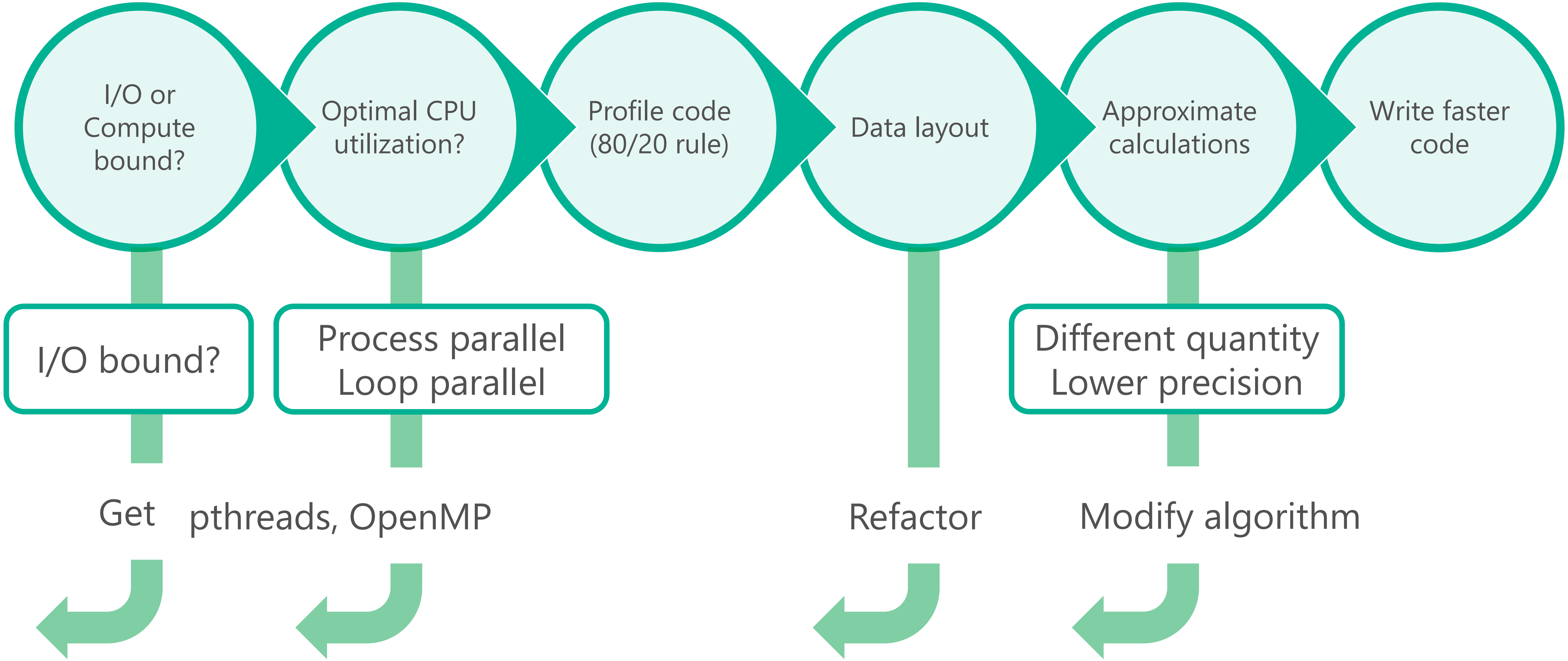
Microsoft Research

Microsoft

Fast code with just enough effort

Pashmina Cameron

Low hanging fruit



Data layout

```
struct Point {
	float x;
	float y;
	float feature[128];
};

std::vector<Point> pts;
```

```
struct Point {
	float x;
	float y;
};
struct Feature {
	float feat[128];
};
// parallel vectors
std::vector<Point> pts;
std::vector<Feature> ptFeatures;
```

Data layout

```
struct Point {
        float x;
        float y;
        float metadata[N];
        float feature[M];
};

std::vector<Point> pts;
```

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        float x;
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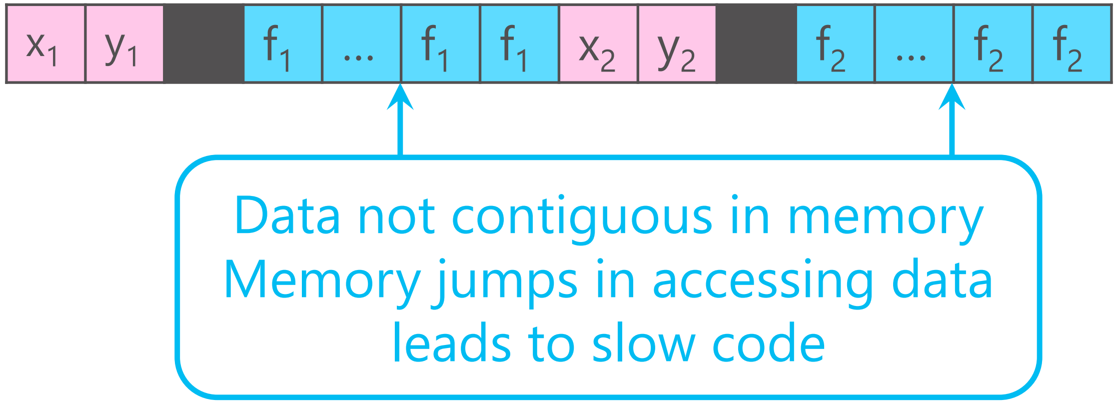


