# L5: HPC for AI applications & Environmental impact of computation

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# HPC for AI & Environmental impact of computation

# Introduction to AI applications

# AI Renaissance: Neural Networks

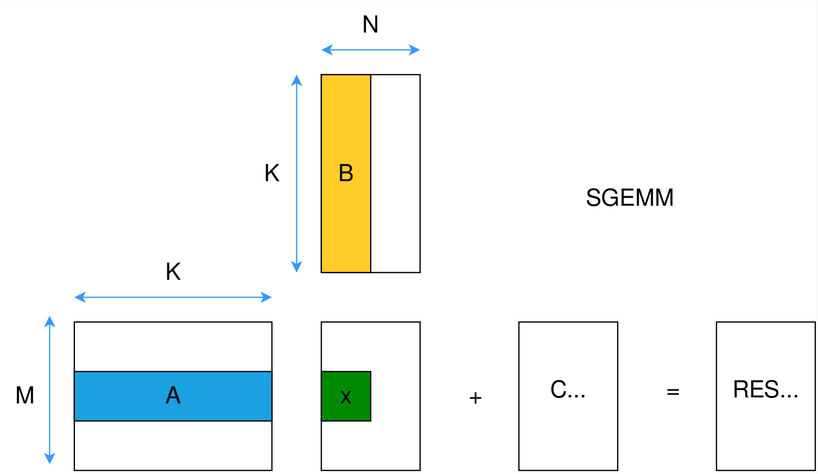
- 2012: **AI renaissance** brought by increased data availability and computation ressources
    - breakthroughs in multiple domains
    - many innovations: algorithms, specialized processors, optimizations
- Most systems use **neural networks**:
    - Training (stochastic gradient descent + backpropagation)
    - Inference (forward pass)
- For both, **the bottleneck is matrix multiplication**

# Objectives

- Explain why dense linear algebra (GEMM) dominates NN compute
- Core SGEMM kernel ideas and common optimizations
- Use Roofline model to identify bottlenecks
- Understand mixed precision & quantization tradeoffs for energy/perf

Single-precision General Matrix-Matrix multiplication (SGEMM):

$$RES = A \times B + C$$



# Naive SGEMM implementation (pseudocode)

```
// Initialize RES to C
for (i = 0; i < M; i++)
    for (j = 0; j < N; j++)
        RES[i][j] = C[i][j];

// Matrix multiply
for (i = 0; i < M; i++) {
    for (j = 0; j < N; j++) {
        for (k = 0; k < K; k++) {
            RES[i][j] += A[i][k] * B[k][j];
        }
}
```

- FLOPS: $2 \times M \times N \times K$
- Memory: $4 \times (M \times K + K \times N + M \times N)$ bytes

# Locality issues in naive SGEMM

order in memory $\longrightarrow$

$$\begin{bmatrix} \color{red}{b_{11}} & b_{12} & b_{13} & b_{14} \\ \color{red}{b_{21}} & b_{22} & b_{23} & b_{24} \\ \color{red}{b_{31}} & b_{32} & b_{33} & b_{34} \\ \color{red}{b_{41}} & b_{42} & b_{43} & b_{44} \end{bmatrix}$$

- Stride in accessing B (column-major)
    - Poor spatial locality
    - Difficult to vectorize
    - Cache misses for large matrices (reuse distance too large)
- **Low arithmetic intensity**: $\approx 0.5$ FLOP/byte for large matrices

# Reordering loops (i,k,j)

- Sums `RES[i][j] += A[i][k] * B[k][j];` are independent → reorder loops:

```
for (i = 0; i < M; i++)
    for (k = 0; k < K; k++)
        for (j = 0; j < N; j++)
            RES[i][j] += A[i][k] * B[k][j];
```

- `A[i][k]` does not depend on `j` → load once, reuse N times
- `RES` and `B` accesses are now stride-1 (row-major)

```
for (i = 0; i < M; i++)
    for (k = 0; k < K; k++) {
        const float temp = A[i][k];
        for (j = 0; j < N; j++)
             RES[i][j] += temp * B[k][j];
        }
```

