



LESSON 11: Hardware (and Frameworks)

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"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E." — Mitchell (1997).

L11: Hardware (and Frameworks)

Agenda

- ▶ AI definition revisited,
- ▶ Frameworks for Machine Learning,
- ▶ Hardware for Machine Learning,
 - ▶ CPUs,
 - ▶ GPUs,
 - ▶ TPUs (and DPUs),
 - ▶ Exotic Hardware,
 - ▶ (Coin-mining, low-hash-rate,)
 - ▶ ML-training costs.
- ▶ MNIST Search Quest Hi-Score Cake,

OUTDATED: ChatGPT and the Press



<https://openai.com/blog/chatgpt-plugins>

<https://www.zetland.dk/historie/s8D3lRNQ-mejv5vgV-9170d>

<https://techmonitor.ai/technology/ai-and-automation/chatgpt-ai-compute-power>

<https://www.version2.dk/artikel/elon-musk-steve-wozniak-og-tusind-andre-i-faelles-opraab-saet-de-gigantiske-ai>

<https://ing.dk/artikel/det-italienske-datatilsyn-forbyder-chatgpt>

<https://www.dr.dk/nyheder/seneste/australsk-borgmester-truer-selskabet-bag-chatgpt-med-injuriesag>

AI and the Press

Nyheder Blogs Debat Avis * Fokus * IDA-adgang Job Mere *

CO2 Transport Digital Tech Summit AI Drivkavand Regioner Energi Eksport Tog Plast Raketter Byggeri Bøt >

Bly abonnement Konto

Lyd Forskning CO2 Transport Digital Tech Summit AI Drivkavand Regioner Energi Eksport

Nyheder Blogs Debat Avis * Fokus * IDA-adgang Job Mere *

Kunstig intelligens trænet til at afgøre om der er liv i rummet

PLUS | Naturvidenskab 27. september kl. 10:45 | 1



I sin sagn efter mye og hurtigere måder at identificere de kemiiske markerer for liv i praver fra rummet, har amerikanske forskere udviklet en kunstig intelligens, som kan spottre biologiske og ikke-biologiske med 90 procent nøjagtighed. Illustration: NASA.

Amerikanske forskere har udviklet en AI-model, som med 90 procents nøjagtighed kan bestemme om en prave fra et rumobjekt er biologisk eller ikke-biologisk.

Artiklen er ældre end 30 dage

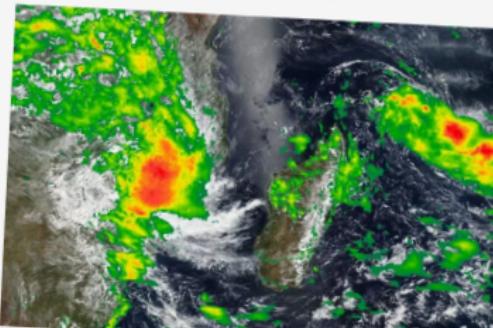


Troen på fund af liv i andre verdens og på andre planeter stiger for hver gang, der udvikles nye observeringstinstrumenter og findes kemiiske tegn på liv på nysddagede eksoplaneter eller galakser.

Hvordan menneskeheden skal genkende liv, når vi ser det, har et amerikansk forskerhold undersøgt. Det har udviklet et system baseret på kunstig intelligens, som med 90 procent nøjagtighed kan opdage

AI leverer lynchurtige vejrudsiger men fejler på cykloner, hedeboelger og skybrud

PLUS | Klima | 17. oktober kl. 05:00 | 1



Den længstlevende tropiske cyklon, Freddy, her fanget i sin voldsomhed af NASA. Cyklonen blev langt værre end AI-vejrmodellerne havde forudset og rasede i fem uger i det sydlige Indiske Ozean i februar og marts 2023. Illustration: NASA/Earthdata.

Det europæiske vejcenter i Bologna har netop installeret en ny supercomputer, men centret risikerer at blive overhalet af en yngre model.

Artiklen er ældre end 30 dage



Det europæiske vejcenter i Bologna har et helt tag fyldt med kolere: Når dem er såkalde chillers, der er vandbaserede, og kan holde temperaturerne nede, når det ikke er særlig varmt.

Men med tæt på 35 grader er det ret varmt i Bologna den

<https://ing.dk/artikel/ai-leverer-lynhurtige-vejrudsiger-men-fejler-paa-cykloner-hedeboelger-og-skybrud>

<https://ing.dk/artikel/kunstig-intelligens-traenet-til-afoere-om-der-er-liv-i-rummet>

Endelig definition af kunstig intelligens klar til at blive godkendt i AI Act

AI Act | 13. november kl. 10:48 | 2



Illustration: Europa-Parlamentet.

OECD har netop vedtaget en ny definition af 'kunstig intelligens'. EU forventes at inddrage den nye afgrænsning i AI Act.

 OECD, The Organisation for Economic Co-operation and Development, har vedtaget sin nye definition af kunstig intelligens. Det skete onsdag i sidste uge, da OECDs udvalg for digital økonomisk politik og

[<https://www.version2.dk/artikel/endelig-definition-af-kunstig-intelligens-klar-til-blive-godkendt-i-ai-act>]

AI Definition Revisited

Der foreligger endnu ikke en dansk oversættelse af den ny definition, men den engelske version lyder:

”An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.

—[oecd.ai/en/ai-principles]

[<https://www.version2.dk/artikel/endelig-definition-af-kunstig-intelligens-klar-til-blive-godkendt-i-ai-act>]

FRAMEWORKS FOR MACHINE LEARNING

Frameworks for Machine Learning

name	note	
Sci-Kit Learn	(INRIA)	
Keras	interface	
Tensorflow	Google	
Pytorch	Facebook	
CNTK	Microsoft	
Apache MXNet	Amazon	
Core ML	Apple	
Caffe	(Berkeley)	
H2O	??	
Shogun	??	將軍

Frameworks for Machine Learning



Intel: scikit-learn-intelex

Intel® Extension for Sci... +

https://intel.github.io/scikit-learn-intelex/ 150% ☆

← ⟲ ⟳ ⌂ ⌂ ⌂ Contents

Usage
Important Links



Intel(R) Extension for Scikit-learn* 2021.5 documentation

Search the docs ...

ABOUT

- Acceleration
- Patching
- Medium Blogs
- System Requirements
- Memory Requirements

GET STARTED

- Installation

Intel® Extension for Scikit-learn*

With Intel® Extension for Scikit-learn* you can accelerate your Scikit-learn applications and still have full conformance with all Scikit-Learn APIs and algorithms. Intel® Extension for Scikit-learn* is a free software AI accelerator that brings over 10-100X acceleration across a variety of applications.

Intel® Extension for Scikit-learn* offers you a way to accelerate existing scikit-learn code. The acceleration is achieved through **patching**: replacing the stock scikit-learn algorithms with their optimized versions provided by the extension.

Designed for Data Scientists and Framework Designers

Intel® Extension for Scikit-learn* was created to provide data scientists with a way to get a better performance while using the familiar scikit-learn package and getting the same results.

HARDWARE FOR MACHINELEARNING



Hardware for Machine Learning

Methods and Terminology (SKIP most except μ, η)

Objective:

Why optimize using 'application specific' hardware?

▶ Effectiveness:

▶ cost of purchasing/operating systems,

$$\mu = \text{FLOPS}/\$$$

$$\eta = \text{FLOPS}/\text{Watt}$$

▶ cut-down developer waiting time,

▶ make modelling iterations fast (say minutes).

▶ Big-data:

▶ enable training on x-large data.

▶ Real-time constraints:

▶ inference (on visual data) in real-time,

▶ low-power constraints.



