Artificiële Intelligentie

RCA AIG 04Q6 18 MAART 2021

Next-wave AI HPC-workstations

Waar Gaming & Machine Learning samenkomen

HOGESCHOOL ROTTERDAM

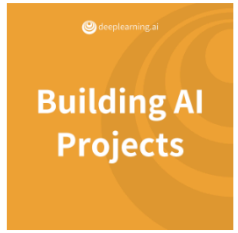
DataLab
Rob van der Willigen

AI For Everyone

AI is not only for engineers. “AI for Everyone”, a non-technical course, will help you understand AI technologies and spot opportunities to apply AI to problems in your own organization. You will see examples of what today’s AI can – and cannot – do. Finally, you will understand how AI is impacting society and how to navigate through this technological change.

If you are a non-technical business professional, “AI for Everyone” will help you understand how to build a sustainable AI strategy. If you are a machine learning engineer or data scientist, this is the course to ask your manager, VP or CEO to take if you want them to understand what you can (and cannot!) do.

Week 1
What is AI



Week 2
Building AI Projects

Week 3
AI in Your Company

Week 4
AI and Society

https://www.deeplearning.ai/ai-for-everyone/

https://towardsdatascience.com/step-by-step-guide-to-building-your-own-neural-network-from-scratch-df64b1c5ab6e

Course syllabus

Week 1: What is AI

- Introduction
- Machine Learning
- What is data
- The terminology of AI
- What makes an AI company?
- What Machine Learning can and cannot do
- Intuitive explanation of deep learning

Week 2: Building AI Projects

- Workflow of a Machine Learning project
- Workflow of a Data Science project
- Every job function needs to learn to use data
- How to choose an AI project
- Working with an AI team
- Technical tools for AI teams

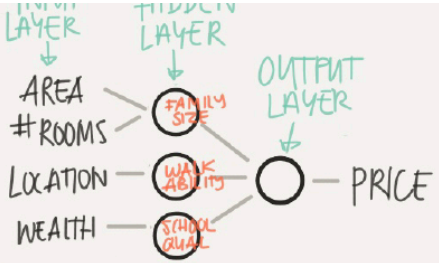
Week 3: AI in Your Company

- Case study: Smart speaker
- Case study: Self-driving car
- Example roles of an AI team
- AI Transformation Playbook
- AI pitfalls to avoid
- Taking your first step in AI
- Survey of major AI applications
- Survey of major AI techniques

Week 4: AI and Society

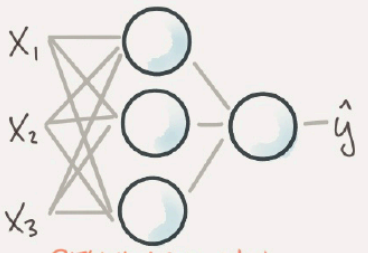
- A realistic view of AI
- Discrimination / Bias
- Adversarial attacks
- Adverse uses
- AI and developing nations
- AI and jobs
- Conclusion

INTRO TO DEEP LEARNING

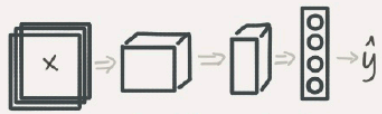


SUPERVISED LEARNING

INPUT: X	OUTPUT: y	NN TYPE
HOME FEATURES AD+USER INFO	PRICE WILL CLICK ON AD (0/1)	STANDARD NN
IMAGE	OBJECT (1...1000)	CONV. NN (CNN)
AUDIO ENGLISH	TEXT TRANSCRIPT CHINESE	RECURRENT NN (RNN)
IMAGE/RADAR	POS OF OTHER CARS	CUSTOM/HYBRID

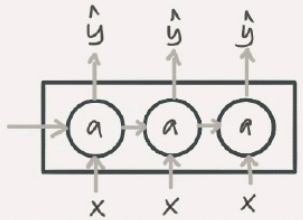


STANDARD NN



CONVOLUTIONAL NN

NETWORK ARCHITECTURES



RECURRENT NN

NNs CAN DEAL WITH BOTH STRUCTURED & UNSTRUCTURED DATA

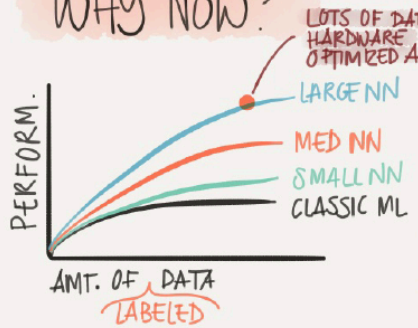
STRUCTURED

"THE QUICK BROWN FOX"

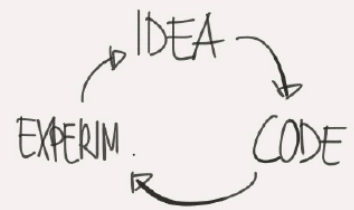
UNSTRUCTURED

HUMANS ARE GOOD AT THIS

WHY NOW?



ONE OF THE BIG BREAKTHROUGHS HAS BEEN MOVING FROM SIGMOID TO RELU FOR FASTER GRADIENT DESCENT



FASTER COMPUTATION IS IMPORTANT TO SPEED UP THE ITERATIVE PROCESS

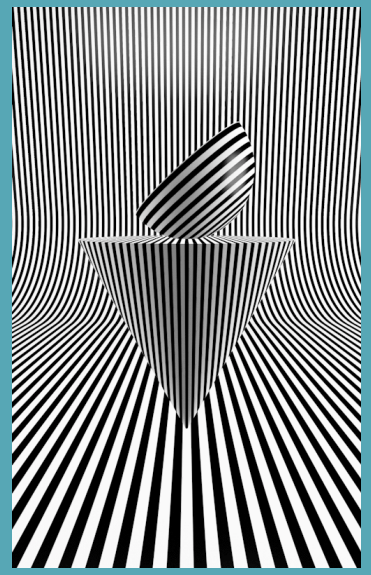
© Tessferrandez

NEURAL NETWORKS & DEEP LEARNING • COURSERA • ANDREW NG • WK 1

a Narrative for Hands on approach to Machine Learning

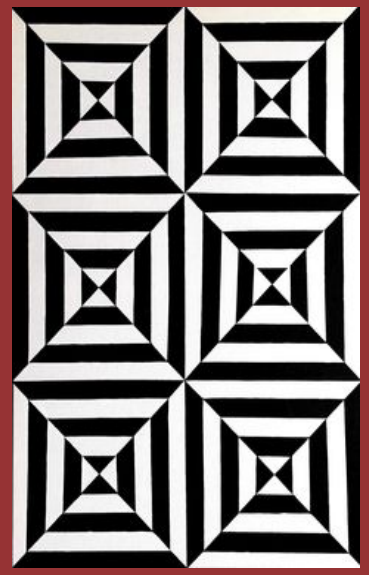
01 AI

Fundamentals



02 Hyper Performance Computing

Buiding blocks

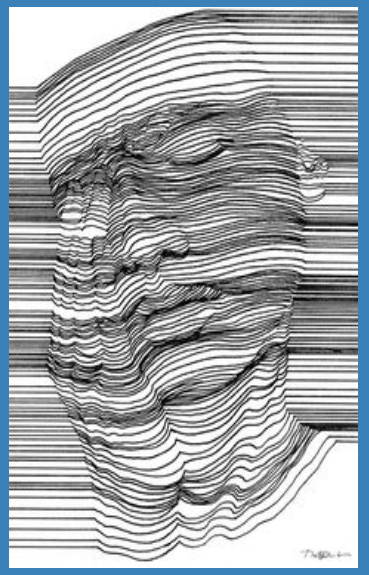


03 Tools

Transforming

04 Proof of Concept

Applying



https://RobFvdW.medium.com

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Fundamentals

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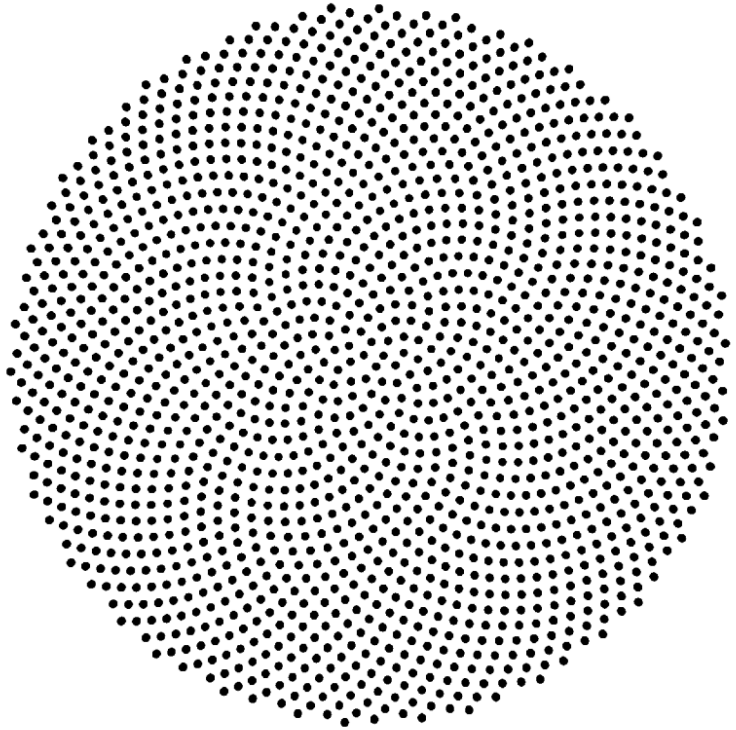

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AI is Modeled on How Humans Proces Information

Scale (sec)	Time Units	System	World (theory)
10^7	Months		SOCIAL BAND
10^6	Weeks		
10^5	Days		
10^4	Hours	Task	RATIONAL BAND
10^3	10 min	Task	
10^2	Minutes	Task	
10^1	10 sec	Unit task	COGNITIVE BAND
10^0	1 sec	Operations	
10^{-1}	100 ms	Deliberate act	
10^{-2}	10 ms	Neural circuit	BIOLOGICAL BAND
10^{-3}	1 ms	Neuron	
10^{-4}	100µs	Organelle	

Sensation: [Sensibilisatie]

'…immediate and basic experiences generated as stimuli fall on our sensory systems'
➔ *Verwerken van ruwe data (prikkels of Fysieke stimuli) volgens een vast patroon*

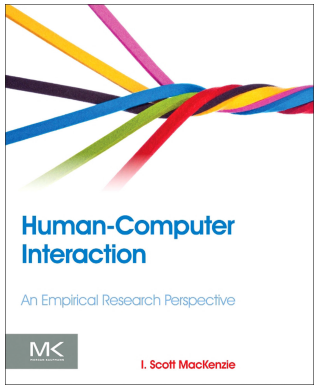
Perception: [Perceptie]

'…interpretation of those sensations, giving them meaning and organization'
➔ *Gestuurd door "ingebouwde" informatie (niet lerend),*

Cognition: [Cognitie]

'…acquisition, storage, retrieval, and use of information'
➔ *Gestuurd door "verworven" informatie (zelf-lerend)*

M.W. Matlin & H.J. Foley, 1992



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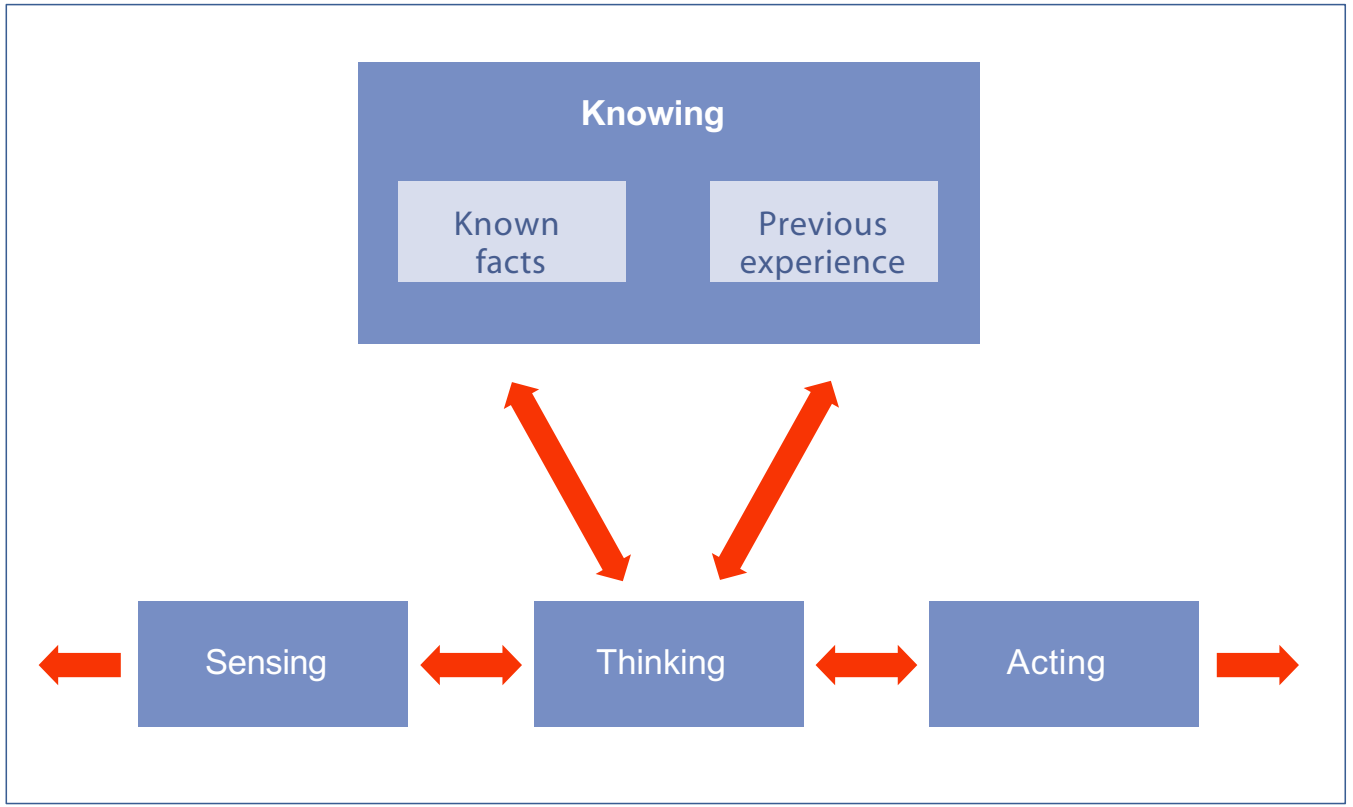
AI is modeled on how humans proces information



The model of mind

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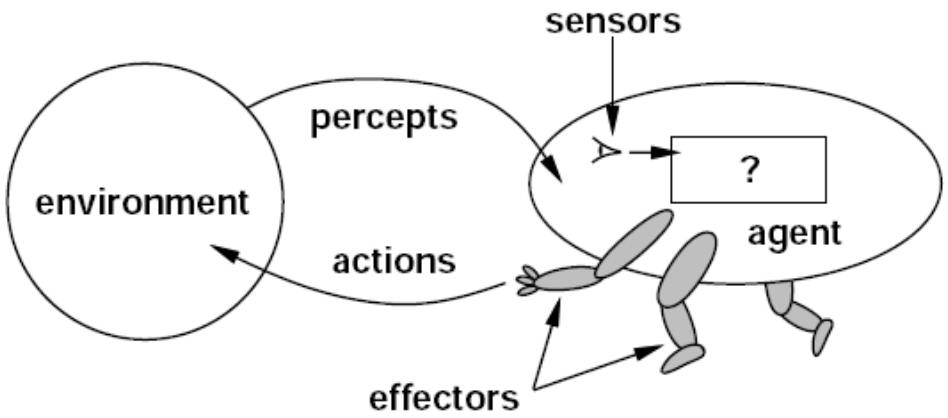
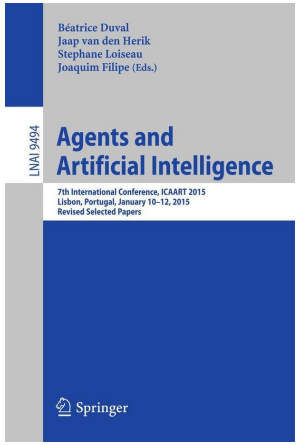
AI is modeled through Agents



An agent

is anything that can perceive its environment through sensors and acts upon that environment through effectors.



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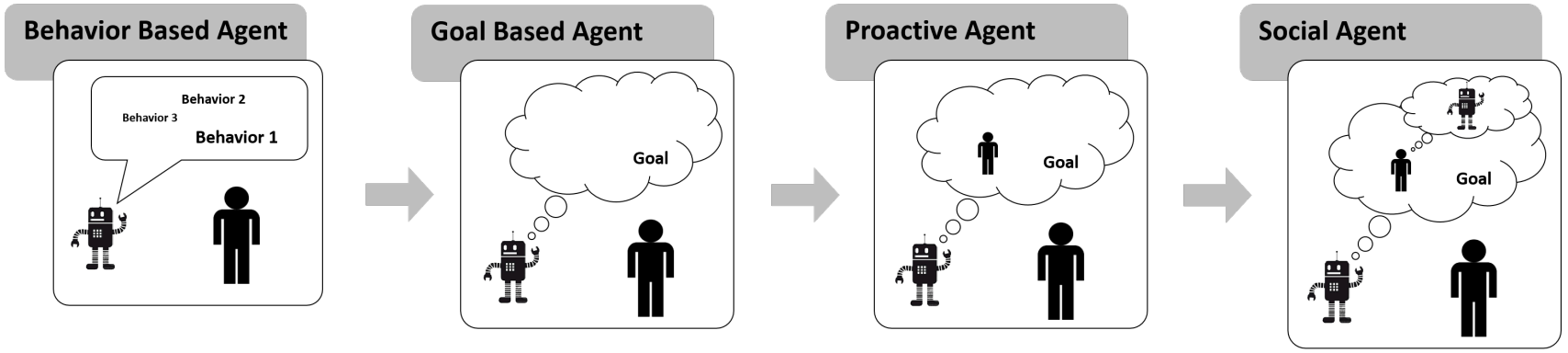
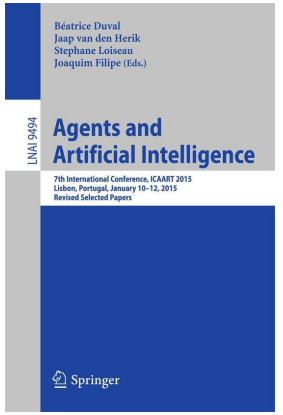
AI is modeled through Agents



Human agent has sensory organs such as eyes, ears, nose, tongue and skin parallel to the sensors, and other organs such as hands, legs, mouth, for effectors.

Robotic agent replaces cameras and infrared range finders for the sensors, and various motors and actuators for effectors.

Software agent has encoded bit strings as its programs and actions.



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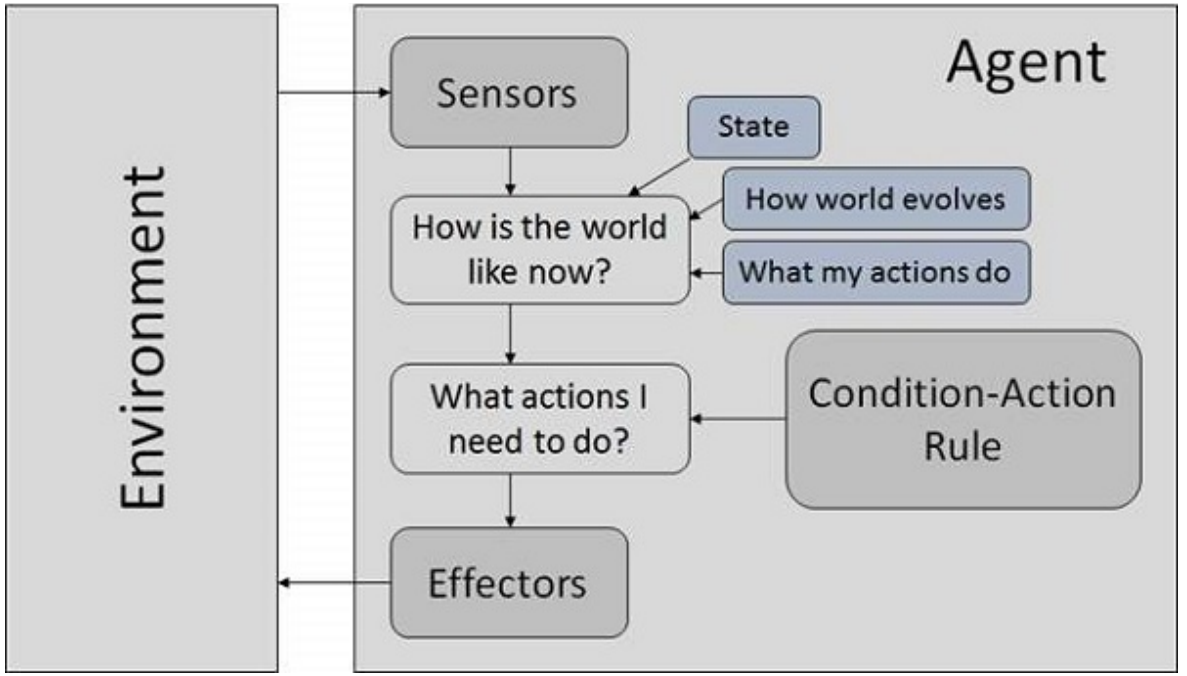
Goal based Robotic Agents need AI (human cognition)



Stanford Encyclopedia of Philosophy

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Fundamentals

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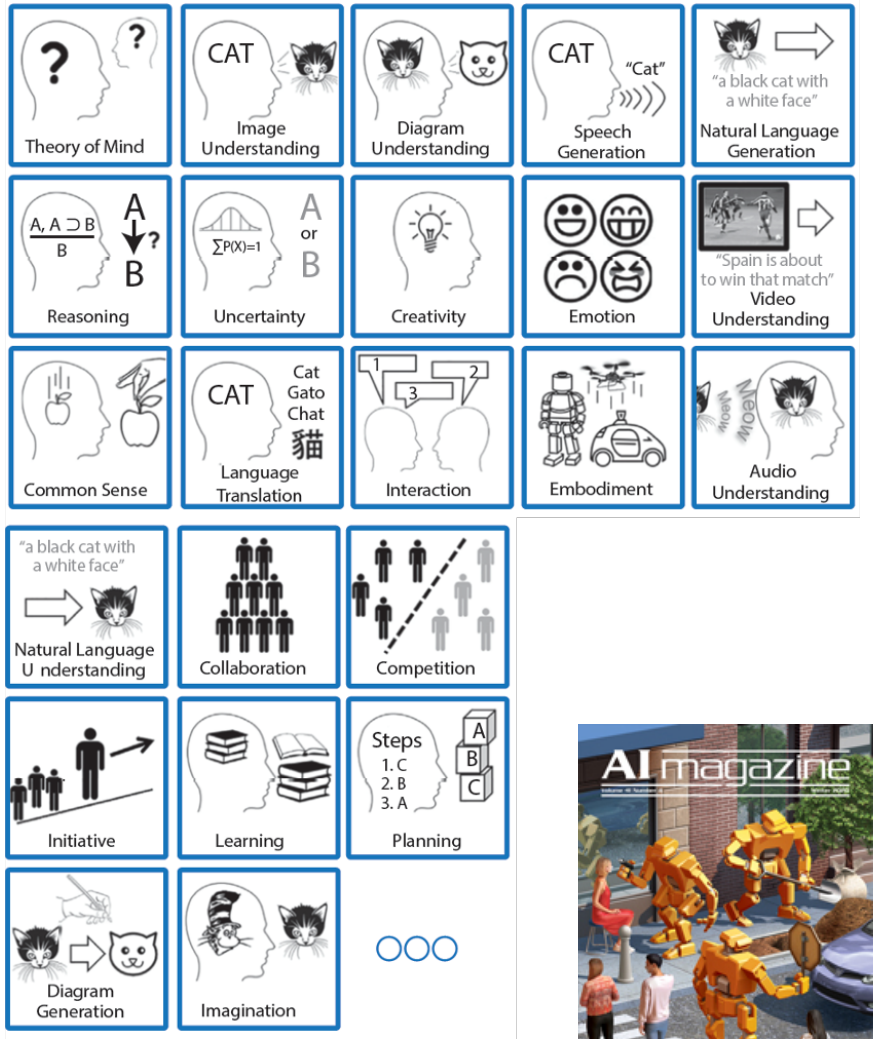
AI aims to **mimic & automatise** tasks which otherwise require human **perception, cognition** and/or **motor skills.**