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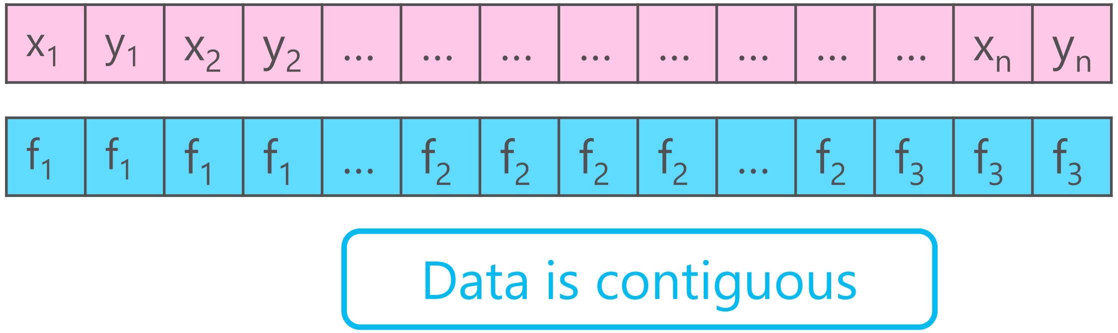
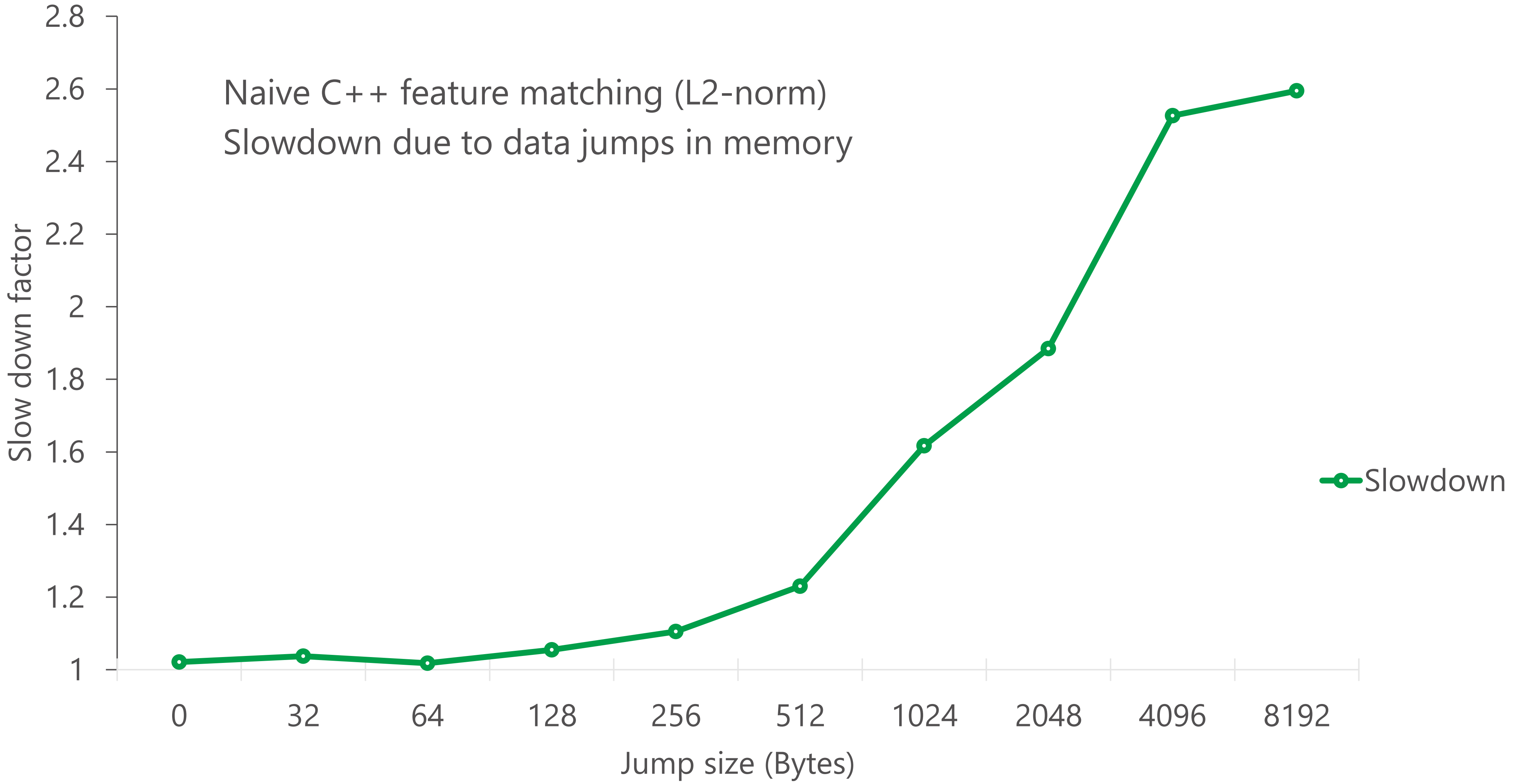


Data layout matters



A bigger example: Cholesky?

