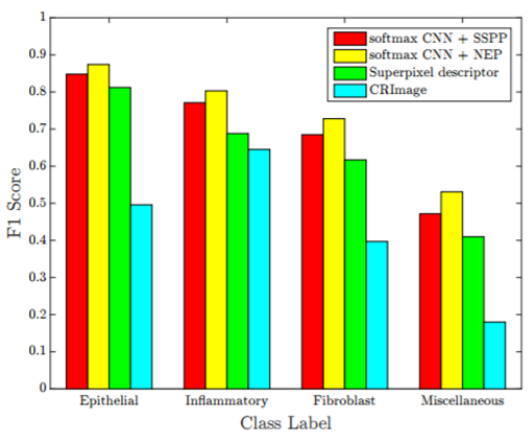
TISSUE IMAGE ANALYTICS LAB

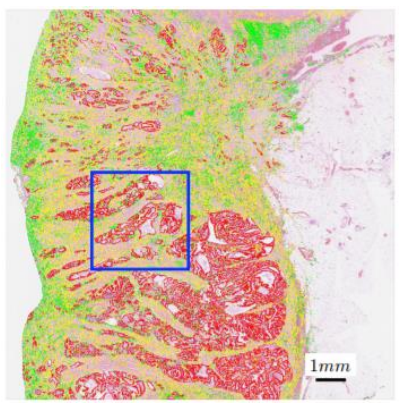
University Hospitals Coventry and Warwickshire NHS Trust