Hardware for Machine Learning

Methods and Terminology

Heterogeneous computing: systems that use more than one kind of processor or cores, say CPU + GPU.

Cluster computing: (loosely or) tightly connected computers that work together; can be viewed as a single system.

HPC: High-performance computing; a '**super-computer**' with high level of performance (vs. general-purpose computer).



Flynn's taxonomy:

SISD: single instruction, single data,



SIMD/SIMT: single instruction, multiple data/threads (data parallel); **this one is our objective,**

(**MISD:** multiple instructions, single data (fault tolerance)),

(**MIMD:** multiple instructions, multiple data (distributed)).

Methods and Terminology

Amdahl's law

What speedup can we expect when optimizing/parallelizing a program?

$$S = \frac{1}{(1 - p) + p/s}$$

where

S : total program speedup,

p : fraction of the program that can be run in parallel,

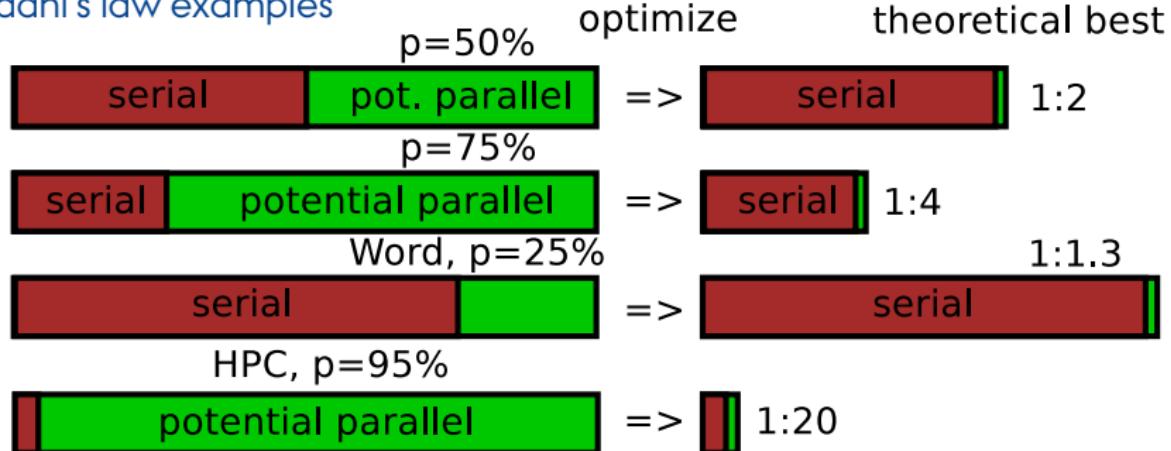
s : parallel fraction speedup factor.

If we take $s = \infty$ the theoretical max. total speedup will be

$$S_{\max} = \frac{1}{(1 - p) + p/\infty} = \frac{1}{1 - p}$$

Methods and Terminology

Amdahl's law examples



And there is seldom need to optimize unless $S_{\max} \gg 2$.

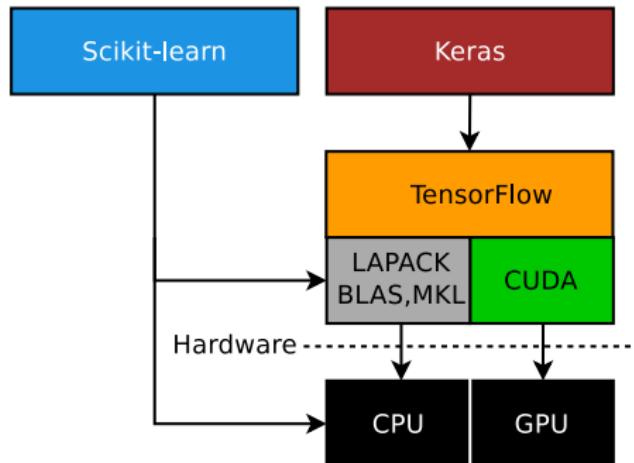
A **1:5 speedup** is a good, ad-hoc compromise btw. a fast program and a costly optimization dev. phase.

What does Donald E. Knuth say about premature optimization?

"Root of all evil!"



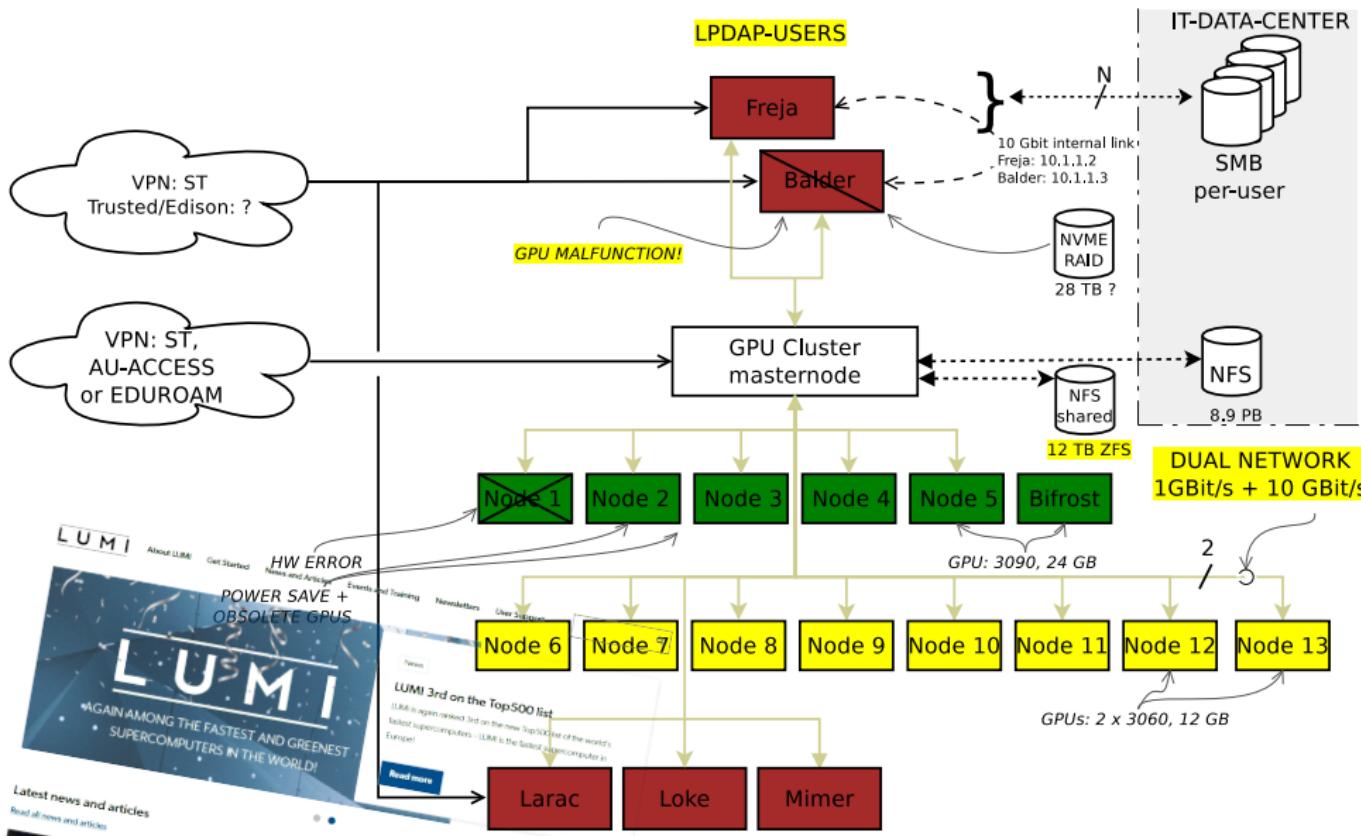
RESUMÉ: Keras and Tensorflow



- GP-GPU:** General-Purpose Graphics Processing Unit...or just **GPU**.
- CUDA:** Compute Unified Device Architecture, API for SIMD/SIMT on GPU,
- LAPACK:** Linear Algebra Package, numerical linear algebra lib, with roots in FORTRAN 77,
- BLAS:** Basic Linear Algebra Subprograms; vector/matrix lib,
- MKL:** Math Kernel Library; fast Intel-arch optimized math lib.