An algorithm that is
- well-understood
- not domain-specific
- suited to multiple programming languages
- is computationally intensive

Kalman filters

Linear least squares

Monte Carlo simulations

Bundle adjustment

Expectation propagation

Computing Cholesky decomposition of A

$$A = L\,L^T$$

simplifies the process of solving $Ax = b$

Cholesky variants: check assumptions

$$A = LL^T$$

return $\begin{pmatrix} L_{11} & 0 & 0 \\ L_{21} & L_{22} & 0 \\ L_{31} & L_{23} & L_{33} \end{pmatrix}$

$$L_{j,j} = \sqrt{A_{j,j} - \sum_{k=1}^{j-1} L_{j,k}^2},$$

$$L_{i,j} = \frac{1}{L_{j,j}} \left(A_{i,j} - \sum_{k=1}^{j-1} L_{i,k} L_{j,k} \right) \quad \text{for } i > j.$$

$$A = LDL^T$$

return $\begin{pmatrix} D_1 & L_{21} & L_{31} \\ L_{21} & D_2 & L_{23} \\ L_{31} & L_{23} & D_3 \end{pmatrix}$

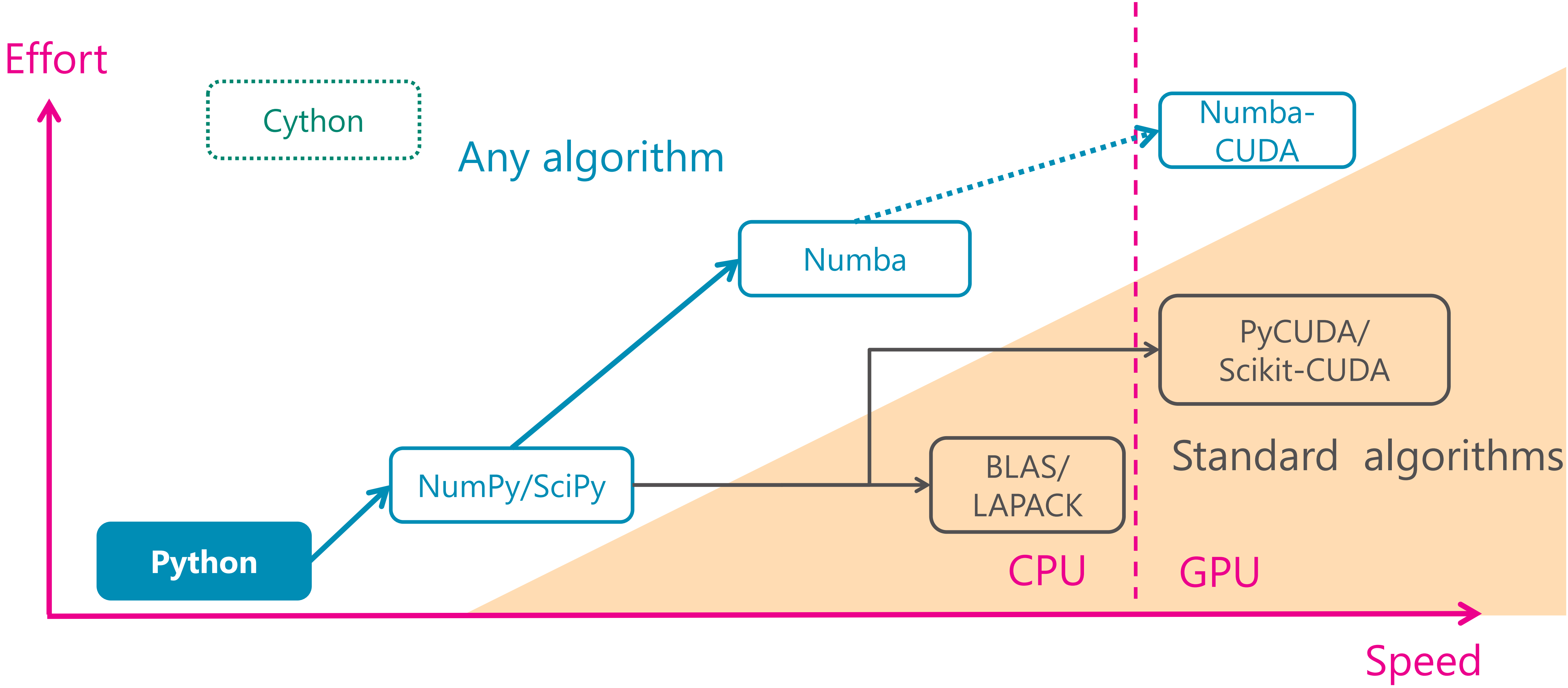
$$D_j = A_{jj} - \sum_{k=1}^{j-1} L_{jk}^2 D_k,$$

$$L_{ij} = \frac{1}{D_j} \left(A_{ij} - \sum_{k=1}^{j-1} L_{ik} L_{jk} D_k \right) \quad \text{for } i > j.$$

