



## LESSON 12: 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

- ▶ MNIST Search Quest Hi-Score Cake.
- ▶ 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.

# OUTDATED: ChatGPT and the Press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>

## 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 inddarbejde 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

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# Frameworks for Machine Learning

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

# 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

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# Hardware for Machine Learning

Methods and Terminology (SKIP most except  $\mu, \eta$ )

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).

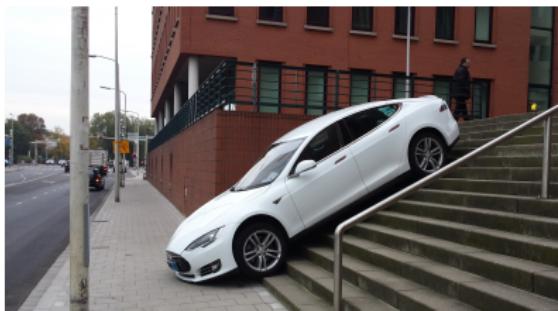
▶ Big-data:

▶ 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,

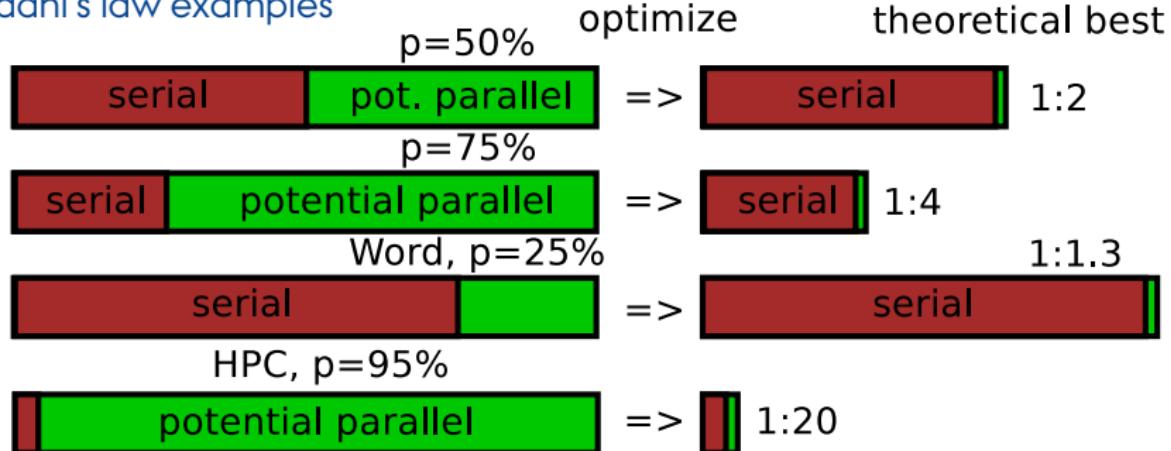
$s$ : parallel fraction speedup factor.

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  $S_{\max} \gg 2$ .

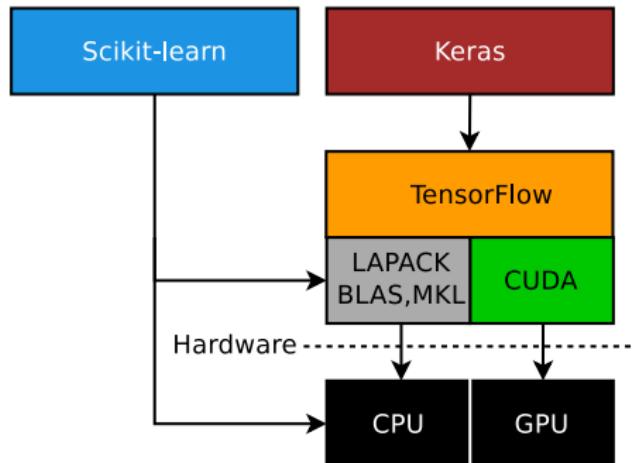
A **1:5 speedup** is a good, ad-hoc compromise btw. a fast program and a costly optimization dev. phase.

What does Donald E. Knuth say about premature optimization?