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Fundamentals

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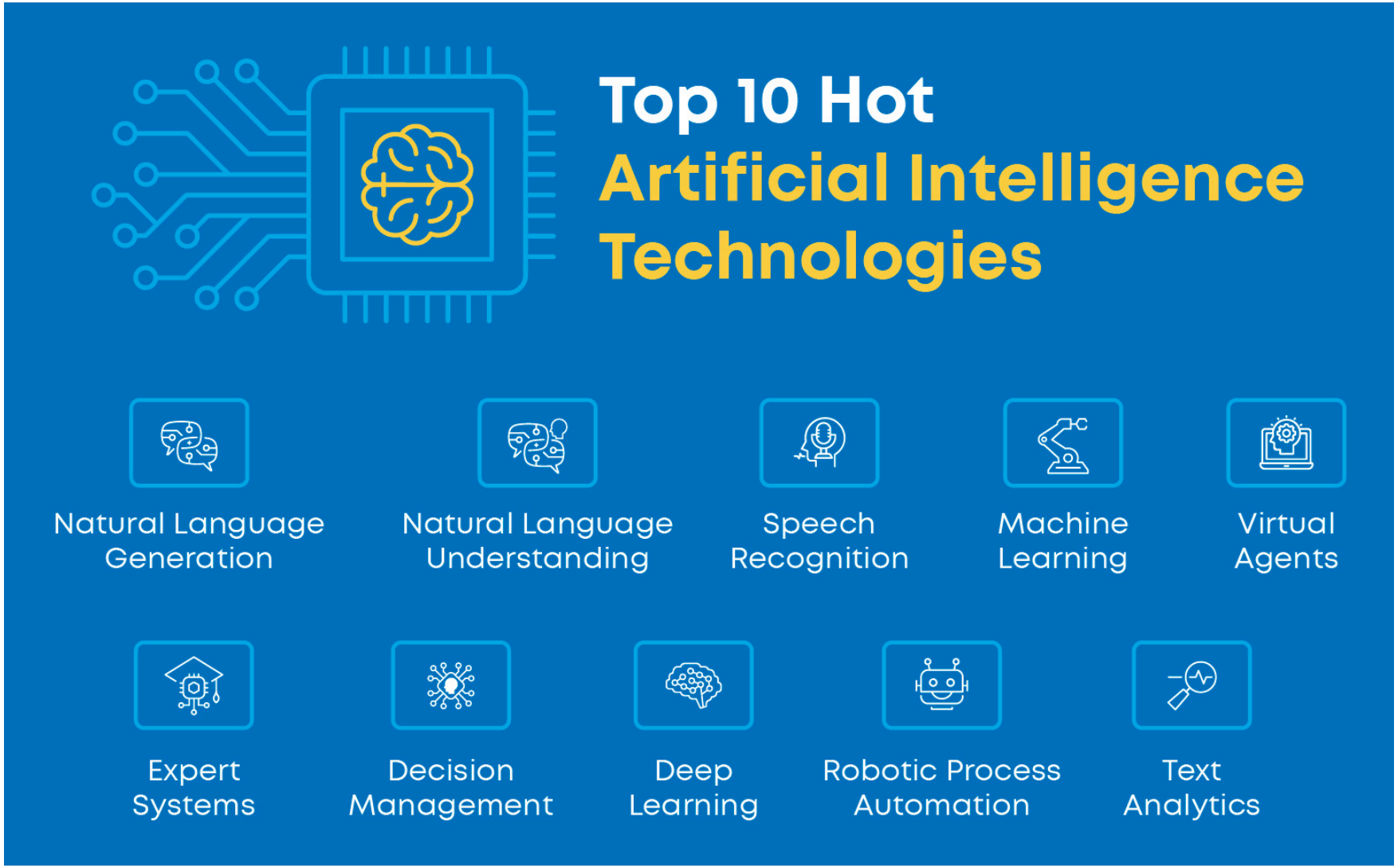

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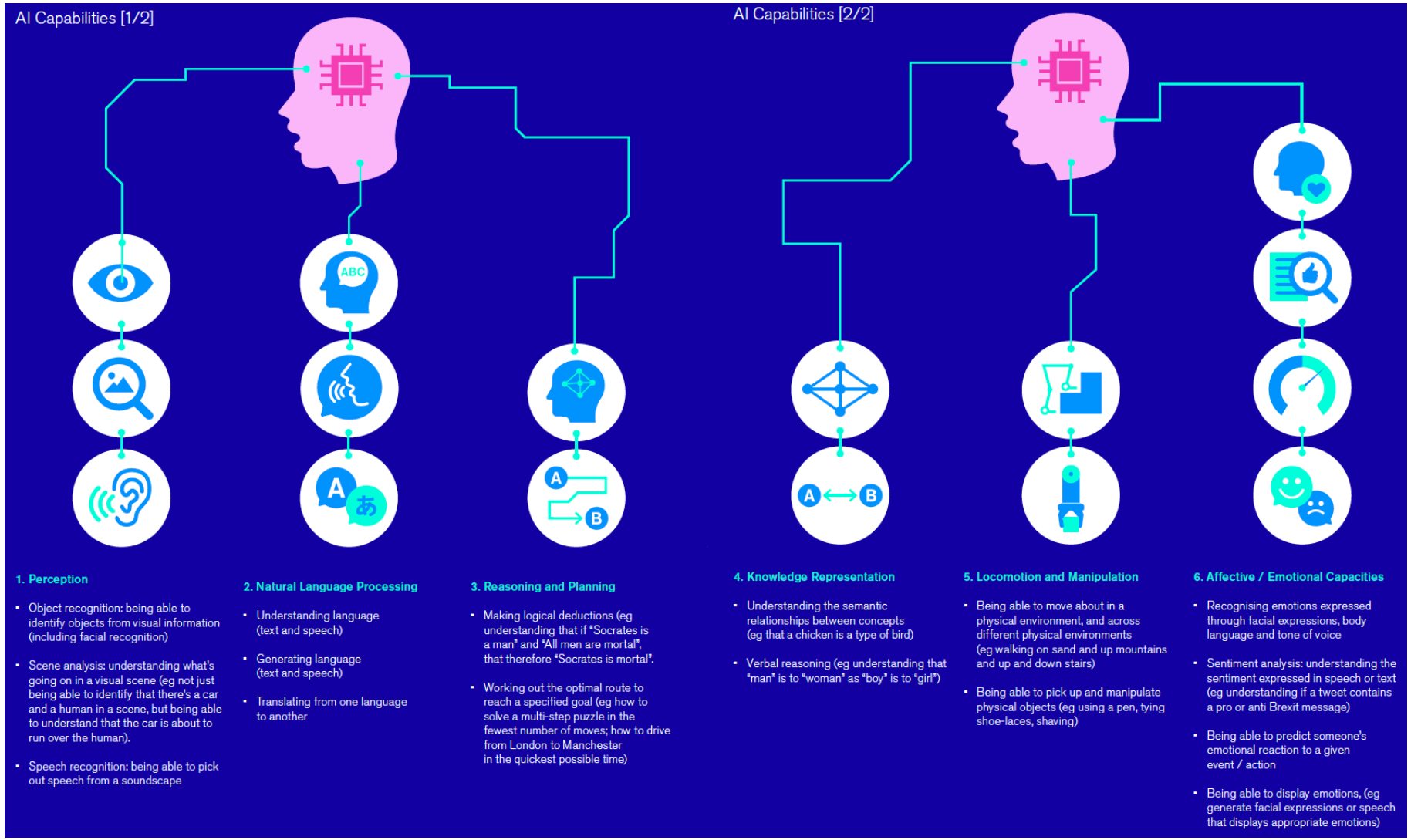
Fundamentals



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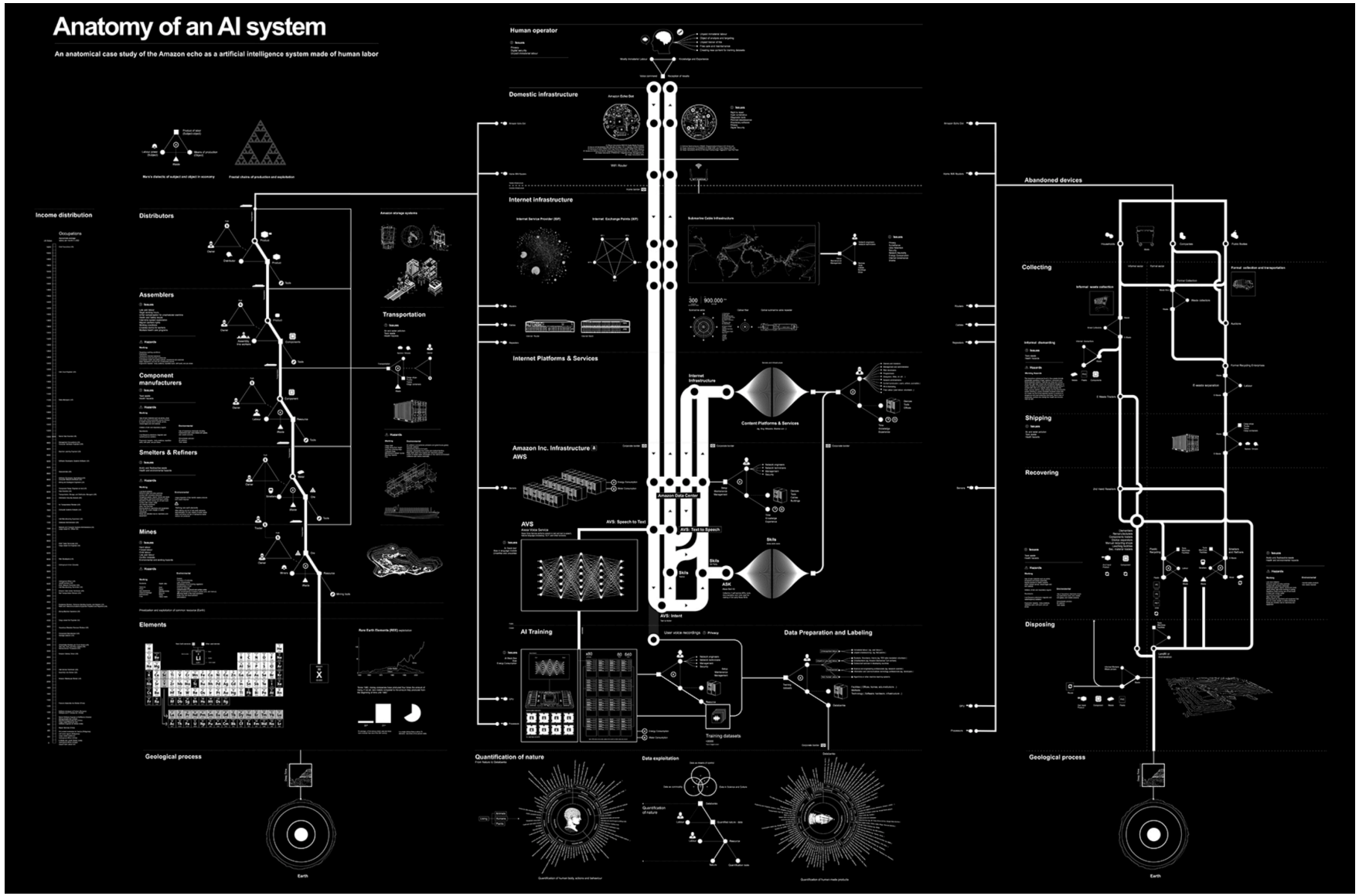

http://www.anatomyof.ai/img/ai-anatomy-map.pdf

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Fundamentals

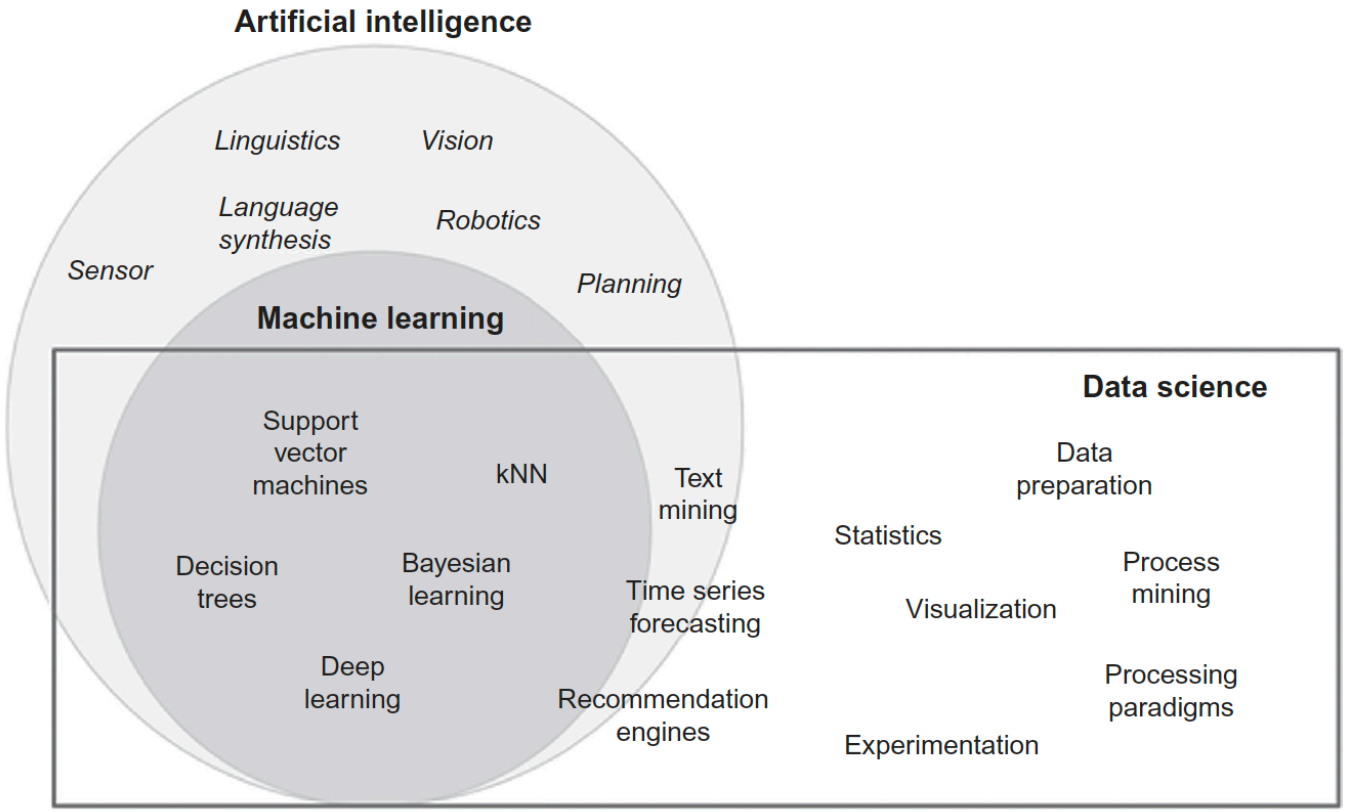
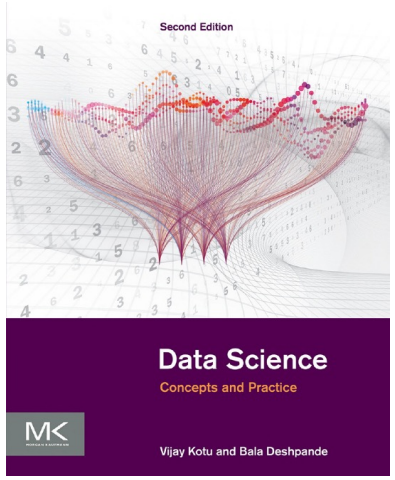


FIGURE 1.1
Artificial intelligence, machine learning, and data science.



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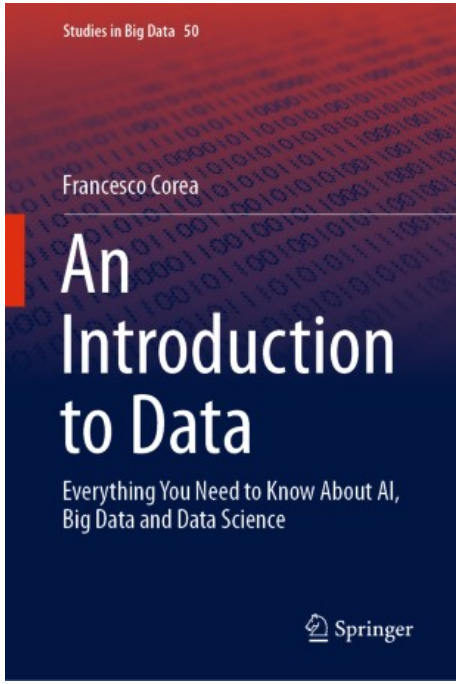
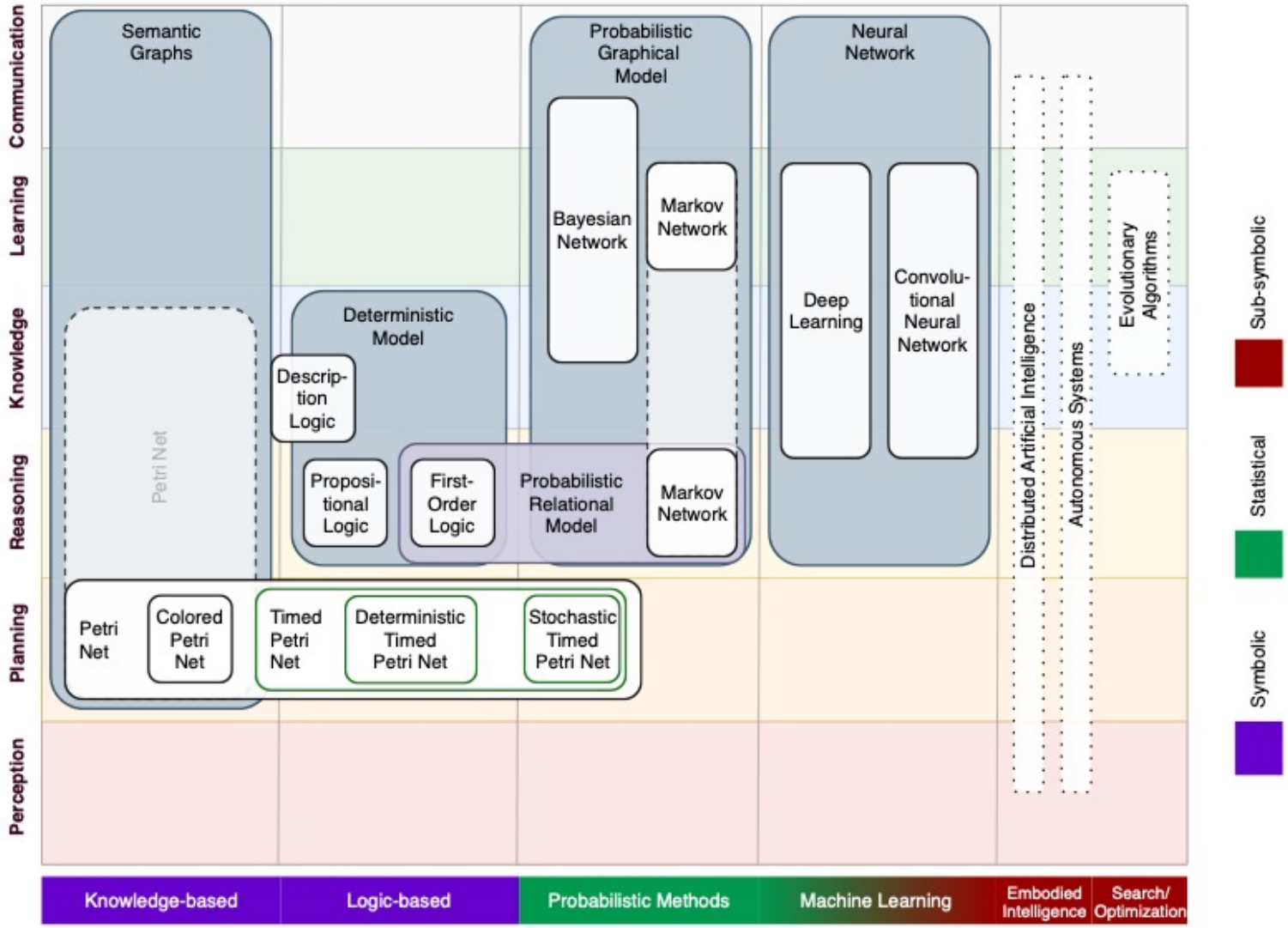
Fundamentals





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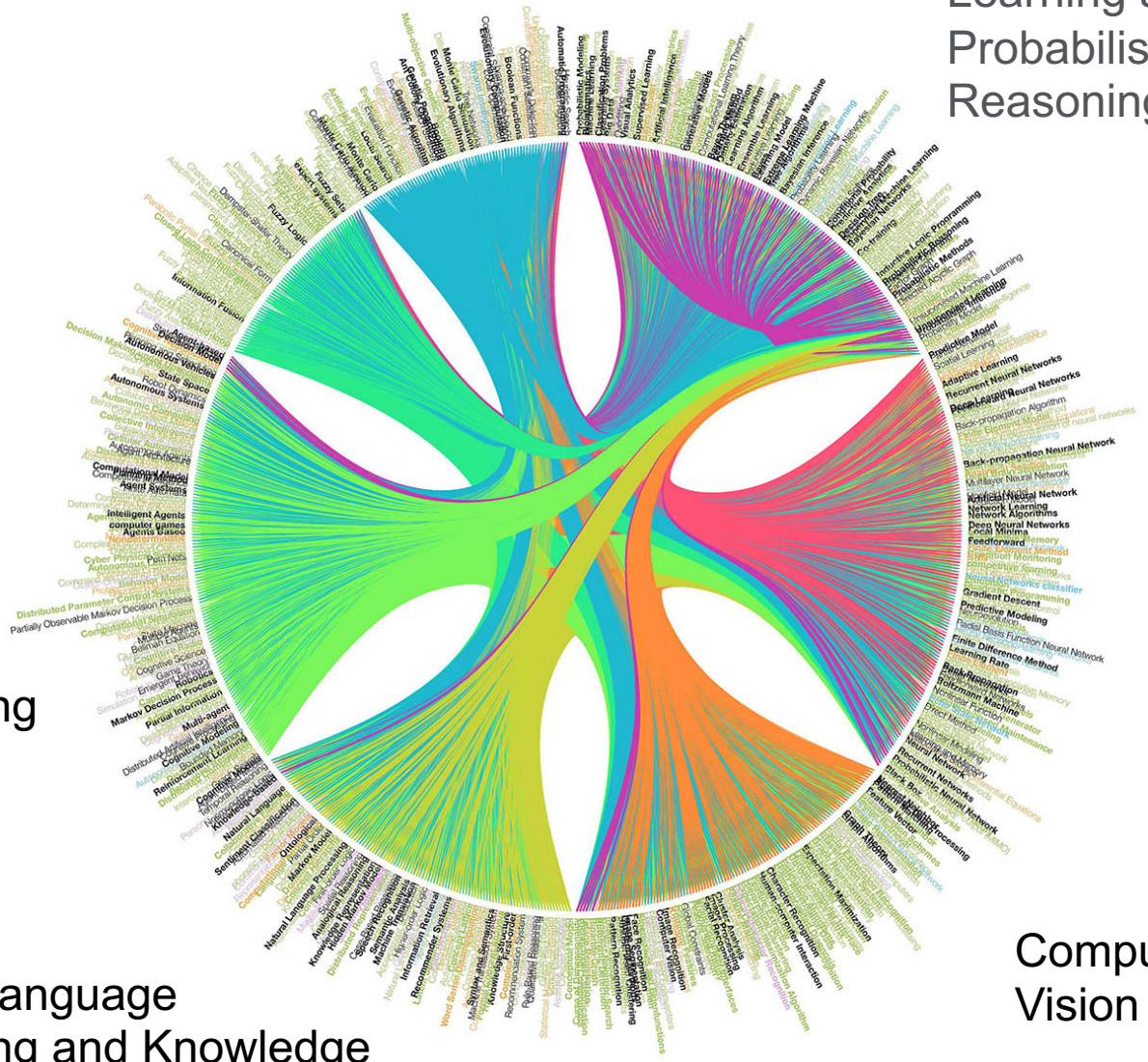
Fundamentals

AI Research Clusters

Search & Optimization

Machine Learning and Probabilistic Reasoning

Fuzzy Systems



Neural Networks

Planning and Decision Making

Computer Vision

Natural Language Processing and Knowledge Representation

Artificial Intelligence:
How knowledge is created, transferred and used

Trends in China, the US and Europe

Maria de Kleijn-Lloyd
SVP, Analytical Services, Elsevier Research Networks
February 5, 2019