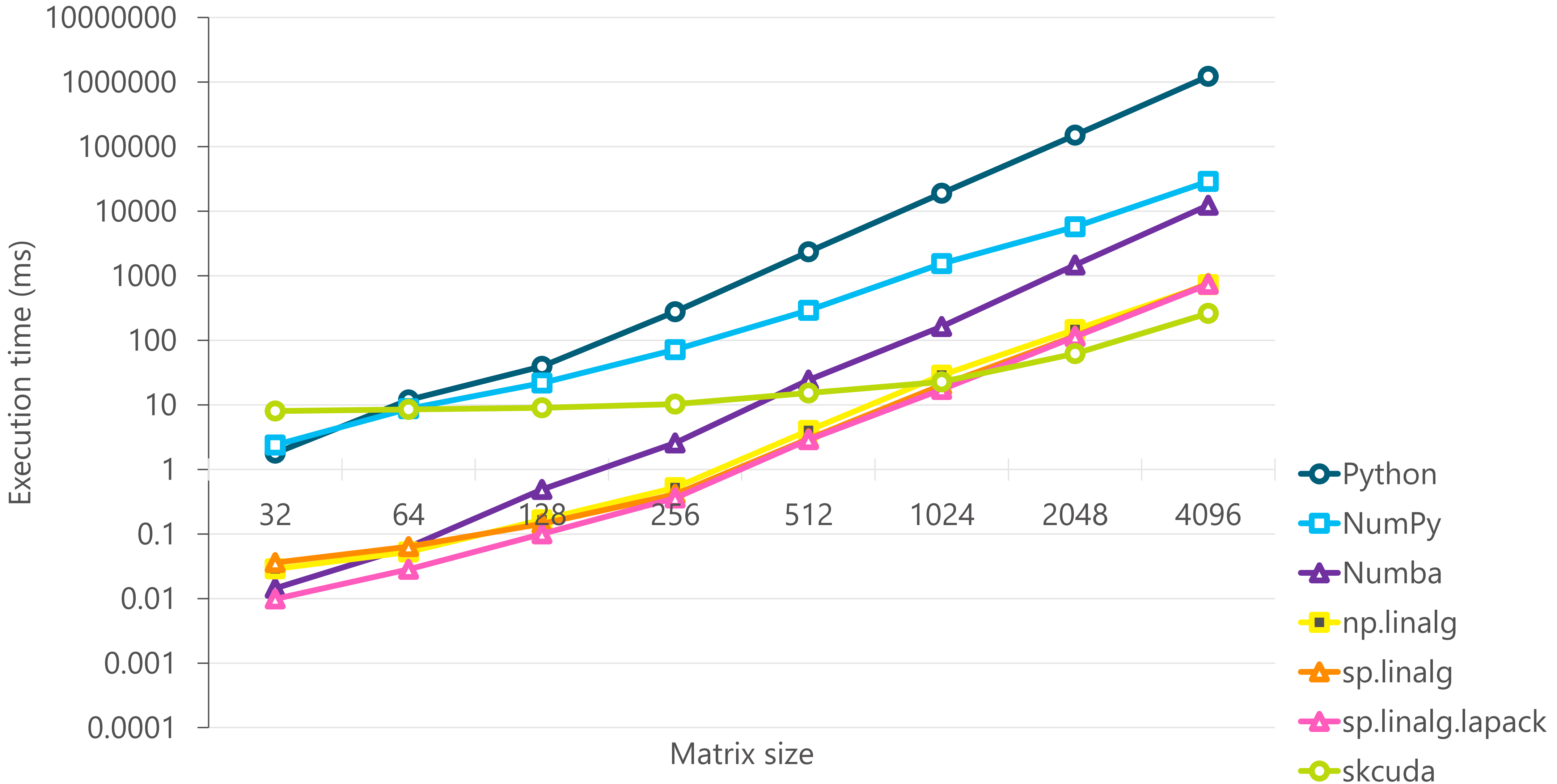
Language choice

	Python	C++
Purpose	prototyping	shipping
Constraints	readability time	power memory speed
	existing software	
Hardware	desktop ARM/Intel	cluster GPU embedded devices