*"Root of all evil!"*



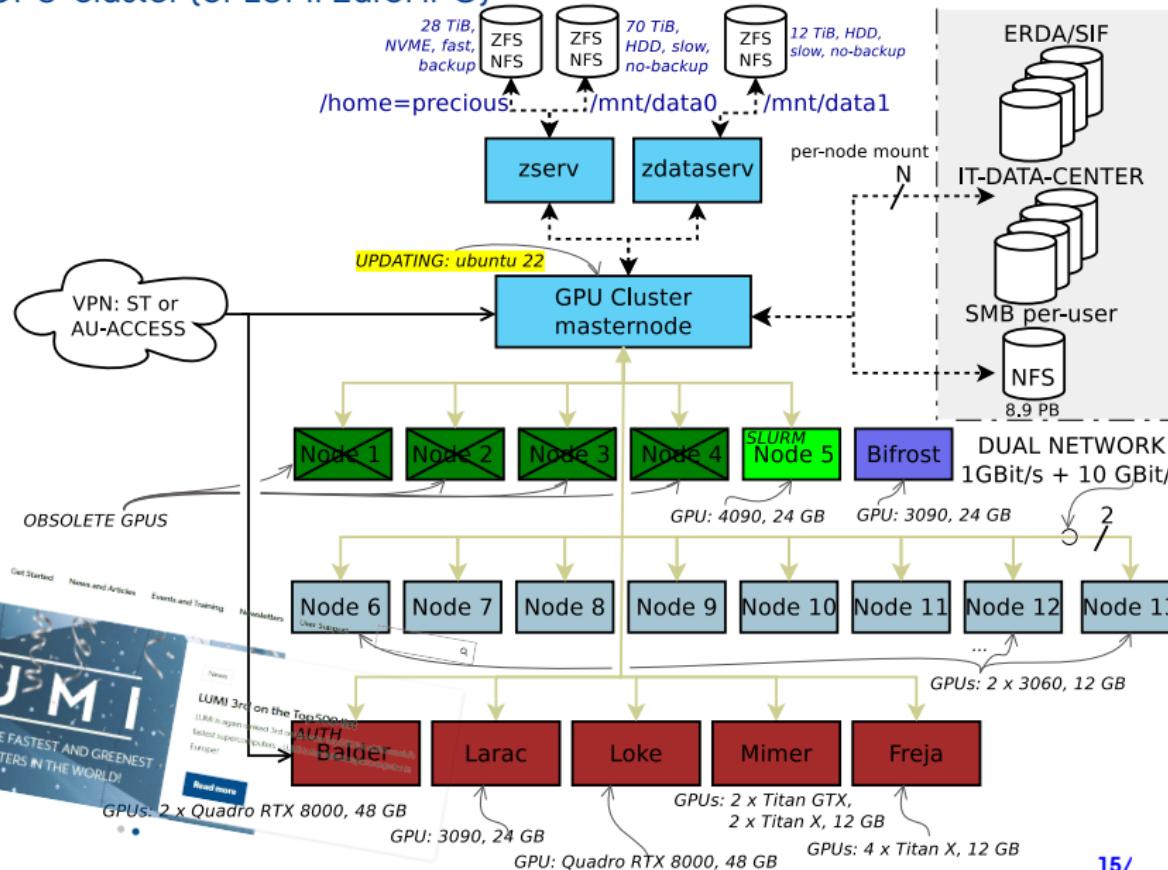
# RESUMÉ: Keras and Tensorflow



- 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)

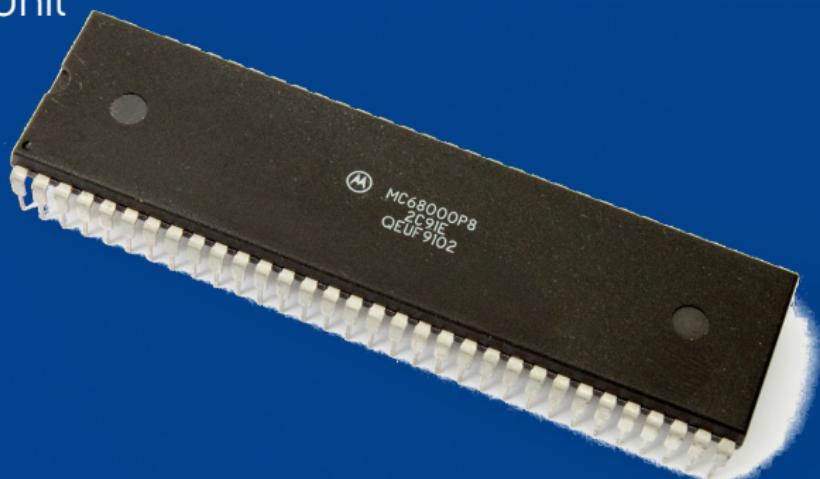
## The ECE GPU-cluster (or LUMI EuroHPC)



# CPUS

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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>

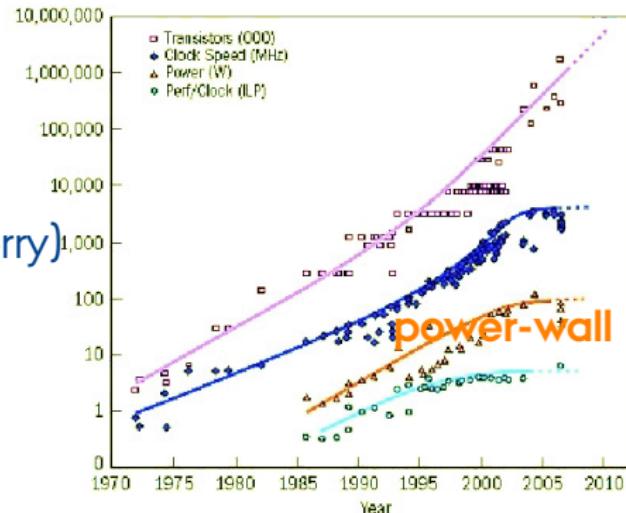
<https://www.pugetsystems.com/labs/hpc/Build-TensorFlow-GPU-with-CUDA-9-1-MKL-and-Anaconda-Python-3-6-using-a-Docker-Container-1134>

# 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:

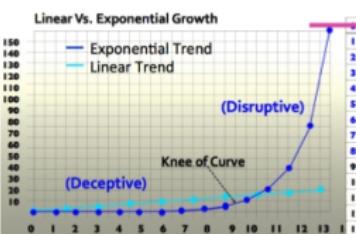
- ▶ no ML-algo GPU hardware enabled,
- ▶ many ML-algo not even multicore aware!