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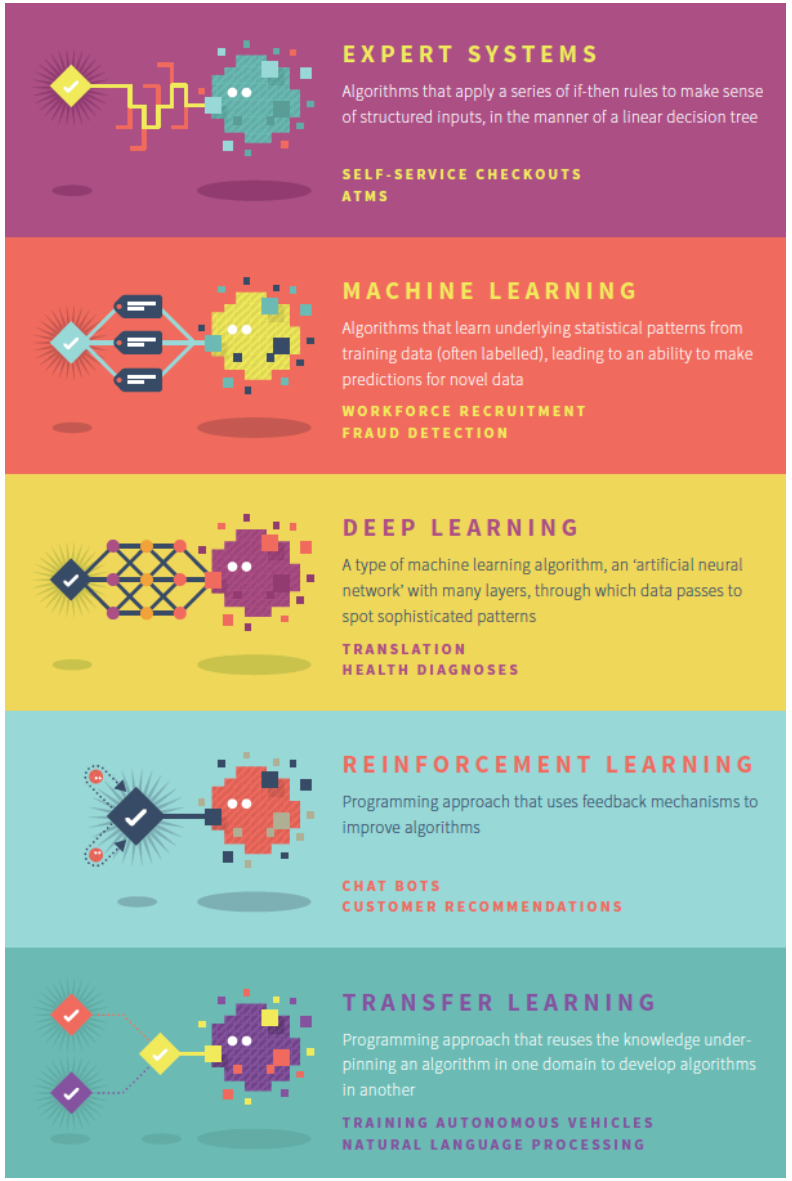
AI is often defined as software agent



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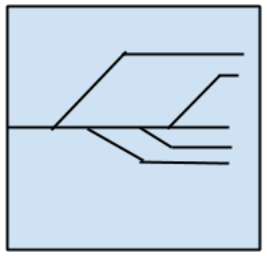
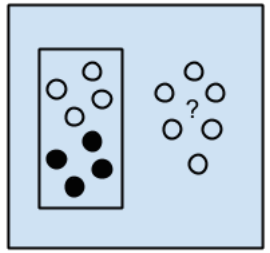
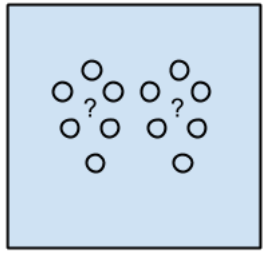
A Tour of Machine Learning Algorithms

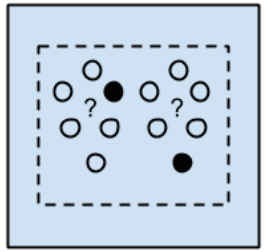
by **Jason Brownlee** on August 12, 2019 in **Machine Learning Algorithms**

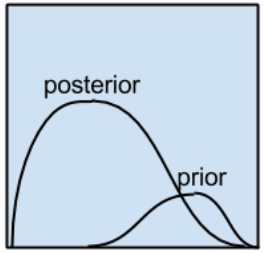
Algorithms Grouped by Learning Style


Regularization Algorithms

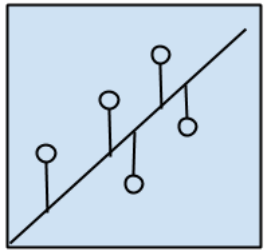

Supervised Learning Algorithms

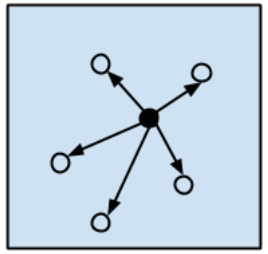

Unsupervised Learning Algorithms

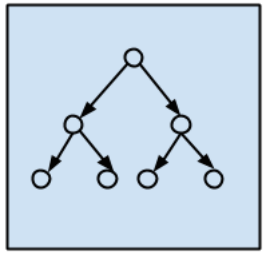

Semi-supervised Learning Algorithms

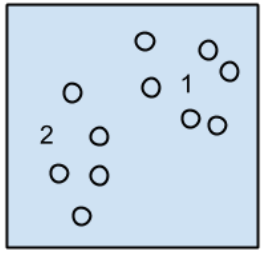


Bayesian Algorithms

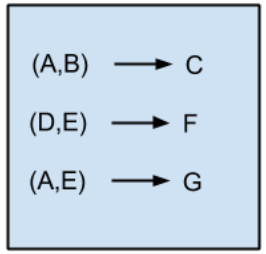

Regression Algorithms


Instance-based Algorithms

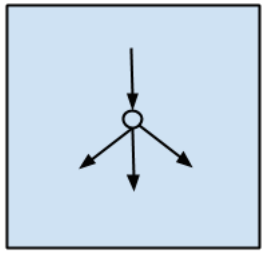

Decision Tree Algorithms

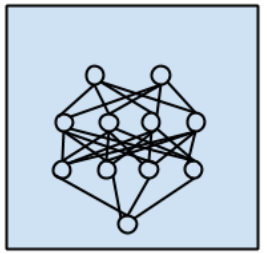


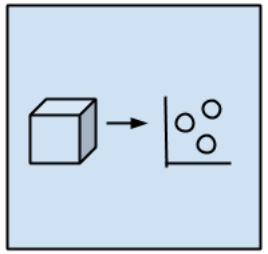
Clustering Algorithms

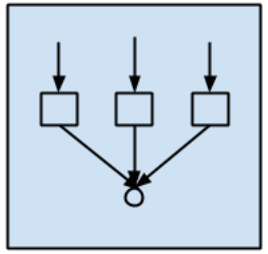


Association Rule Learning Algorithms


Artificial Neural Network Algorithms


Deep Learning Algorithms


Dimensional Reduction Algorithms


Ensemble Algorithms

https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/

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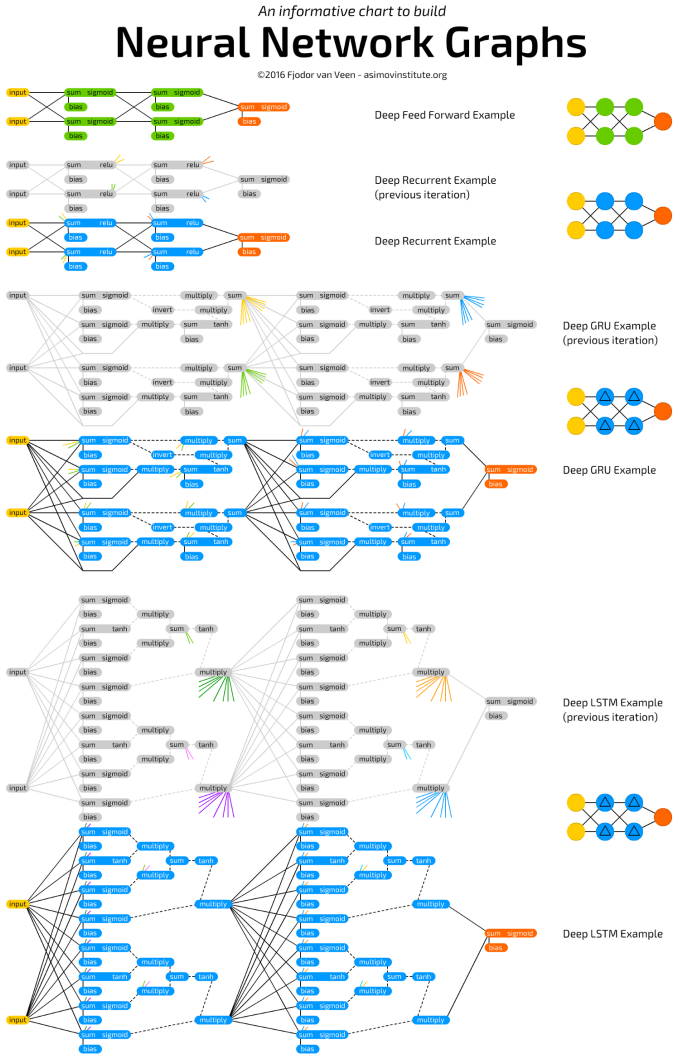
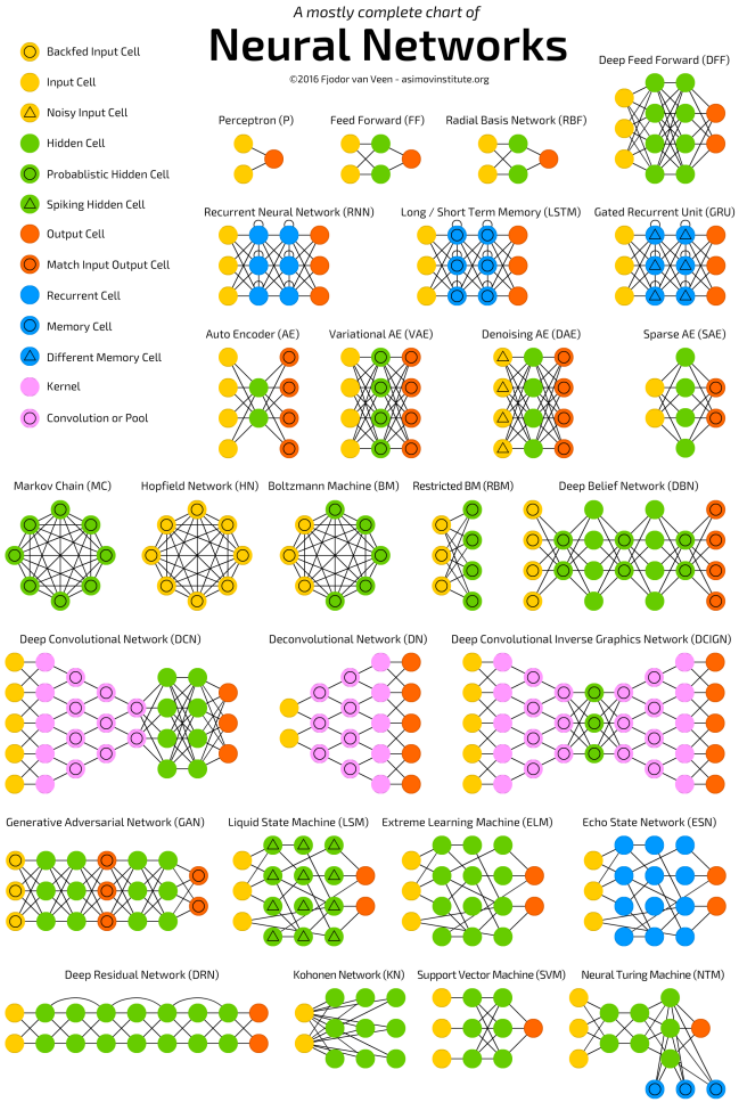
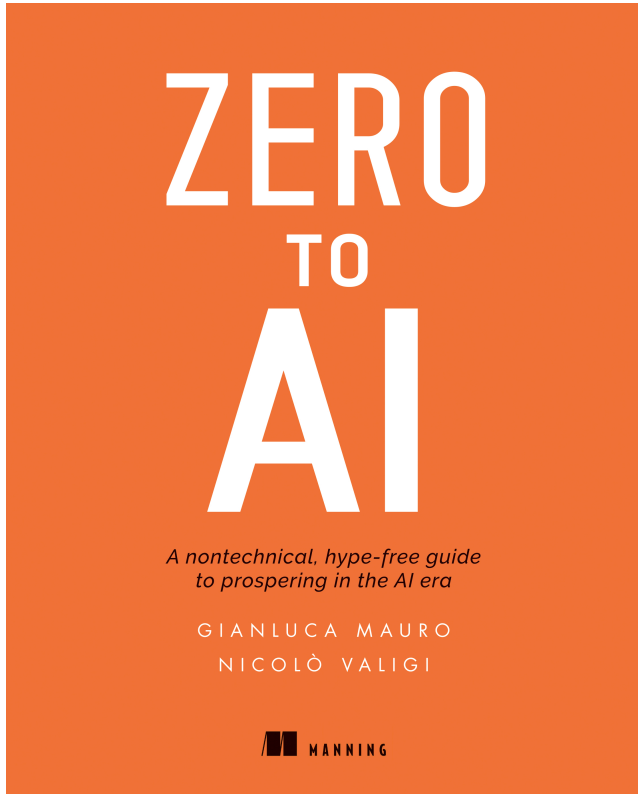
Fundamentals





https://www.asimovinstitute.org/neural-network-zoo/



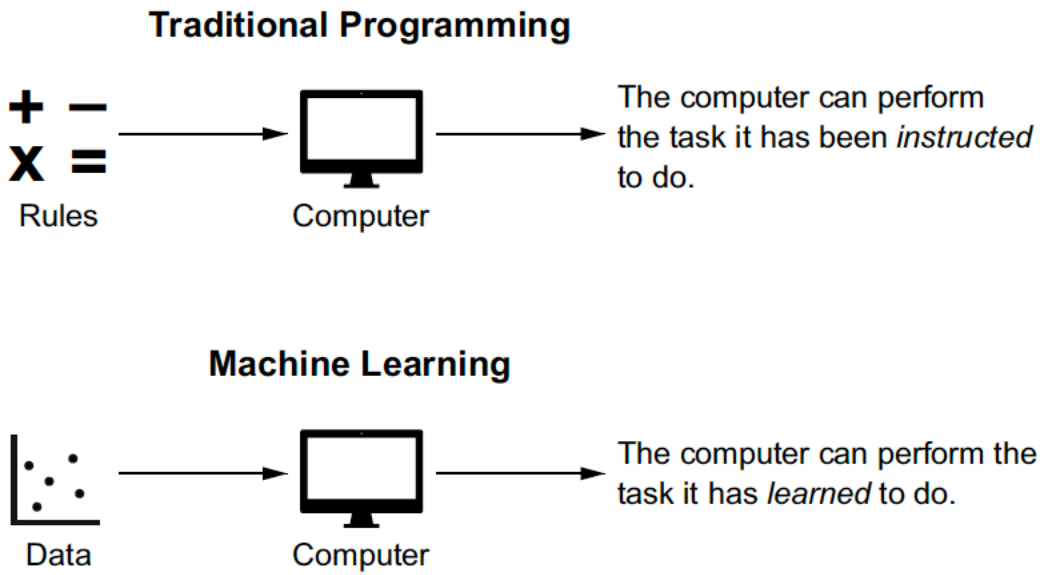
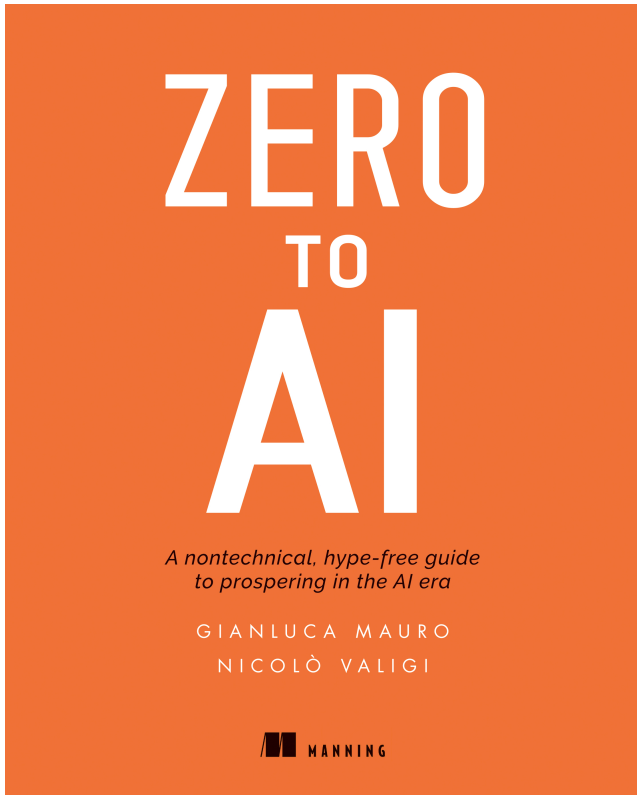


Figure 1.1 The difference between the traditional programming approach and machine learning: the first relies on precise rules and instructions, the latter on data and learning.



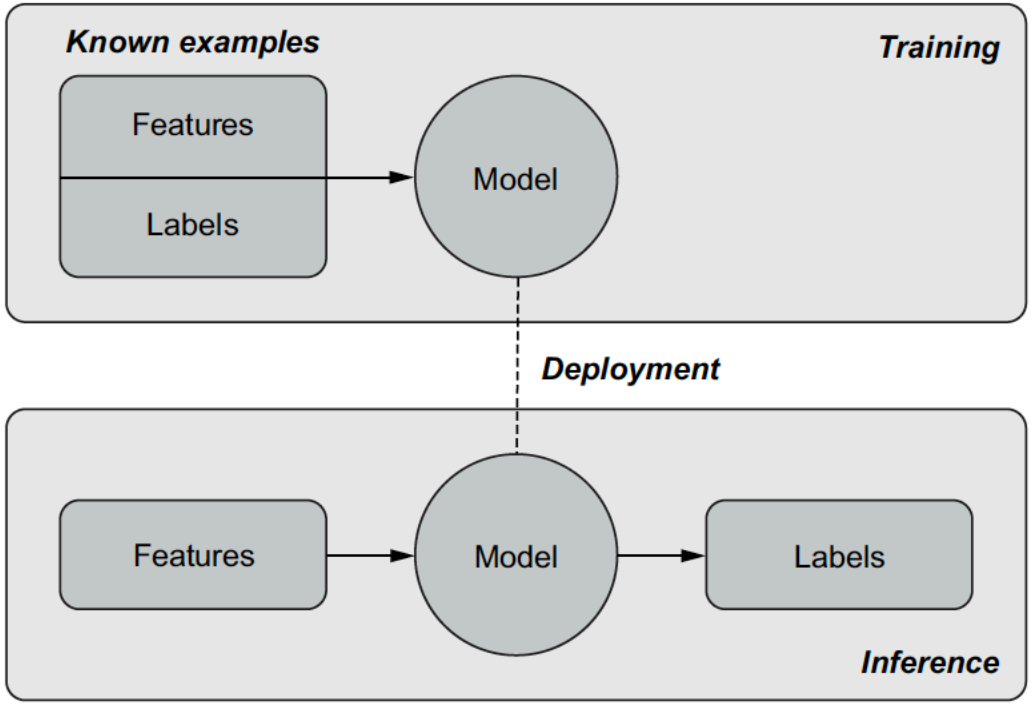


Figure 2.3 The two phases of machine learning: training and inference

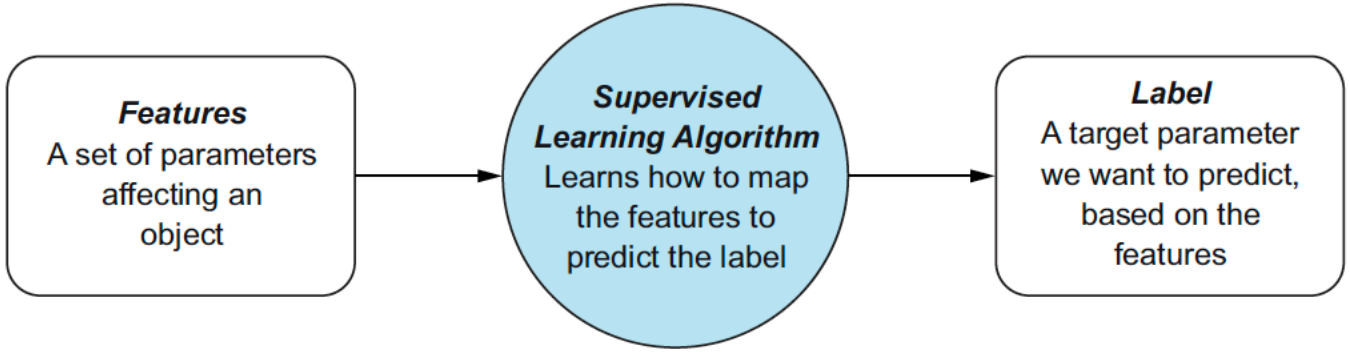


Figure 2.4 The core concept of supervised learning: finding a mapping between a set of features and a label

{02}
High Performance Computing

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Data Deluge: to much data

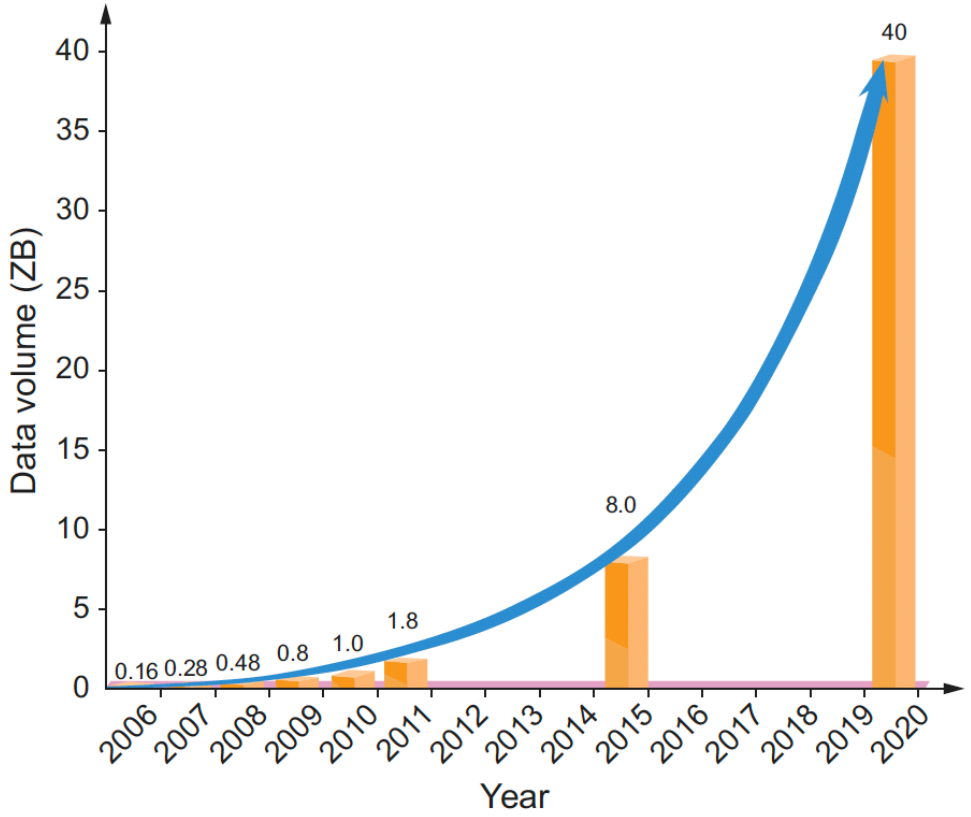
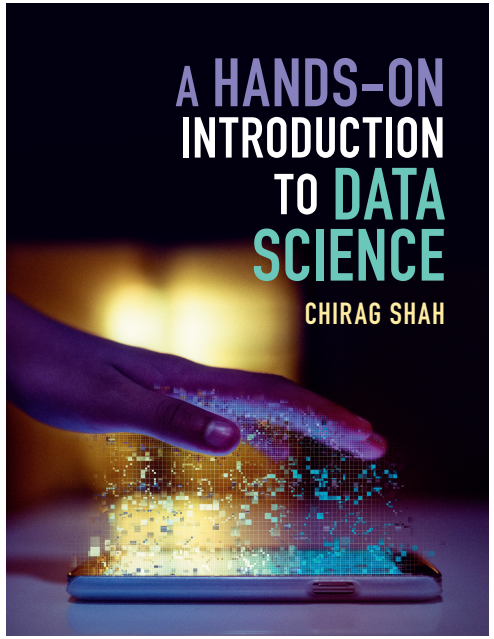


