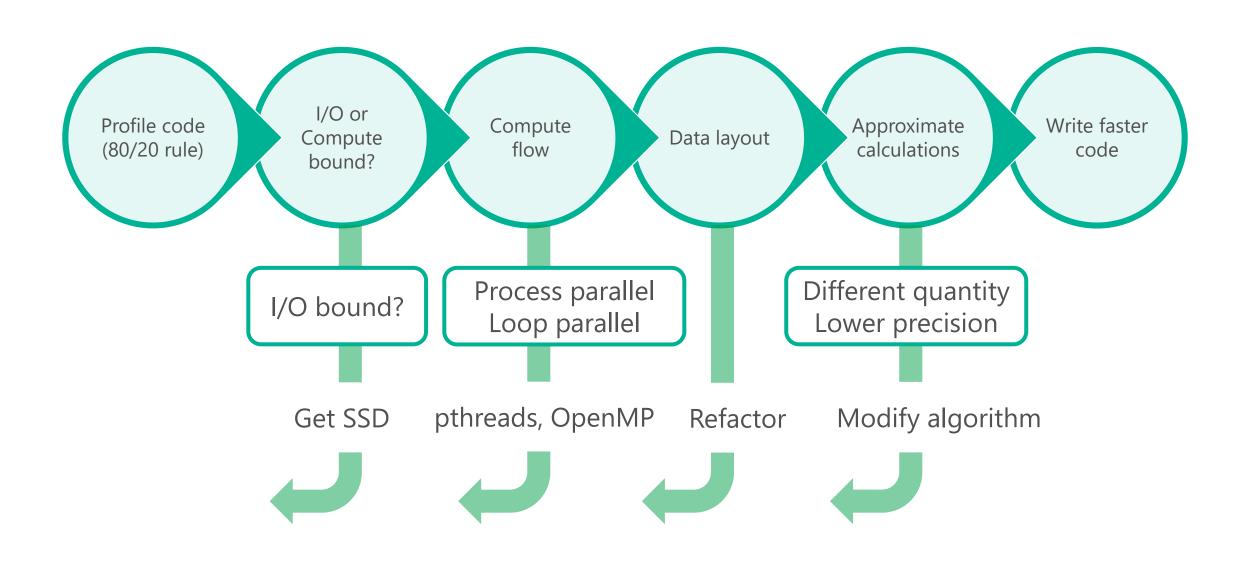




# Fast code with just enough effort

Pashmina Cameron

# Low hanging fruit



# Understanding data layout

# Data layout

```
struct Point {
        float x;
        float y;
        float feature[M];
};
std::vector<Point> pts;
```

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

# Data layout

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

```
struct Point {
     float x;
     float y;
     float metadata[N];
};
struct Feature {
     float feature[M];
};
// parallel vectors
std::vector<Point> pts;
std::vector<Feature> ptFeatures;
```