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



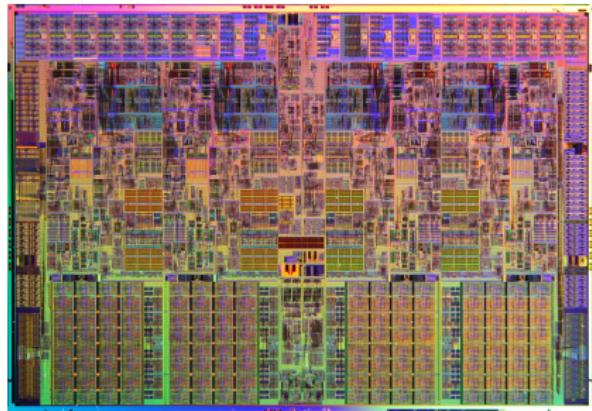
# GP-GPUS

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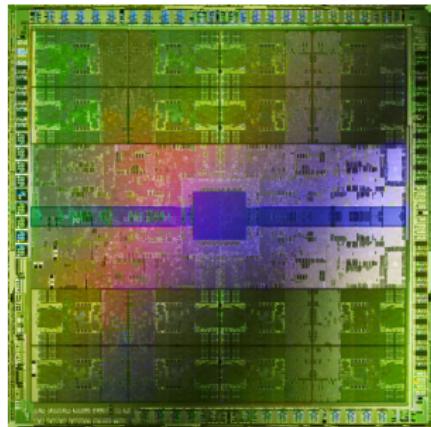
General-Purpose Graphical Processing Unit



# CPUs vs GPUs



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



Fermi GPU  
die size:  $520 \text{ mm}^2$   
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?

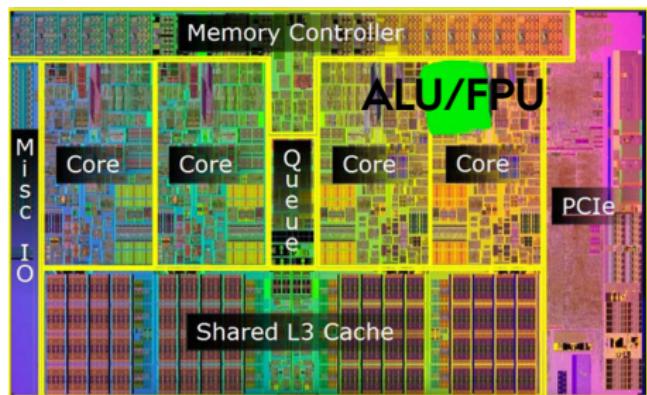
*What makes GPUs such excellent HW for Machine Learning?*

**ALU:** Arithmetic logic unit

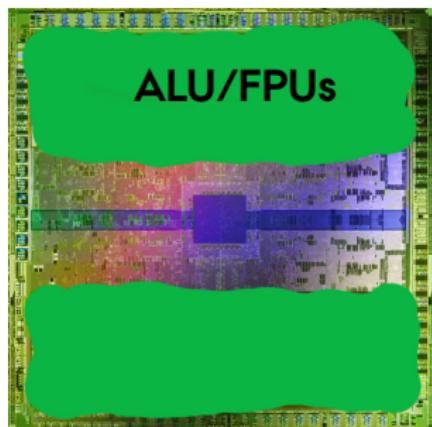
**FPU:** Floating-point unit

**Memory Controller:** six controllers on GPU,

**CPU:** lots of speculative execution; waste of transistors.



CPU (type?)  
with one ALU/FPU marked



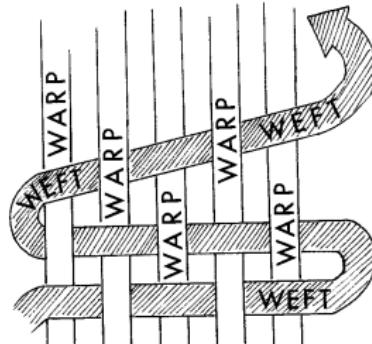
Fermi GPU  
ALUs/FPUs all over

# 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 L<sub>1</sub> and L<sub>2</sub> 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

