Challenges for Scaling:

Co-Design for Memory Bottleneck, Power and Miniaturization

Group B

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Synthesis

- Large amount of data, that is mostly irregular and at times need to be processed at the edge, poses new challenges for scaling:
- Need for programming, architecture and power improvements.
    - Memory Bottlenecks
    - Portability (Miniaturization and Power efficiency)
    - Programmer productivity

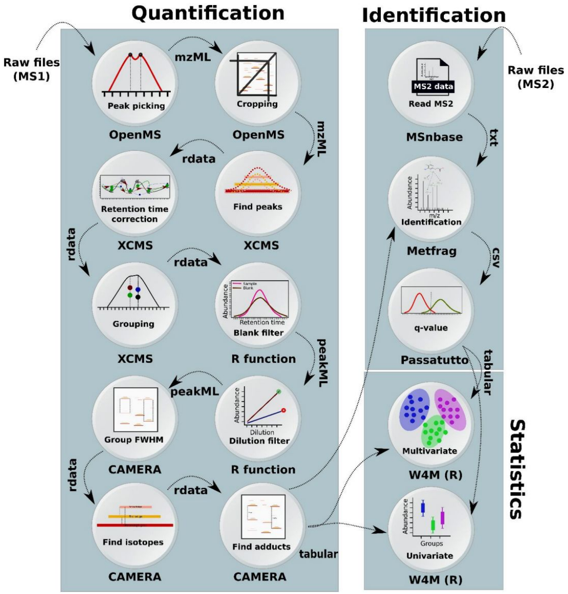
Motivations

- Democratizing Compute: (Bioinformatics & Smart Medical Systems)
  - Dataflow in Scientific Workflows
  - Intelligent Medical Systems Real Time Processing
- Scientific Simulations: (Quantum physics & Weather Forecasting)
  - Multi Precision Arithmetics
  - Data Assimilation & Learning
- Memory Acceleration: (Graph Processing & Machine Intelligence)
  - Non-von Neumann Architectures
    - Continuum Computer Architecture
    - Neuromorphic

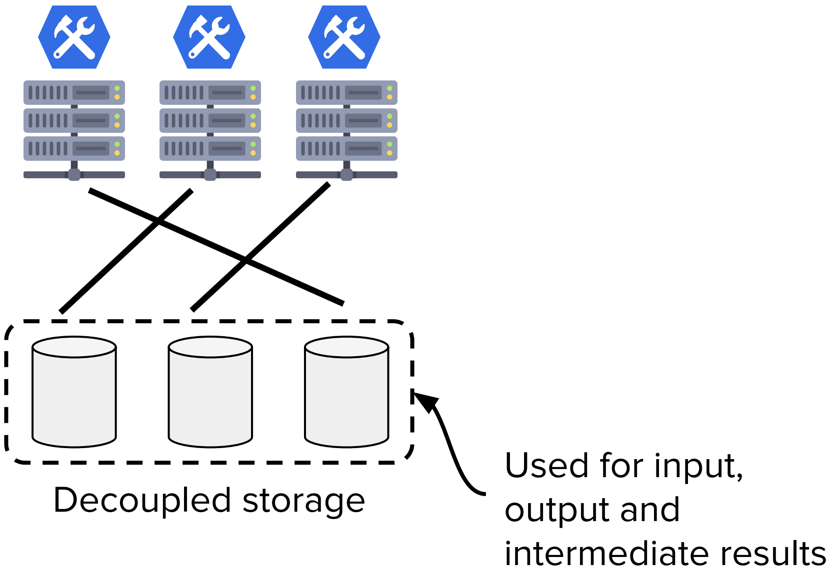
Problem Domain: Scientific Workflow with Containers

Omics (genomics, metabolomics, proteomics), machine learning pipelines, virtual drug screening

