# Memory Bound Computing

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#### Goals

- Recognize when your computation is memory bounded, not CPU-bounded
- Learn techniques that helps you getting more performance for memory-bound problems
- Learn to use existing packages for tackling these problems

### Let's Start with Some Exercises

Within the computing machine, clone the repo at:

https://github.com/FrancescAlted/MemoryBoundComputations

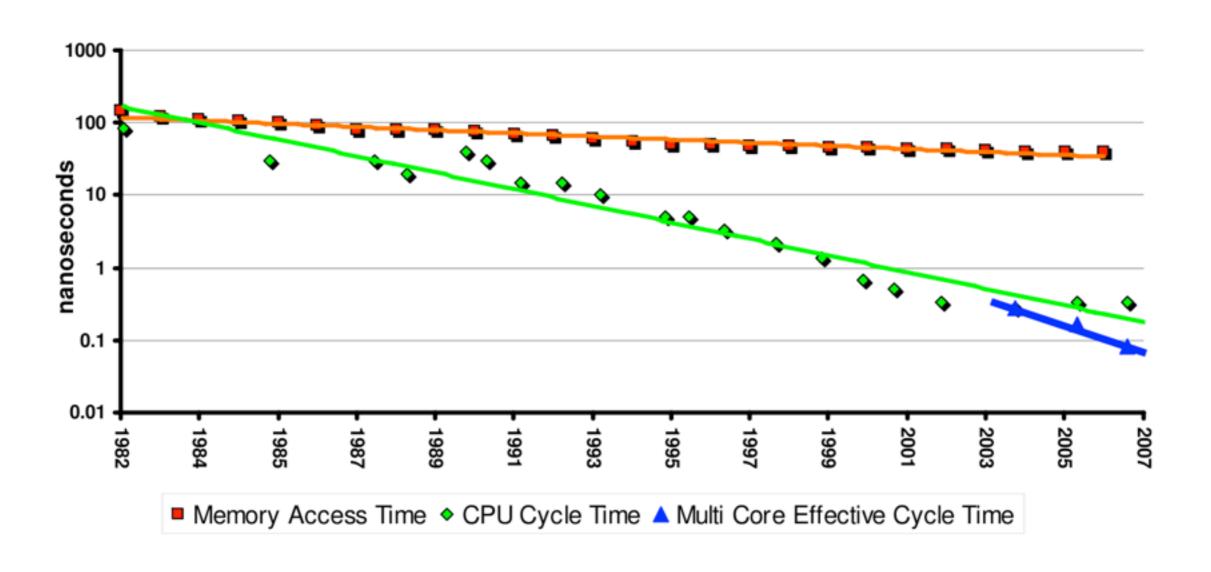
and start doing exercises 0 to 3 (inclusive)

"Across the industry, today's chips are largely able to execute code faster than we can feed them with instructions and data."

Richard Sites, after his article
 "It's The Memory, Stupid!",
 Microprocessor Report, 10(10), 1996

# The Starving CPU Problem

# Memory Access Time vs CPU Cycle Time



The gap is wide and still opening!



#### MORGAN&CLAYPOOL PUBLISHERS

#### The Memory System

You Can't Avoid It, You Can't Ignore It, You Can't Fake It

Bruce Jacob

#### Synthesis Lectures on Computer Architecture

Mark D. Hill, Series Editor

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## Book in 2009

### The Status of CPU Starvation in 2016

- Memory latency is much slower (between 250x and 1000x) than processors.
- Memory bandwidth is improving at a better rate than memory latency, but it is also slower than processors (between 30x and 100x).

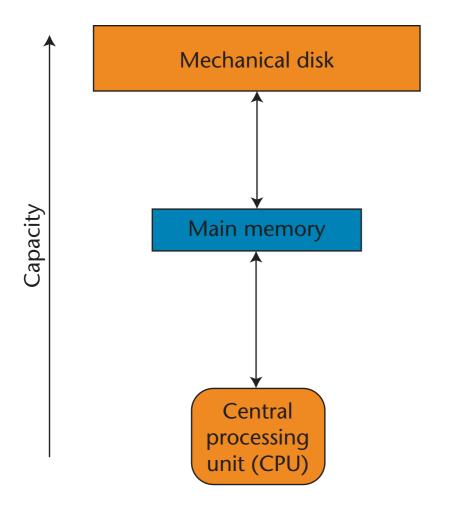
#### CPU Caches to the Rescue

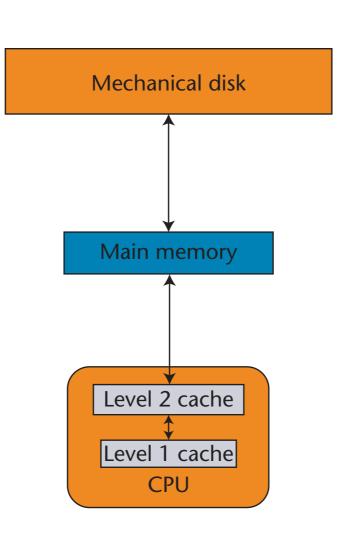
- CPU cache latency and throughput are much better than memory
- However: the faster they run the smaller they must be (because of heat dissipation problems)