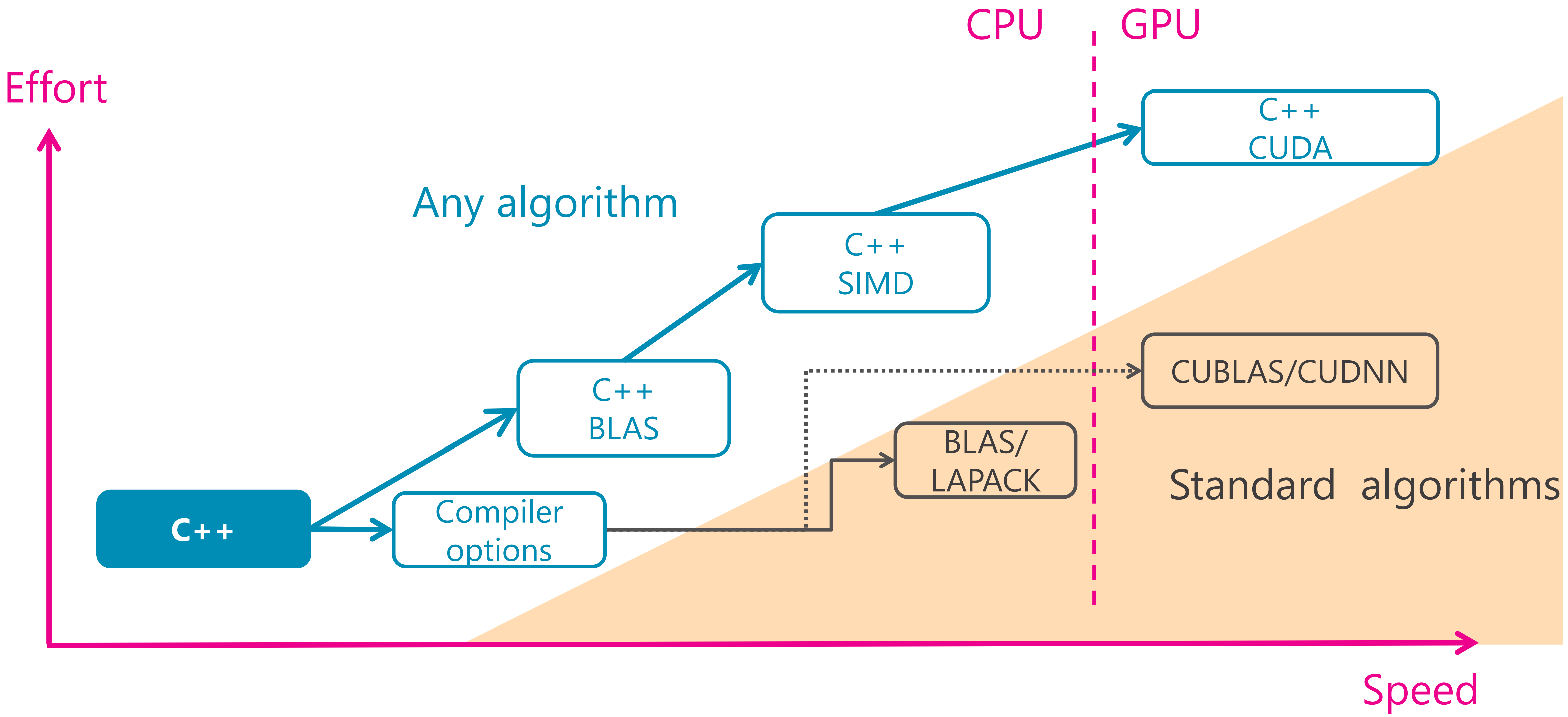
Python


Effort
Cython
Any algorithm
Numba-
CUDA
Numba
PyCUDA/
Scikit-CUDA
Standard algorithms
BLAS/
LAPACK
NumPy/SciPy
Python
CPU
GPU
Speed