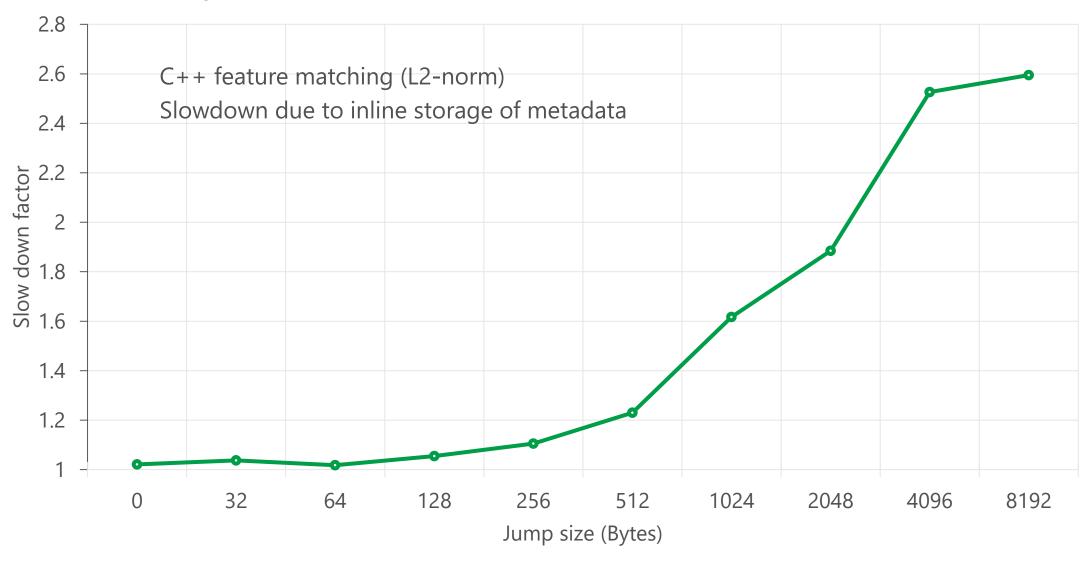
# Data layout

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

```
Data not contiguous in memory
Memory jumps in accessing data
leads to slow distance calculations
```

```
struct Point {
       float x;
       float y;
       float metadata[N];
};
struct Feature {
       float feature[M];
};
// parallel vectors
std::vector<Point> pts;
std::vector<Feature> ptFeatures;
               Data is contiguous
```