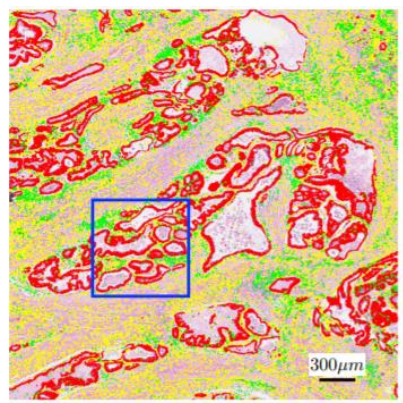


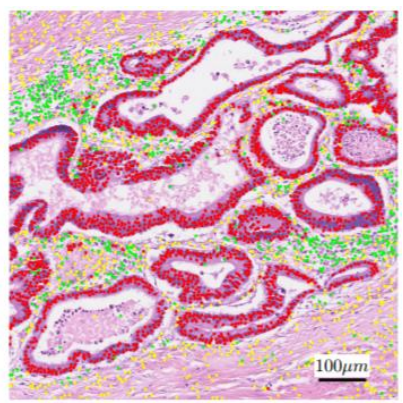








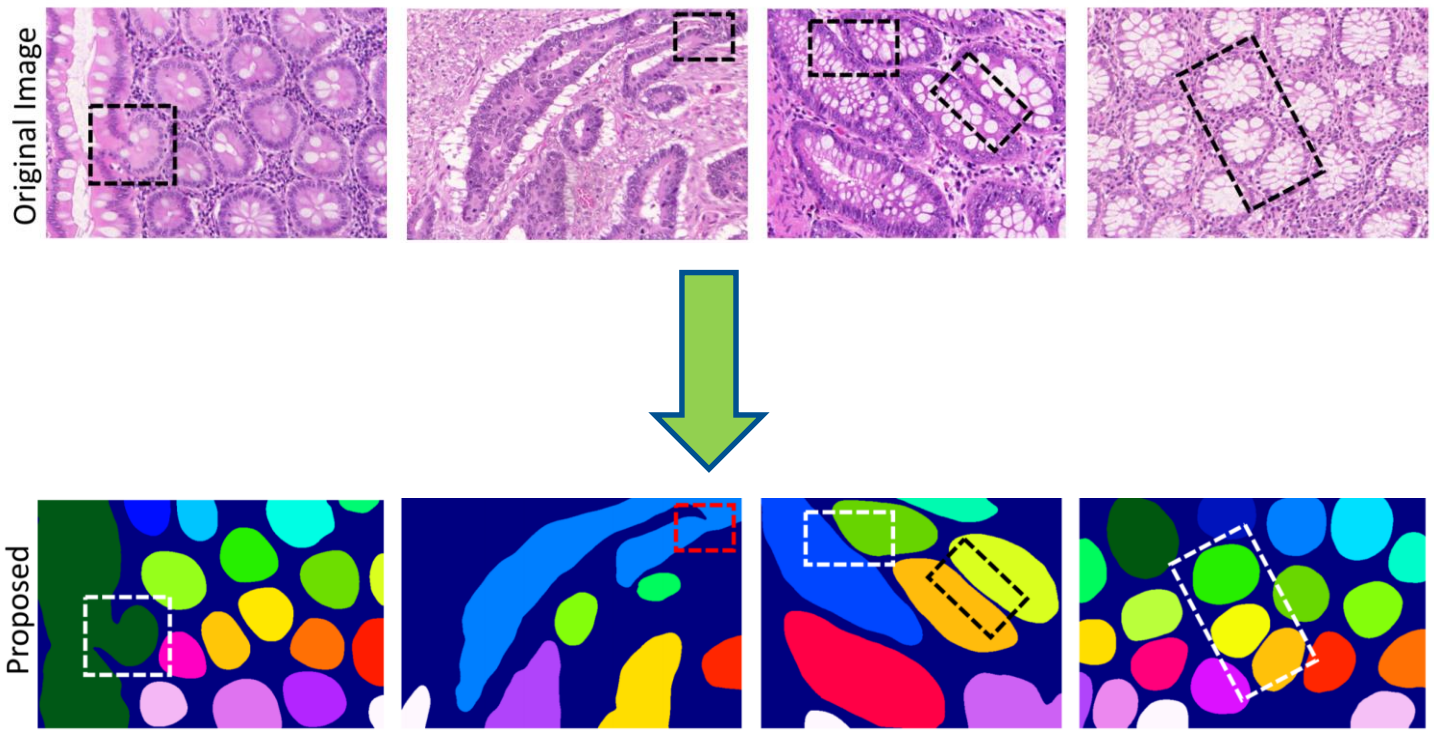




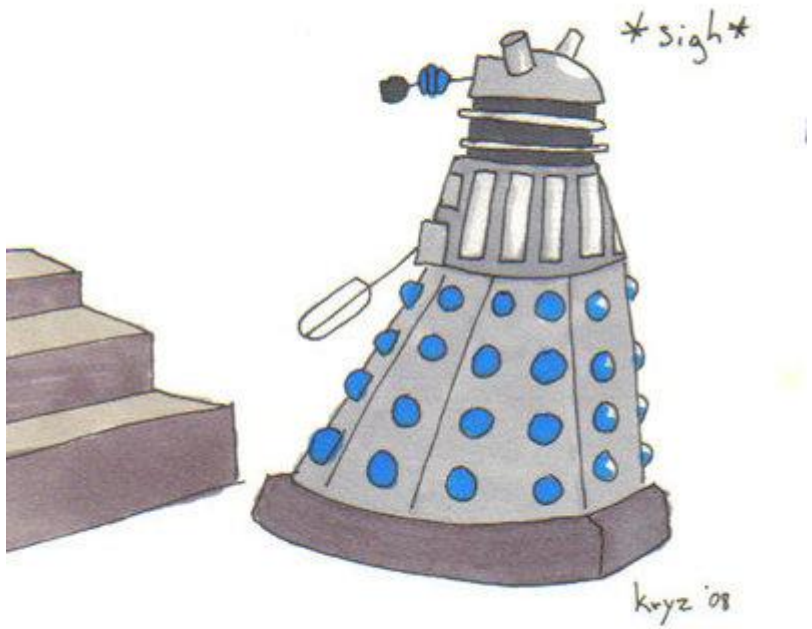
https://warwick.ac.uk/fac/sci/dcs/people/research/csrkbb/tmi2016_ks.pdf

TISSUE IMAGE ANALYTICS LAB

University Hospitals Coventry and Warwickshire NHS Trust



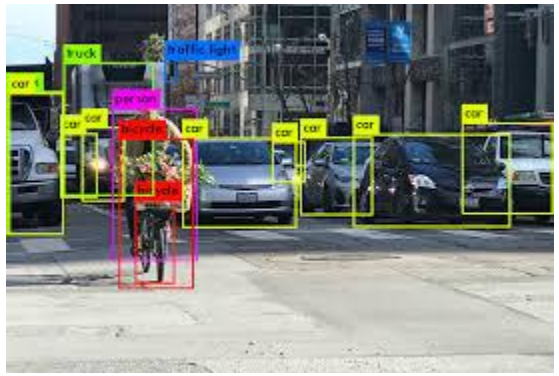
CHALLENGES

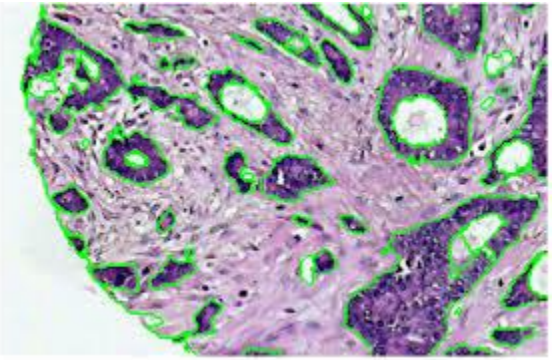


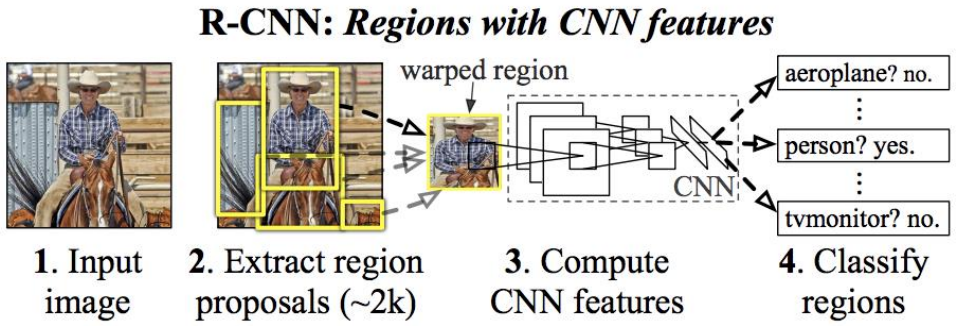
https://www.deviantart.com/kryz-flavored/art/dalek-vs-stairs-99091404