Tex

Tex

Tex

Tex

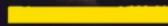
# GPUs

## 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

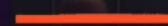


Sharpen

\*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

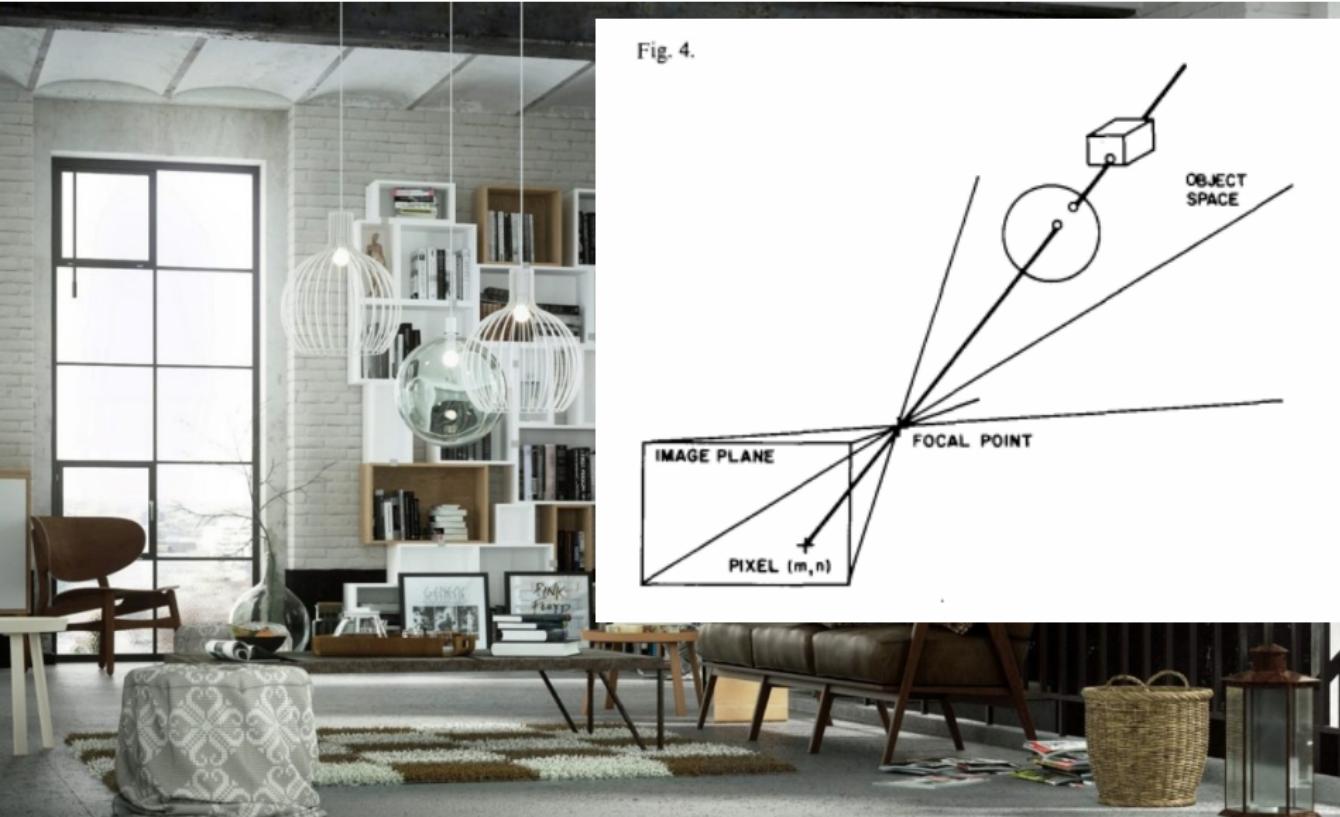
FPS 31 fps



Ray Tracing+Sharpen

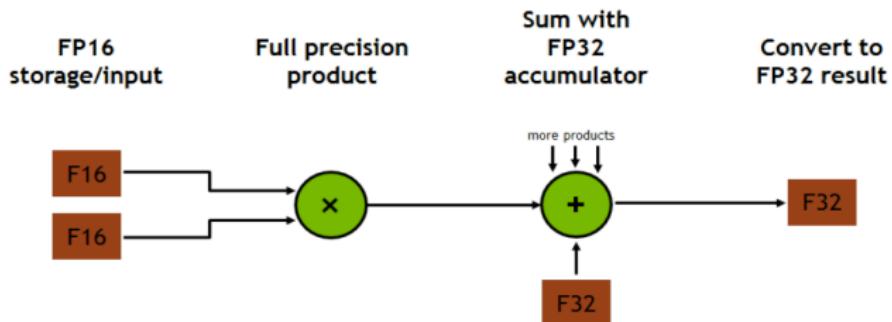
# GPUs

## Tensor cores: Raytracing vs Rasterization on GPUs



# GPUs

Tensor Cores  
(SKIP most)



$$D = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix}_{\text{FP16 or FP32}} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix}_{\text{FP16}} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}_{\text{FP16 or FP32}}$$

FP16 or FP32

FP16

FP16

FP16 or FP32

Tesla V100's Tensor Cores deliver up to **125 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](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

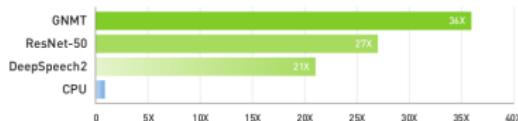
## Turing Tensor Core GPU (this is not a commercial!)

### GPU Acceleration Core Mainstream

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

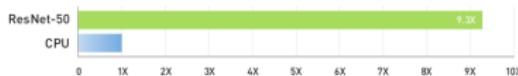
Its low-profile, 70-watt (W) design is designed for enterprise data centers, making it ideal for demanding workloads including machine learning, deep learning, and virtual desktop infrastructure (VDI). It also offers the efficiency of smaller PCIe form factors for maximum system options and convenience.