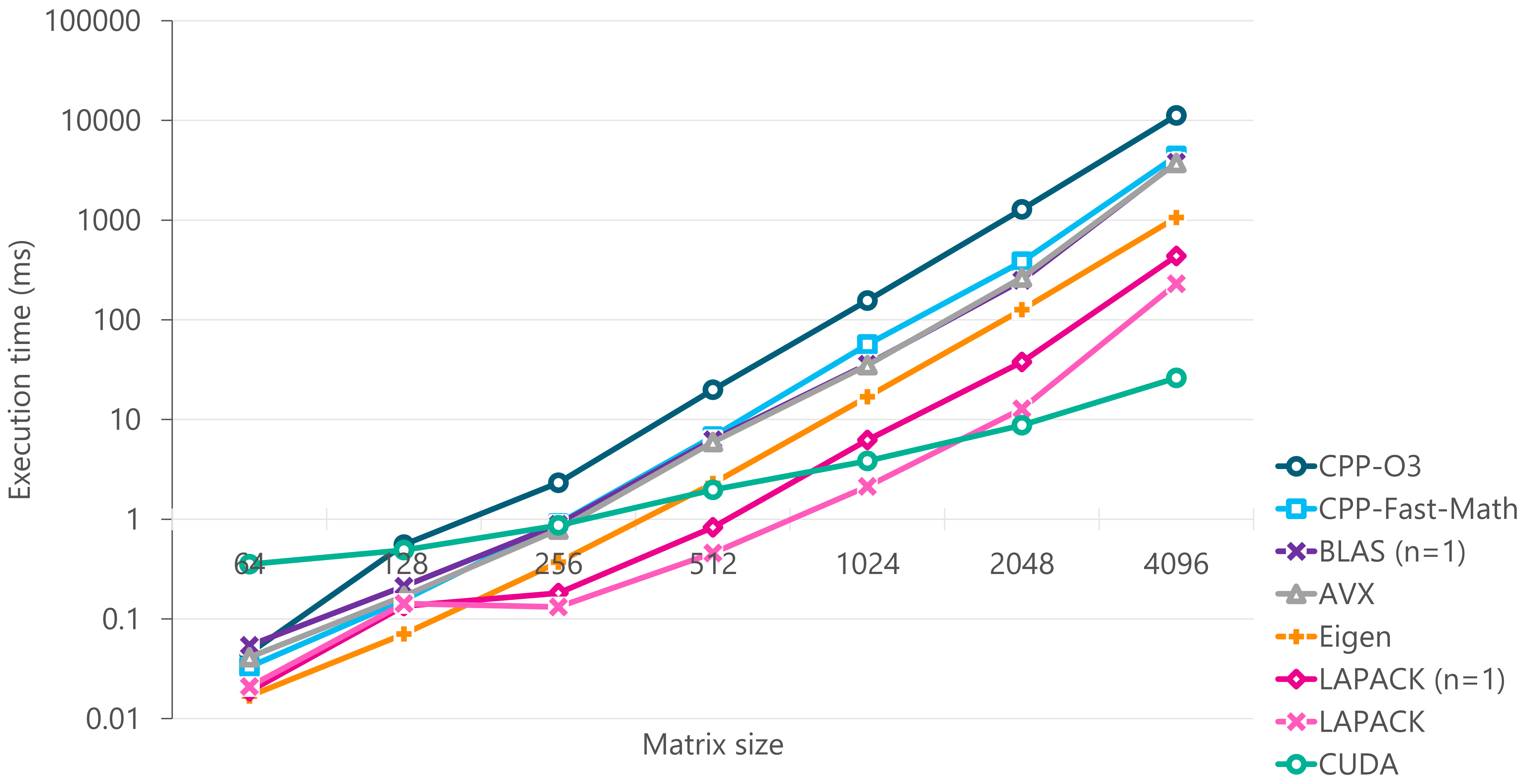
Python Cholesky implementations



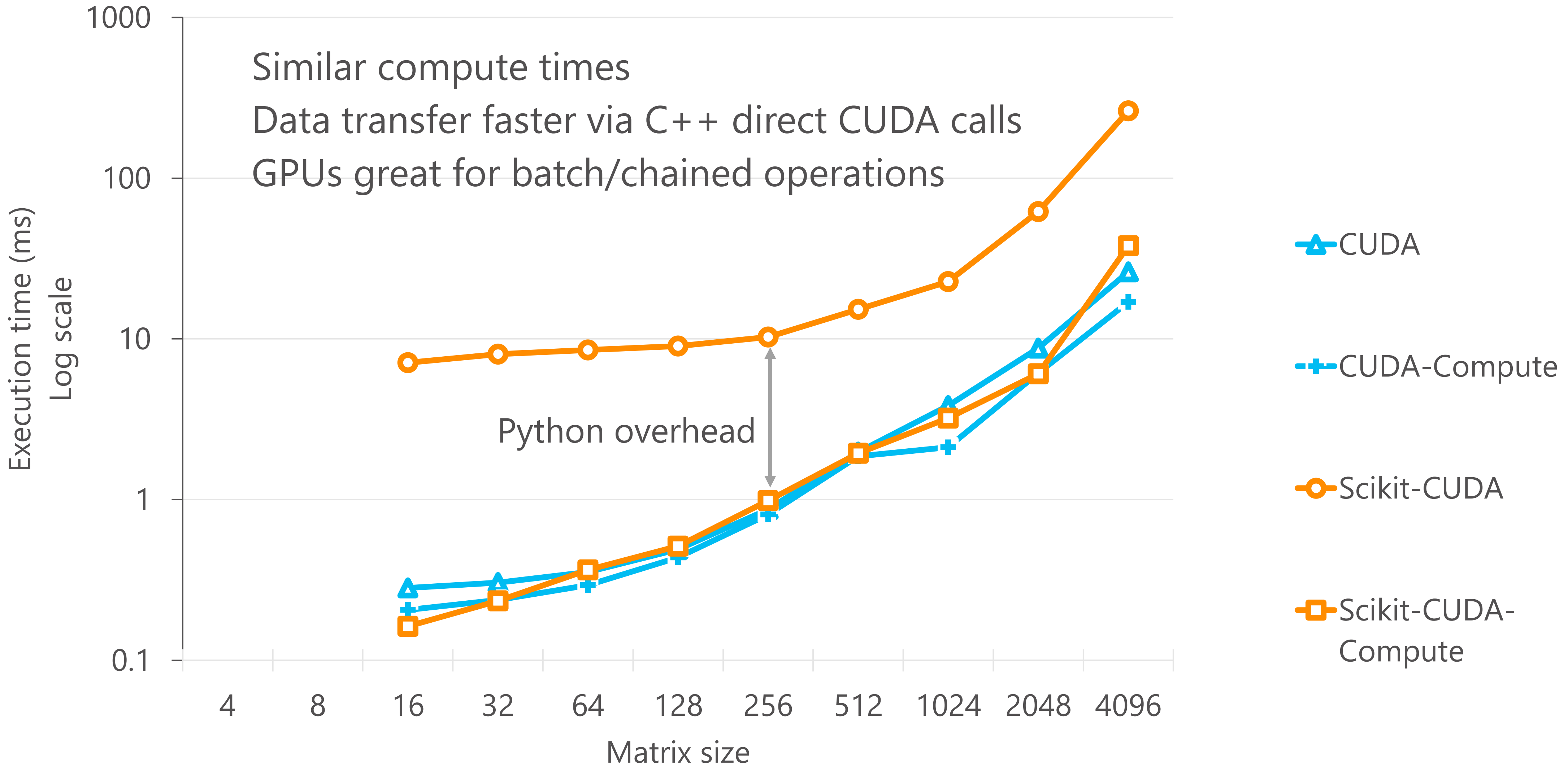
C++


CPU
GPU
Effort
Any algorithm
C++
CUDA
C++
SIMD