MULTIPLE INSTANCES

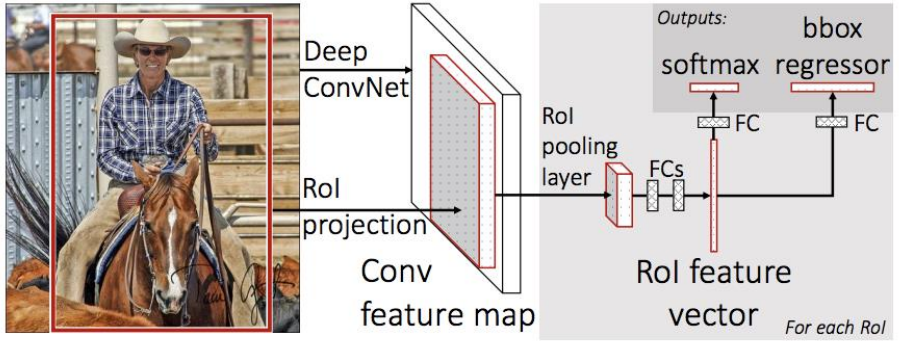
What if there are lots of objects on the same image?







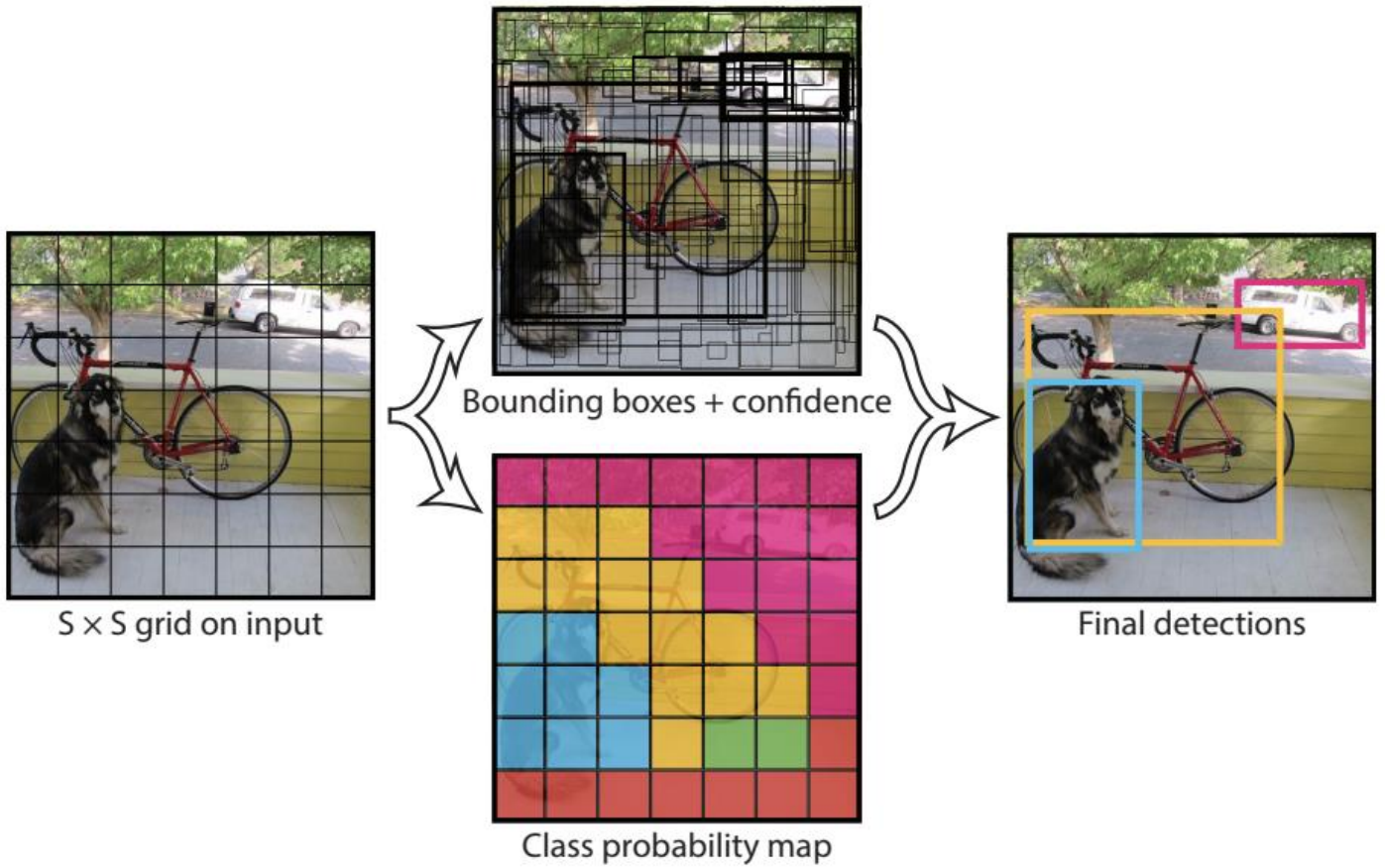
https://arxiv.org/pdf/1311.2524.pdf



https://arxiv.org/pdf/1504.08083.pdf

MULTIPLE INSTANCES

One recent and promising technique is called ‘YOLO’ (You only look once)