#### 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():`

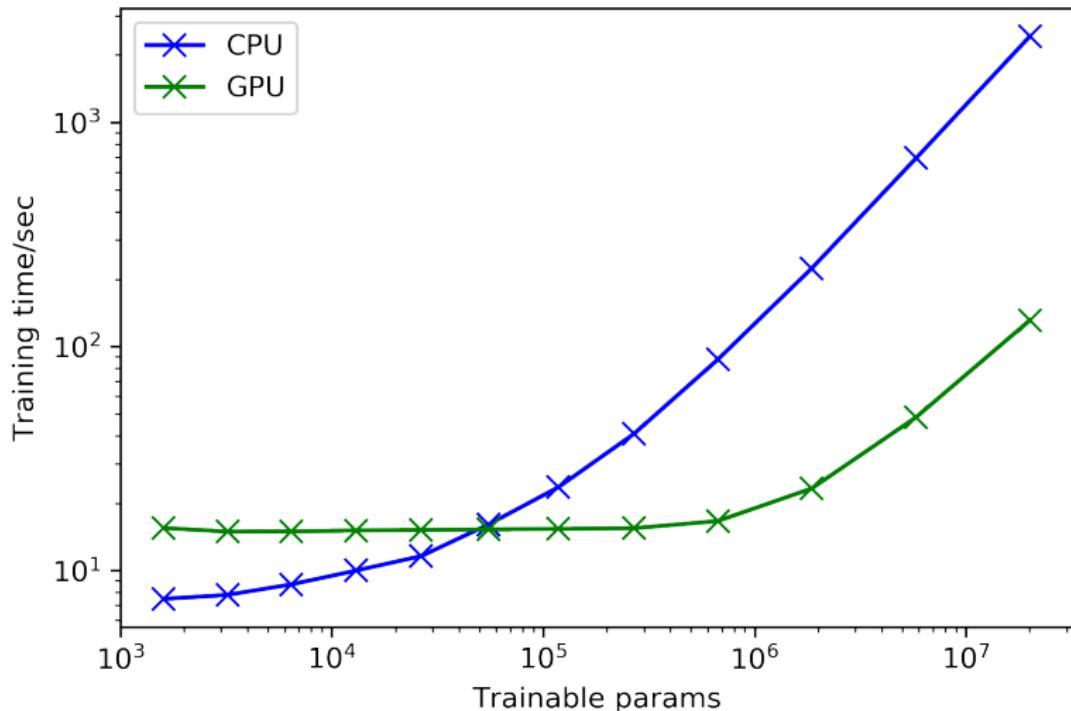
```
1 # i=12, n=4096
2 #
3 # Layer (type)          Output Shape       Param #
4 # =====
5 # dense_46 (Dense)     (None, 4096)        3215360
6 #
7 # dropout_31 (Dropout) (None, 4096)        0
8 #
9 # dense_47 (Dense)     (None, 4096)        16781312
10 #
11 # dropout_32 (Dropout) (None, 4096)        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...

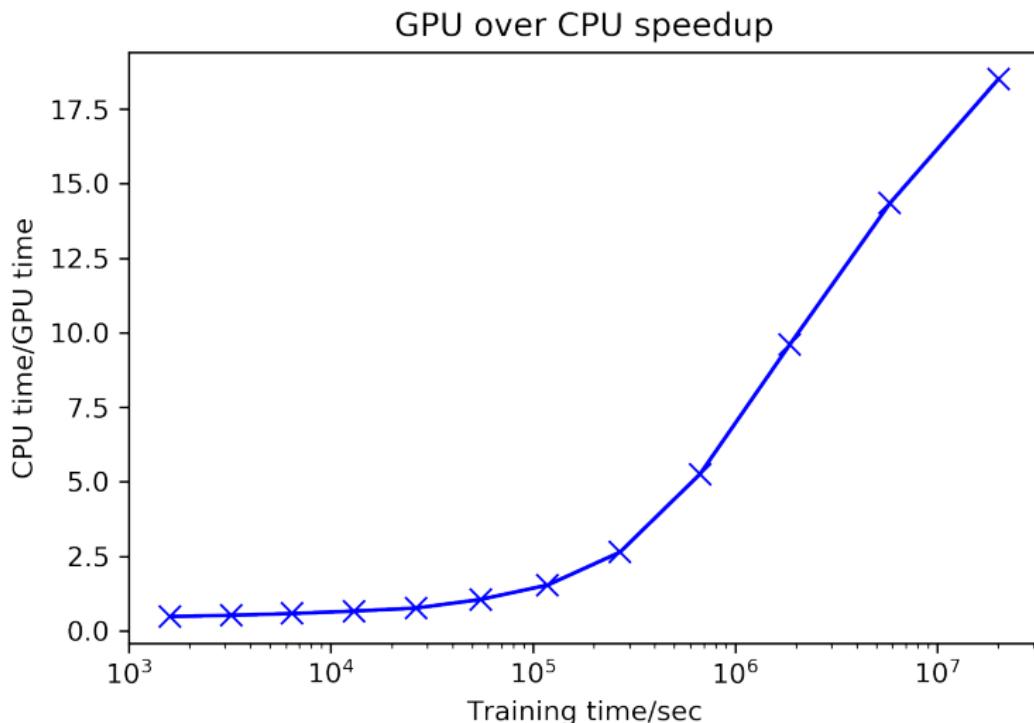
Training time-vs-Trainable params



# GPUs

Actual test on the GPU-server

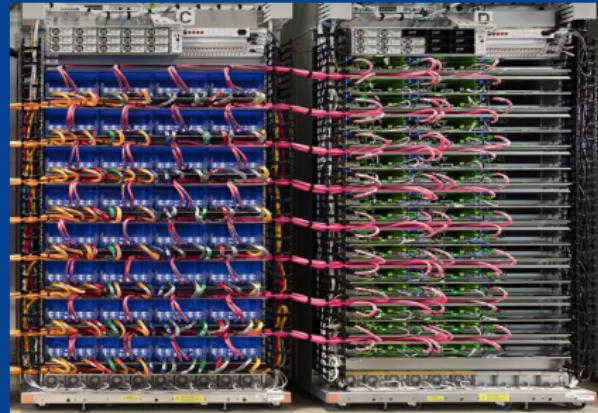
CPU vs GPU on MNIST for a three layer NN with dropout...



# TPUS

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Tensor Processing Units



# TPUs

## Tensor Processing Units

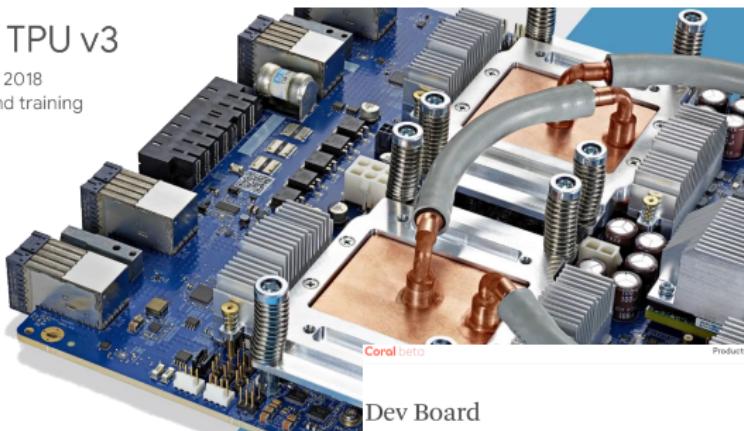
### Custom ASICs by Google



#### 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

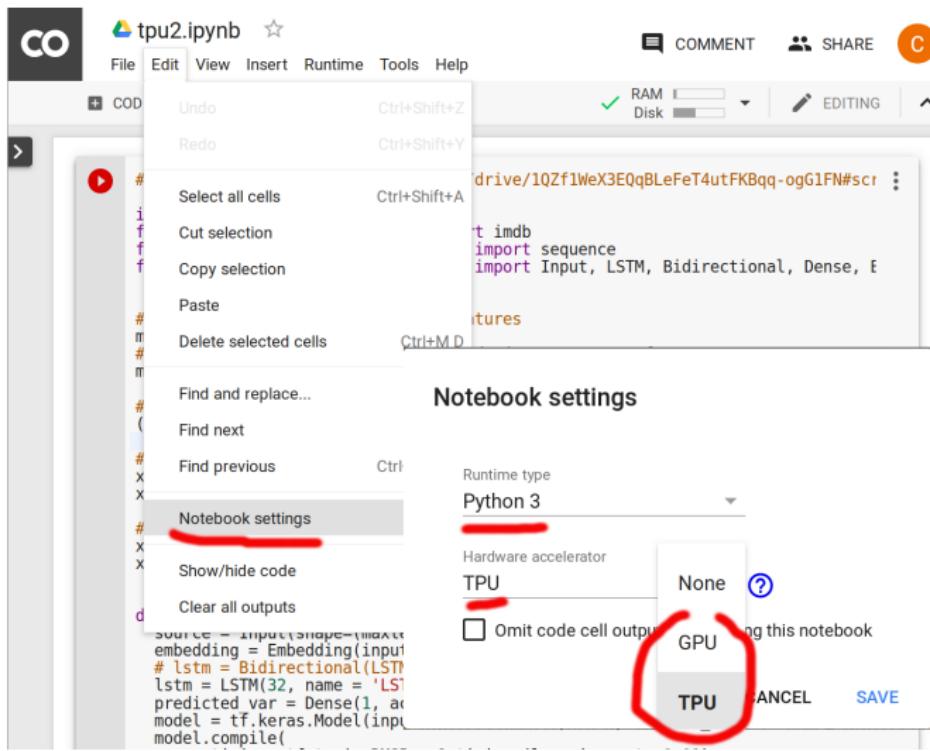
[\[https://coral.withgoogle.com/products/dev-board/\]](https://coral.withgoogle.com/products/dev-board/)



# TPUs

## Access to TPUs (SKIP)

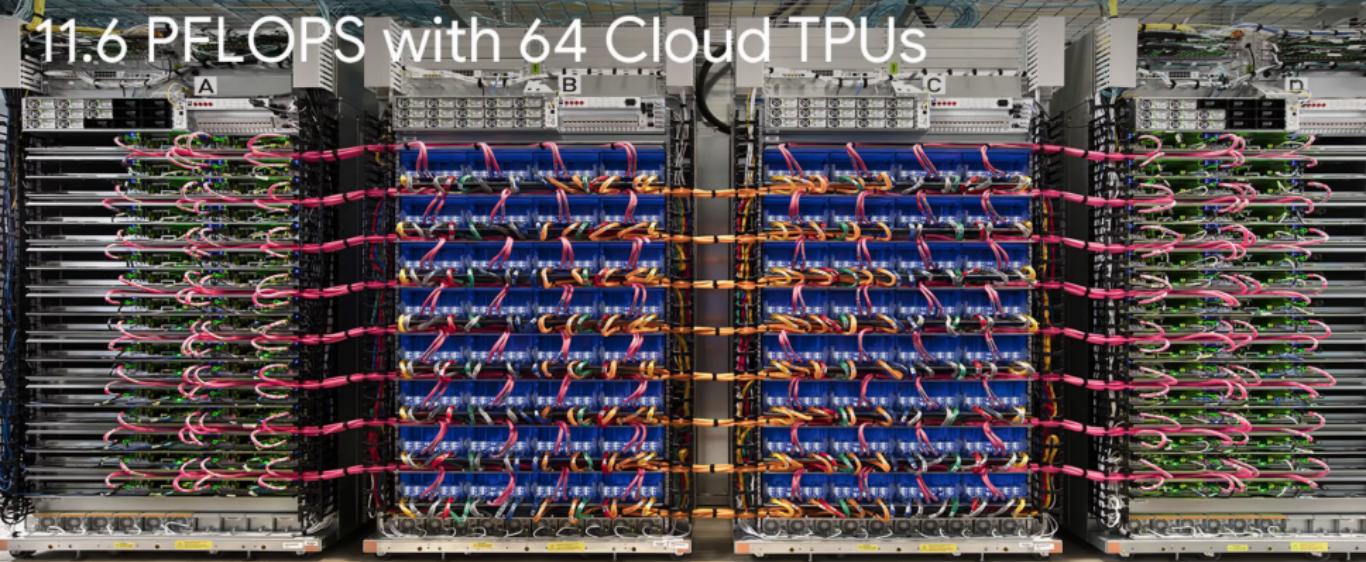
Free Jupyter Notebook environment with access to TPUs:  
<https://colab.research.google.com>



# 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

The screenshot shows a web browser window with the URL <https://www.nvidia.com/en-us/networking/products/data-processing-unit/>. The page title is "BlueField Data Processing Unit". The main heading is "Explore Leading Portfolio of DPUs". Below the heading is a large image of a BlueField-3 DPU card, which is a black printed circuit board with several yellow circular components and two metal heat sinks. A white cursor arrow points towards the center of the card. Below the image is the product name "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

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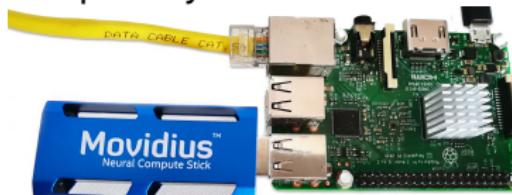


# Exotic Hardware

- ▶ Intel Phi multicore CPU, 64 i386 cores:



- ▶ Raspberry PIs + Intel Movidious stick



- ▶ FPGAs



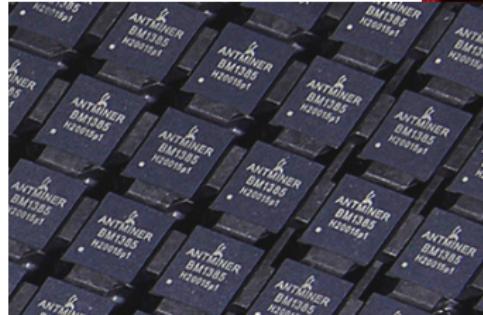
# ASICs vs GPUs

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

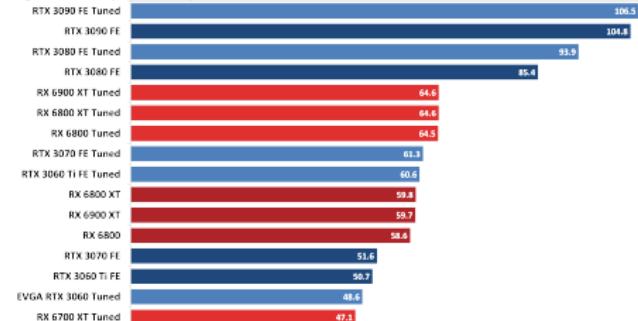
78 x GeForce RTX 3080 Mining Rig..



# ASICs vs GPUs

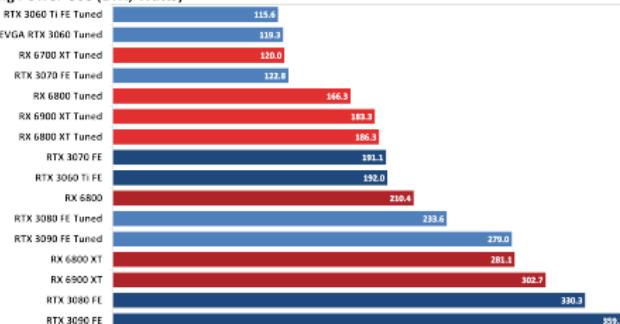
## Coin-mining and Low-hash-rate GPUs

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

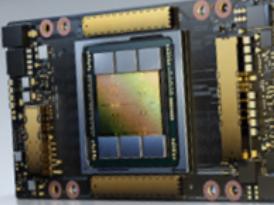
Model	Optimal LLM Training Cost			
	Size (# Parameters)	Tokens	GPU	Optimal Training Compute Cost
MosaicML GPT-30B	30 Billion	610 Billion	A100	\$ 325,855
Google LaMDA	137 Billion	168 Billion	A100	\$ 368,846
Yandex Yalm	100 Billion	300 Billion	A100	\$ 480,769
Tsinghua University Zhipu.AI GLM	130 Billion	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, accounting for the people required. More