- Better spatial locality and easier to vectorize

Inner loop assembly for (i,k,j) ordering with AVX (8 `float` in a vector):

```
.loop:                                       # Inner loop
    vmovss  xmm0, DWORD PTR A[i][k]          # Load A[i][k]
    vbroadcastss ymm0, xmm0                  # Broadcast scalar to
    all lanes
    vmovaps ymm1, YMMWORD PTR B[k][j]        # Load B[k][j:j+8]
    vfmadd231ps ymm2, ymm1, ymm0             # Fused multiply-add
    vmovaps YMMWORD PTR RES[i][j], ymm2      # Store RES[i][j:j+8]
    add     j, 8                             # Increment j by 8 (
    vector width)
    cmp     j, N                             # Compare j with N
    jl      .loop                            # Loop if j < N
```

# Problems with (i,k,j) ordering

- Temporal locality analysis:
  - **GOOD**: $A[i][k]$ reused in the inner loop, reuse distance $1$.
  - **MEDIUM** : For a fixed $(i,j)$, each $RES[i][j]$ revisited once per k. So reuse distance $K$ (one full row).
    - To keep RES in cache between uses you would need cache $\geq K \times 4B$
  - **BAD** : For a fixed $(k,j)$, $B[k][j]$ used once per i. So reuse distance $K \times N$ (entire B matrix).
    - To keep B in cache between uses you would need cache $\geq K \times N \times 4B$
- Still poor temporal locality for large matrices
- Solution: **tiling / blocking** to increase reuse

# Blocking (tiling)

- **Idea:** operate on sub-matrices blocks that fit in cache

$$\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \times \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} = \begin{bmatrix} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \end{bmatrix}$$

```
#define BS 64 // Block size
// Loop over blocks
for (ii = 0; ii < M; ii += BS)
    for (kk = 0; kk < K; kk += BS)
        for (jj = 0; jj < N; jj += BS)

            // Operate on blocks A[ii:ii+BS, kk:kk+BS],
            // B[kk:kk+BS, jj:jj+BS], RES[ii:ii+BS, jj:jj+BS]
            for (i = ii; i < min(ii+BS, M); i++)
                for (k = kk; k < min(kk+BS, K); k++)
                    for (j = jj; j < min(jj+BS, N); j++)
                        RES[i][j] += A[i][k] * B[k][j];
```

# Parallelization

- Each block operation is independent → parallelize over blocks

```
#pragma omp parallel for collapse(3)
for (ii = 0; ii < M; ii += BS)
    for (jj = 0; jj < N; jj += BS)
        for (kk = 0; kk < K; kk += BS)
            // Block multiplication as before
```

- Each thread works on its own block → no false sharing
- Synchronization only at the end of the parallel region
- NUMA considerations: pin threads to cores, allocate memory close to threads
- Load balancing: static scheduling usually works well for large matrices