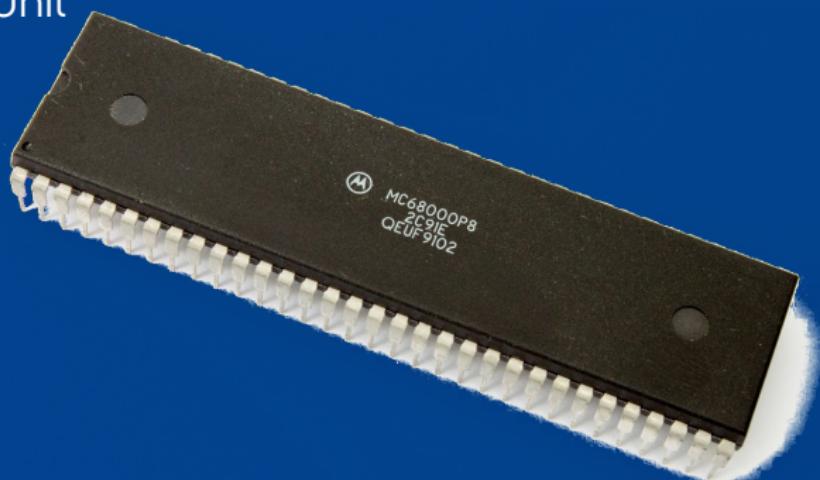
High-Performance-Computing (HPC)

The ECE GPU-cluster (or LUMI EuroHPC)



CPUS

Central Processing Unit



CPUs

Build Tensorflow from source (SKIP)

- ▶ for specific architecture, say ARM,
 - ▶ or for HPC optimization for all CPU feature
- > lscpu

```
Architecture: x86_64
Model name: Intel(R) Core(TM) i7-6600U CPU @ 2.60GHz
Flags: fpu vme de pse tsc msr pae mce cx8 apic sep mtrr
      pge dts acpi mmx fxsr fma..sse sse2..sse4_1sse4_2..
```



Using Docker and pulling TF from GIT + a lot of scripting!

```
> git clone https://github.com/tensorflow/tensorflow
> git checkout 1.12
(lots of scripting and pain..)
> bazel build -copt=-mfma -copt=-msse4.2 tensorflow
```

Howtos:

<https://www.tensorflow.org/install/source>

<https://www.pugetsystems.com/labs/hpc/Build-TensorFlow-CPU-with-MKL-and-Anaconda-Python-3-6-using-a-Docker-Container-1133>

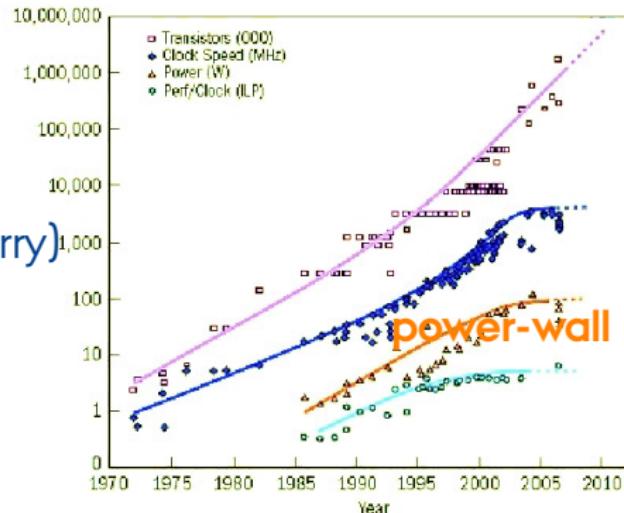
<https://www.pugetsystems.com/labs/hpc/Build-TensorFlow-GPU-with-CUDA-9-1-MKL-and-Anaconda-Python-3-6-using-a-Docker-Container-1134>

CPUs

SIMD/Data parallel compute using CPU

CPU architectures:

- ▶ i386/AMD64,ARM (Raspberry)
- ▶ all CPU types: lots of cores; end of Moore's Law, 'Singularity University', problem w. exp. growth?



Scikit-learn problem with SIMD:

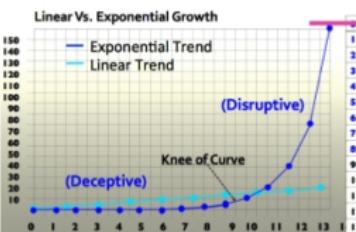
- ▶ no ML-algo GPU hardware enabled,
- ▶ many ML-algo not even multicore aware!

Keras/TensorFlow:

- ▶ CPU optimization of TF possible,
- ▶ (GPU enabled TF possible, using CUDA + cudNN).

Exponential Technologies

- Artificial Intelligence
- Robotics
- Biotech
- Manufacturing
- Computation / Networks
- Synthetic Biology
- Digital Medicine

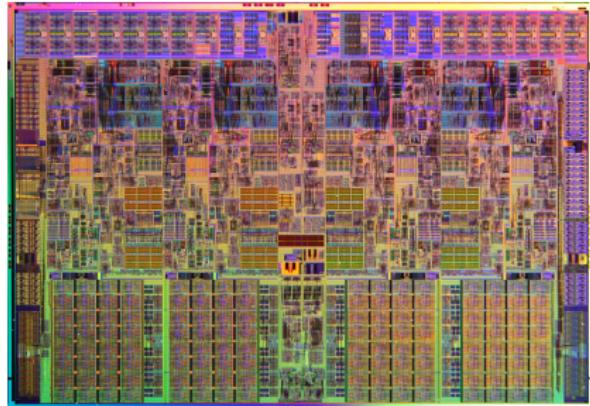


GP-GPUS

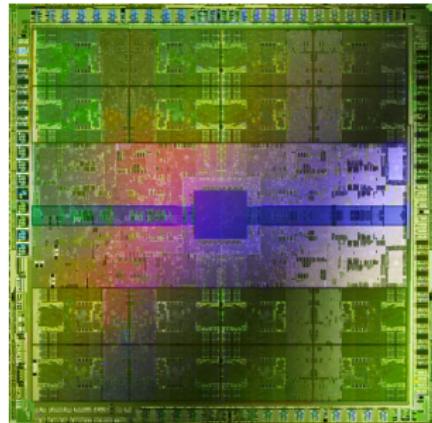
General-Purpose Graphical Processing Unit



CPUs vs GPUs



Nehalem CPU
die size: $\sim 700 \text{ mm}^2$
transistors: $\sim 2.3 \cdot 10^9$



Fermi GPU
die size: 520 mm^2
transistors: $\sim 3 \cdot 10^9$

Nvidia arch. transistor counts

Pascal	$\sim 15 \cdot 10^9$
Turing	$\sim 19 \cdot 10^9$
Volta	$\sim 21 \cdot 10^9$
Ampere	$\sim 28 \cdot 10^9$ (GPU 3090, 8nm)

CPUs vs GPUs

So many transistors, but how many for the ALUs/FPUs?