## 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. Powered by the NVIDIA Ampere architecture, the A100 is the most powerful GPU ever made, featuring 40GB of memory and a massive 40 trillion floating-point operations per second (TFLOPs) of compute performance.

Amazon Deliver to Denmark All - A100 BOGB

All Today's Deals Customer Service Registry Gift Cards Sell

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

Brand: Generic 5 ★★★★☆ 2 ratings -5% \$8,009.99 Median price: \$8,599.66 ⓘ Eligible for Return, Refund or Replacement within 30 days of receipt ⓘ

Graphics Processor NVIDIA Tesla A100

Brand Generic

Graphics 40 GB

RAM Size 1410 MHz

GPU Clock 1410 MHz

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

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

44/49

# Training Cost and Hardware

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## Artificial Intelligence Is Booming—So Is Its Carbon Footprint

Greater transparency on emissions could also bring more scrutiny



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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)

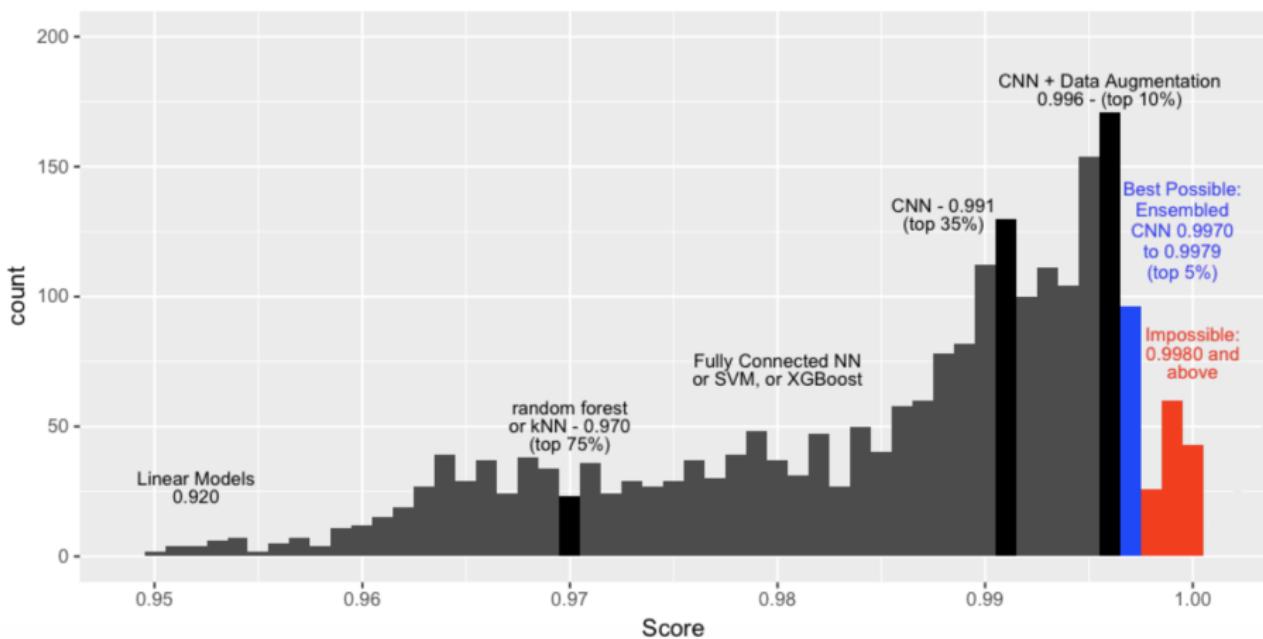


# Qd MNIST Search Quest II

## The LeNET-5 Architecture on MNIST

## Histogram of Kaggle MNIST

public leaderboard scores, July 15 2018



# Qd MNIST Search Quest II

Fra tidligere semester

E2023: Grp13: score=0.984, SVC

F2023: Grp01: score=0.981, SVC

E2022: Grp05: score=0.983, SVC

F2022: Grp05: score=0.990, SGDClassifier (iris?)

E2021: Grp28: score=0.973, KNN

F2021: Grp20: score=0.979, SVC

# Qd MNIST Search Quest II

F2024: Grp25, RandomForestClassifier(..) , dat and training time??