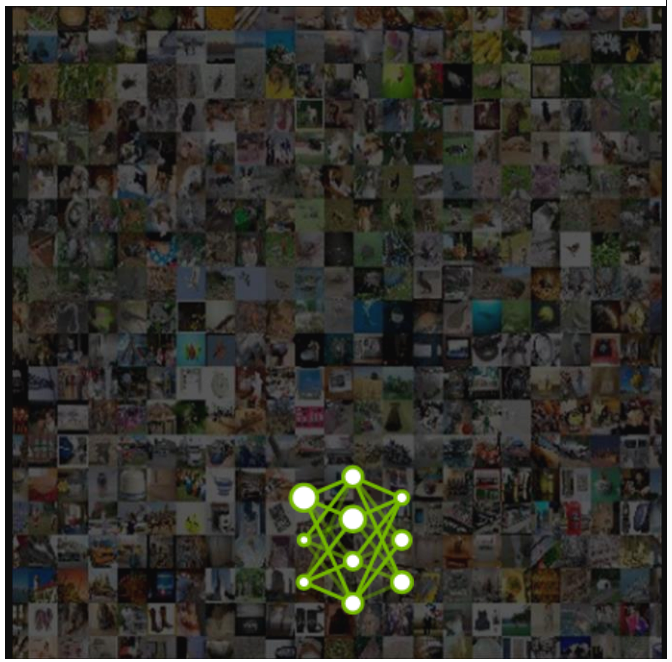


https://arxiv.org/pdf/1506.02640v5.pdf

NEURAL NETWORK COMPLEXITY IS EXPLODING

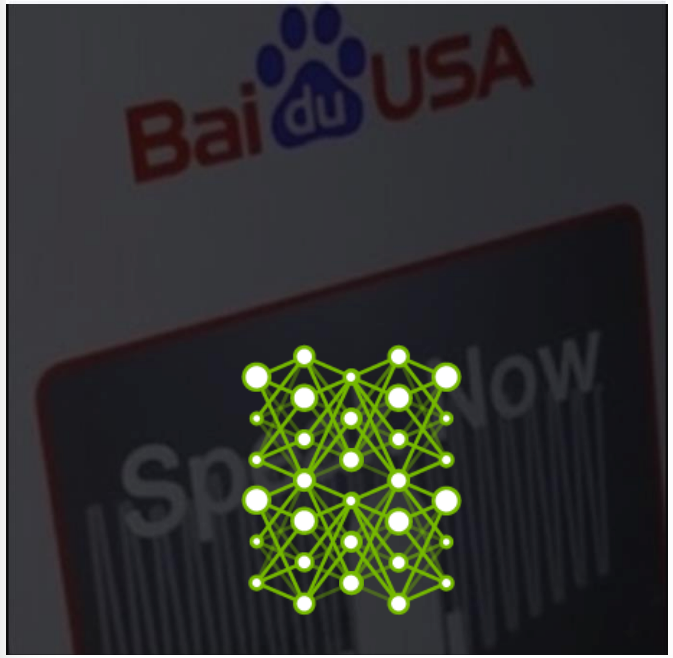
To Tackle Increasingly Complex Challenges

7 ExaFLOPS
60 Million Parameters



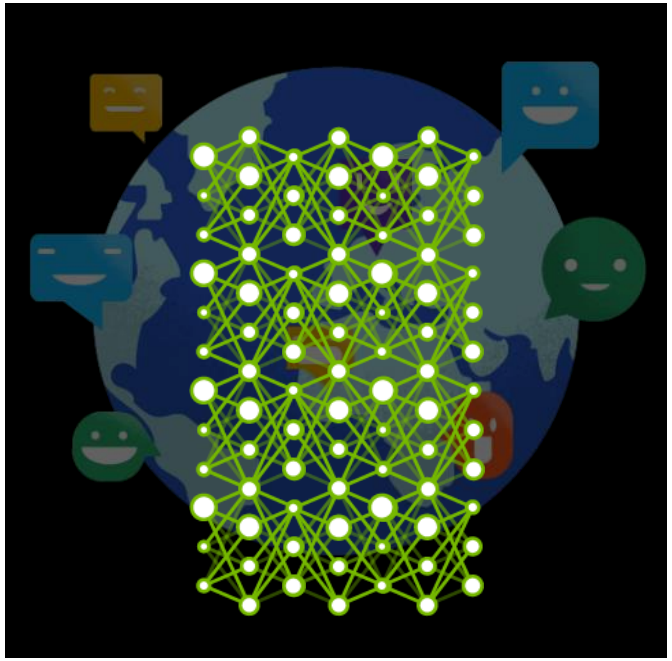
2015 – Microsoft ResNet
Superhuman Image Recognition