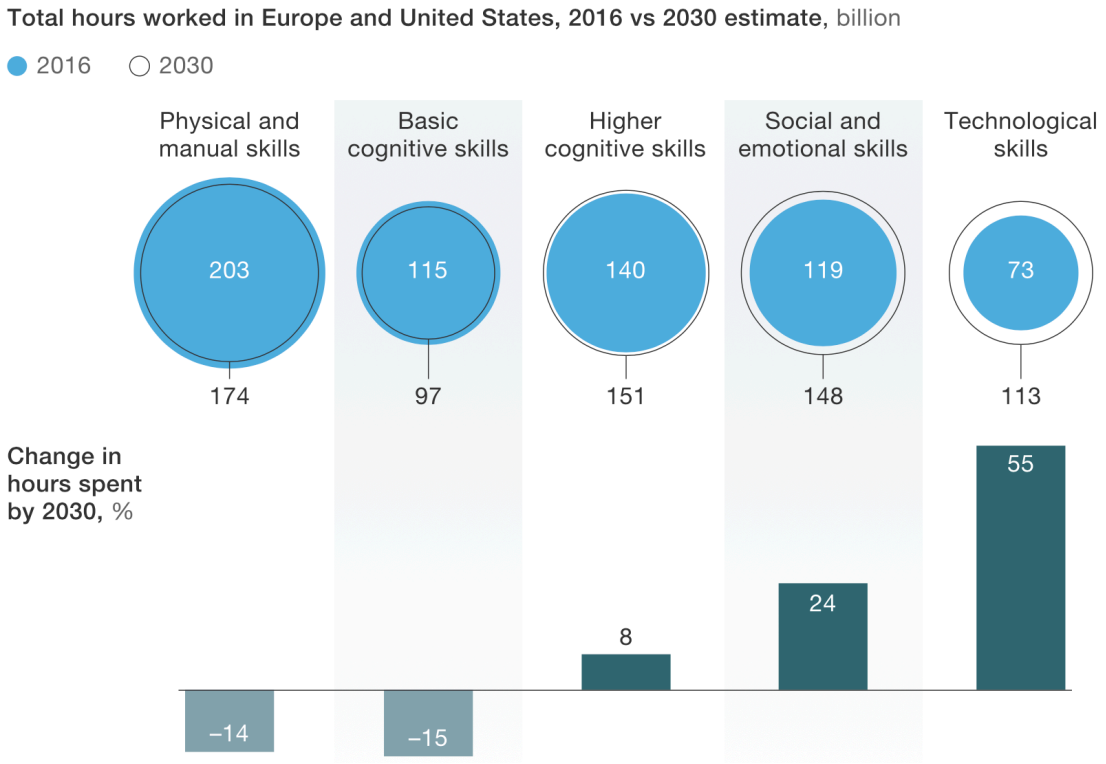
Figure 1.1 Increase of data volume in last 15 years. (Source: IDC's Digital Universe Study, December 2012.[5])



HOGESCHOOL ROTTERDAM

Wy do we need access to HCP in higher education:

Automation and artificial intelligence will accelerate the shift in workforce skills



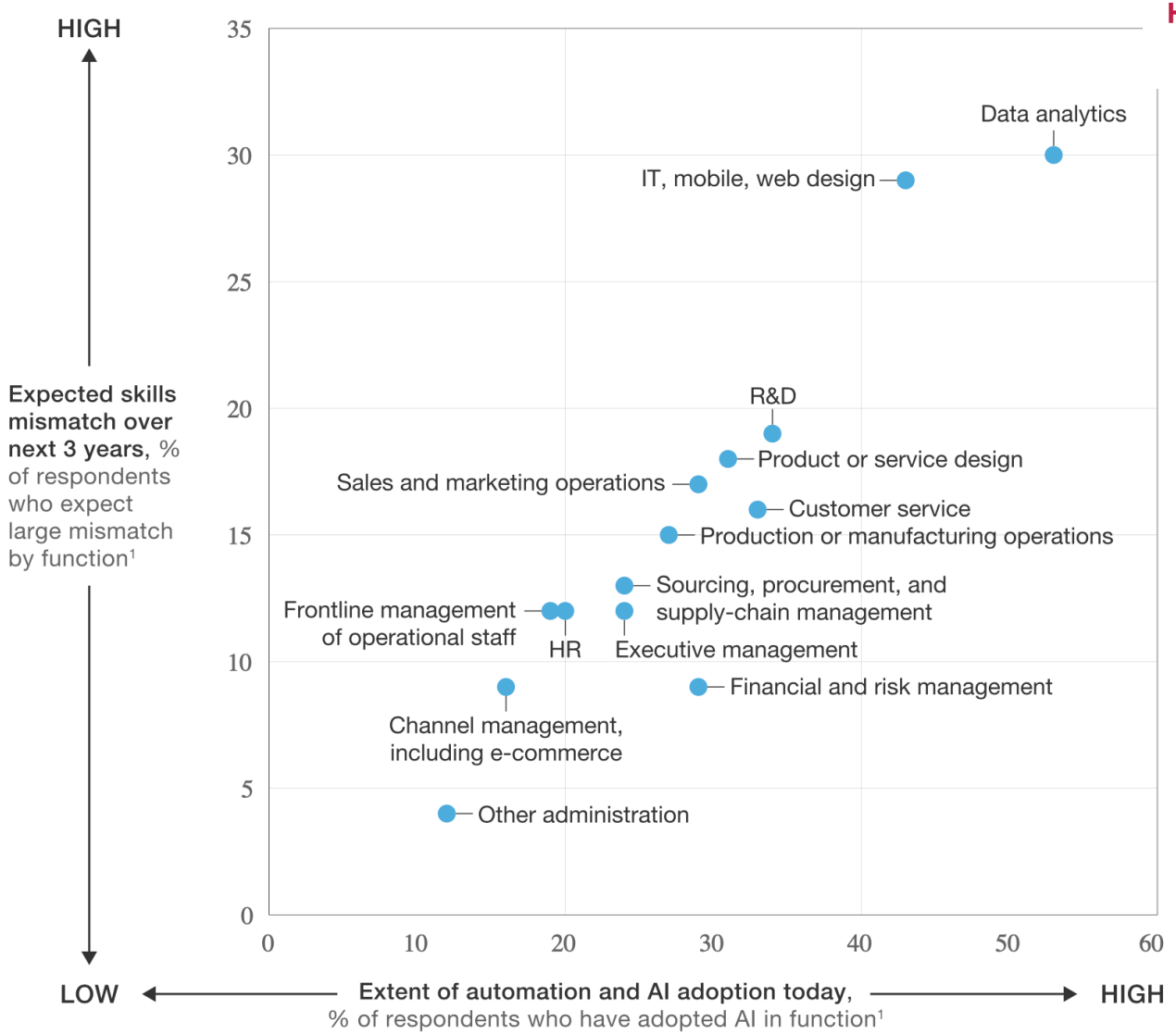
https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce#

{02}
High Performance Computing

HOGESCHOOL ROTTERDAM

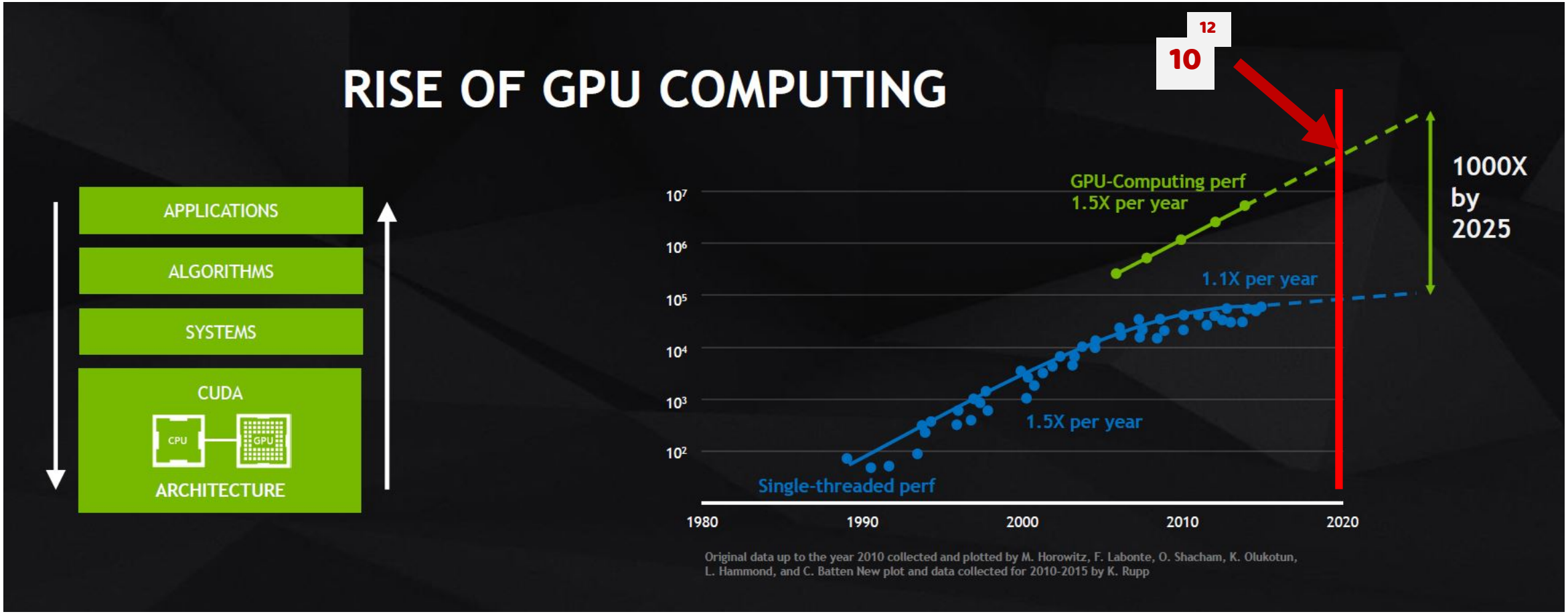
Wy do we need access to HCP in higher education:

Skills mismatch vs automation and artificial intelligence (AI) adoption



https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce#

High Performance Computing



{02}

High Performance Computing

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Prefix	Abbreviation	Order of magnitude (as a factor of 10)	Computer performance	Storage capacity
giga-	G	10^9	gigaFLOPS (GFLOPS)	gigabyte (GB)
tera-	T	10^{12}	teraFLOPS (TFLOPS)	terabyte (TB)
peta-	P	10^{15}	petaFLOPS (PFLOPS)	petabyte (PB)
exa-	E	10^{18}	exaFLOPS (EFLOPS)	exabyte (EB)
zetta-	Z	10^{21}	zettaFLOPS (ZFLOPS)	zettabyte (ZB)
yotta-	Y	10^{24}	yottaFLOPS (YFLOPS)	yottabyte (YB)

One sec TeraFLOPS equivalent to one calculation every second for 31,688.77 years.

One sec PetaFLOPS equivalent to one calculation every second for 31,688,765 years.

One sec ExaFLOPS equivalent to one calculation every second for 31,688,765,000 years.

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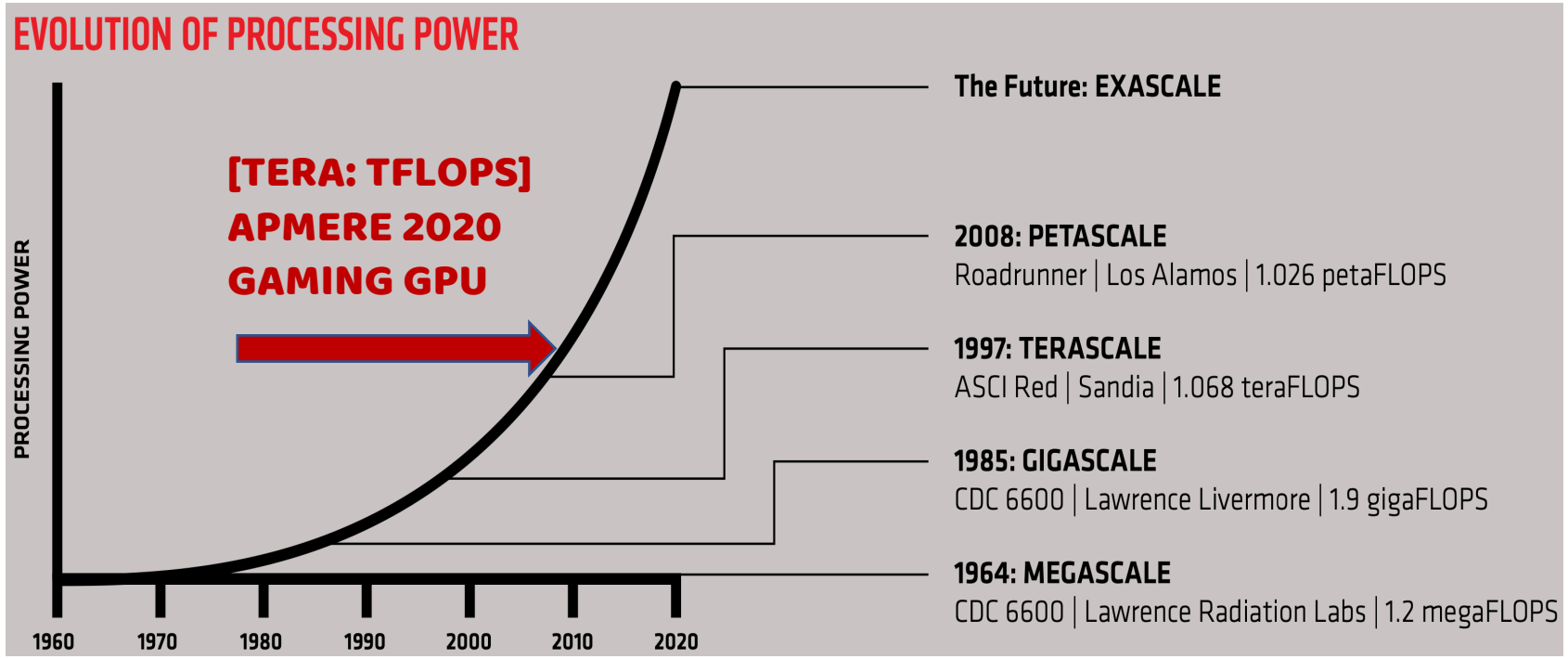
TFLOPS is anno 2021
Possible on
GPU-based
Workstations



https://www.amd.com/system/files/documents/hpc-explained.pdf

{02}

High Performance Computing

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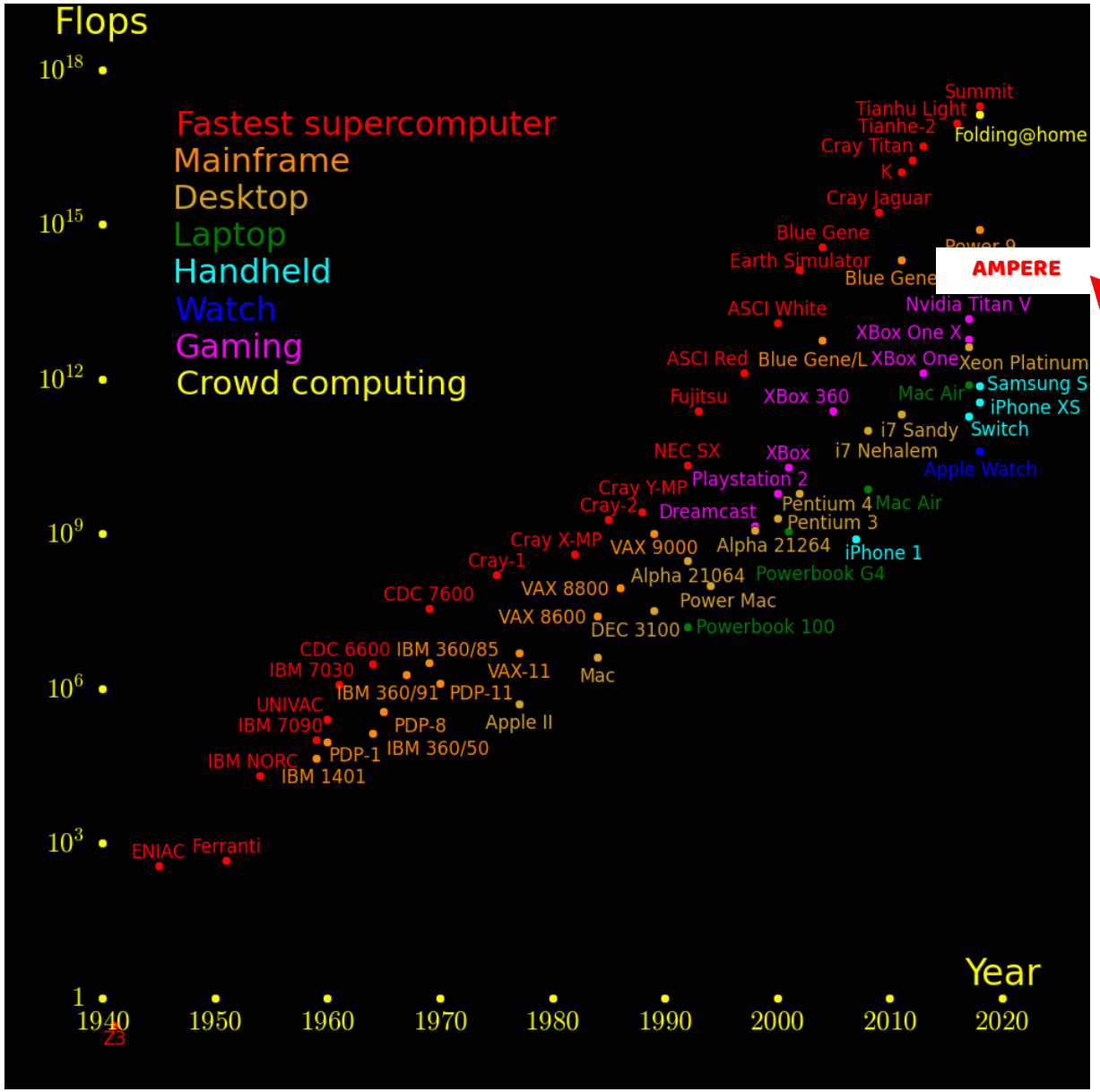
Novel Ampere GPUs
Are capable of TFLOPS
enabling
Deep Learning



{02}
High Performance Computing

HOGESCHOOL ROTTERDAM

Novel Ampere GPUs
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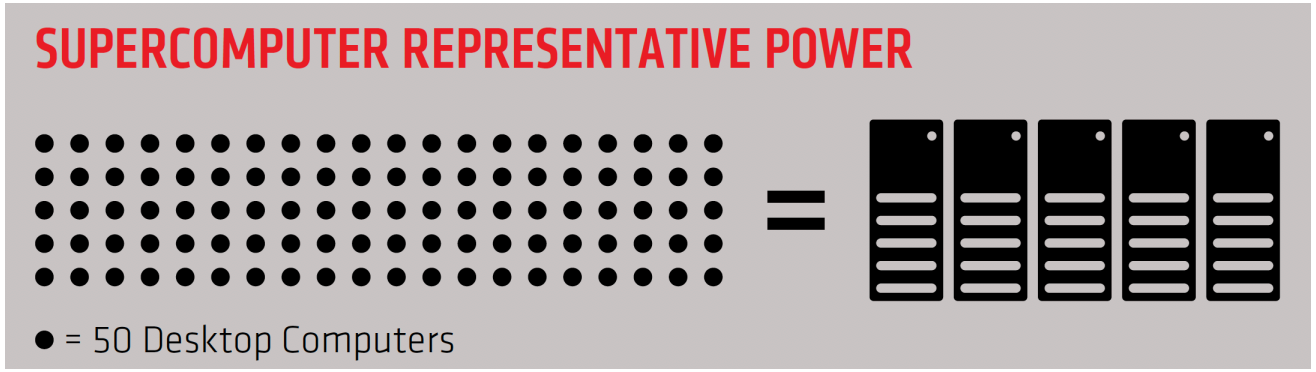

It would take 5,000 standard [2020] CPU-based PCs to achieve 1 TERAFLOPS

Graphics Processor	
GPU Name:	GA102
GPU Variant:	GA102-300-A1
Architecture:	Ampere
Foundry:	Samsung
Process Size:	8 nm
Transistors:	28,300 million
Die Size:	628 mm²

Theoretical Performance	
Pixel Rate:	189.8 GPixel/s
Texture Rate:	556.0 GTexel/s
FP16 (half) performance:	35.58 TFLOPS (1:1)
FP32 (float) performance:	35.58 TFLOPS
FP64 (double) performance:	556.0 GFLOPS (1:64)

https://www.techpowerup.com/gpu-specs/geforce-rtx-3090.c3622

	RTX 3090	RTX 3080	RTX 3070	RTX 2080 Ti
CUDA Cores	10496	8704	5888	4352
Boost Clock	1.7GHz	1.71GHz	1.73GHz	1545MHz
Memory Clock	19.5Gbps GDDR6X	19Gbps GDDR6X	16Gbps GDDR6	14Gbps GDDR6
Memory Bus Width	384-bit	320-bit	256-bit	352-bit
VRAM	24GB	10GB	8GB	11GB
Single Precision Perf.	35.7 TFLOPs	29.8 TFLOPs	20.4 TFLOPs	13.4 TFLOPs
Tensor Perf. (FP16)	285 TFLOPs	238 TFLOPs	163 TFLOPs	114 TFLOPs
Ray Perf.	69 TFLOPs	58 TFLOPs	40 TFLOPs	?
TDP	350W	320W	220W	250W
GPU	GA102?	GA102?	GA104?	TU102
Transistor Count	28B	28B	?	18.6B
Architecture	Ampere	Ampere	Ampere	Turing
Manufacturing Process	Samsung 8nm	Samsung 8nm	Samsung 8nm	TSMC 12nm "FFN"
Launch Date	09/24/2020	09/17/2020	10/2020	09/20/2018
Launch Price	MSRP: $1499	MSRP: $699	MSRP: $499	MSRP: $999 Founders $1199

{03}
Tools

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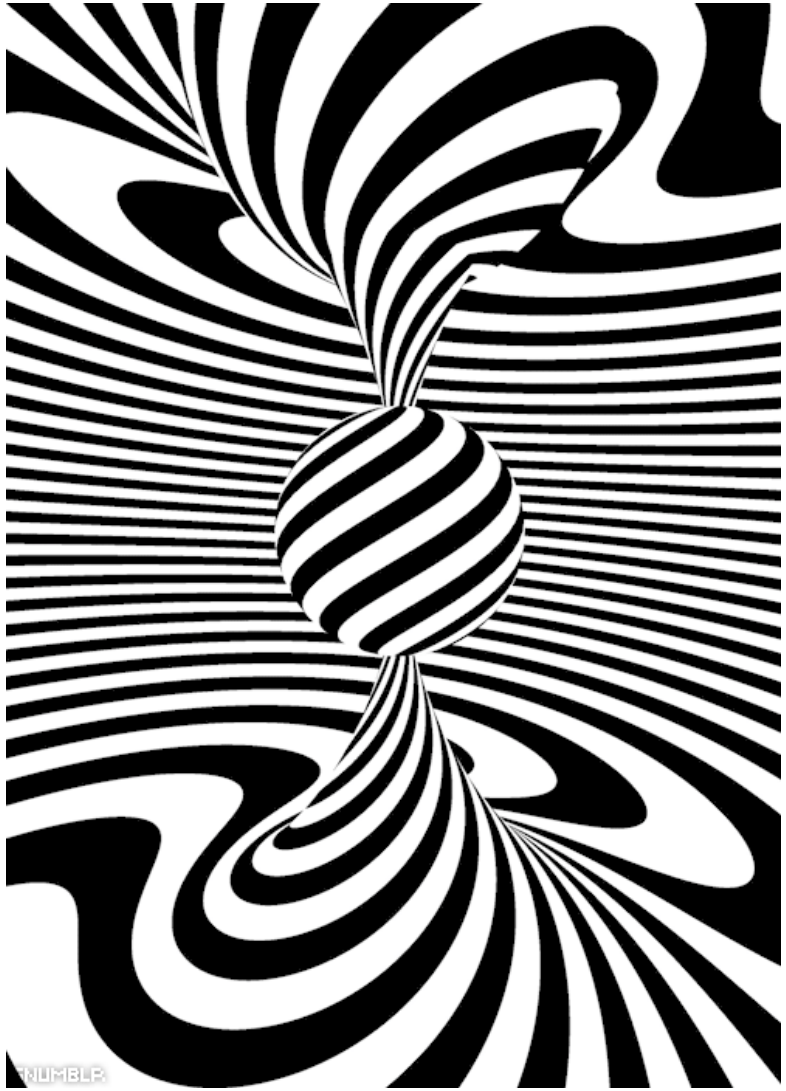