# Data layout matters



# Understanding language and compiler

# Language choice

Python

C++

Purpose

prototyping

shipping

dependencies

Constraints

readability
time
existing software

memory speed security hardware

## A simple benchmark

An algorithm that is

- well-understood
- not domain-specific
- computationally intensive

Kalman filters

Linear least squares

Monte Carlo simulations

Bundle adjustment

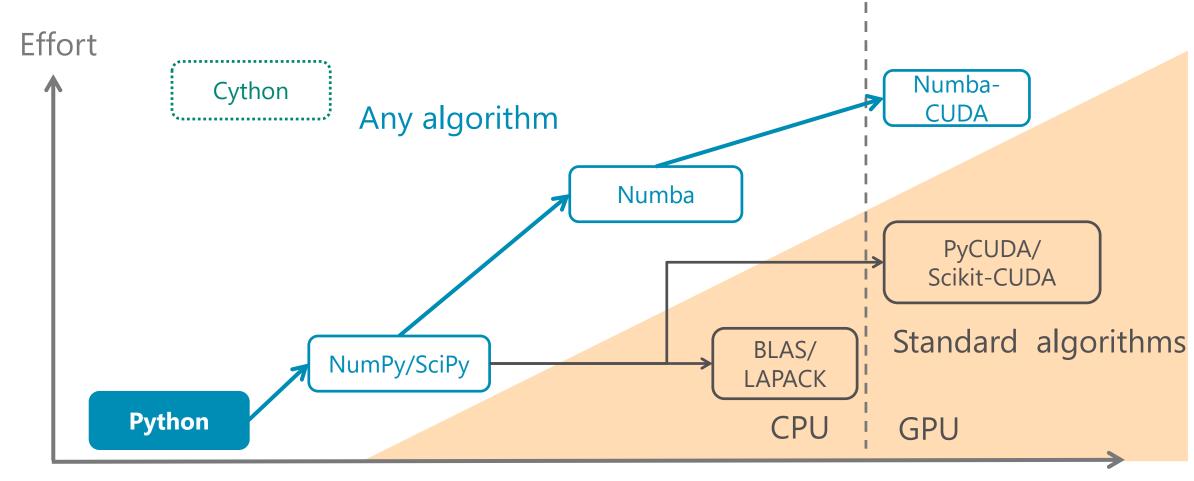
Expectation propagation

Computing Cholesky decomposition of A

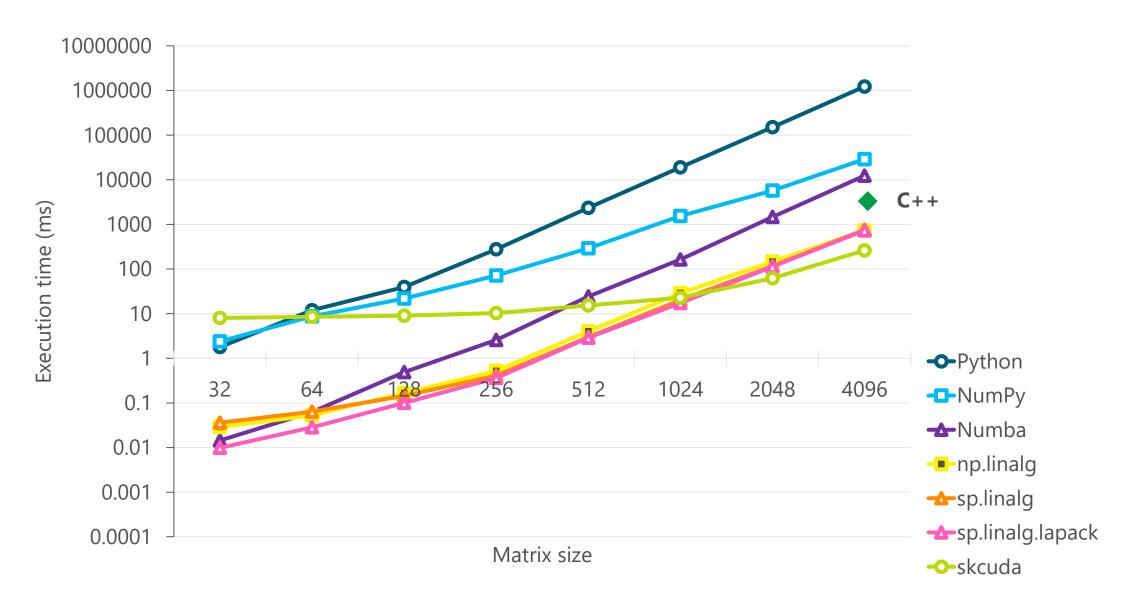
$$A = L L^T$$

simplifies the process of solving Ax = b