Scientific workflows

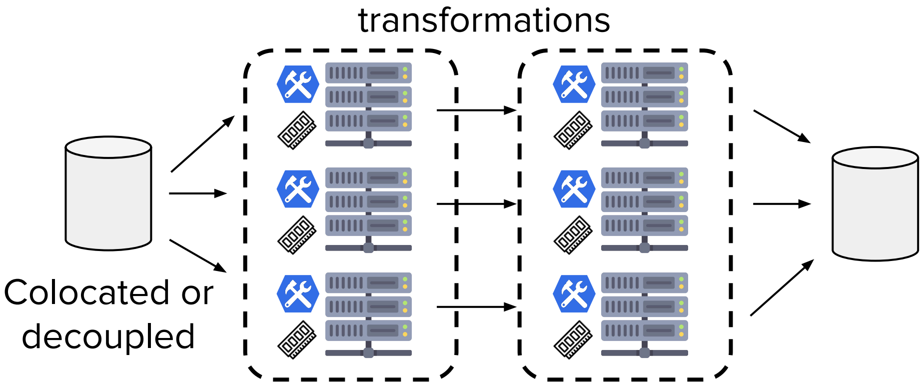


Problem: network contention



Solution: Dataflow programming model

MaRe 🐳 https://github.com/mcapuccini/MaRe



Memory is used for intermediate results.
How move data to/from containers?

- UNIX pipes
- Memory-mapped files
- Tmpfs

High-level API hides parallel computing challenges

- User productivity

Scales on cloud and commodity HW

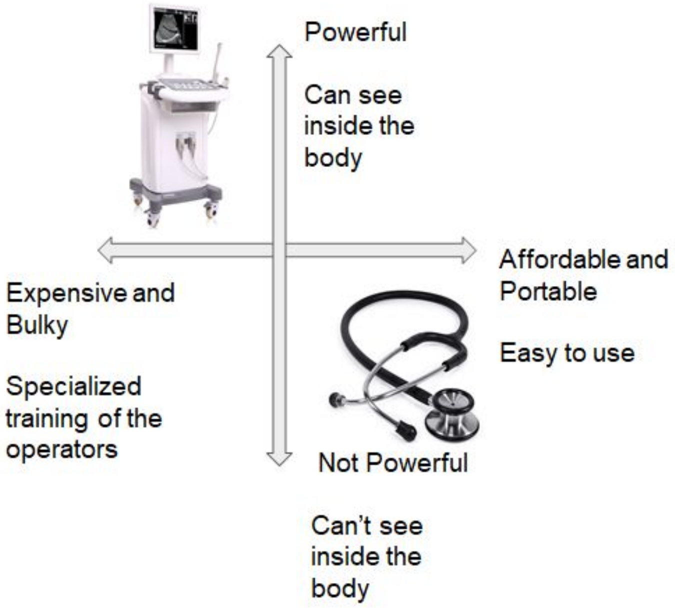
Problem Domain: Biomedical Diagnosis

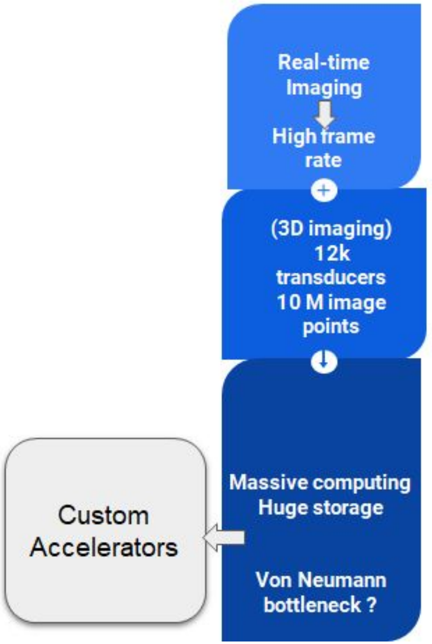
- Processing massive streams of data is an important problem in Biomedical diagnosis systems.
    - Biomedical diagnosis involves real time signal processing
    - A large number of transducers used, which generate massive data
    - Signal processing algorithms require huge memory to store pre computed coefficients
    - Accessing memory makes system performance slow : a bottleneck in real-time diagnosis

Example -

3D Ultrasound imaging requires 50 GB LUT (Lookup tables) space

Solution: Biomedical Diagnosis

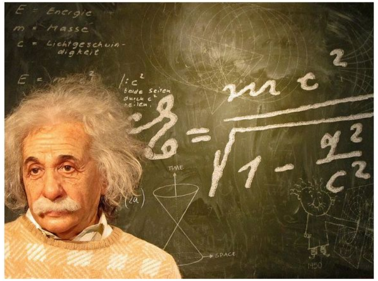




- Exploring sparsity of the data : compressive sensing
- Customized hardware : parallel computing
- On the fly computation : reduced memory access

Problem Domain: Quantum Physics

Numerical calculation for quantum physics



①What is the presence problem about quantum physics ?