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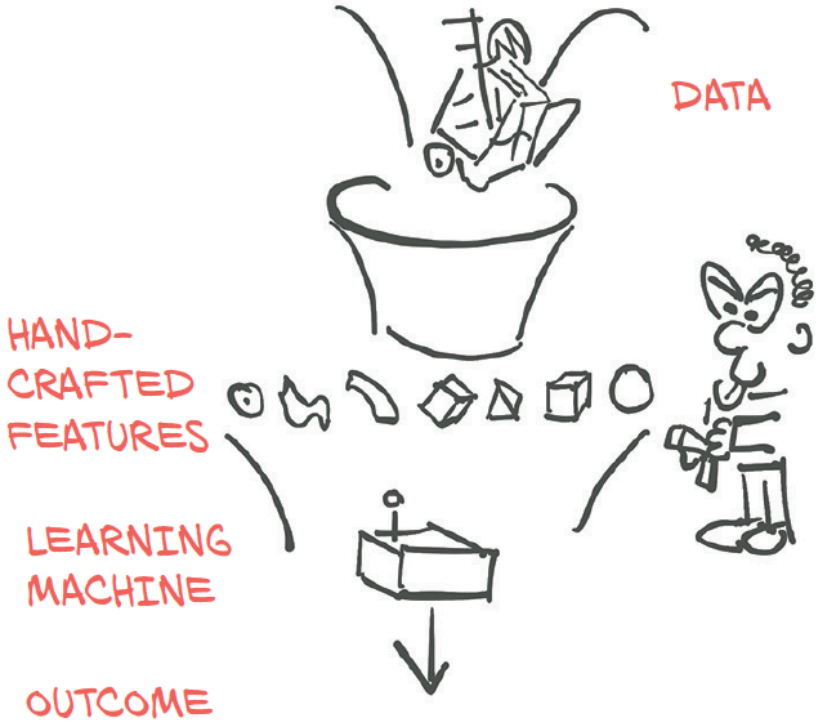
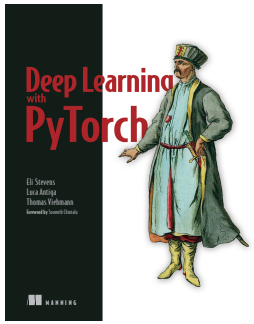
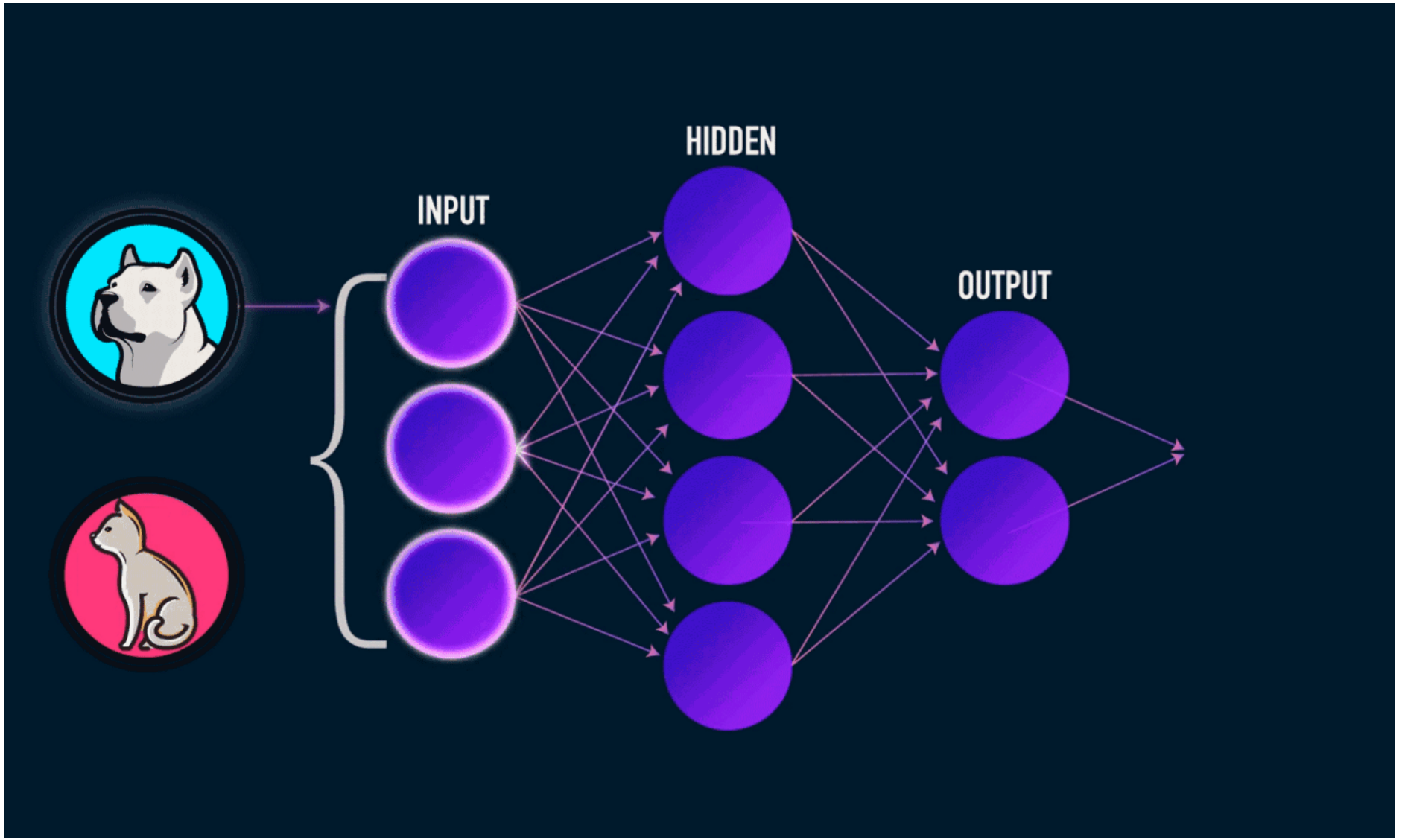
MACHINE LEARNING [ML]





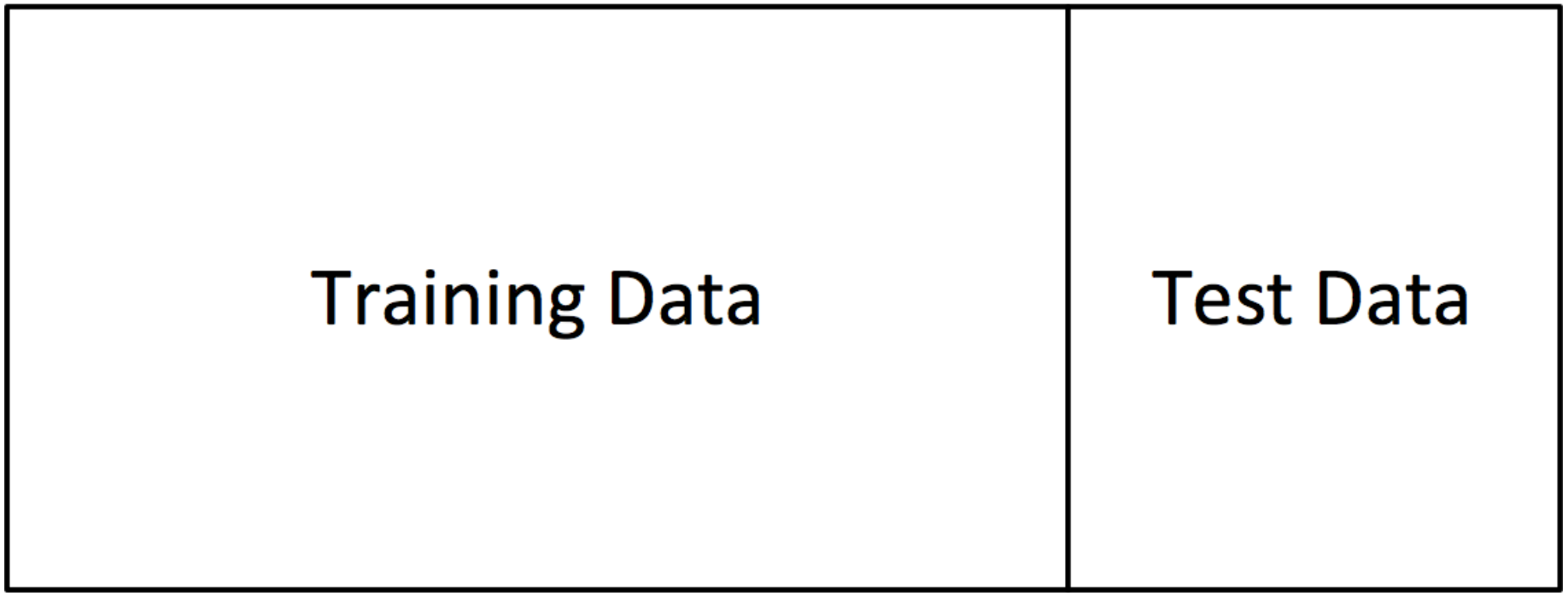
{03}
Tools

HOGESCHOOL ROTTERDAM



HOGESCHOOL ROTTERDAM

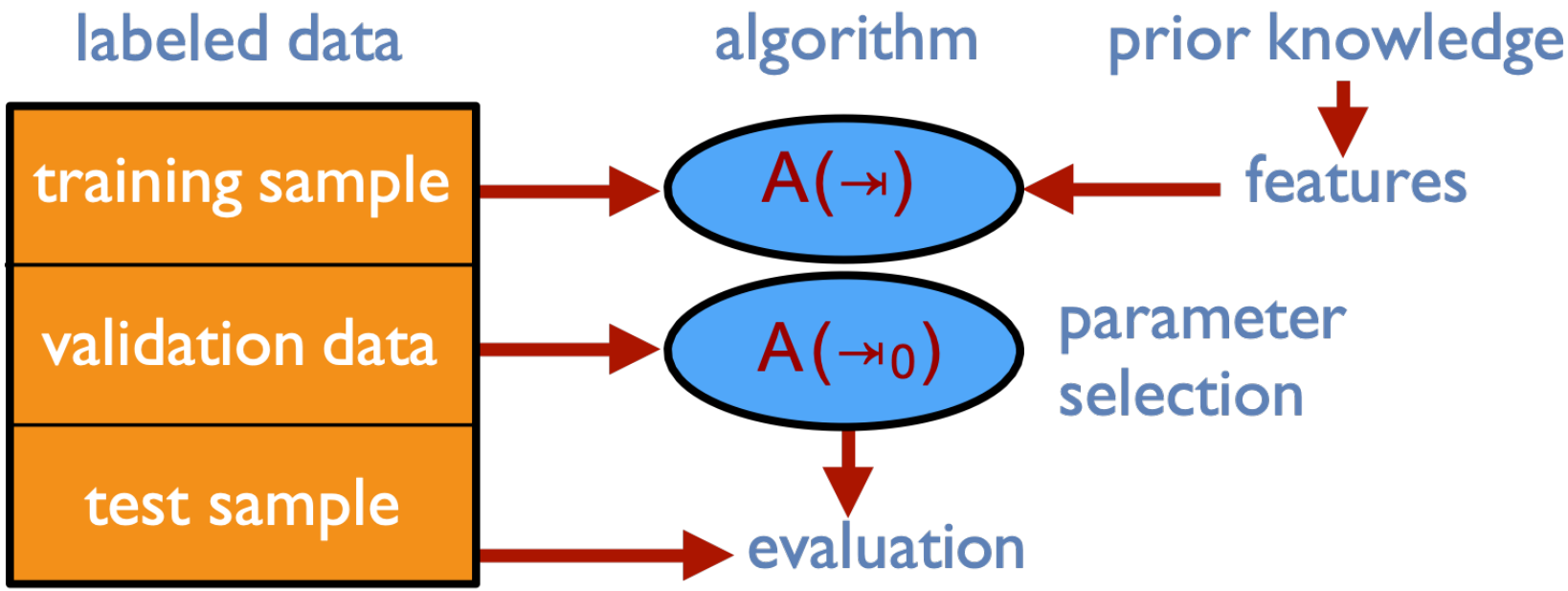
Full Dataset:

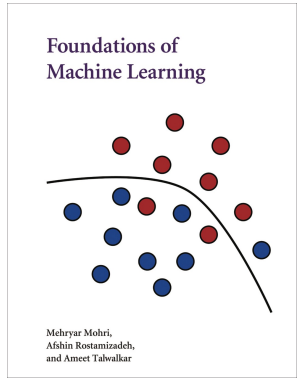


Foundations of Machine Learning

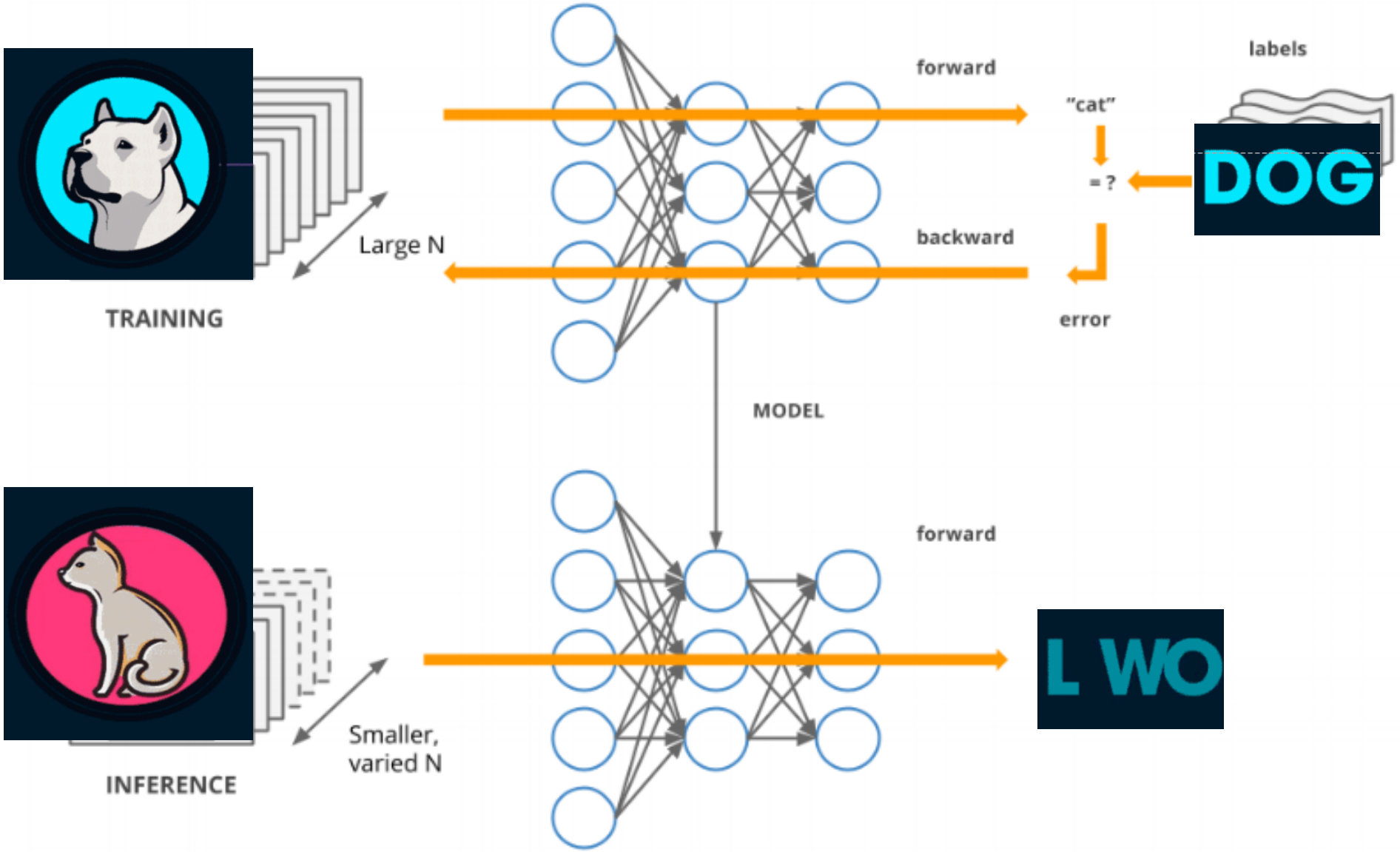
Introduction to ML

Mehryar Mohri
Courant Institute and Google Research
mohri@cims.nyu.edu



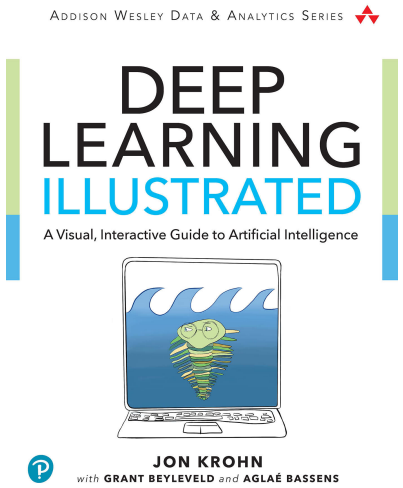


TRAINING vs TESTING

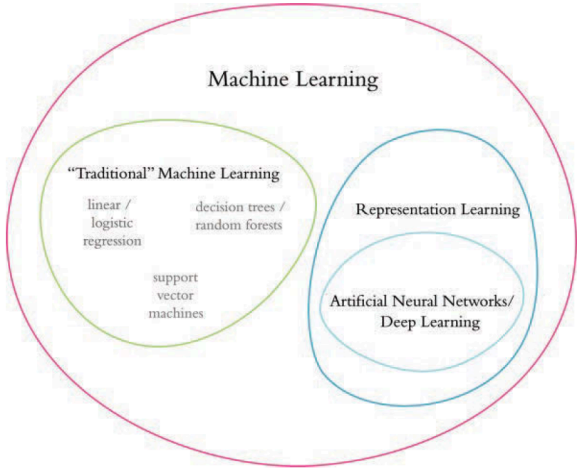


DEEP LEARNING vs MACHINE LEARNING

HOGESCHOOL ROTTERDAM



Deep learning is
a machine learning technique
that learns **features and tasks**
directly from data.



Data can be **images, text,** or **sound.**

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MACHINE LEARNING data-flow

DEEP LEARNING data-flow

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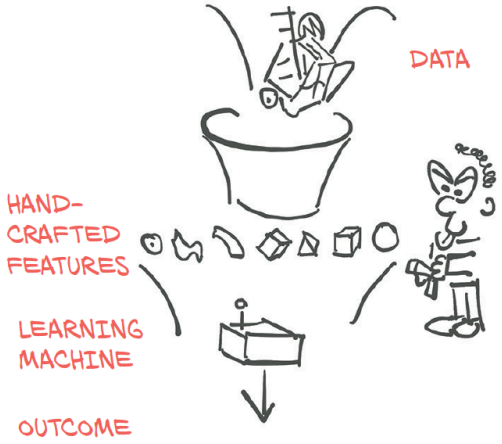
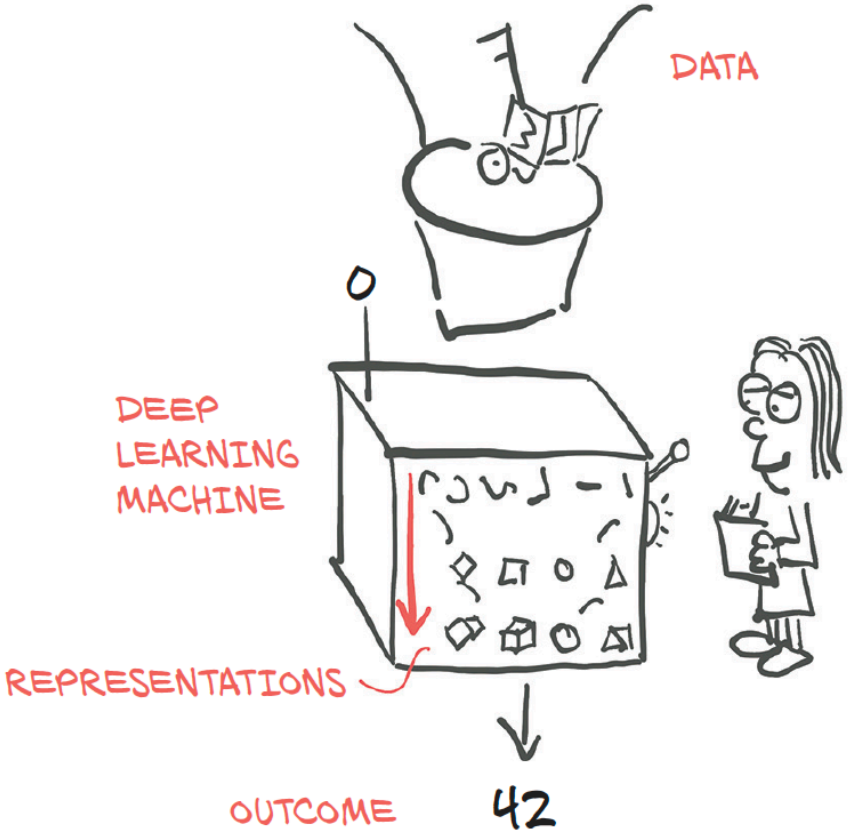
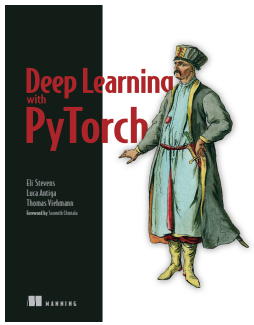
DEEP LEARNING [DL]



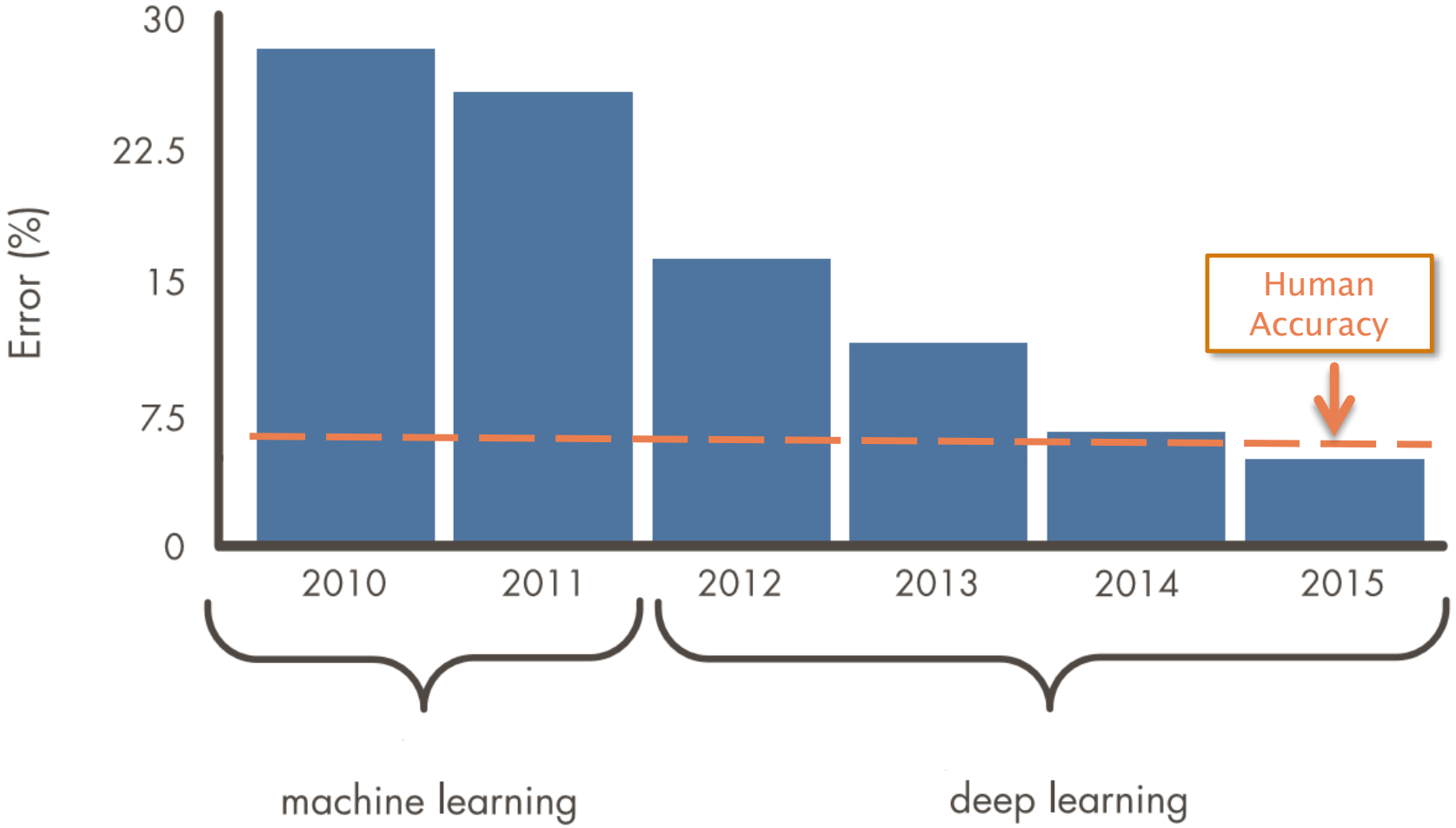
MACHINE LEARNING [ML]





Why is Deep Learning So Popular Now?