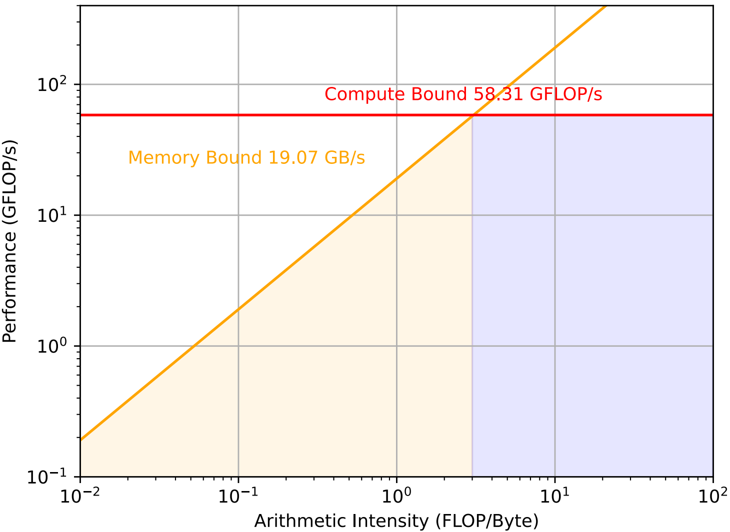
# Libraries & autotuners

- Highly optimized SGEMM implementations exist:
    - OpenBLAS, Intel MKL for CPU
    - NVIDIA cuBLAS for GPU
- Implementations use blocking, vectorization, parallelization, and many architecture-specific optimizations
- Libraries are carefully tuned for different sizes and shapes of matrices.
- Autotuners (e.g., ATLAS, TVM, **MLKAPS**) can generate optimized code for specific hardware and problem sizes.

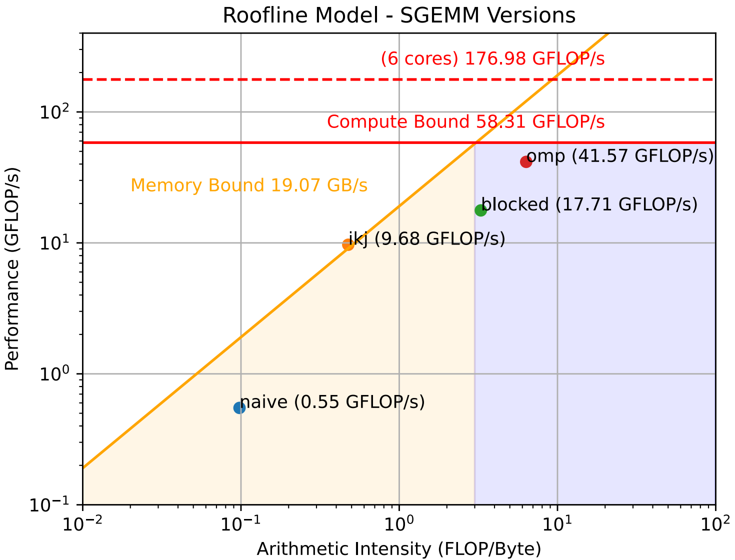
# Roofline model - Definitions

- Hypothesis: performance is limited by either compute or memory bandwidth
  - performance: FLOP/s (vertical axis)
  - memory bandwidth: Bytes/s
  - arithmetic intensity: FLOP/byte (horizontal axis)
- Simple visual model to understand bottlenecks

# Roofline model - Bounds



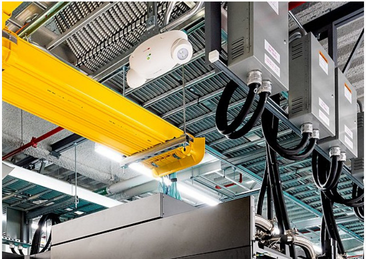
# Roofline model - SGEMM analysis



# Environmental impact of computation

# Introduction

- **Major ecological crisis**: French roadmap targets carbon neutrality in 2050 (Stratégie Nationale Bas Carbone).
- Requires a **40% energy consumption reduction**.
- HPC **part of the solution**: modeling and improving complex systems
- HPC **part of the problem**: Frontier system at ORNL
    - More than $10^{18}$ floating point operations per second
    - Consumes **21MW**: the energy of a small town ($16\,000$ french houses)