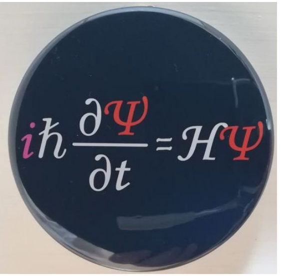
②Making program for numerical calculation

Considering computation time and capacity of files

Einstein equation

$$R_{\mu\nu} - \frac{1}{2}g_{\mu\nu}R = \frac{8\pi G}{c^4}T_{\mu\nu}$$

Schrodinger equation



Problem Domain: Weather Forecasting

Data size issues in data assimilation

Observational data size issues:

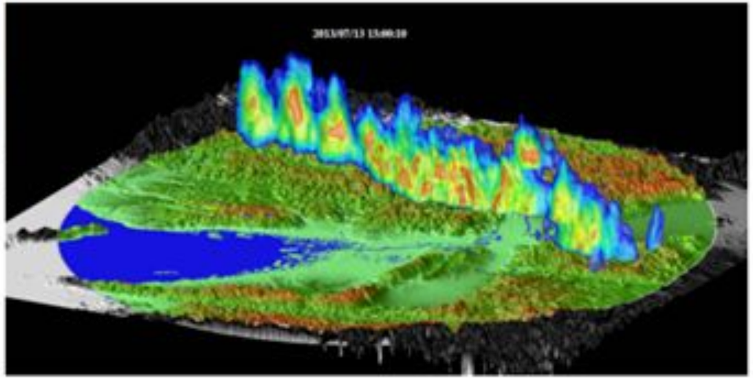
Real-time finescale weather forecast requires much observational data input

- conventional techniques (radar, satellites) with higher resolution
- new data sources (vehicles, portable devices)

Fast computation and data transfer are both essential

Possible solutions:

- improved pre-processing schemes



Problem Domain: Linear Algebra

Multi precision arithmetic

Double-Double and Quad-Double arithmetic uses the combinations of double precision numbers. # of operations would become large.

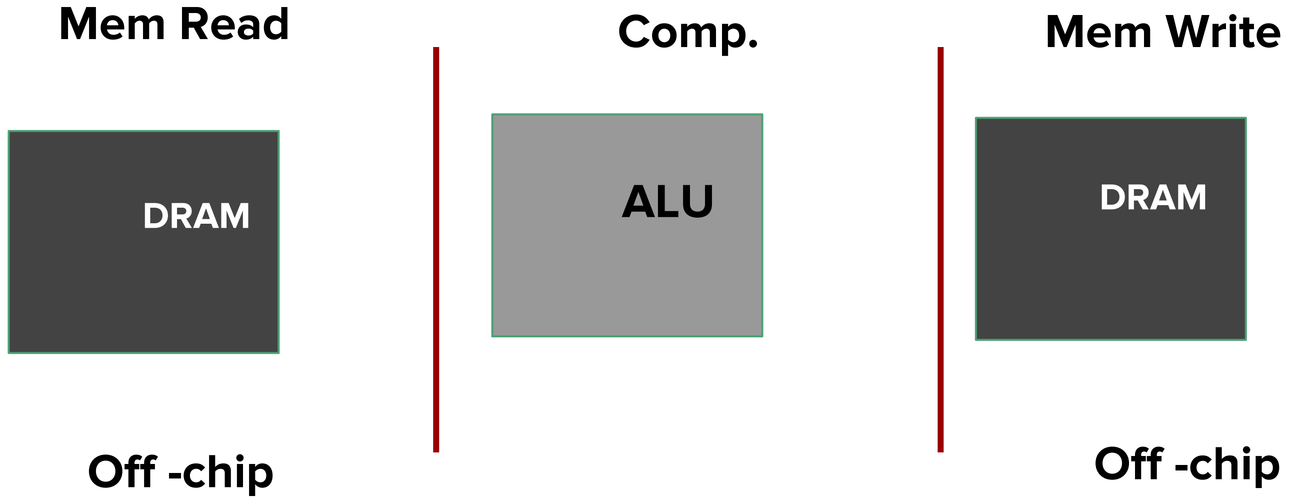
In the conventional laptop computer,

- Without parallelization, a kernel (BLAS 1 2 3) is computation bottleneck.
- With parallelization(FMA, SIMD, OpenMP), some kernels are memory bottleneck.