20 ExaFLOPS
300 Million Parameters



2016 – Baidu Deep Speech 2
Superhuman Voice Recognition

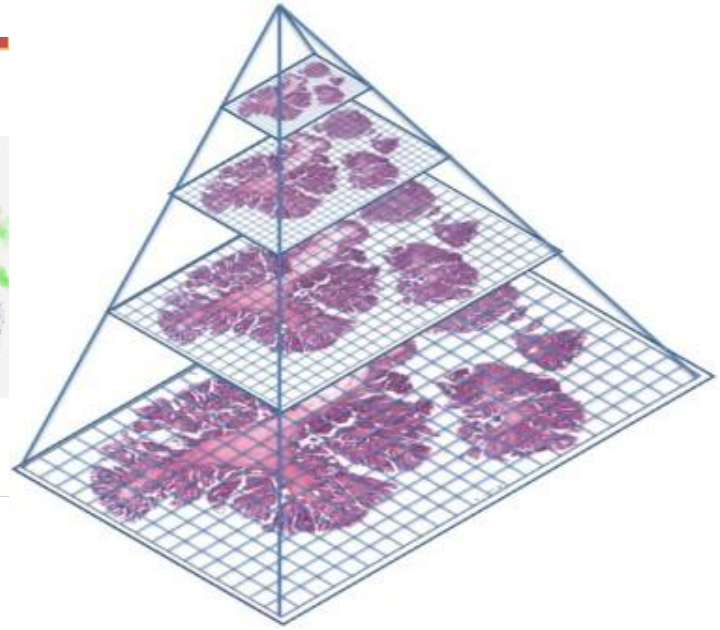
100 ExaFLOPS
8700 Million Parameters



2017 – Google Neural Machine Translation
Near Human Language Translation

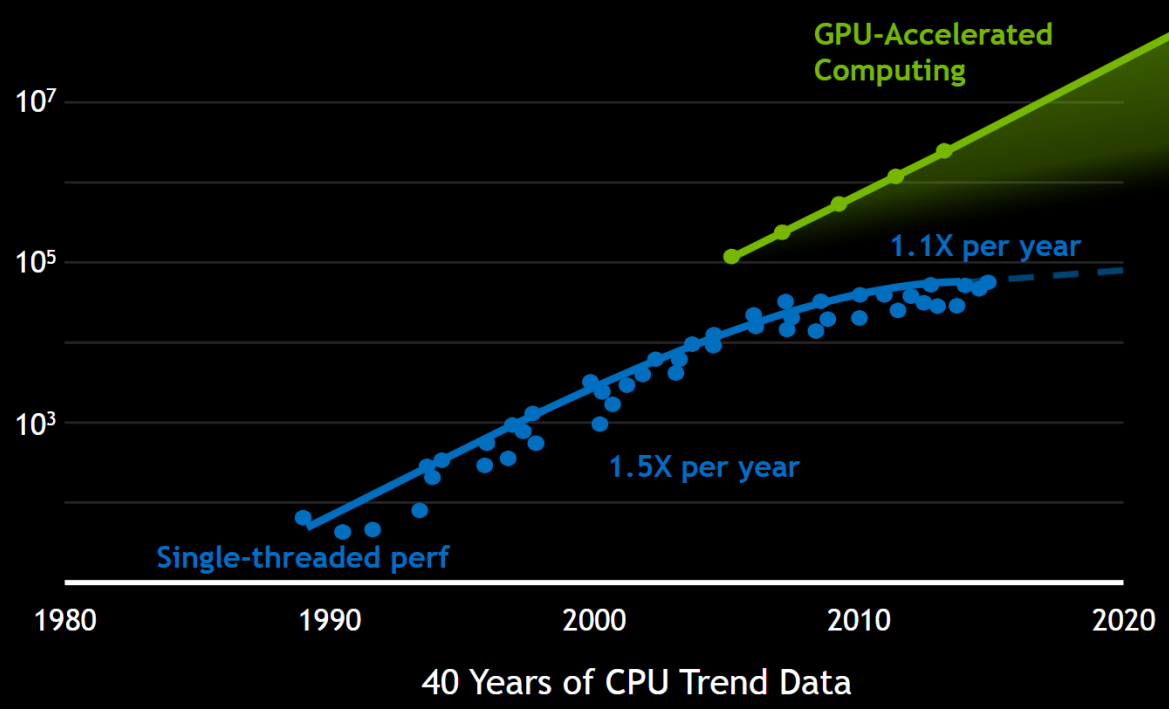
THE NEED FOR CONTEXT AND FOCUS…

https://blog.tcea.org/grants/

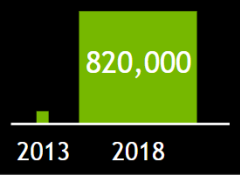


https://www.sciencedirect.com/science/article/pii/S1046202314002370

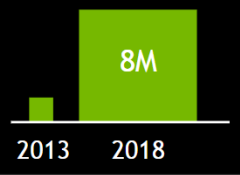
RISE OF GPU COMPUTING



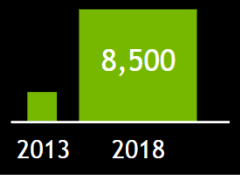
Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten New plot and data collected for 2010-2015 by K. Rupp