```
16/03 22:43> "Grp25: dat=mnist, score=0.97224, model=RandomForestClassifier(  
    bootstrap=False, ccp_alpha=0.0, class_weight='balanced', criterion='gini',  
    max_depth=None, max_features='sqrt', max_leaf_nodes=None,  
    min_samples_leaf=1, min_samples_split=2, n_estimators=500, warm_start=False)"  
  
Grp05: score=0.97210, model=RandomForestClassifier(..)  
Grp25: score=0.97204, model=RandomForestClassifier(..)  
Grp10: score=0.96873, model=RandomForestClassifier(..)  
Grp15: score=0.96869, model=RandomForestClassifier(..)  
Grp17: score=0.95753, model=RandomForestClassifier(..)  
Grp13: score=0.95196, model=HistGradientBoostingClassifier(..)  
Grp08: score=0.94330, model=RandomForestClassifier(..)  
Grp01: score=0.94131, model=RandomForestClassifier(..)  
Grp06: score=0.91504, model=Pipeline(..)  
Grp12: score=0.90963, model=LinearSVC(..)  
Grp23: score=0.90963, model=LinearSVC(..)  
Grp09: score=0.90780, model=SGDClassifier(..)  
Grp09: score=0.89559, model=SGDClassifier(..)  
Grp20: score=0.88518, model=SGDClassifier(..)  
Grp21: score=0.88390, model=SGDClassifier(..)  
Grp04: score=0.87820, model=SGDClassifier(..)  
Grp30: score=0.86241, model=LinearSVC(..)  
Grp11: dat=iris !!, score=0.99048, model=SGDClassifier(..)  
  
missing groups: 7+14+16+19+22
```