Parallelization have memory performance constraint for some multi precision kernels.

Problem Domain: Machine Learning

Memory Access - Bottleneck for DL applications.



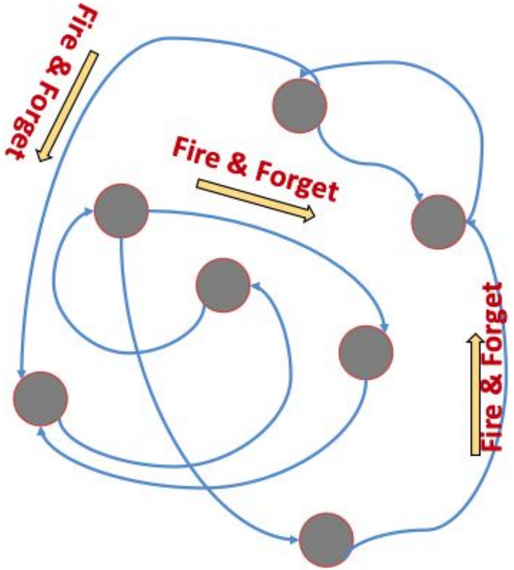
1. DRAM access: Data movement DRAM to ALU is expensive.
2. Mapping data-flow over the architecture: Memory hierarchy to computation units.
3. For DL application training and inferencing, loading huge data for training affects the training time, which may be critical for many real-time applications.

Solution: Machine Learning

1. Data compression to reduce the storage and movement.
2. Network pruning e.g based on magnitude of weights.
3. Reduce precision for computation: (Floating point -> Fixed point): 8 bit int used in (Google TPU).
    a. Binary weight, ternary weight..
    b. Non linear quantization (Log-domain)
4. Improve the reuse of data and local (computational) accumulation.
5. Exploit sparsity in the computation map: skip memory access and compute for zero.
6. Reduce operation while mapping DNN to matrix multiplication, example using FFT.
7. On-chip memory partition, putting memory and processor on same silicon substrate, increase the memory Bandwidth.
8. Moving from temporal architecture (SIMD) (MEM-> REG File -> ALU -> control) to Spatial architecture (more advanced for memory accessing) (MEM -> ALU).
9. Advance memory techniques: Stacked DRAMs and non-volatile memories.
10. Explore possibility of neuromorphic computing with asynchronous operation.

Problem Domain: Graph Processing

- Graph processing generally involves:
  - Low FLOP to Byte ratio
  - Irregular data access pattern
- Bulk Synchronous Model (BSP) leads to under exploitation of the large inherent parallelism that is naturally available in graph structures.
- Think like a Vertex, asynchronously:
- Send an active message asynchronous (fire-and-forget).
- No DAG. Because there could be cycles in the graph.
- We implement Dijkstra–Scholten algorithm for termination detection