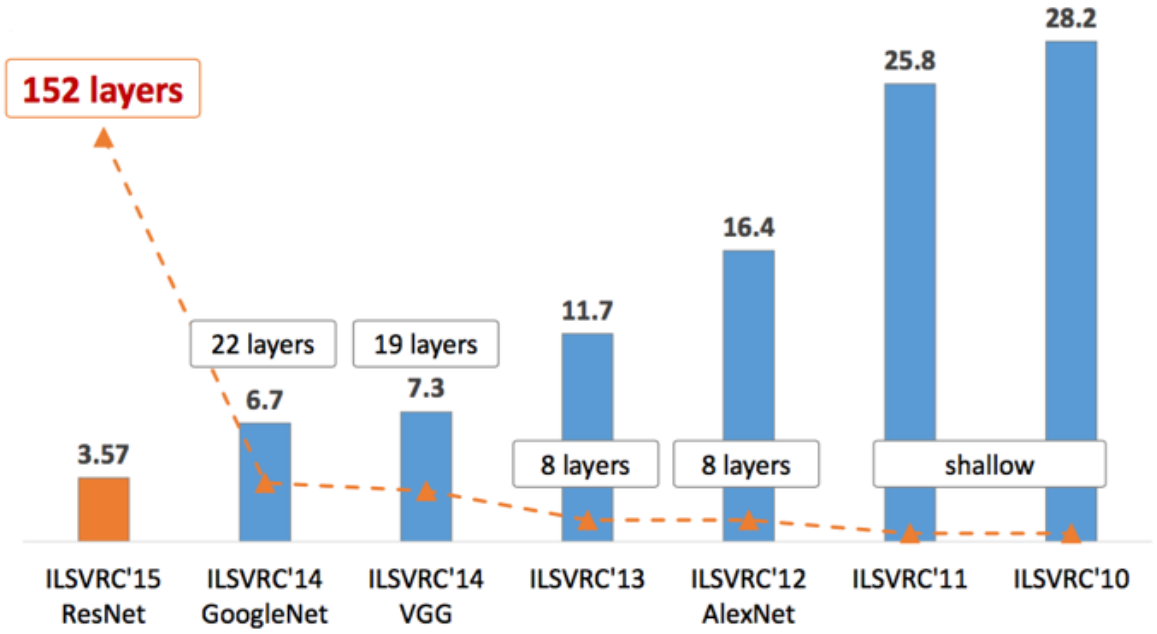
HOGESCHOOL ROTTERDAM

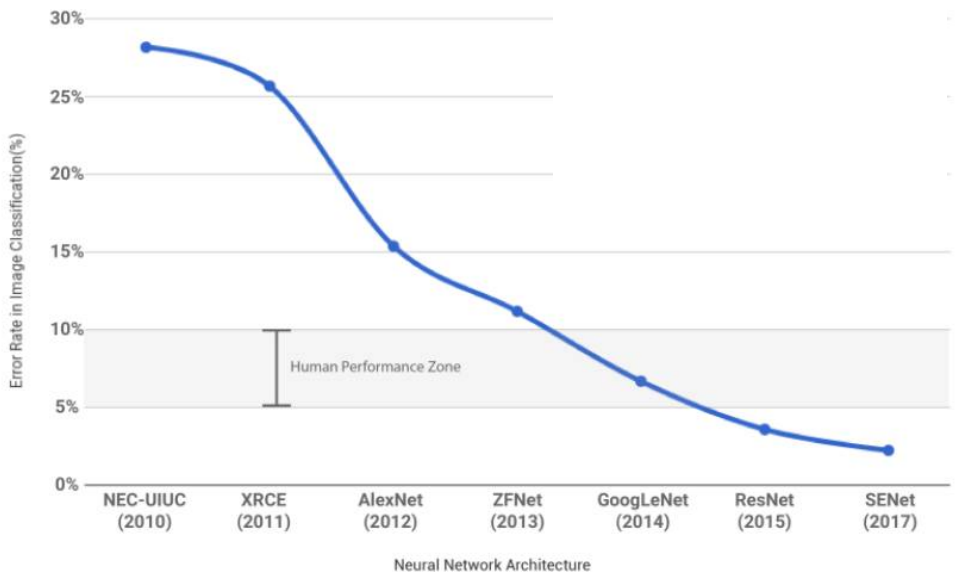


Source: ILSVRC Top-5 Error on ImageNet

Why is Deep Learning So Popular Now?

DL reduces error by adding hidden layers

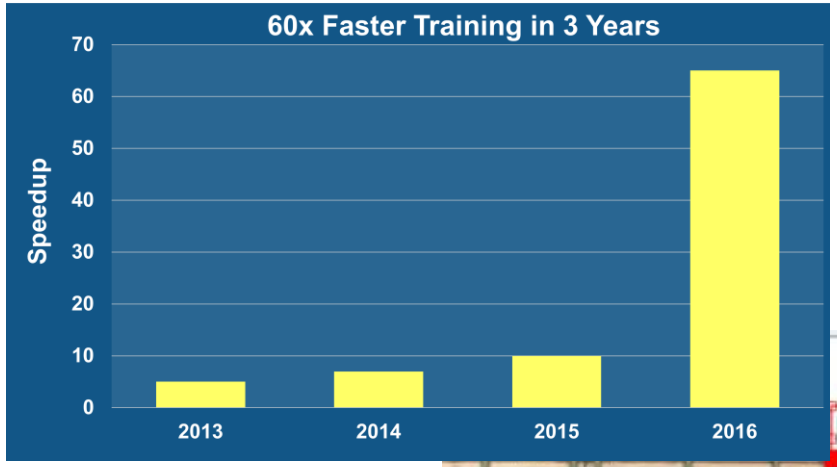




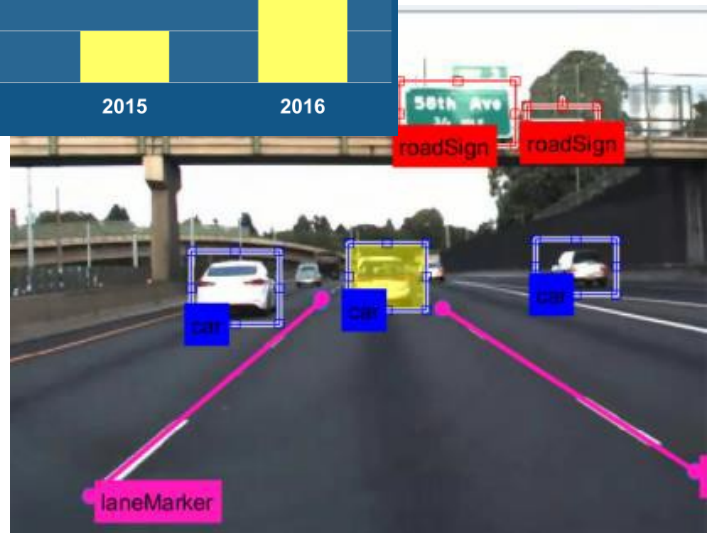
Source: ILSVRC Top-5 Error on ImageNet

Deep Learning Enablers

Acceleration with GPUs



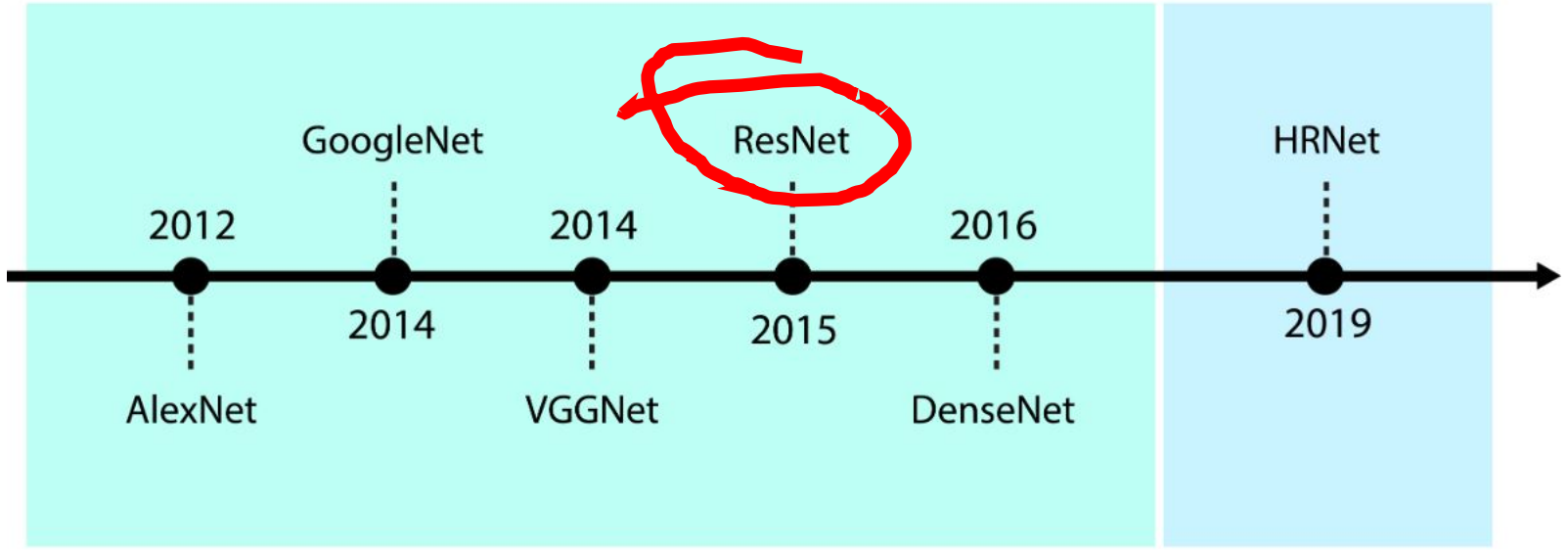
Massive sets of labeled data



Availability of state of the art models from experts

AlexNet
PRETRAINED MODEL
VGG-16
PRETRAINED MODEL
Caffe
MODELS

DEEP LEARNING MILESTONES



https://www.microsoft.com/en-us/research/blog/high-resolution-network-a-universal-neural-architecture-for-visual-recognition/

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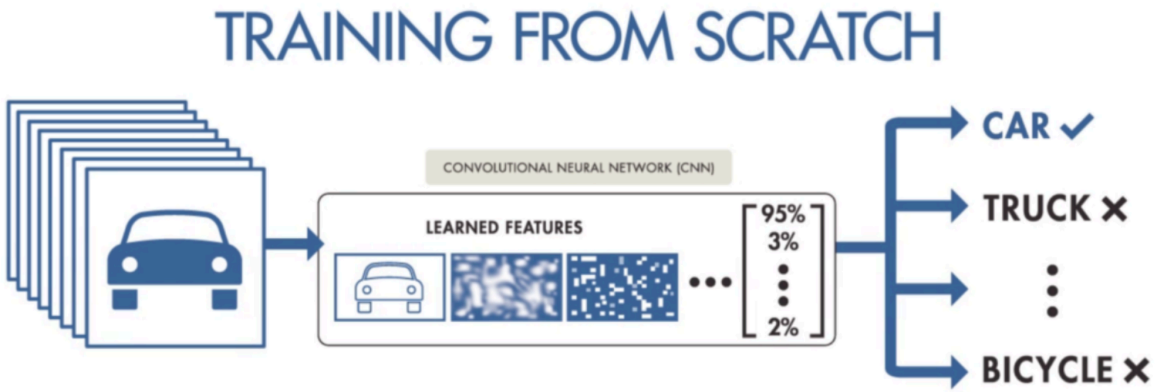
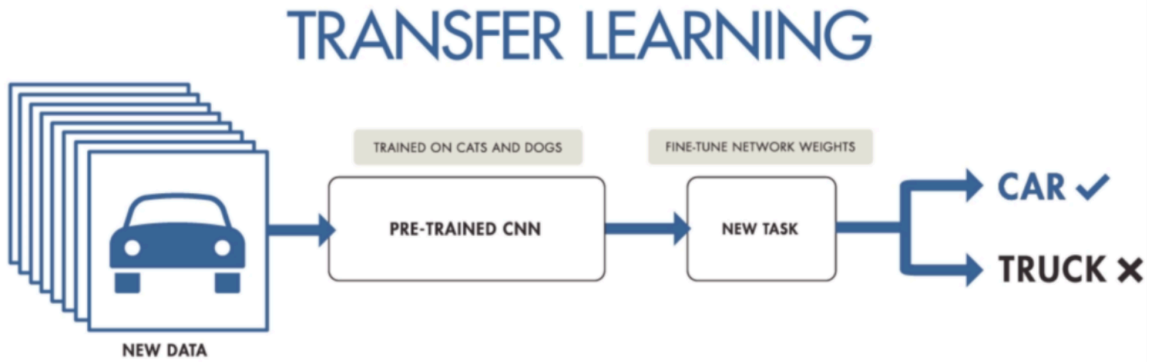
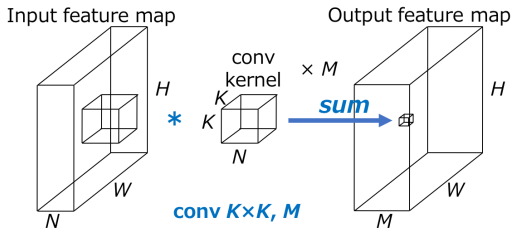
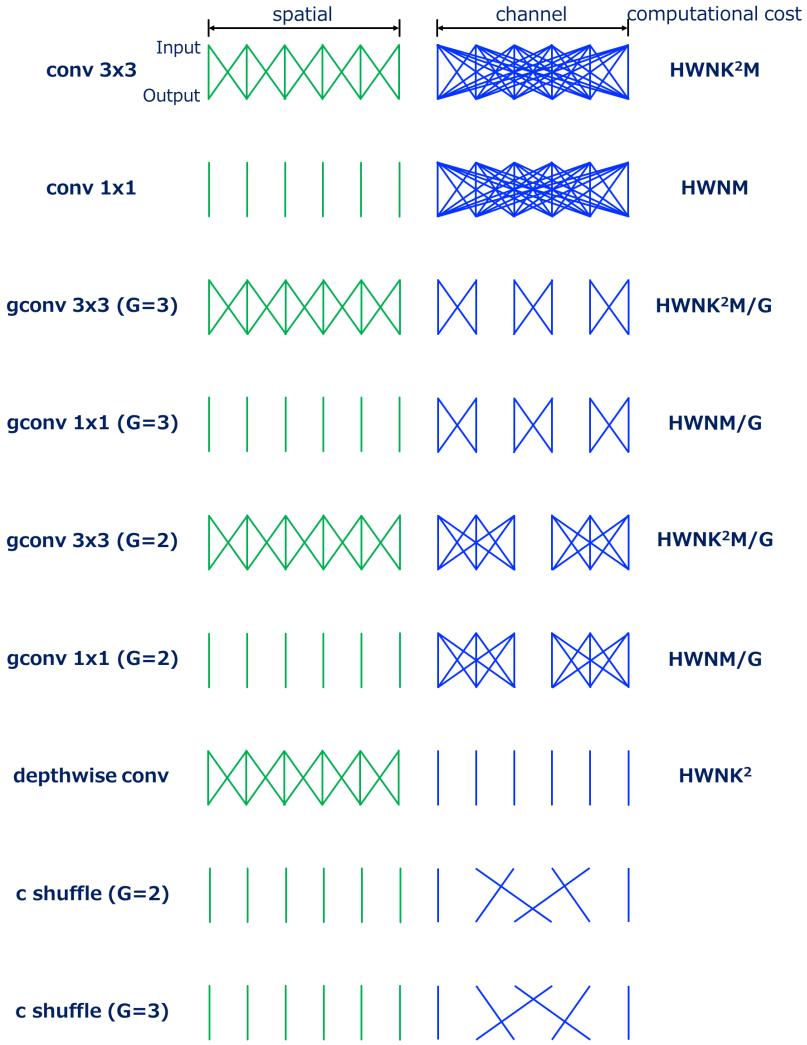
Deep Learning has onle pratical value through the use of pre-trained networks

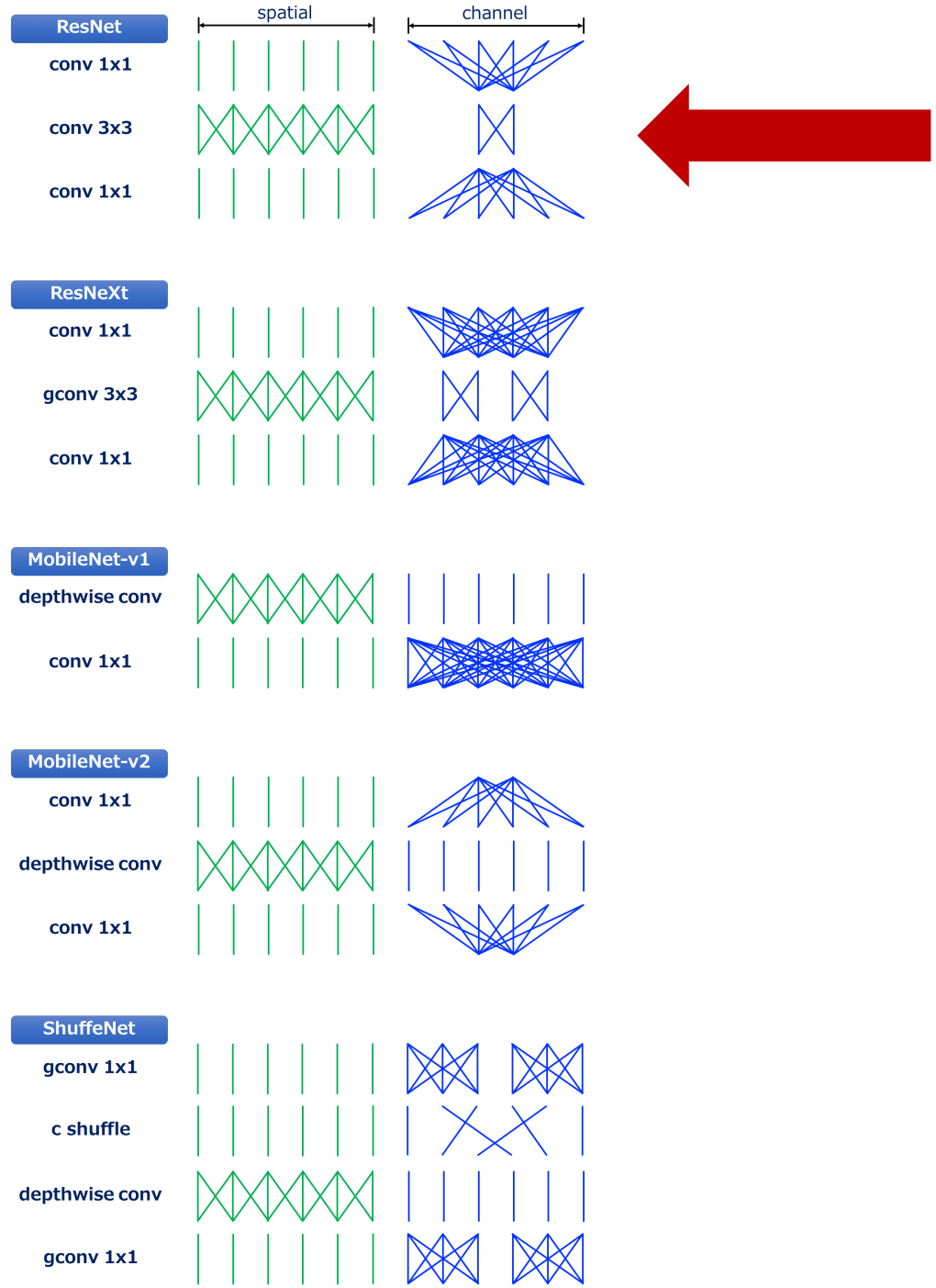




HOGESCHOOL ROTTERDAM







Build Networks with Deep Network Designer

Build and edit deep learning networks interactively using the Deep Network Designer app. Using this app, you can:

- Import and edit networks.
- Build new networks from scratch.
- Drag and drop to add new layers and create new connections.
- View and edit layer properties.
- Generate MATLAB® code to create the network architecture.

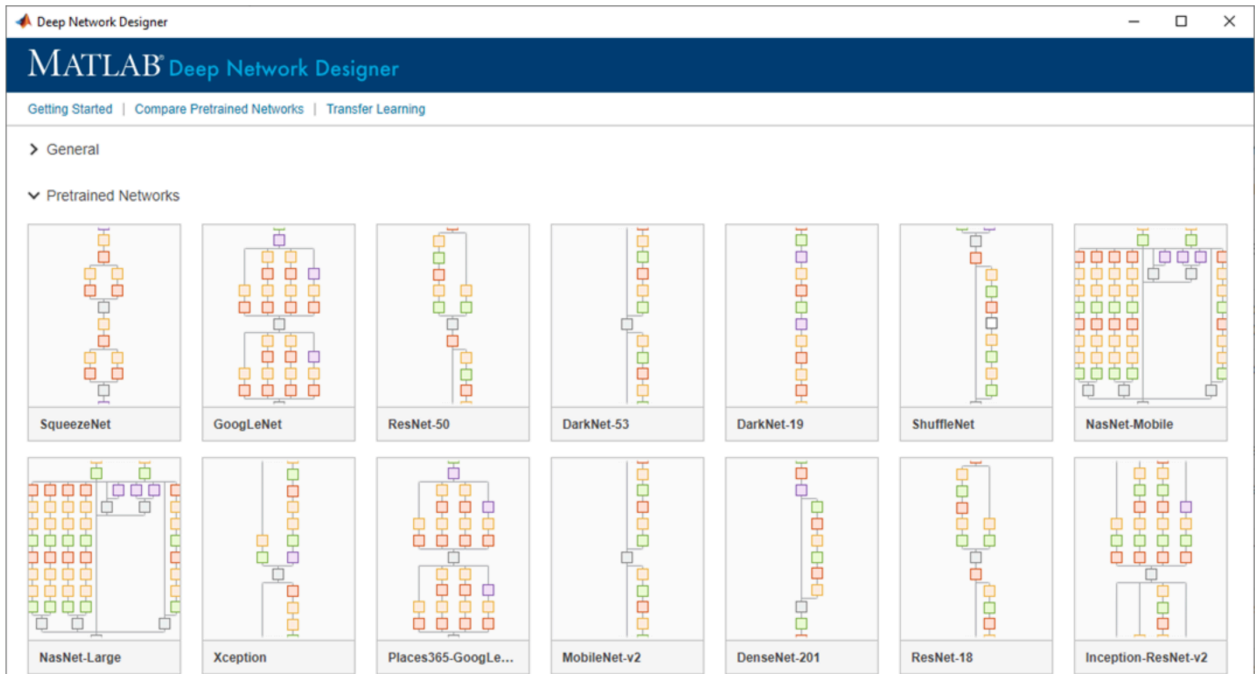
> **Tip**
>
> Starting with a pretrained network and fine-tuning it with transfer learning is usually much faster and easier than training a new network from scratch. For an example showing how to perfo

Open App and Import Networks

To open Deep Network Designer, on the **Apps** tab, under **Machine Learning and Deep Learning**, click the app icon. Alternatively, you can open the app from the command line:

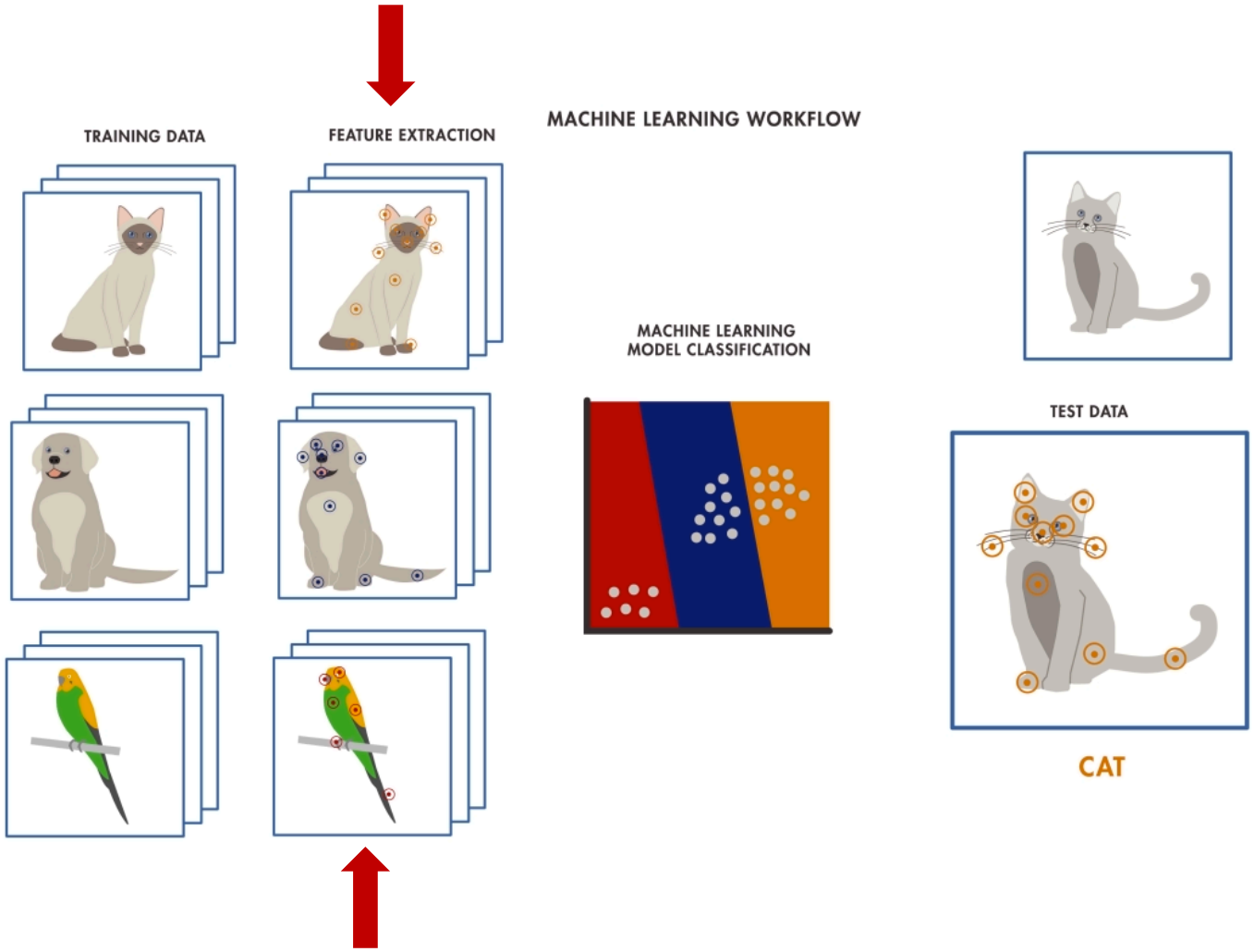
```
deepNetworkDesigner
```

If you want to modify or copy an existing pretrained network, you can select it from the start page.