C++
BLAS
CUBLAS/CUDNN
BLAS/
LAPACK
Standard algorithms
C++
Compiler
options
Speed

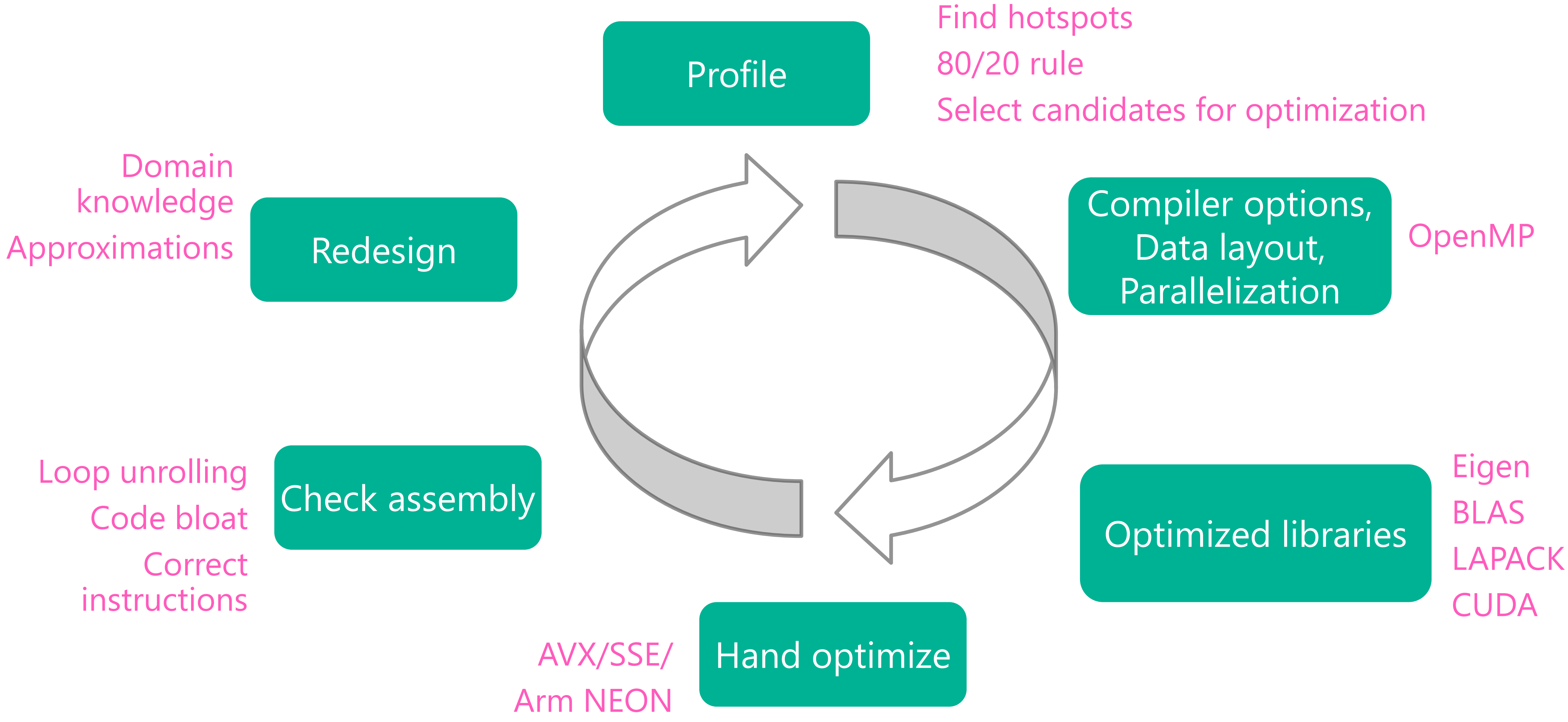
C++ Cholesky implementations ($M = L L^T$)