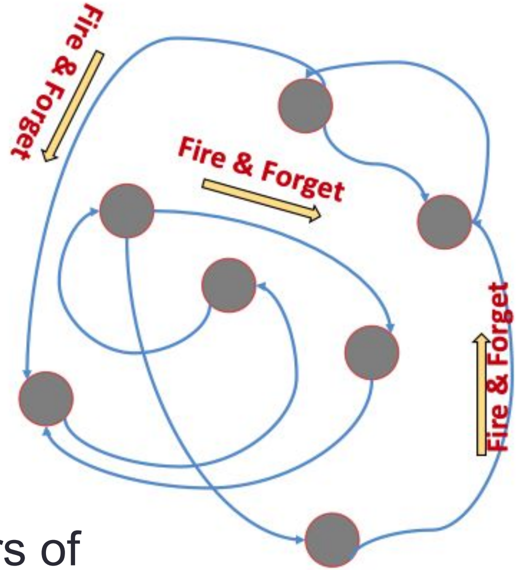


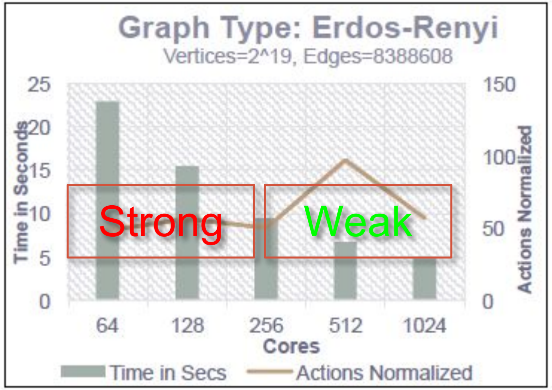
Problem Domain: Graph Processing

```
diffuse(vertex v, int distance):
  if v.distance >= distance:
    v.distance = distance
    for u in v.neighbors:
      diffuse(u, v.distance + u.weight)

SSSP(vertex src):
  src.distance = 0
  for u in src.neighbors:
      diffuse(u, u.weight)
```

Listing 1: Asynchronous SSSP

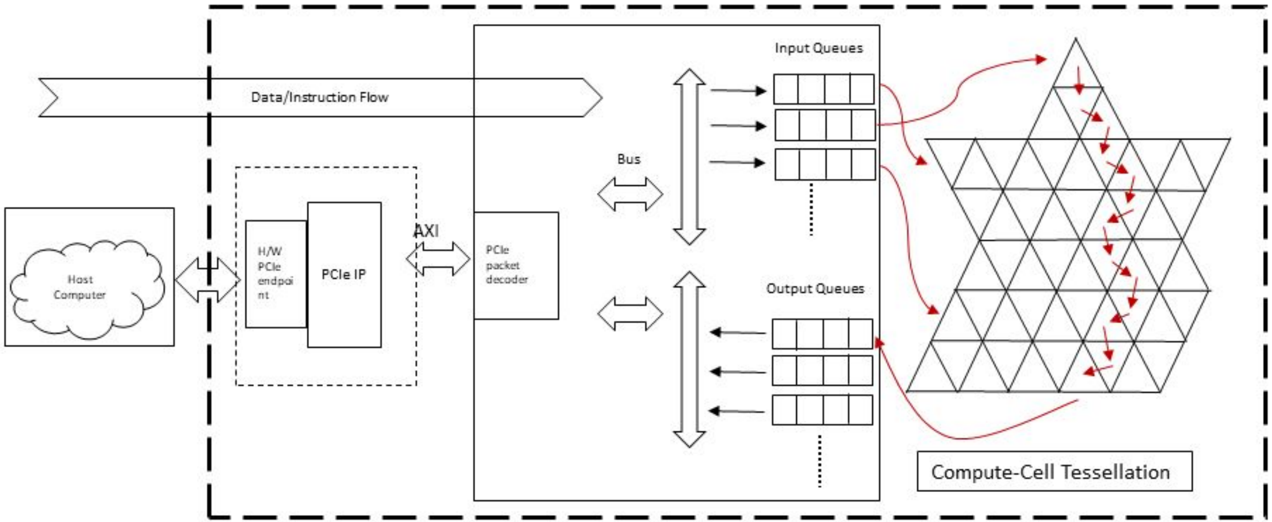




Presents both behaviors of Strong and Weak Scaling: Transcendental Scaling

Problem Domain: Graph Processing

- Continuum Compute Architecture is a new class of non von Neumann architectures.
- Offers fine grain parallelism.
- Small compute cells organized such that it creates an active memory.
- Low Power
- Less space footprint



Conclusion

- New Challenges posed by Big Data
  - Irregular memory access
  - Memory bottleneck
  - Latency sensitive
  - Low Power requirements
- Solutions:
  - 3D stacked Memory
  - Non-von Neumann architectures: send work/compute to memory and process there
  - Custom hardware for inference (and other compute) ➔ less power and less areas footprint, critical for portability
  - Dataflow-oriented workflows
    - Programmer productivity
    - Auto optimizations (lazy evaluation, concurrency, locality optimization)