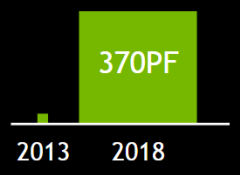
GPU Developers
10X in 5 Yrs



CUDA Downloads
5X in 5 Yrs



GTC Registrations
4X in 5 Yrs

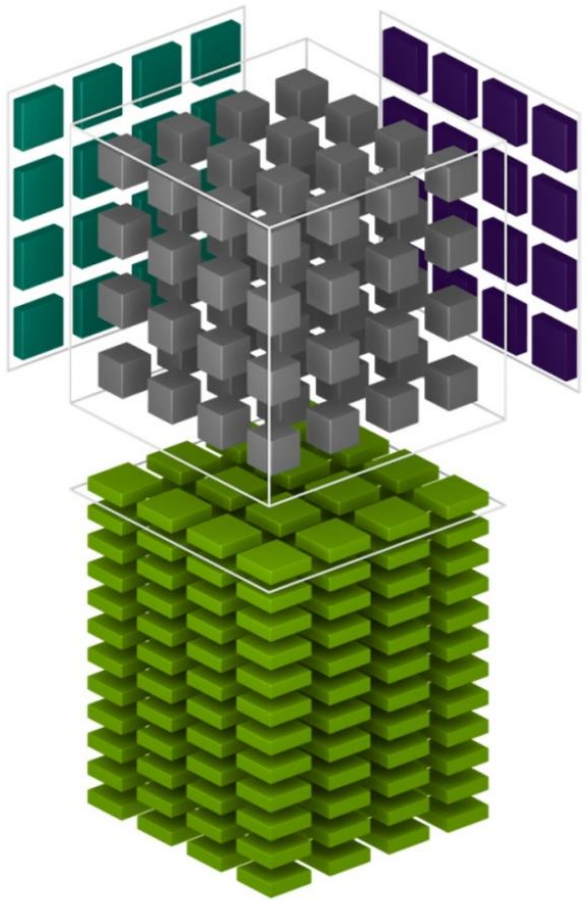


Total GPU FLOPS
of Top 50 Systems
15X in 5 Yrs

FUSING AI AND HIGH PERFORMANCE COMPUTING

5,120 CUDA cores
640 NEW Tensor cores
7.8 FP64 TFLOPS | 15.7 FP32 TFLOPS | 125 Tensor TFLOPS
20MB SM RF | 16MB Cache
16GB/ 32GB HBM2 @ 900GB/s | 300GB/s NVLink