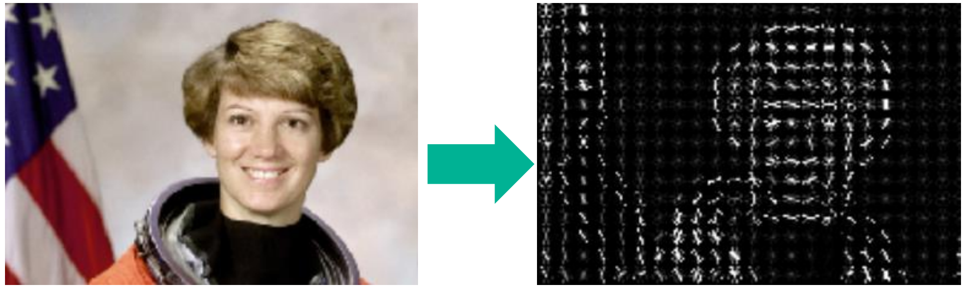
Using CUDA from Python vs C++



C++ optimization cycle



Using domain knowledge



Algorithm
- Compute gradients
- Bin gradients into orientation bins
- PopCount on spatial distribution
- Form a feature vector
- L2 norm to match features

Tricks
- Use uint or fixed point to store features instead of floats
- Store distances with double precision
- Approximate magnitude (53*min(dx,dy))>>7 + max(dx,dy)
- Use 8 bins and use bit comparison instructions for binning instead of nested branching
- Precompute spatial distribution kernels

4x less storage

8-12x faster feature computation

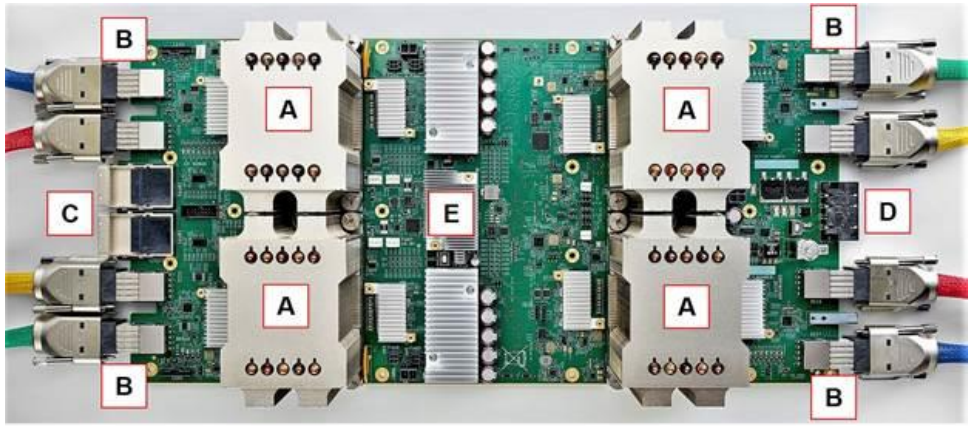
64x faster feature matching

Dalal and Triggs, HOG, CVPR 2005

David Lowe, SIFT, IJCV 2004

End of general purpose H/W

Heterogeous comoute
will likely be the norm

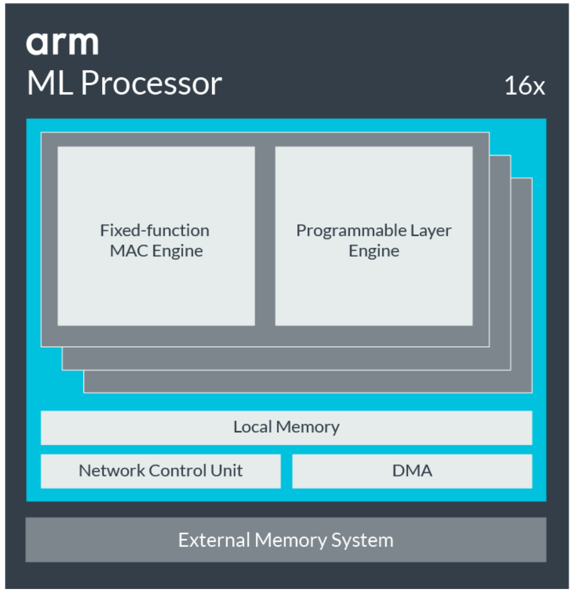


Google TPU

Intel Xeon FPGA

Intel Movidius NCS

Microsoft Catapult



ARM ML Processor

Thank you for listening

Blog:
https://pashminacameron.github.io/

Code:
github.com/pashminacameron/cholesky_benchmarking

Contact:
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