https://www.mathworks.com/help/deeplearning/ug/build-networks-with-deep-network-designer.html

Pre-trained RESNET & ALEXnet can be use to Classify Images



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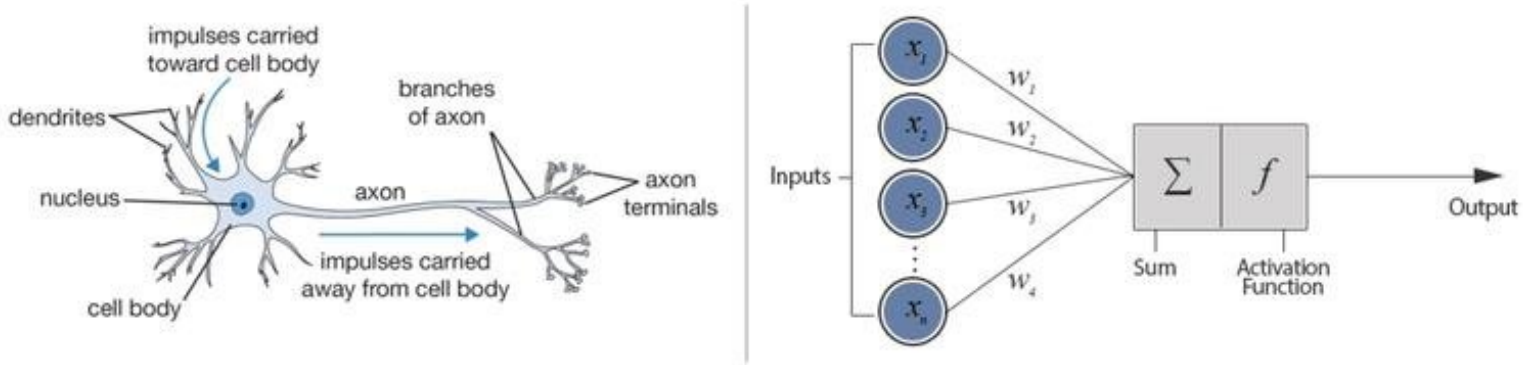
Biological Neuron versus Artificial Neural Network



{03}
Tools

HOGESCHOOL ROTTERDAM

{03}
Tools

HOGESCHOOL ROTTERDAM

{03}
Tools

HOGESCHOOL ROTTERDAM

{03}
Tools

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{04}
Proof of Concept

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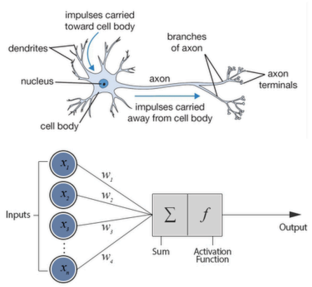
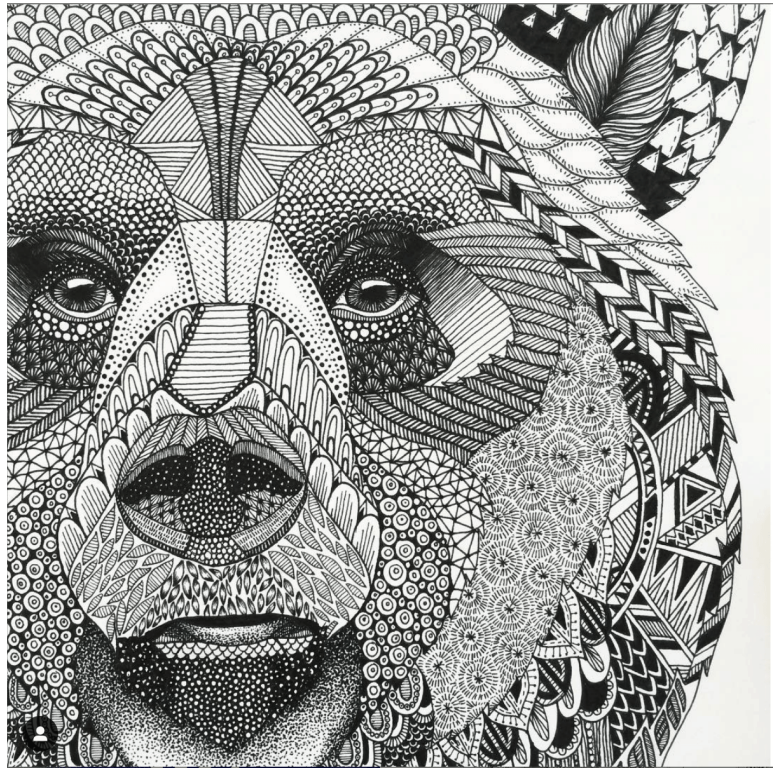
Making Human-Centered Sense of Functional Brain Imaging Data in a Smart Brave World

Designing artificial neural networks trough sensory ecology



"Our model of the cosmos must be as inexhaustible as the cosmos.
A complexity that includes not only duration but creation.
not only being but becoming,
not only geometry but ethics.
It is not the answer we are after,
but only how to ask the question."

—Ursula K. Le Guin, *The Dispossessed*



PROOF OF CONCEPT

Low-cost
high performance
deep -learning

HOGESCHOOL ROTTERDAM

Deep Learning Enablers

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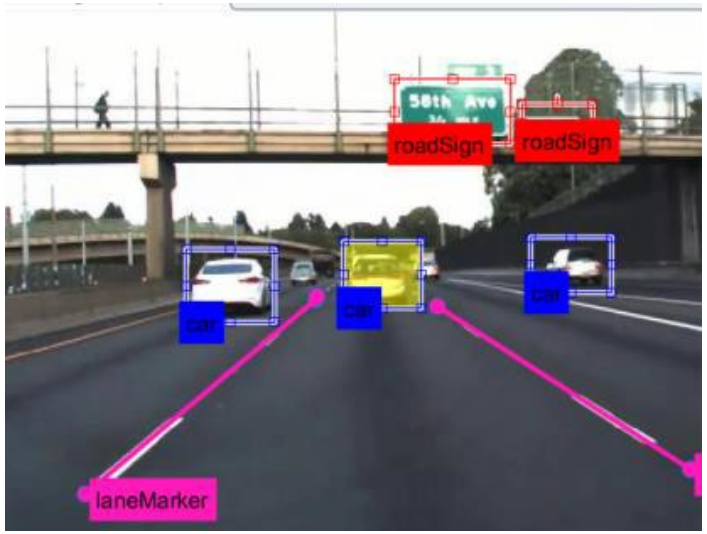
Acceleration with GPUs

Massive sets of labeled data

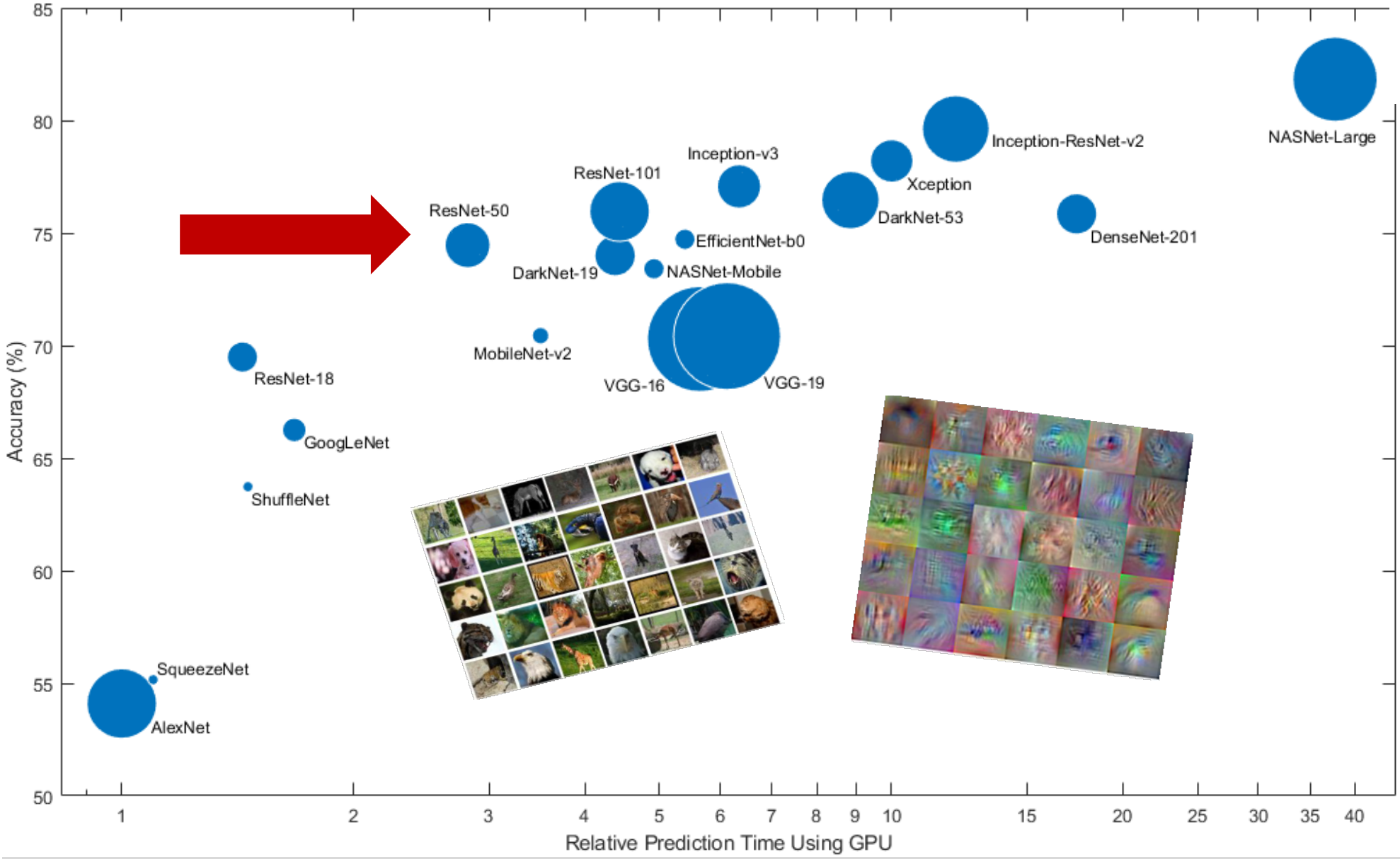


Availability of state of the art models from experts

AlexNet
PRETRAINED MODEL
VGG-16
PRETRAINED MODEL
Caffe
MODELS

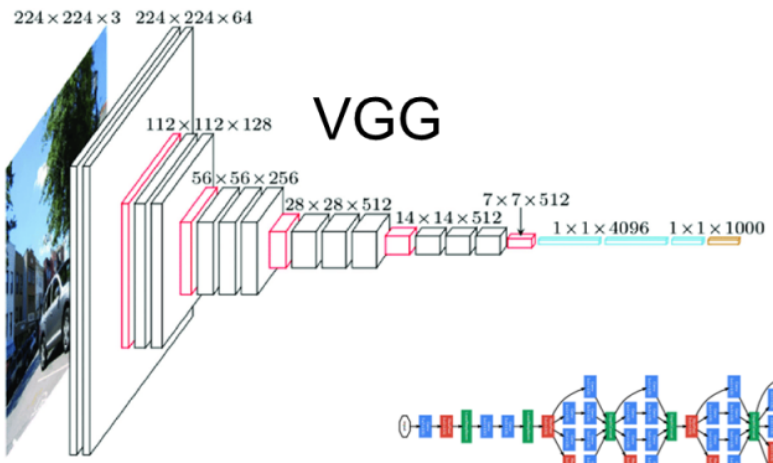
PRE-TRAINED DEEP NETWORKS

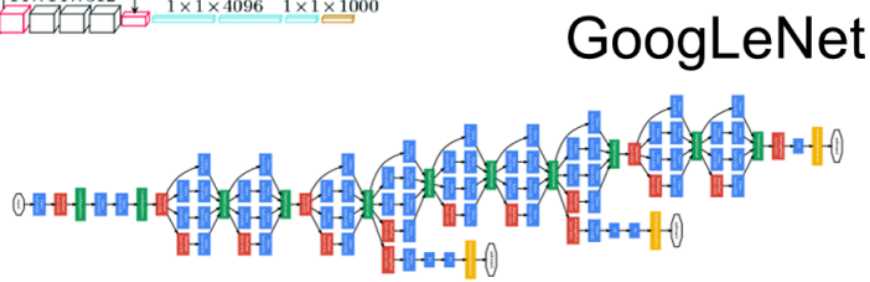
HOGESCHOOL ROTTERDAM

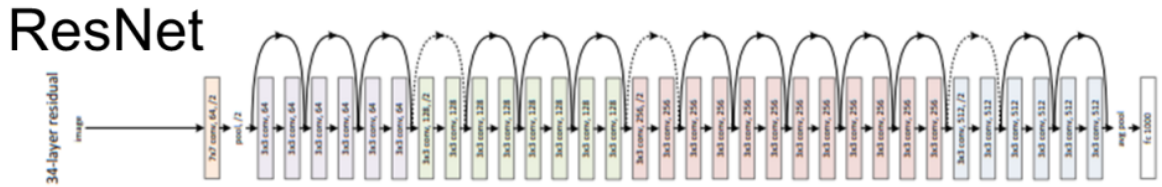


https://nl.mathworks.com/help/deeplearning/ug/pretrained-convolutional-neural-networks.html

Keras







https://keras.io/api/applications/

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
ResNet152	232 MB	0.766	0.931	60,419,944	-
ResNet50V2	98 MB	0.760	0.930	25,613,800	-
ResNet101V2	171 MB	0.772	0.938	44,675,560	-
ResNet152V2	232 MB	0.780	0.942	60,380,648	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
MobileNet	16 MB	0.704	0.895	4,253,864	88
MobileNetV2	14 MB	0.713	0.901	3,538,984	88
DenseNet121	33 MB	0.750	0.923	8,062,504	121
DenseNet169	57 MB	0.762	0.932	14,307,880	169
DenseNet201	80 MB	0.773	0.936	20,242,984	201
NASNetMobile	23 MB	0.744	0.919	5,326,716	-
NASNetLarge	343 MB	0.825	0.960	88,949,818	-
EfficientNetB0	29 MB	-	-	5,330,571	-
EfficientNetB1	31 MB	-	-	7,856,239	-
EfficientNetB2	36 MB	-	-	9,177,569	-
EfficientNetB3	48 MB	-	-	12,320,535	-
EfficientNetB4	75 MB	-	-	19,466,823	-
EfficientNetB5	118 MB	-	-	30,562,527	-
EfficientNetB6	166 MB	-	-	43,265,143	-
EfficientNetB7	256 MB	-	-	66,658,687	-

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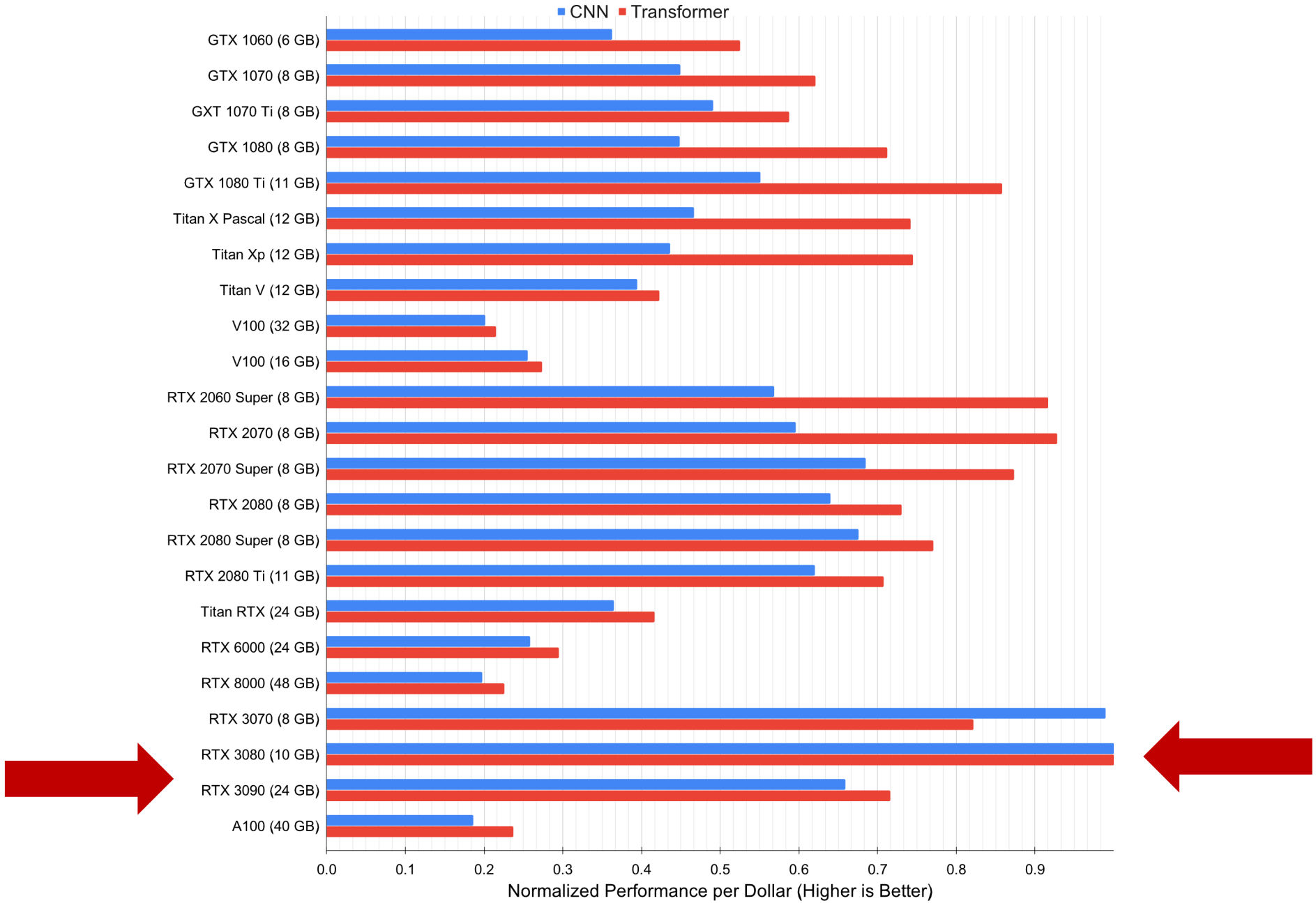
Low-Cost GPU GAMING-PC
→tuned for Deep Learning

BENCH MARK DEMO
RESnet & ALEXnet

Normalized 1 vs 2 GPU deep learning performance per Dollar



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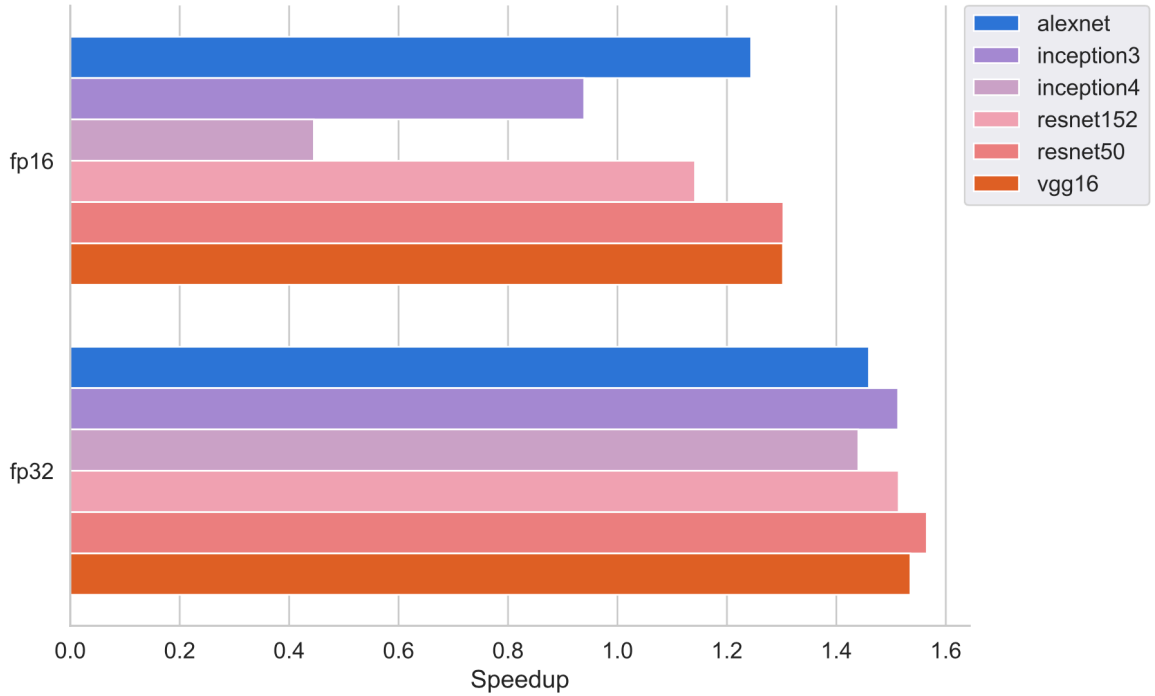
Training performance in images processed per second

	FP16		FP32	
	Titan RTX	**RTX 3090**	**Titan RTX**	**RTX 3090**
AlexNet	6634.31	8255.43	4448.46	6493.16
Inception3	656.13	616.25	222.95	337.31
Inception4	298.11	132.73	99.74	143.65
ResNet152	423.92	484.02	134.47	203.58
ResNet150	966.77	1259.95	335.96	525.88
VGG16	339.73	442.49	212.06	325.60



Speedup of RTX 3090 over Titan RTX

TensorFlow GPU Benchmarks

Visualization	Metric	Precision	Number of GPUs	Model
table	throughput	fp16	1x	alexnet

Search GPUs...