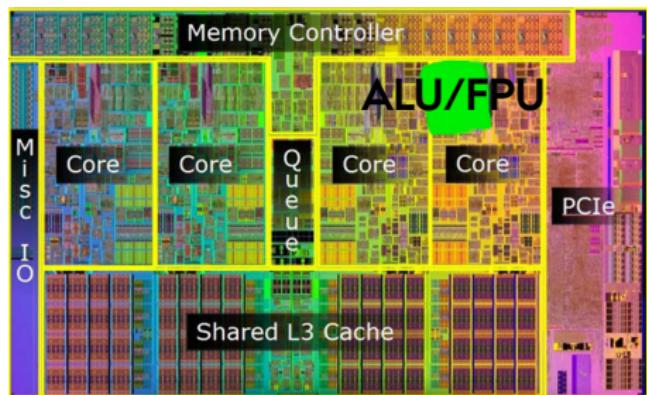
What makes GPUs such excellent HW for Machine Learning?

ALU: Arithmetic logic unit

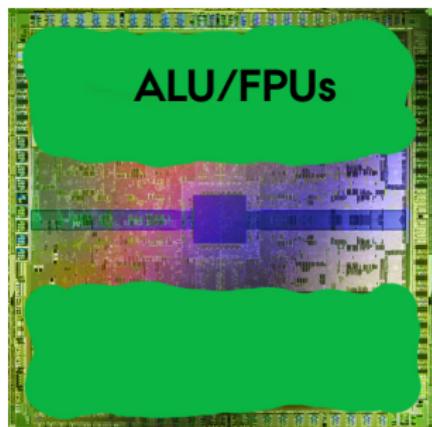
FPU: Floating-point unit

Memory Controller: six controllers on GPU,

CPU: lots of speculative execution; waste of transistors.



CPU (type?)
with one ALU/FPU marked



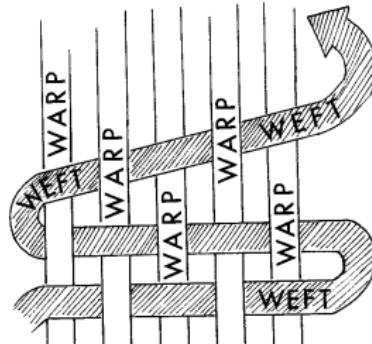
Fermi GPU
ALUs/FPUs all over

GPUs

Fundamental Problems with the GPUs Hardware (SKIP most, except WARP)

GPUs had several *Achilles heels* related to its hardware, many of them addressed in the latest Volta V100 architecture:

- ▶ coding problems graphically, now CUDA,
- ▶ no STACK, now added,
- ▶ no CACHE (or Texture only), now both L₁ and L₂ cache,
- ▶ distinct GPU memory, now UNIFIED memory,
- ▶ SIMT WARP-bunch of 32-threads, now true SIMD,



GPUs

GPU architecture: Core Design, Streaming Multiprocessors



GPUs

Core Design for a SM
(Streaming Multiprocessor)

Volta SM design
(new gen. GPU):

FP64/32:FPUs
INT: ALUs
TENSOR CORES: ?

Ampere, RTX, 3090:
Raytracingkerner: ?



GEFORCE RTX 3090	
NVIDIA CUDA® kerner	10496
Høj CPU-hastighed (GHz)	1.70
Normal CPU-hastighed (GHz)	1.40
Raytracingkerner	2. generation
Tensor Cores	3. generation
Standard hukommelseskonfiguration	24 GB GDDR6X
Hukommelsesgrænsefladens bredde	384-bit

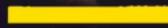
GPUs

Demo: RTX and raytracing

2070 S 99 %
VRAM 5,461 MB
M.CLOCK 7001 MHz
C.CLOCK 1920 MHz
PWR 212.4 W
TEMP. 67 °c
32GB RAM 11,561 MB
I7 9700K 15 %
CLOCK 5000 MHz
TEMP. 51 °c
low 0.1% 55
low 1% 58
FPS avg 67

FRAME TIME 15.6 ms

FPS 65 fps



Original

2070 S 98 %
VRAM 5,453 MB
M.CLOCK 7001 MHz
C.CLOCK 1920 MHz
PWR 210.5 W
TEMP. 67 °c
32GB RAM 11,564 MB
I7 9700K 22 %
CLOCK 5000 MHz
TEMP. 56 °c
low 0.1% 54
low 1% 56
FPS avg 65

FRAME TIME 16.3 ms

FPS 61 fps

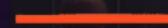


Sharpen

2070 S 99 %
VRAM 5,277 MB
M.CLOCK 7001 MHz
C.CLOCK 1980 MHz
PWR 205.6 W
TEMP. 66 °c
32GB RAM 11,559 MB
I7 9700K 15 %
CLOCK 5000 MHz
TEMP. 58 °c
low 0.1% 31
low 1% 31
FPS avg 36