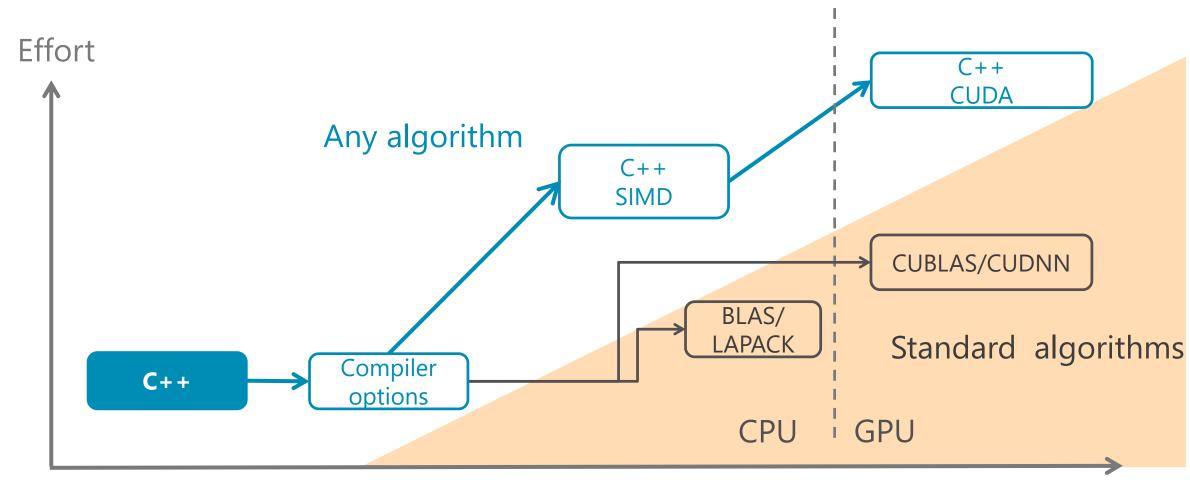
# Python



## Python Cholesky implementations

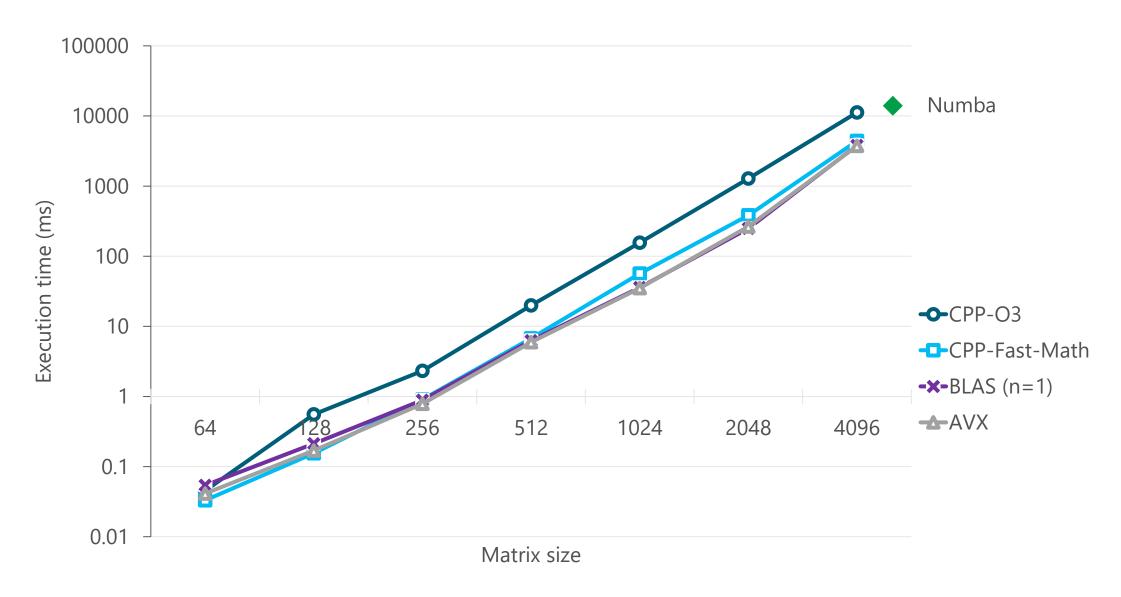


$$(++$$

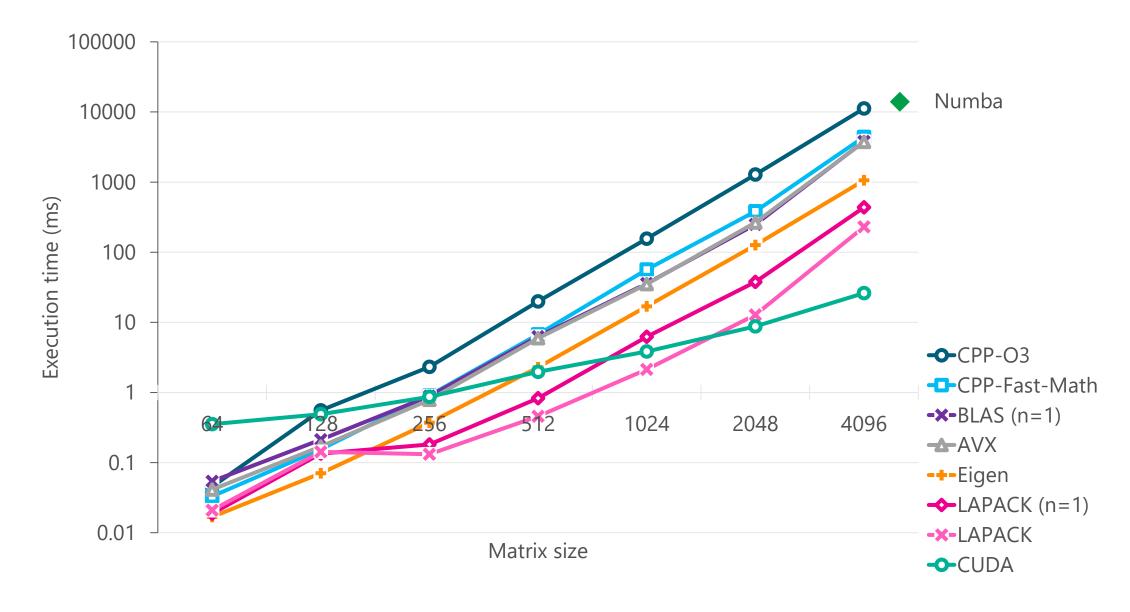


Speed

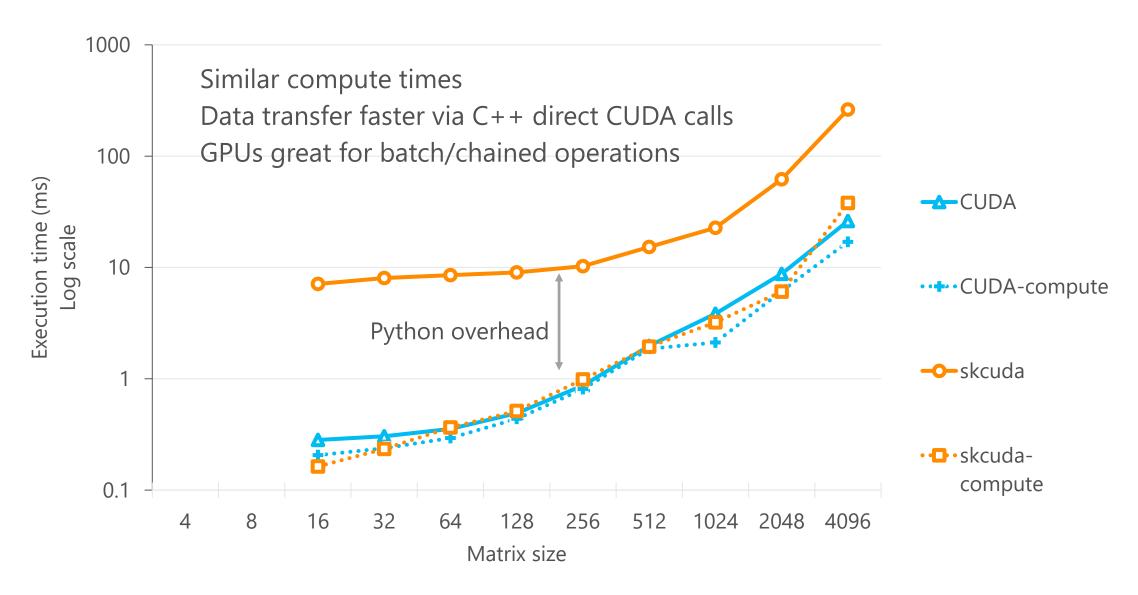
## C++ Cholesky implementations ( $M=LL^T$ )