Configuration	alexnet
A100 40GB PCIe	16487
GTX 1080Ti	2914
RTX 2070 MAX-Q	2509
RTX 2080 MAX-Q	2831
RTX 2080 SUPER MAX-Q	2955
RTX 2080Ti	5297
RTX 3080	7047
RTX 3090	8104
RTX 8000	7135
RTX A6000	10001
V100 32GB	9319

https://lambdalabs.com/gpu-benchmarks

```
TensorFlow:  2.4
Model:       alexnet
Dataset:     imagenet (synthetic)
Mode:        forward only
SingleSess:  False
Batch size:  896 global
896 per device
Num batches: 100
Num epochs:  0.07
Devices:     ['/gpu:0']
NUMA bind:   False
Data format: NCHW
Optimizer:   sgd
Variables:   replicated
AllReduce:   nccl
==========
Generating training model
/home/rob/.local/lib/python3.8/site-packages/tensorflow/python/keras/legacy_tf_layers/convolutional.py:414:
warnings.warn('`tf.layers.conv2d` is deprecated and '
/home/rob/.local/lib/python3.8/site-packages/tensorflow/python/keras/engine/base_layer_v1.py:1719: UserWarni
warnings.warn('`layer.apply` is deprecated and '
me/rob/.local/lib/python3.8/site-packages/tensorflow/python/keras/legacy_tf_layers/pooling.py:310: UserWa
nings.warn('`tf.layers.max_pooling2d` is deprecated and '
/home/rob/.local/lib/python3.8/site-packages/tensorflow/python/keras/legacy_tf_layers/core.py:268: UserWarni
warnings.warn('`tf.layers.dropout` is deprecated and '
Initializing graph
WARNING:tensorflow:From /media/rob/MULTIMEDIA/RECOURCES/LAMBDA/lambda-tensorflow-benchmark/benchmarks/script
Instructions for updating:
Please switch to tf.train.MonitoredTrainingSession
W0217 21:16:36.660380 139794761701184 deprecation.py:333] From /media/rob/MULTIMEDIA/RECOURCES/LAMBDA/lambda
Instructions for updating:
Please switch to tf.train.MonitoredTrainingSession
2021-02-17 21:16:36.742128: I tensorflow/compiler/jit/xla_gpu_device.cc:99] Not creating XLA devices, tf_xla
2021-02-17 21:16:36.743232: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1720] Found device 0 with pro
pciBusID: 0000:65:00.0 name: GeForce RTX 3090 computeCapability: 8.6
coreClock: 1.755GHz coreCount: 82 deviceMemorySize: 23.70GiB deviceMemoryBandwidth: 871.81GiB/s
2021-02-17 21:16:36.743266: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743310: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743319: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743328: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743336: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743343: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743350: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.743358: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:36.744882: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1862] Adding visible gpu devi
2021-02-17 21:16:36.744909: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1261] Device interconnect St
2021-02-17 21:16:36.744913: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1267]      0
2021-02-17 21:16:36.744917: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1280] 0:   N
2021-02-17 21:16:36.746373: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1406] Created TensorFlow devi
2021-02-17 21:16:36.748379: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:196] None of the MLIR
2021-02-17 21:16:36.751289: I tensorflow/core/platform/profile_utils/cpu_utils.cc:112] CPU Frequency: 30000
INFO:tensorflow:Running local_init_op.
I0217 21:16:36.938742 139794761701184 session_manager.py:505] Running local_init_op.
INFO:tensorflow:Done running local_init_op.
I0217 21:16:36.950370 139794761701184 session_manager.py:508] Done running local_init_op.
Running warm up
2021-02-17 21:16:36.995224: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:37.461592: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:37.463526: I tensorflow/stream_executor/platform/default/dso_loader.cc:49] Successfully ope
2021-02-17 21:16:40.782163: I tensorflow/stream_executor/cuda/cuda_blas.cc:1838] TensorFloat-32 will be used
Done warm up
Step    Img/sec total_loss      top_1_accuracy  top_5_accuracy
1       images/sec: 16549.2 +/- 0.0 (jitter = 0.0)      0.000   0.002   0.009 1613593001
10      images/sec: 16977.3 +/- 249.5 (jitter = 222.5)  0.000   0.000   0.003 1613593001
20      images/sec: 17117.5 +/- 149.5 (jitter = 169.0)  0.000   0.001   0.009 1613593002
30      images/sec: 17155.6 +/- 112.5 (jitter = 125.4)  0.000   0.001   0.002 1613593002
40      images/sec: 17170.8 +/- 94.1 (jitter = 130.6)   0.000   0.000   0.007 1613593003
50      images/sec: 17190.7 +/- 82.1 (jitter = 151.4)   0.000   0.000   0.003 1613593003
60      images/sec: 17201.9 +/- 72.5 (jitter = 149.4)   0.000   0.001   0.006 1613593004
70      images/sec: 17198.2 +/- 66.4 (jitter = 133.7)   0.000   0.000   0.003 1613593004
80      images/sec: 17200.5 +/- 61.3 (jitter = 128.8)   0.000   0.000   0.004 1613593005
90      images/sec: 17202.2 +/- 55.7 (jitter = 136.7)   0.000   0.000   0.007 1613593005
100     images/sec: 17200.9 +/- 52.4 (jitter = 136.7)   0.000   0.000   0.009 1613593006
----------------------------------------------------------------
total images/sec: 17167.41
----------------------------------------------------------------
rob@UBUpromet:/media/rob/MULTIMEDIA/RECOURCES/LAMBDA/lambda-tensorflow-benchmark$
```

HOGESCHOOL ROTTERDAM

HOGESCHOOL ROTTERDAM

```
13 -    parallel.gpu.enableCUDAForwardCompatibility(true)
```

Command Window

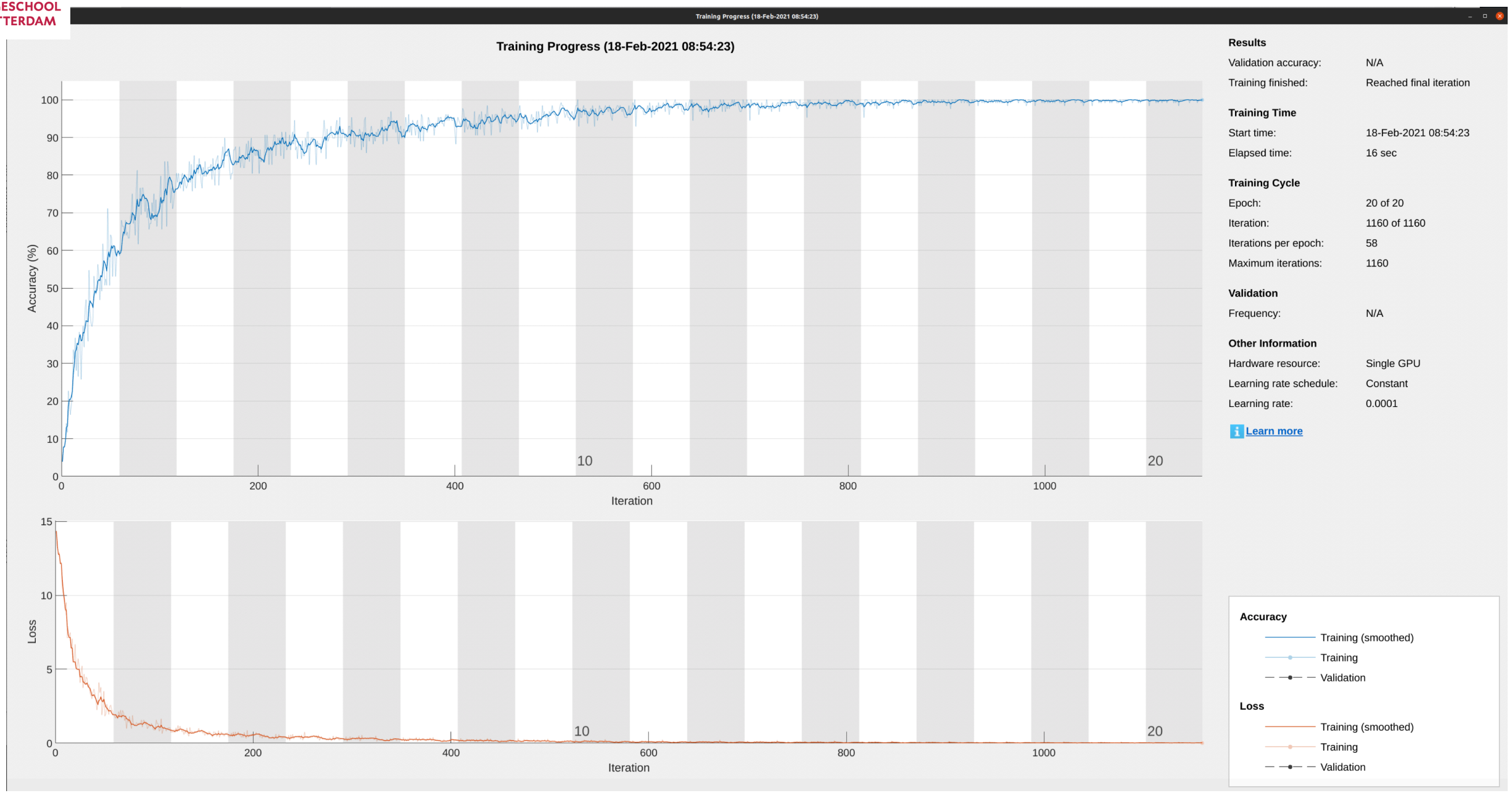
New to MATLAB? See resources for Getting Started.

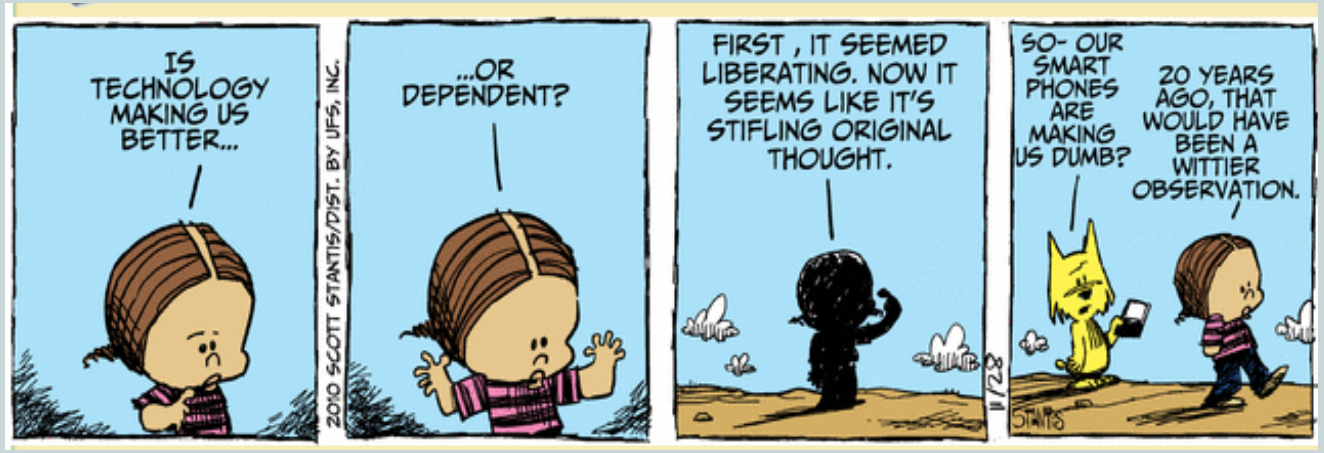
```
CUDADevice with properties:

                     Name: 'GeForce RTX 3090'
                    Index: 1
      ComputeCapability: '8.6'
         SupportsDouble: 1
          DriverVersion: 11.2000
         ToolkitVersion: 10.2000
    MaxThreadsPerBlock: 1024
      MaxShmemPerBlock: 49152
    MaxThreadBlockSize: [1024 1024 64]
           MaxGridSize: [2.1475e+09 65535 65535]
             SIMDWidth: 32
           TotalMemory: 2.5444e+10
       AvailableMemory: 2.3419e+10
  MultiprocessorCount: 82
         ClockRateKHz: 1755000
          ComputeMode: 'Default'
  GPUOverlapsTransfers: 1
KernelExecutionTimeout: 1
       CanMapHostMemory: 1
        DeviceSupported: 1
        DeviceSelected: 1

fx >>
```

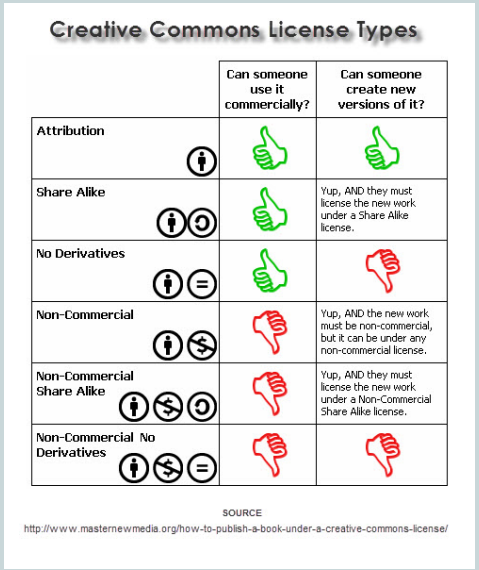
HOGESCHOOL ROTTERDAM





This lesson was developed by:

Robert Frans van der Willigen
CMD, Hogeschool Rotterdam
OKT 2020



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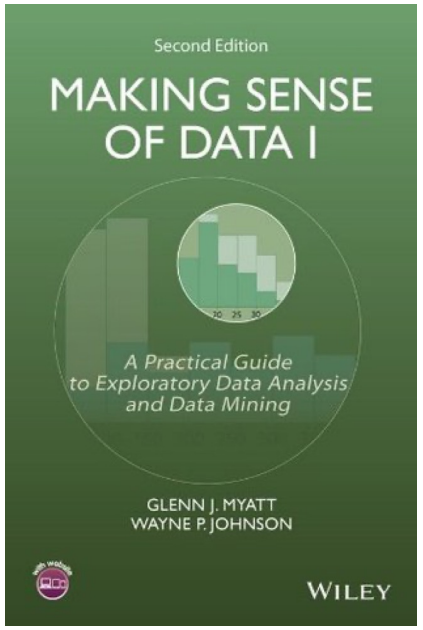
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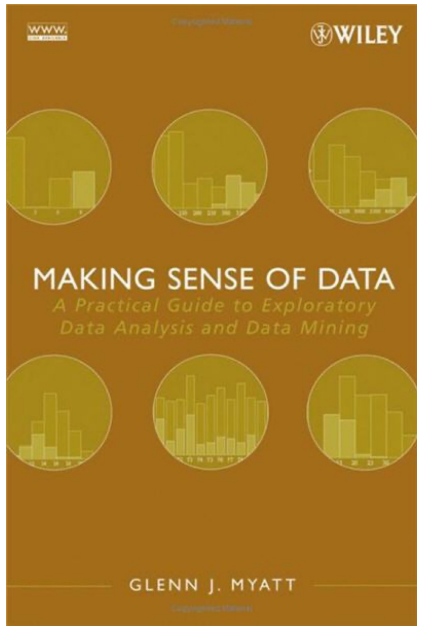
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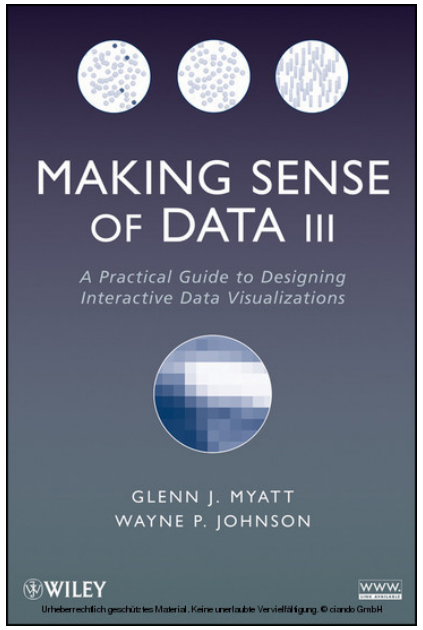
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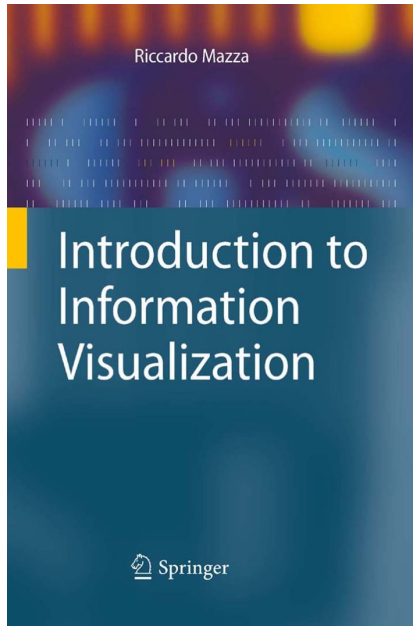
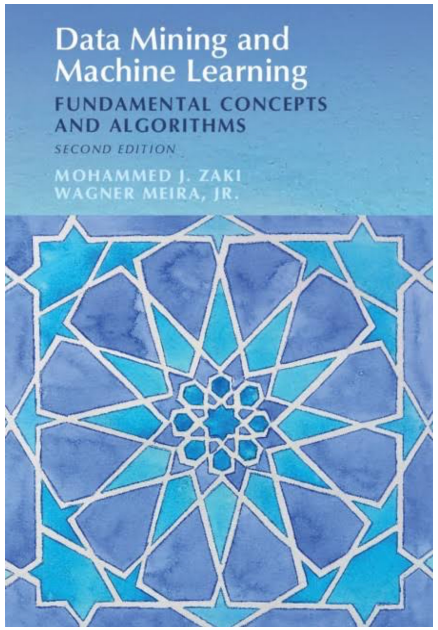

Riccardo Mazza
Introduction to Information Visualization
Springer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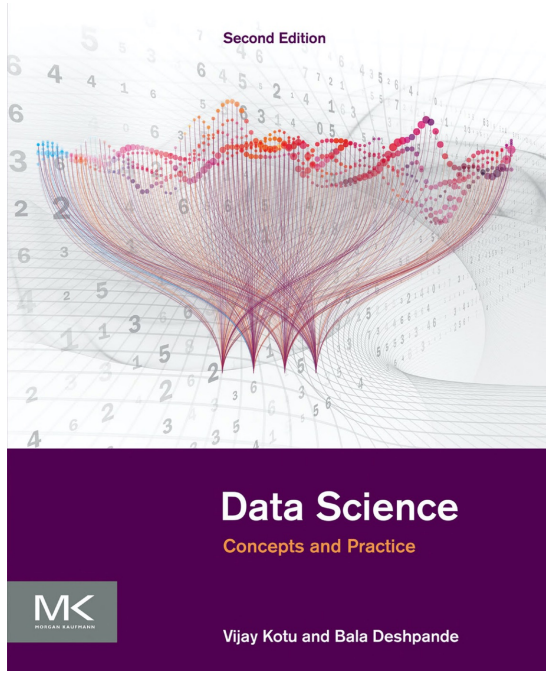
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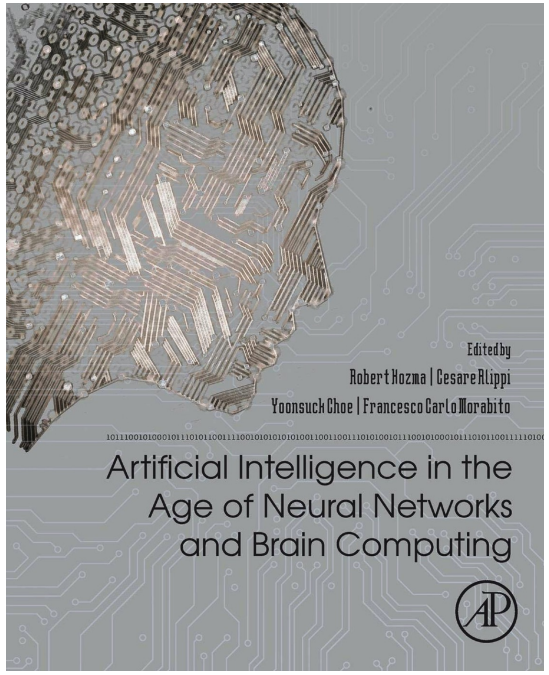
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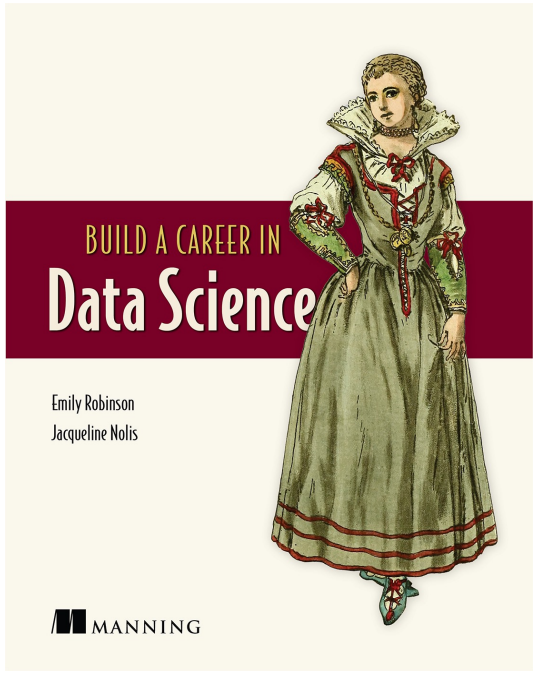
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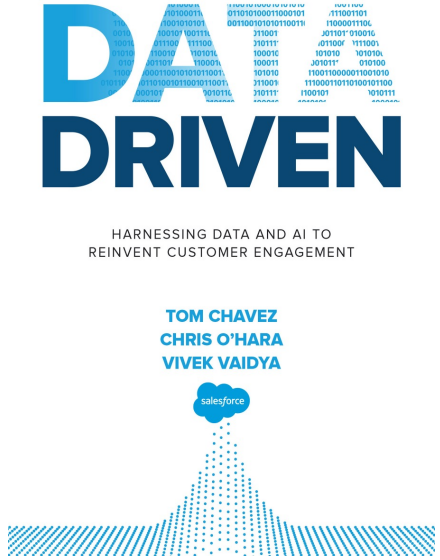
Jacqueline Nolis
MANNING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TOM CHAVEZ
CHRIS O'HARA
VIVEK VAIDYA
salesforce

Top 10 Technology Blogs/Magazines

#1 The Verge – Founded in 2011 The Verge (always in italics!) covers broad spectrum of topics with features, product reviews and podcasts across tech and science and culture, including the arts.

#2 Mashable – Founded in 2005 in New York Mashable provides plenty of news and resources for the "Connected Generation." It's got perhaps one of the most engaged audiences of all tech communities with 20m monthly unique visitors and over 6m followers on social media platforms.

#3 TechCrunch – Like Mashable founded in 2005. TechCrunch enjoys over 12m unique visitors a month, with its community numbering over 2m followers on social media networks. As well as often breaking stories on tech businesses – acquisition and fundraising – its CrunchBase database has become the place to go for information on techn companies, funding and major stories.

#4 The Next Web – Founded in 2008 The Next Web has more than 7.2m monthly unique visitors. The Next Web prides itself on giving an international angle to Internet and technology news and culture, and expands its readership through adding new channels and content partnerships. Like TechCrunch is runs events in Europe and North America.

#5 LifeHacker – Launched in 2005 Lifehacker bills itself as the place for "Tips, tricks, and downloads for getting things done." Covering topics as diverse as "From the Tips Box", anything Windows, Mac, Linux, Android or iOS related, careers, health and wine. Lifehacker also has two international editions – Lifehacker Japan & Lifehacker Australia.

#6 Wired – Wired.com (home to WIRED magazine first published in 1993) is part of the massive Conde Nast publishing group – which also owns Reddit (see below) as well as other great blogs such as Ars Technica. Wired's angle is to look at how ideas and innovation are changing the world. Chris Anderson (writer of The Long Tail, Free) set up his blog GeekDad which was later to become Wired.com. WIRED and Wired.com reach more than 14m readers a month.

#7 Reddit – If you've not come across Reddit where have you been? A massive community with a simple bulletin board, users post links or self-posts – other members of the community ranking the post or links up or down. The most popular links making the site's front page. Users build up kudos through the amount of ups/downs their posts and links get – "karma". Although part of Conde Nast, feels far from commercial.

#8 Geek – One of the oldest blogs on our list bust still going strong. Founded in 1996 Geek.com features cover anything from buying guides and review for mobile, gaming, gadgets and computer hardware and software.

#9 Forbes – More of a business and lifestyle website than the rest on the list, but Forbes.com has a vast network of writers meaning that there's always new content – news and commentary. And given Forbes' size and reputation often with CEOs and senior execs of many of the major technology companies.

#10 Hongkiat – The creation of Hongkiat Lim, since 2007 this website has been giving its readers hints, tips and ideas on technology and design. Based in Malaysia this website has grown considerably and is often mentioned itself by many of the bigger sites – such as Lifehacker and TheNextWeb above.

https://www.statuscake.com/statuscakes-top-10-technology-blogs-how-do-you-start-your-day/

HOGESCHOOL ROTTERDAM


the functional art
alberto cairo
TECHNOLOGY TRENDS TO WATCH
Christian Leborg
Visual Grammar
the analytics revolution
Bill Franks
generative art
matt pearson
MADE to STICK
EMPATHIC THINGS
Intieme technologie van wearables tot biohacking
INTERNET OF THINGS!
MAKERS
THE NEW INDUSTRIAL REVOLUTION
CHRIS ANDERSON
MARITIEME MAAKINDUSTRIE TERUG NAAR RDM
TV AND VIDEO
An analysis of evolving consumer habits
THE DISRUPTION MACHINE
Learning to Program with MATLAB
BUILDING GUI TOOLS
Port Management Program
R Data Analysis
10 TRENDS FOR 2014
A giant cage
Design for Information
HACKATHO
OPEN HAVE
1 VOLLE DAG
7 SEPTEMBER
WEREldHAVENDAGEN 2013
the myths of innovation
scott berkun
O'REILLY
resonate
Cool Infograph
Effective Communication with Data Visualization and Design
The VISU
PHIL SIMON
INVENT TO LEARN
Making, Tinkering, and Engineering in the Classroom
10RE SECRETS with Big Data Analytics
Processing
A Programming Handbook for Visual Designers and Artists
OUR WORK HERE IS DONE
VISIONS OF A ROBOT ECONOMY
THE WALL STREET JOURNAL.
Guide to Information Graphics
Dona M. Wong
Customer Journey Mapping
Wearable Technology Design
The Hidden Pitfall in your Design
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Protecting Data and Privacy in the Cloud
The Internet of Things
Business Adapts to a New Style of Computer
Making Things Talk
TEACHING that STICKS
Chip Heath & Dan Heath
EVOLUTION OF AGILE