FRAME TIME 31.0 ms

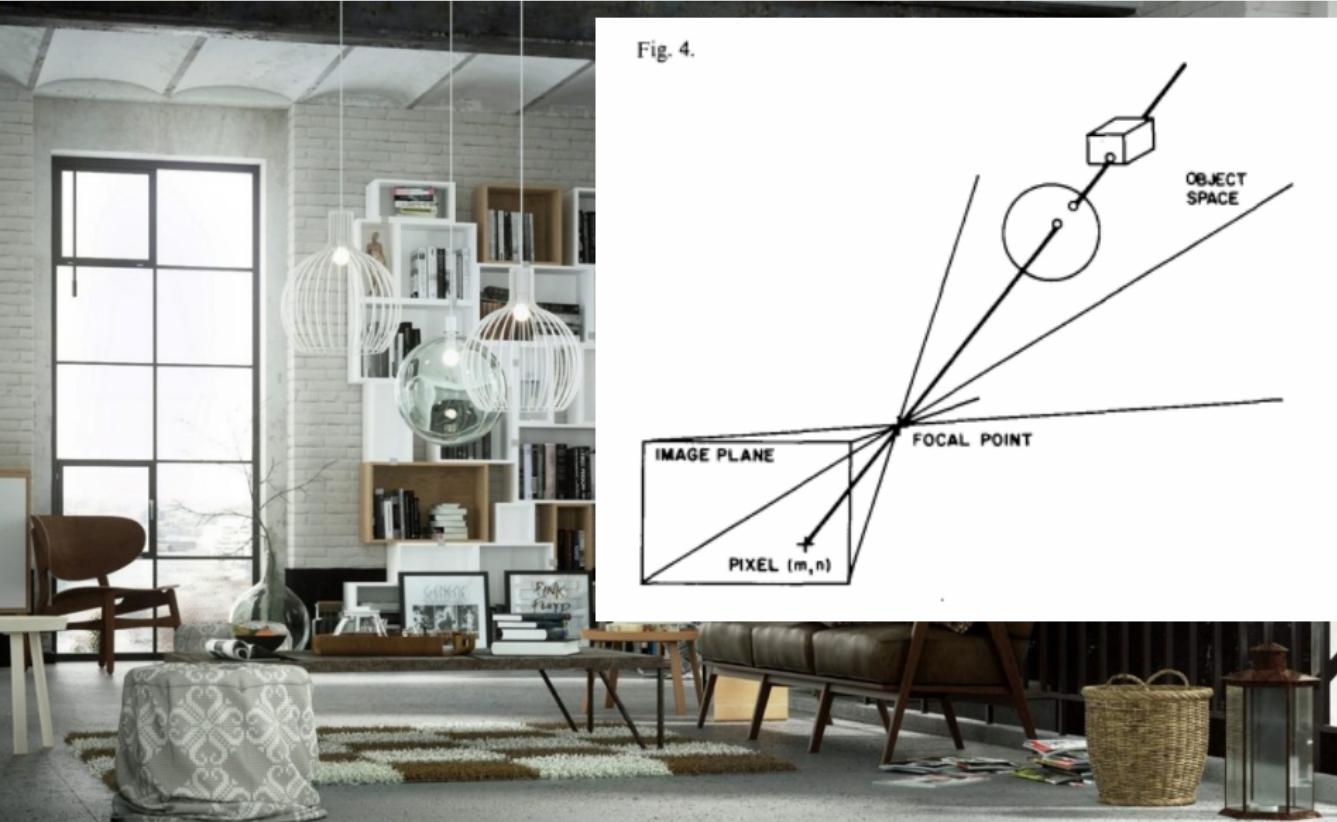
FPS 31 fps



Ray Tracing+Sharpen

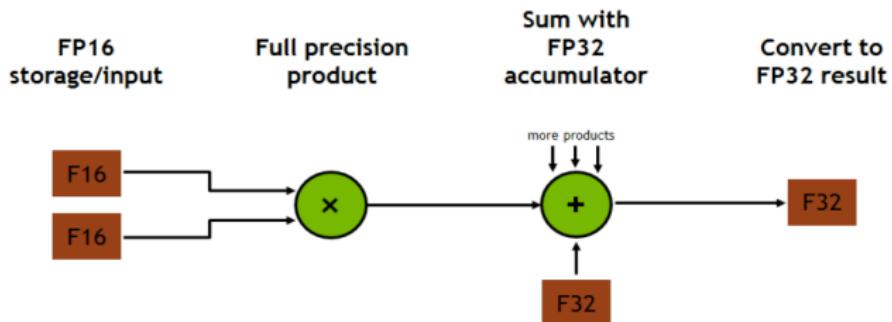
GPUs

Tensor cores: Raytracing vs Rasterization on GPUs



GPUs

Tensor Cores (SKIP most)



$$D = \left(\begin{array}{cccc} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{array} \right) \text{FP16} + \left(\begin{array}{cccc} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{array} \right) \text{FP16} + \left(\begin{array}{cccc} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{array} \right) \text{FP16 or FP32}$$

Tesla V100's Tensor Cores deliver up to **125 Tensor TFLOPS** for training and inference applications.

[volta-architecture-whitepaper.pdf]

HPC Top500

Best High-Performance Computer

[<https://www.top500.org/list/2007/06/>]

[https://en.wikipedia.org/wiki/List_of_Nvidia_graphics_processing_units]



HOME	LISTS	STATISTICS	RESOURCES
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Home » Lists » TOP500 » June 2007

JUNE 2007

Rank	System	Cores	Rmax (TFlop/s)	Rpeak (TFlop/s)	Power (kW)
1	BlueGene/L - eServer Blue Gene Solution, IBM DOE/NNSA/LLNL United States	131,072	280.6	367.0	1,433
2	Jaguar - Cray XT4/XT3, Cray/HPE DOE/SC/Oak Ridge National Laboratory United States	23,016	101.7	119.3	
3	Red Storm - Sandia/ Cray Red Storm, Opteron 2.4 GHz dual core, Cray/HPE NNSA/Sandia National Laboratories United States	26,544	101.4	127.4	

GPUs

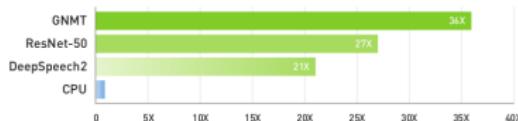
Turing Tensor Core GPU (this is not a commercial!)

GPU Acceleration Core Mainstream

NVIDIA T4 enterprise GPUs supercharge the world's most trusted mainstream servers, bla bla...

Its low-profile, 70-watt (W) design is designed for enterprise data centers, making it ideal for demanding workloads including machine learning, deep learning, and virtual desktop infrastructure (VDI). It also offers the efficiency of smaller PCIe form factors for maximum system options and convenience.

Inference Performance



Comparisons made of one NVIDIA Tesla T4 GPU and servers with a dual-socket Xeon Gold 6140 CPU.

Training Performance



Comparison made between dual NVIDIA Tesla T4 GPUs and servers with a dual-socket Xeon Gold 6140 CPU.



SPECIFICATIONS

GPU Architecture	NVIDIA Turing
NVIDIA Turing Tensor Cores	320
NVIDIA CUDA® Cores	2,560
Single-Precision	8.1 TFLOPS
Mixed-Precision (FP16/FP32)	65 TFLOPS
INT8	130 TOPS
INT4	260 TOPS
GPU Memory	16 GB GDDR6 300 GB/sec
ECC	Yes
Interconnect Bandwidth	32 GB/sec
System Interface	x16 PCIe Gen3
Form Factor	Low-Profile PCIe
Thermal Solution	Passive
Compute APIs	CUDA, NVIDIA TensorRT™, ONNX

GPUs

When is the GPU faster than the CPU for NN?

GPU slower for CPU for a three-layer NN + MNIST, why?

- ▶ GPU needs a reasonable amount of trainable parameters + data to beat the CPU!

`model.summary():`

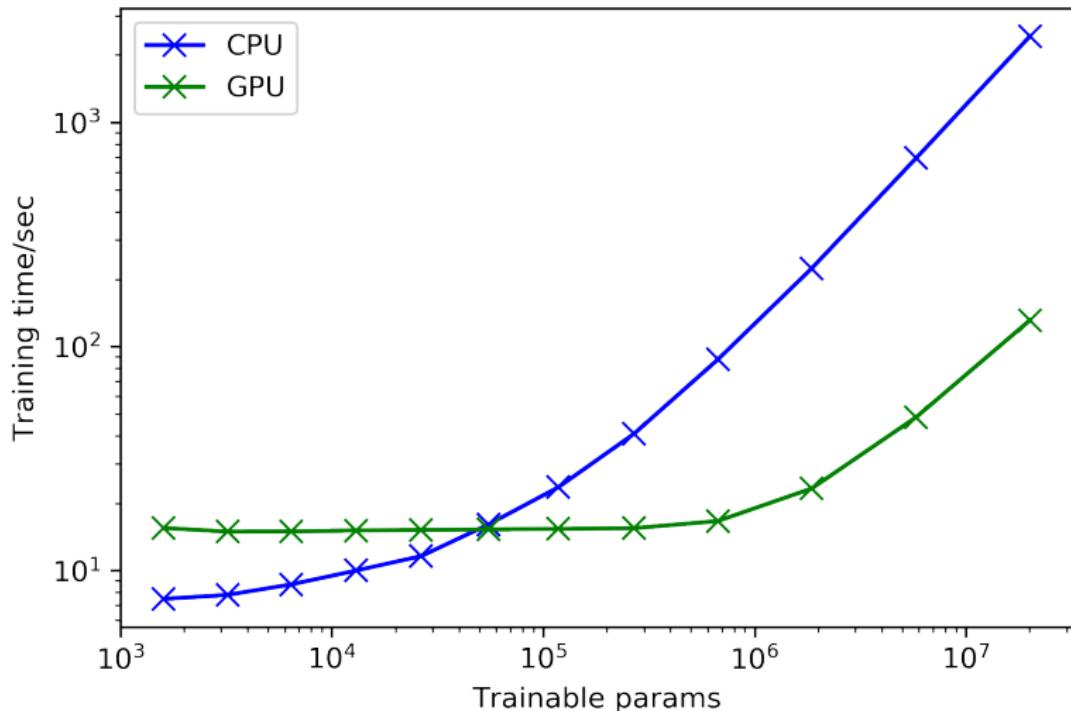
```
1 # i=12, n=4096
2 #
3 # Layer (type)          Output Shape       Param #
4 # =====
5 # dense_46 (Dense)     (None, 4096)        3215360
6 #
7 # dropout_31 (Dropout) (None, 4096)        0
8 #
9 # dense_47 (Dense)     (None, 4096)        16781312
10 #
11 # dropout_32 (Dropout) (None, 4096)        0
12 #
13 # dense_48 (Dense)     (None, 10)          40970
14 # =====
15 # Total params: 20,037,642
16 # Trainable params: 20,037,642
17 # Non-trainable params: 0
```

GPUs

Actual test on the GPU-server

CPU vs GPU on MNIST for a three layer NN with dropout...