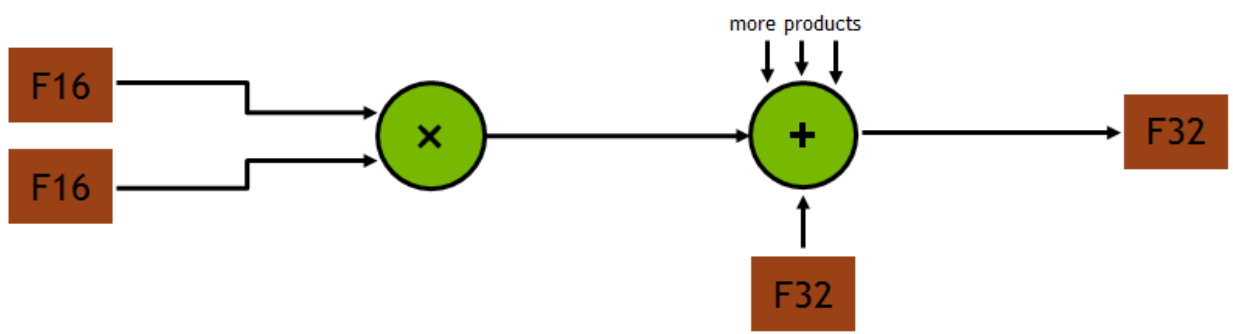
TENSOR CORES



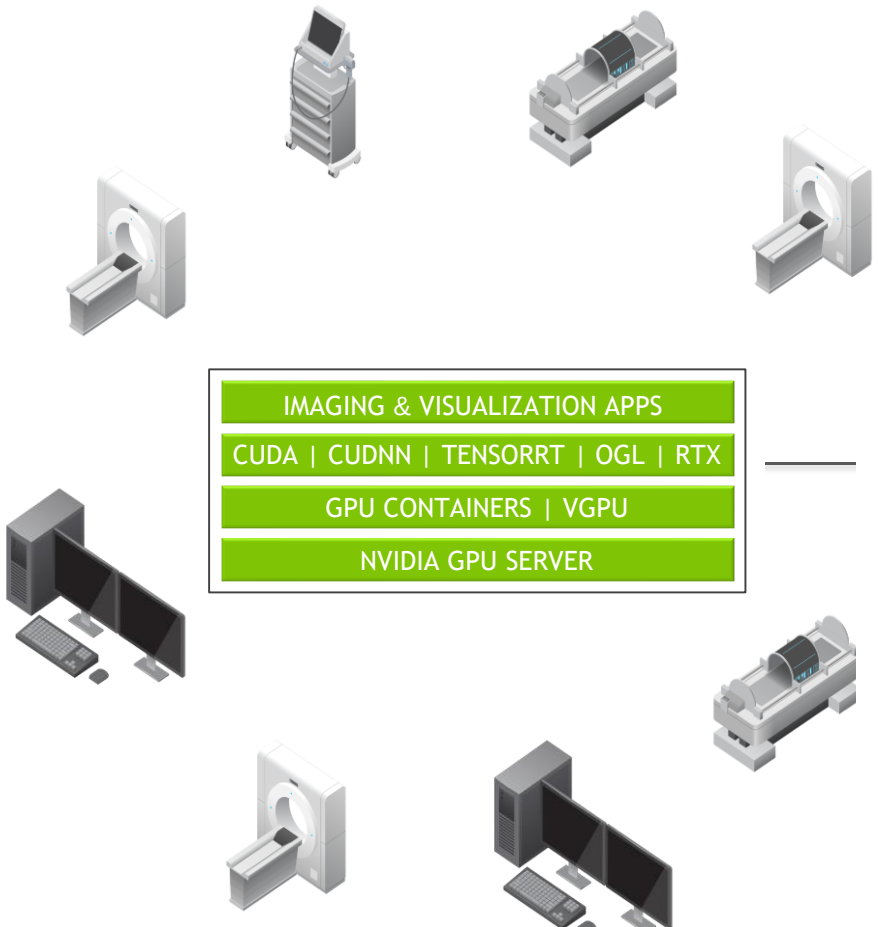
$$D = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}$$

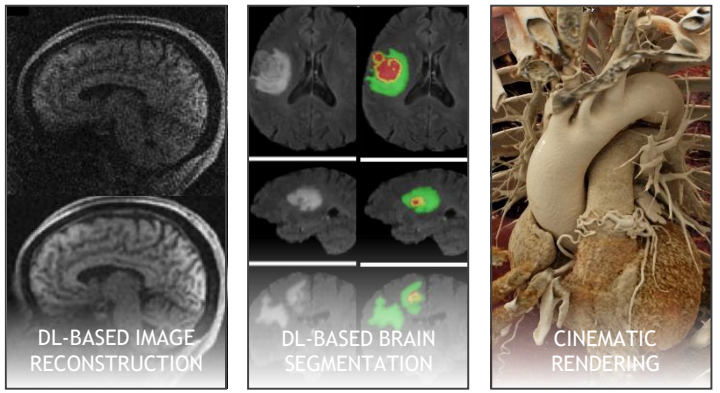
FP16 or FP32 — FP16 — FP16 — FP16 or FP32

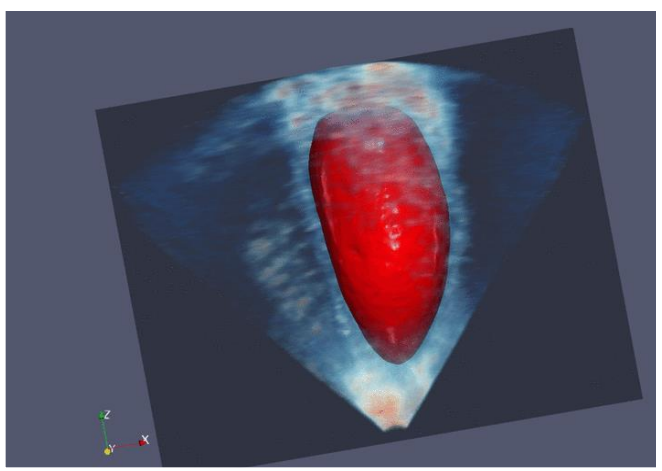
FP16 storage/input | **Full precision product** | **Sum with FP32 accumulator** | **Convert to FP32 result**