# Environmental impact of computation

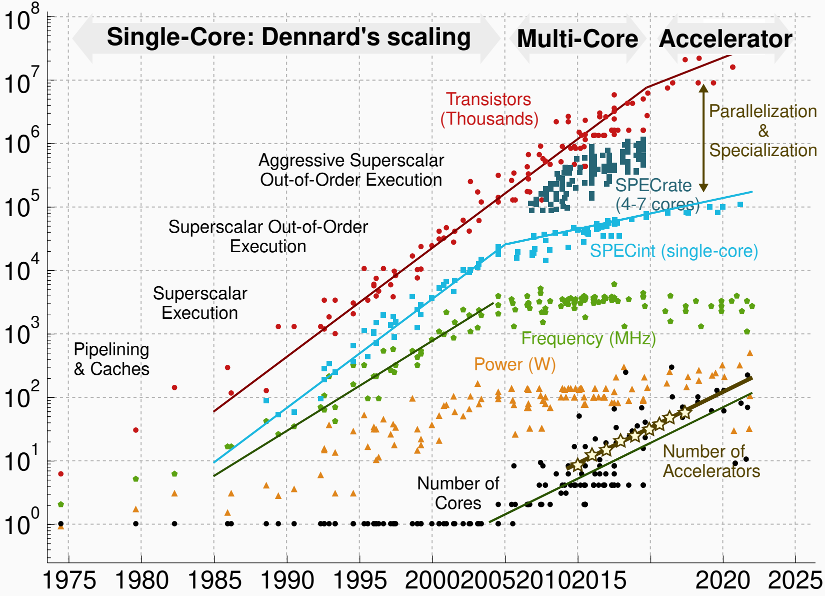
- The ICT sector consumes $\approx$ **5% of the energy** wordwide
- It accounts for **1.8% - 2.8%** of emitted GHG [Freitag, 2021]:
    - Accounts for embodied emissions.
    - Shadow energy during the **whole life-cycle: mining, fabrication, transportation, recycling**.
- GHG emmissions are only one of the sustainability issues
    - rare-earth mining and waste disposal (eg. Agbogbloshie).
        - human-right abuses, health issues, pollution.
- **This presentation focus on energy consumption of HPC**

# What about renewable energies?

- Low-carbon electricity is a **limited ressource**
- Decarbonation $\rightarrow$ huge increase in electricity demand
  - Heating, Transportation, Industry
  - Computing will compete for low-carbon electricity.

# Energy consumption of HPC

# Evolution of processing units [Batten, 2023]




C. Batten, M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, K. Rupp & [Y. Shao, IEEE Micro'15] & [C. Leiserson, Science'20]

CMOS Power $P = \underbrace{1/2.C.V^2.f}_{P_{\text{dynamic}}} + \underbrace{V.I_{\text{leak}}}_{P_{\text{static}}}$

For each generation, transistors dimensions reduced by **30%,**

- Voltage and capacitance reduced by 30%
- Frequency increases: $\times 1.4 \approx 1/0.7$
- Surface halved: $0.5 \approx 0.7 \times 0.7$
- Power halved: $\Delta P = 0.7 \times 0.7^2 \times 1/0.7 \approx 0.5$

**Power per surface unit remains constant** but manufacturers double number of transistors and frequency increases:

- Power efficiency doubles every 1.57 years
- Total power increases

# Multicore 2005-2020

- At current scale, leak currents start increasing ($P_{\text{static}} \nearrow$).
  **Power wall slows Dennard's scaling.**
- Computing demand $\rightarrow$ **parallelism** and **specialization**.
- Number of cores increases exponentially since 2005.
- Power efficiency still improving:
  - selectively turning-off inactive transistors;
  - architecture design optimizations;
  - software optimizations.

# AI Accelerators 2020-2024

- For domain specific applications, such as AI, specialized accelerators are used
  - Memory and compute units tuned for a specific problem (matrix multiplication) ;
  - Faster and better power efficiency: GPU, TPU, FPGA, ASIC.