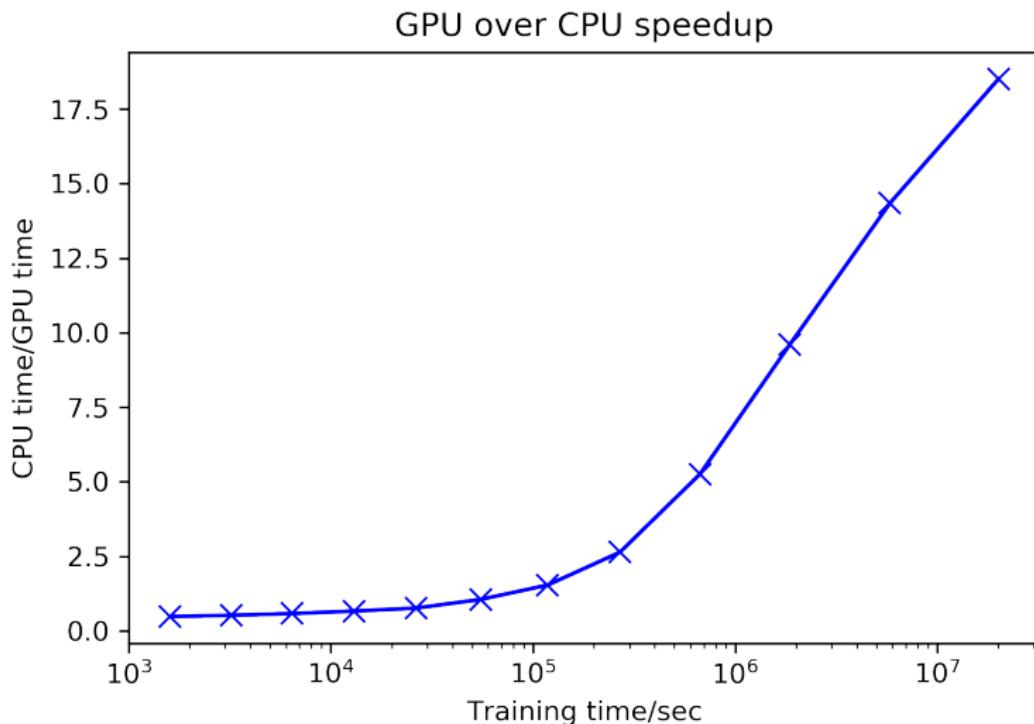
Training time-vs-Trainable params



GPUs

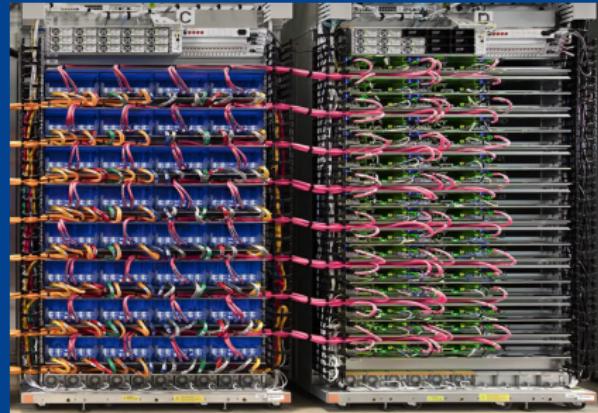
Actual test on the GPU-server

CPU vs GPU on MNIST for a three layer NN with dropout...



TPUS

Tensor Processing Units



TPUs

Tensor Processing Units

Custom ASICs by Google



Cloud TPU v3

Launched in 2018

Inference and training



Dev Board

A development board to quickly prototype on-device ML products. Scale from prototype to production with a removable system-on-module (SoM).

→ Datasheet
→ Get started guide

\$149.99

Buy



TPU v2

Launched in 2015

Inference only

Launched in 2017
Inference and training

Dev board with Google Edge TPU ML accelerator coprocessor

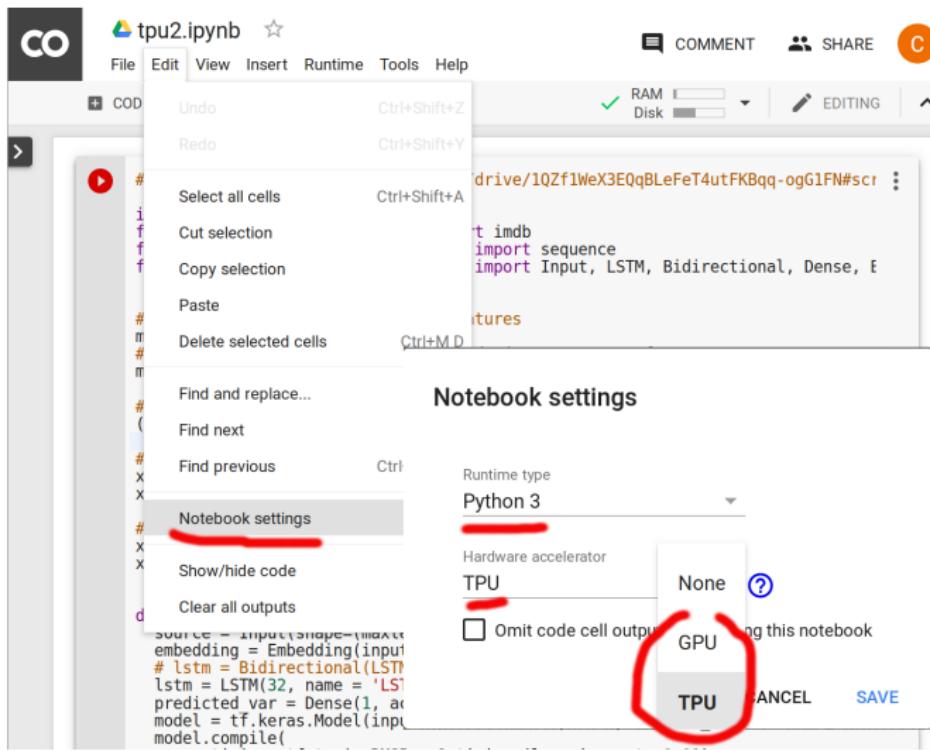
[\[https://coral.withgoogle.com/products/dev-board/\]](https://coral.withgoogle.com/products/dev-board/)



TPUs

Access to TPUs (SKIP)