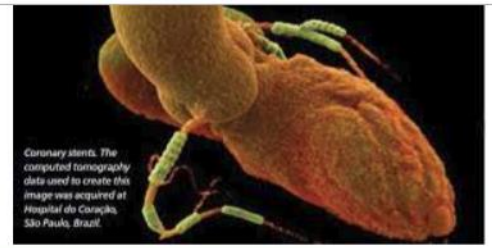
THE FUTURE

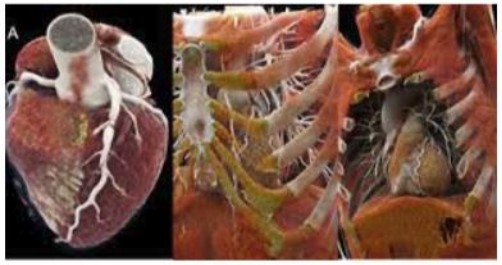


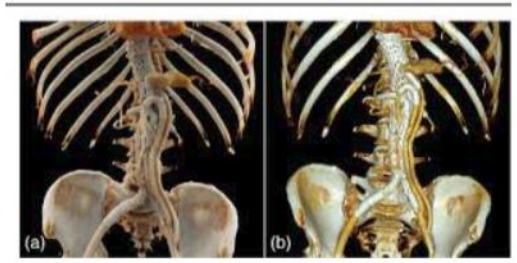


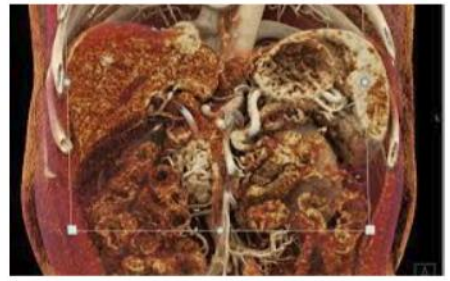


https://www.philips.com/a-w/about/news/archive/standard/news/press/2017/20170508-philips-new-ob-gyn-ultrasound-innovations-with-anatomical-intelligence-provide-lifelike-3d-images.html

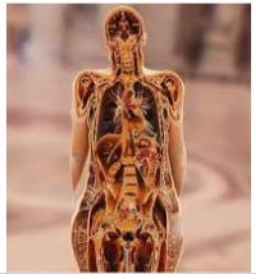

Coronary stents. The computed tomography data used to create this image was acquired at Hospital do Coração, São Paulo, Brazil.

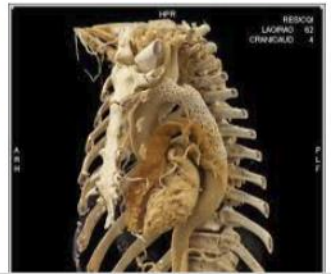

A

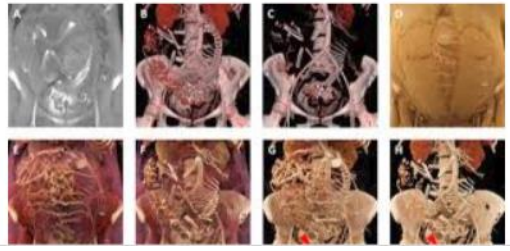

(a)
(b)




NT




HPR
RISCO
LAGRIMAS 02
CRANCIAIS 4



KEY TAKEAWAYS

- Detection is really just a sub-type of image classification
- CNNs are best for image-related work, but come in many flavours
- Imaging is not easy but is ripe for DL-based automation
- For large images, you need lots of GPU – with tensor cores !

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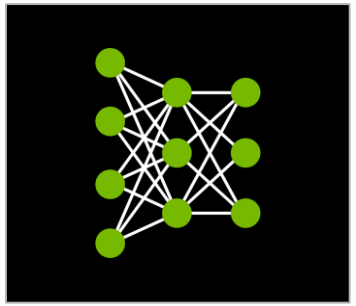
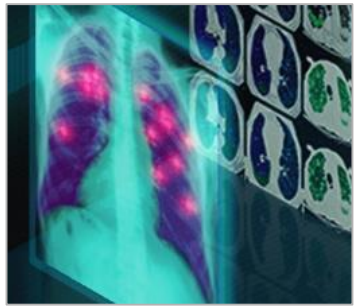
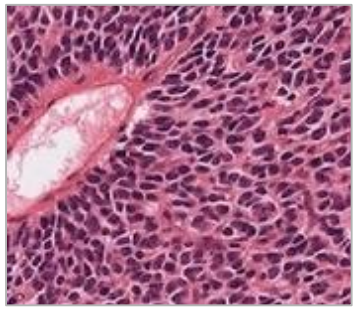


Deep Learning Fundamentals

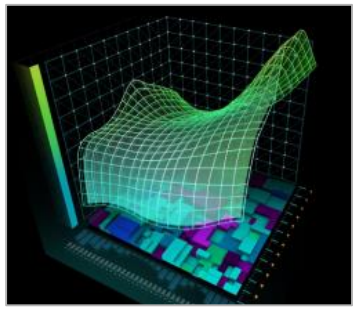
Autonomous Vehicles



Medical Image Analysis

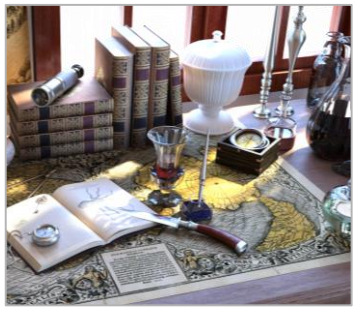


Genomics

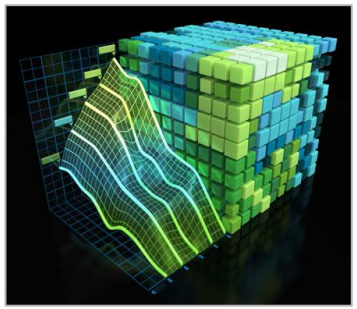


Finance

Digital Content Creation



Game Development



Accel. Computing Fundamentals

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Thank you!
QUESTIONS?
jhancox@nvidia.com