# Analysis of TOP-100 HPC systems

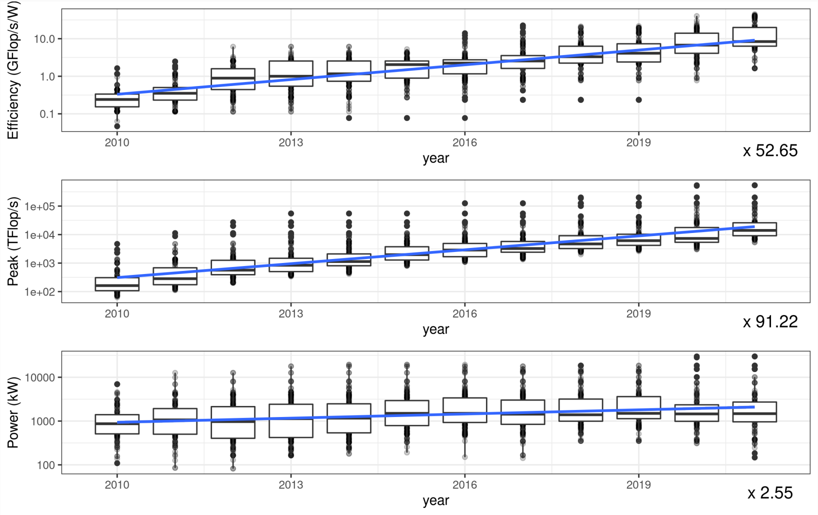



Figure 6: image

# Rebound effects

- In 1865, Jevons shows that steam engine improvements translate into increased coal consumption.
- In HPC, efficiency gains contribute to the rising computation demand.
    1. **net increase of the total power consumption.**
- Rebound effects for data-centers [Masanet, 2020]
    1. 6% increase in energy consumption from 2010 to 2018 (255 % increase in nodes).
- **Indirect rebound effects**: computation advances can contribute to the acceleration of other fields.

# AI energy and computation costs

# Training cost doubles every 3.4 months [OpenAI, 2020]

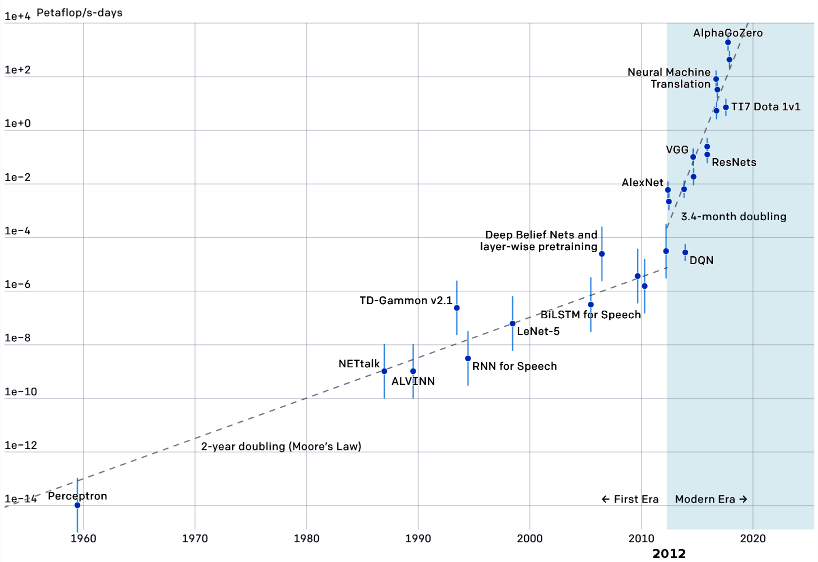
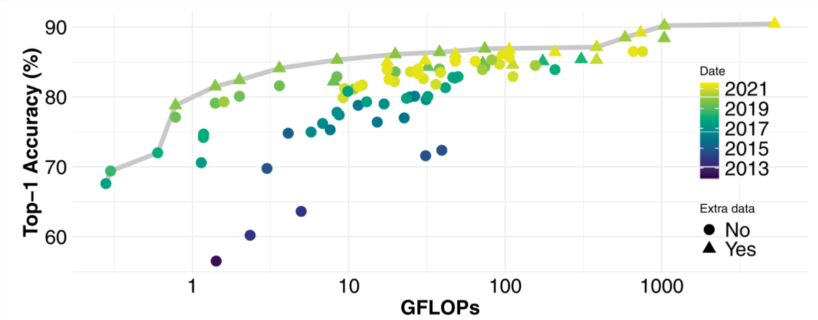