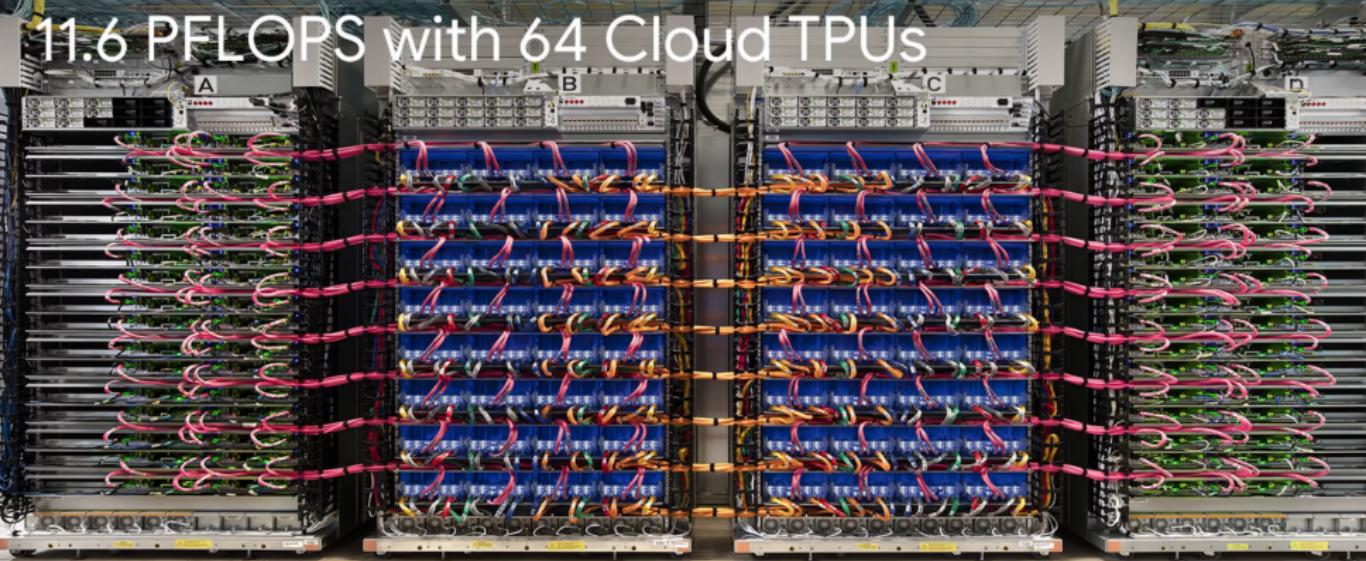
Free Jupyter Notebook environment with access to TPUs:
<https://colab.research.google.com>



TPUs

TPU Cloud

TPU v2 Pod: Google's HPC cluster for ML
11.6 PFLOPS with 64 Cloud TPUs



[<https://storage.googleapis.com/nexttpu/index.html>]

TPUs vs GPUs

Performance, TPUs vs GPUs, who wins? (SKIP most)

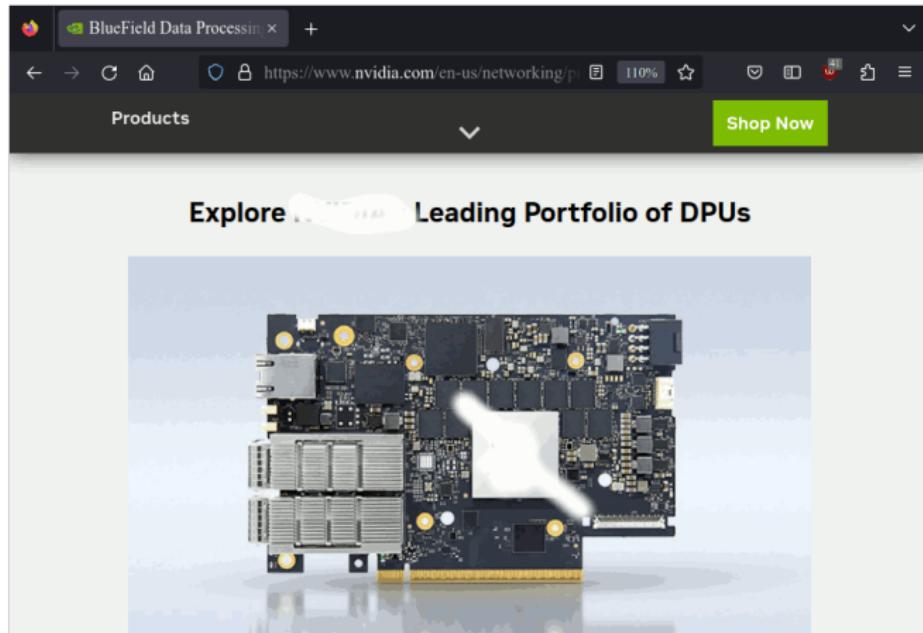
- ▶ Huge advantage for TPU performance-per-watt,
- ▶ Colab performance:
inconclusive (TPU part does not work yet),
- ▶ TPU only for inference?

	K80 2012	TPU 2015	P40 2016
Inferences/Sec <10ms latency	1/13 TH	1X	2X
Training TOPS	6 FP32	NA	12 FP32
Inference TOPS	6 FP32	90 INT8	48 INT8
On-chip Memory	16MB	24 MB	11 MB
Power	300W	75W	250W
Bandwidth	320 GB/S	34 GB/S	350 GB/S

[<https://www.extremetech.com/computing/247403-nvidia-claims-pascal-gpus-challenge-googles-tensorflow-tpu-updated-benchmarks>]

DPU

Data Processing Units



BlueField-3 DPU

The NVIDIA BlueField-3 DPU is a 400 Gb/s infrastructure compute platform with line-rate processing of software-defined networking, storage, and cybersecurity. BlueField-3 combines powerful computing, high-speed networking, and extensive programmability to deliver software-defined, hardware-accelerated solutions for the most demanding workloads. From

[<https://www.nvidia.com/en-us/networking/products/data-processing-unit/>]

EXOTIC HARDWARE

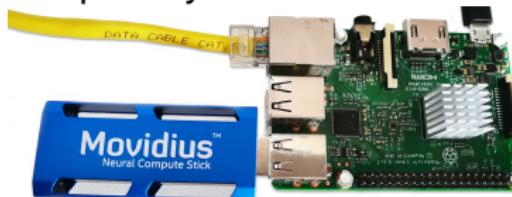


Exotic Hardware

- ▶ Intel Phi multicore CPU, 64 i386 cores:



- ▶ Raspberry PIs + Intel Movidius stick



- ▶ FPGAs



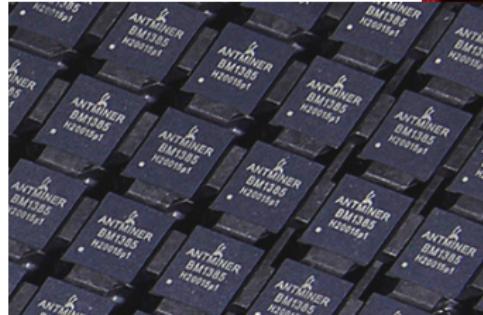
ASICs vs GPUs

Bitcoin-mining and Low-hash-rate GPUs

AntMiner S7: based on ASICs.

Some specs:

- ▶ hash rate: 4.8 THash/s
- ▶ chips per unit: 162 x BM1385
- ▶ power consumption: **1210 W**
- ▶ power efficiency: 0.25 W/GHash
- ▶ price: \$479.95 ~ 2880,- DKK
- ▶ production: **0.16 bitcoin/month**



ASICs vs GPUs

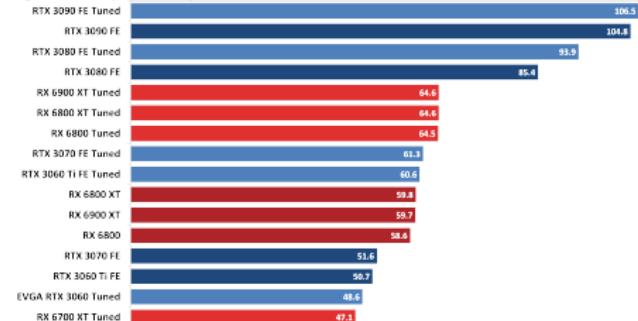
78 x GeForce RTX 30180 Mining Rig..