## C++ Cholesky implementations ( $M=LL^T$ )



## Using CUDA from Python vs C++



# Harnessing domain knowledge

# Using domain knowledge

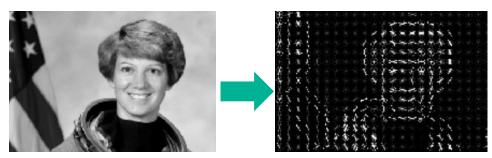


Image courtesy of scikit-cuda docs

#### Algorithm

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

#### **Tricks**

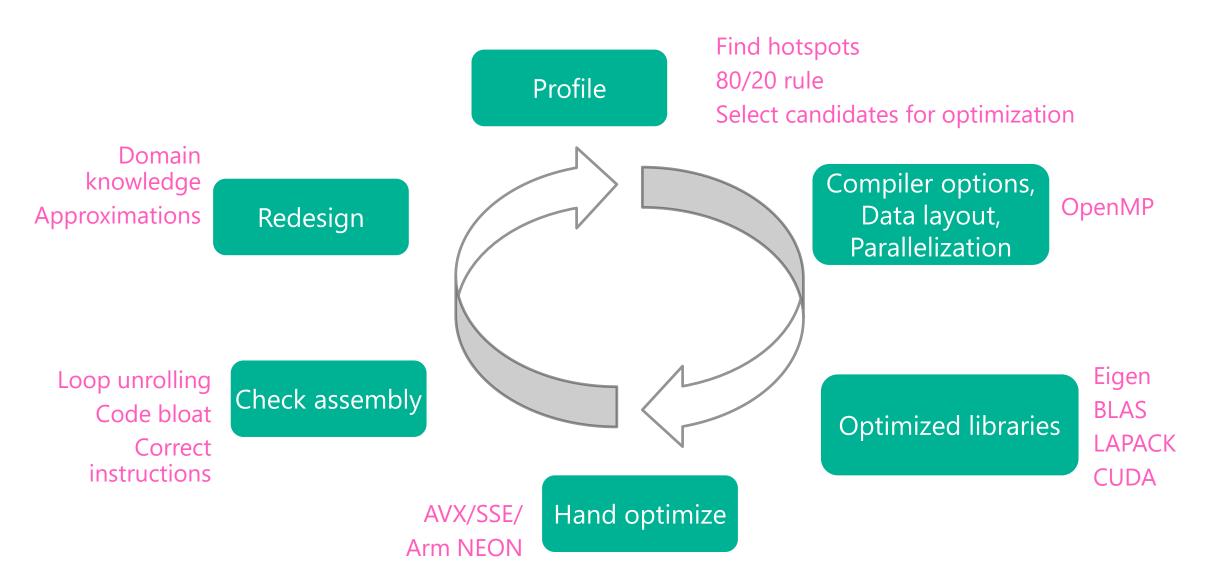
- Use uint8\_t or fixed point to store features instead of floats
- Approximate magnitude (53\*min(dx,dy))>>7 + max(dx,dy)
- Use 8 bins and use bit comparison instructions for binning instead of nested branching
- Store distances with 2x precision

#### SIMD implementation

- 4x less storage
- 8-12x faster feature computation
- 64x faster feature matching

Dalal and Triggs, HOG, CVPR 2005 David Lowe, SIFT, IJCV 2004

# C++ optimization cycle

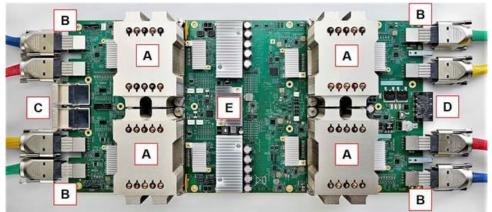


When everything else fails....

# End of general purpose H/W

Co-designing software and hardware is the future

Domain specific hardware aims to do just that.





Intel Xeon FPGA

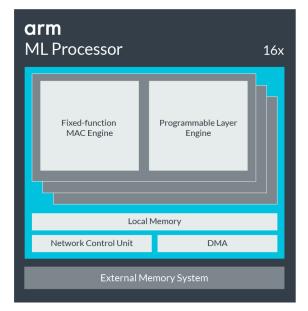


Intel Movidius NCS

Google TPU



Microsoft Catapult



**ARM ML Processor** 

Images from company web pages/press releases

## Thank you for listening

### Blog:

https://pashminacameron.github.io/

### Code:

github.com/pashminacameron/optimization\_examples

#### Contact:

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