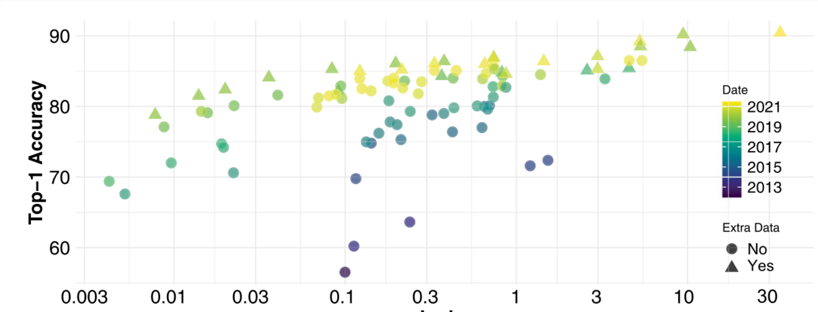

Figure 7: image

# Should we study training or inference?

- **Training**: huge cost but done once
  - GPT3, 175 billion parameters, $\approx$ 314 ZettaFLOP
  - GPT4, 1.7 trillion parameters
- **Inference**: millions of users and requests
  - 80-90% cost of a deployed AI system is spend on inference [NVIDIA, 2019]

# Inference cost - Diminishing returns for computer vision



# More frugal computing?

# Smaller precision / Smaller models for AI

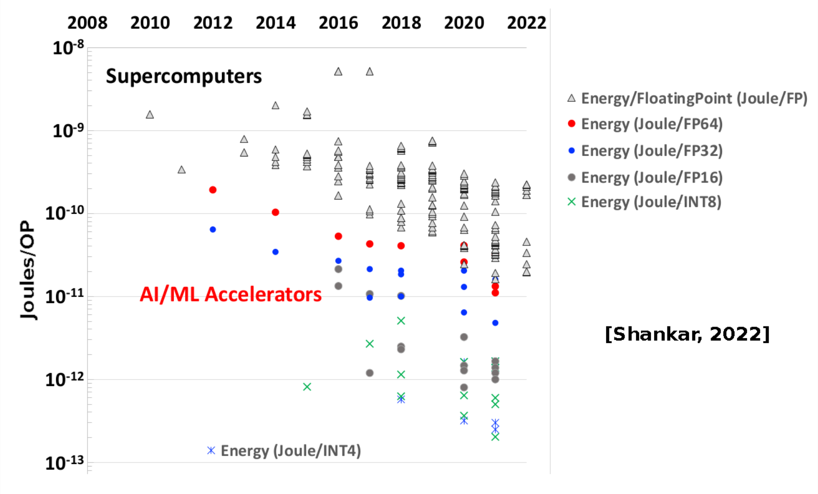


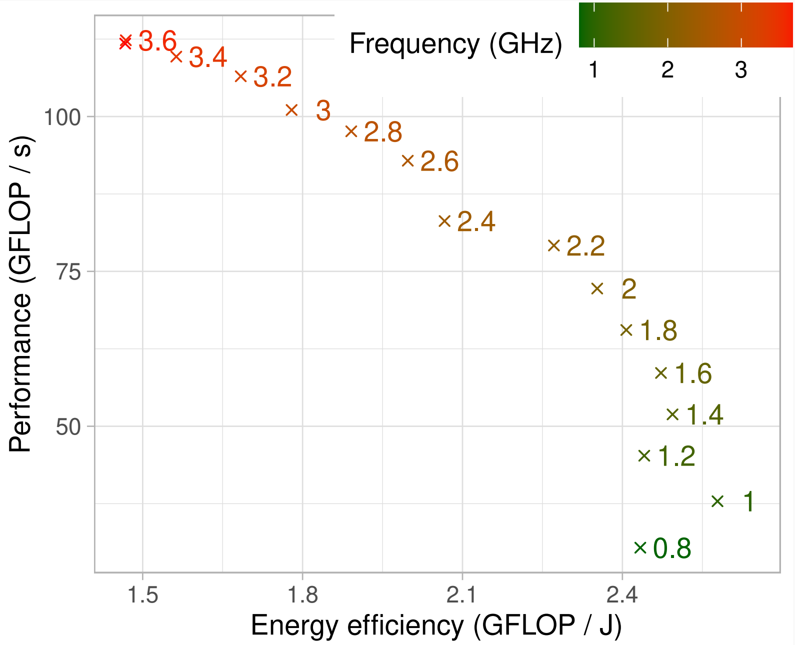

Figure 8: image

LLM success of smaller models (Llama, Chinchilla) fine-tuned for specific tasks with LoRA.

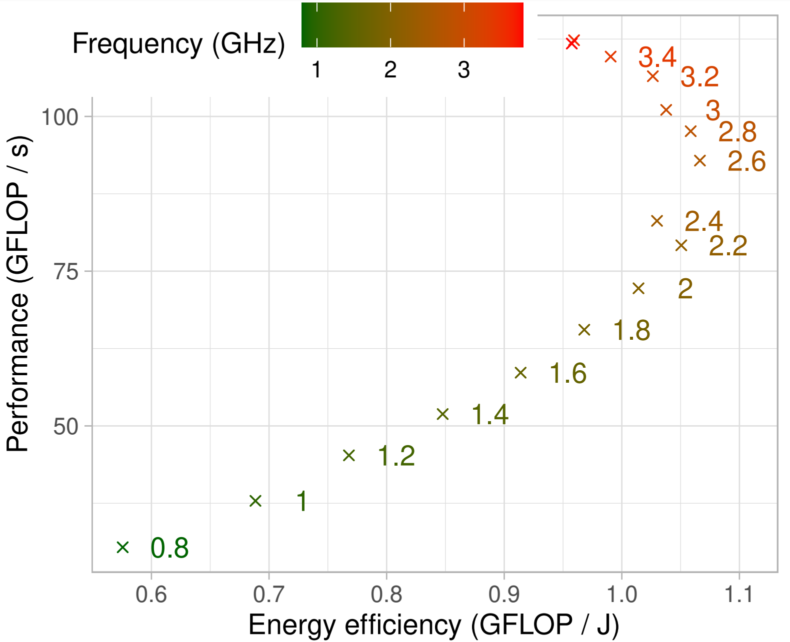
# Tradeoff: Model complexity - Cost - Explainability

- Inference cost grows with model complexity
- Simpler models are often more interpretable
    - Traditional science also prefers simpler models
- DNN not necessary for all tasks

# DVFS study of LU decomposition



# When accounting for the whole system



# Need for an interdisciplinary discussion

- AI / HPC can contribute towards sustainability (eg. acceleration of weather forecast models) ... **but its energy cost must be reduced**
- **Efficiency:**
  - Improve hardware and software
  - Use smaller models / smaller precision

  ... **subject to rebound effects**
- **Frugality in computing:**
  - Balance computation cost vs. outcomes for each task
  - Choose the right sized model
  - Assess the environmental impact

# Exemple: e-health solution in Tanzania [d'Acremont, 2021]

Treatment of febrile children illnesess in dispensaries.

- **IMCI:** Paper-based decision tree WHO
- **e-POCT** CART tree tailored to real data on a standalone tablet
  - Final CART tree easy to interpret and manually checked
  - Randomized-trial $\rightarrow$ better clinical outcomes and antibiotic prescription reduction
- Sophisticated AI that continuously collects patient data and adapts the algorithm ?
  - Increase in hardware and computation costs.
  - Loss in explainability and verification of the algorithm.

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# References - Environmental impact of computation


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