ASICs vs GPUs

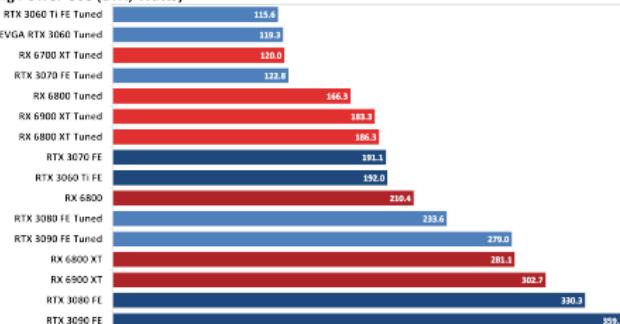
Coin-mining and Low-hash-rate GPUs

GPU Mining Performance
Mining Hash Rate (ETH, MH/s)



tom'sHARDWARE

GPU Mining Performance
Mining Power Use (ETH, Watts)



tom'sHARDWARE

Training Cost and Hardware

The AI Brick Wall - A Practical Limit

Once you know the parameter count, token count, and model architecture, you can easily calculate the theoretical training costs for many popular models. In this example, we will use Nvidia A100s, using \$1.5 per hour per GPU. Model/hardware "FLOPS utilization" will increase from 40% to 60% with larger model sizes, as we explained here, but generally, there isn't much room to go higher on large distributed systems.

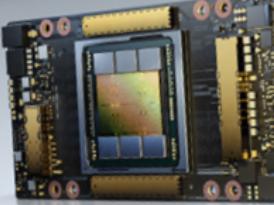
State-Of-The-Art Training Costs

Model	Optimal LLM Training Cost			
	Size (# Parameters)	Tokens	GPU	Optimal Training Compute Cost
MosaicML GPT-30B	30 Billion	610 Billion	A100	\$ 325,855
Google LaMDA	137 Billion	168 Billion	A100	\$ 368,846
Yandex YALM	100 Billion	300 Billion	A100	\$ 480,769
Tsinghua University Zhipu.AI GLM	130 Billion	400 Billion	A100	\$ 833,333
OpenAI GPT-3	175 Billion	300 Billion	A100	\$ 841,346
A121 Jurassic	178 Billion	300 Billion	A100	\$ 855,769
Bloom	176 Billion	366 Billion	A100	\$ 1,033,756
DeepMind Gopher	280 Billion	300 Billion	A100	\$ 1,346,154
DeepMind Chinchilla	70 Billion	1,400 Billion	A100	\$ 1,745,014
MosaicML GPT-70B	70 Billion	1,400 Billion	A100	\$ 1,745,014
Nvidia Microsoft MT-NLG	530 Billion	270 Billion	A100	\$ 2,293,269
Google PaLM	540 Billion	780 Billion	A100	\$ 6,750,000

This table is a theoretical optimal cost to train the model. It does not account for the people required, M

NVIDIA A100 Tensor Core GPU

Unprecedented acceleration at every scale



Operating the Most Important Work of Our Time

A A100 Tensor Core GPU delivers unprecedented acceleration at every scale to power the world's highest-performing elastic data center platform.

Amazon Deliver to Denmark All - A100 BOGB

All Today's Deals Customer Service Registry Gift Cards Sell

Back to results



NVIDIA Tesla

A100 Ampere 40 GB Graphics Card - PCIe 4.0 - Dual Slot

Brand: Generic 2 ratings

-5% \$8,009.99

Median price: \$8,599.60 ±
Eligible for Return, Refund or Replacement within 30 days of receipt.

Graphics Coprocessor NVIDIA Tesla A100

Brand: Generic

Graphics Ram Size 40 GB

GPU Clock 1410 MHz

Click image to open expanded view

[<https://www.semanalysis.com/p/the-ai-brick-wall-a-practical-limit>]

[<https://www.nvidia.com/en-us/data-center/a100/>]

Training Cost and Hardware

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Green | New Energy

Artificial Intelligence Is Booming—So Is Its Carbon Footprint

Greater transparency on emissions could also bring more scrutiny



[https://www.bloomberg.com/news/articles/2023-03-09/
how-much-energy-do-ai-and-chatgpt-use-no-one-knows-for-sure?leadSource=uverify%20wall](https://www.bloomberg.com/news/articles/2023-03-09/how-much-energy-do-ai-and-chatgpt-use-no-one-knows-for-sure?leadSource=uverify%20wall)

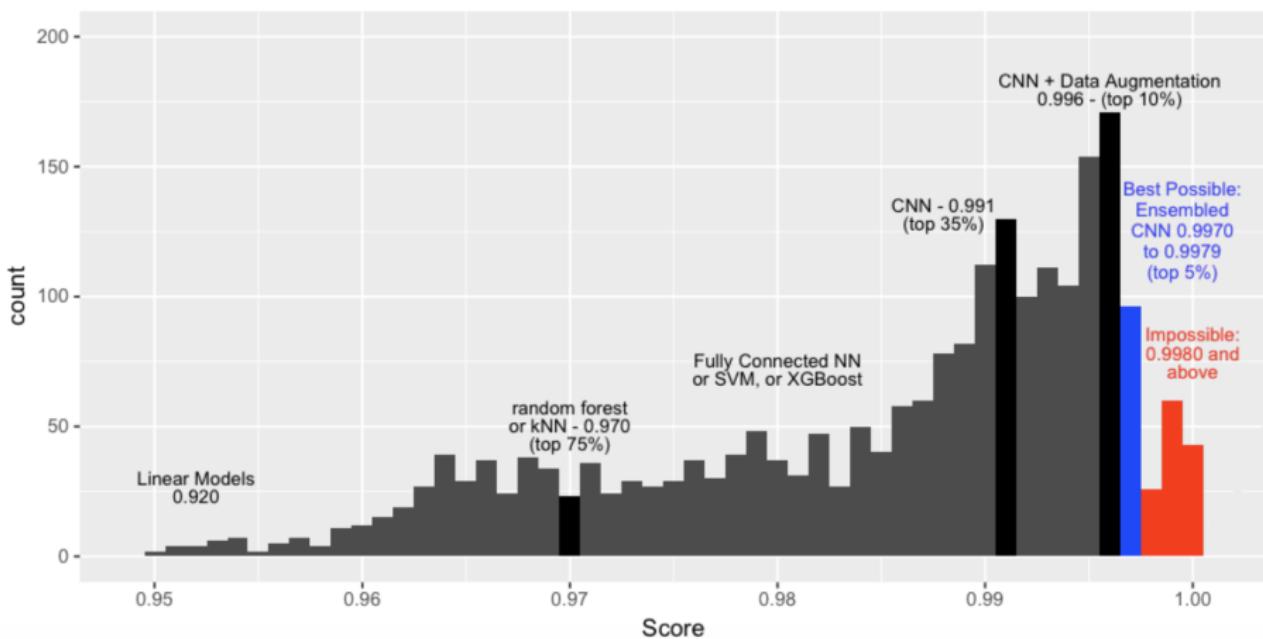


Qd MNIST Search Quest II

The LeNET-5 Architecture on MNIST

Histogram of Kaggle MNIST

public leaderboard scores, July 15 2018



Qd MNIST Search Quest II

```
F23: Grp01: score=0.9809 SVC  
E22: Grp05: score=0.983, SVC, F22: Grp05: score=0.990, SGDClassifier  
E21: Grp28: score=0.973, KNN, F21: Grp20: score=0.979, SVC
```

E2023: Grp27, SVC dat and traning time??

```
14/10 09:04> Grp 27: ('best: dat=N/A, score=0.98163,  
model=SVC(C=11,gamma='2.309171593150975e-09',kernel='rbf')', SVC(C=11,  
gamma=2.309171593150975e-09))
```

```
Grp27: score=0.98163, model=SVC(..), dat correct?  
Grp10: score=0.96863, model=RandomForestClassifier(..)  
Grp26: score=0.96963, model=Pipeline(..)  
Grp25: score=0.96190, model=Pipeline(..)  
Grp08: score=0.95150, model=SVC(..)  
Grp09: score=0.95150, model=SVC(..)
```