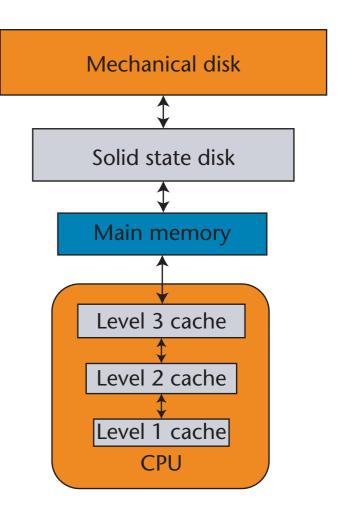
### Computer Architecture Evolution

Up to end 80's 90's and 2000's

2010's







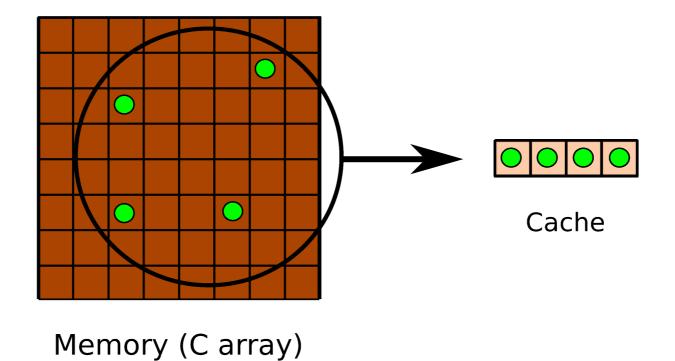
### When CPU Caches Are Effective?

Mainly in a couple of scenarios:

- Time locality: when the dataset is reused
- Spatial locality: when the dataset is accessed sequentially

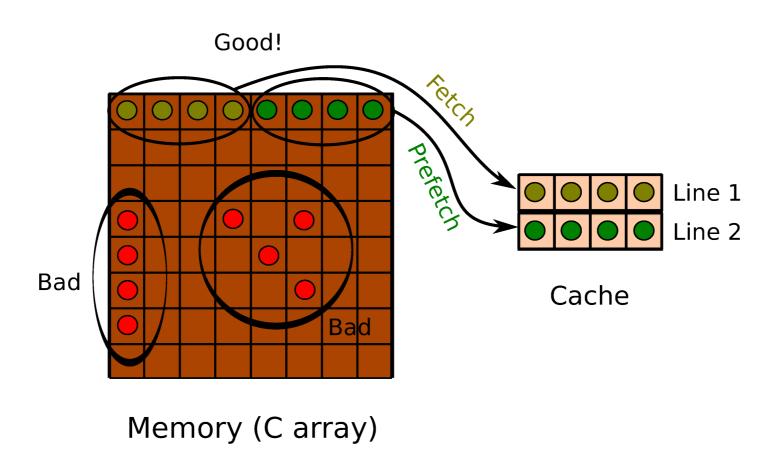
#### Time Locality

Parts of the dataset are reused



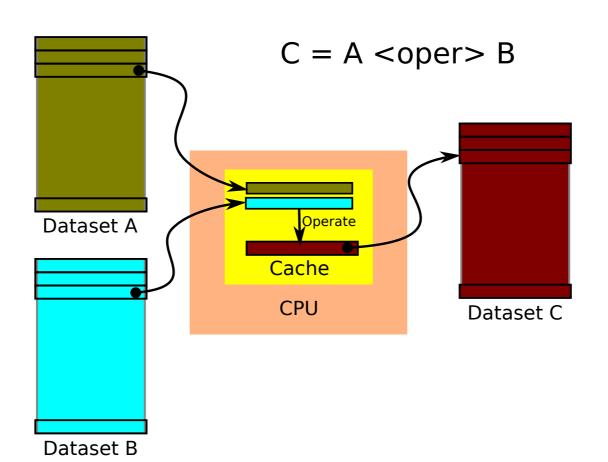
### Spatial Locality

Dataset is accessed sequentially



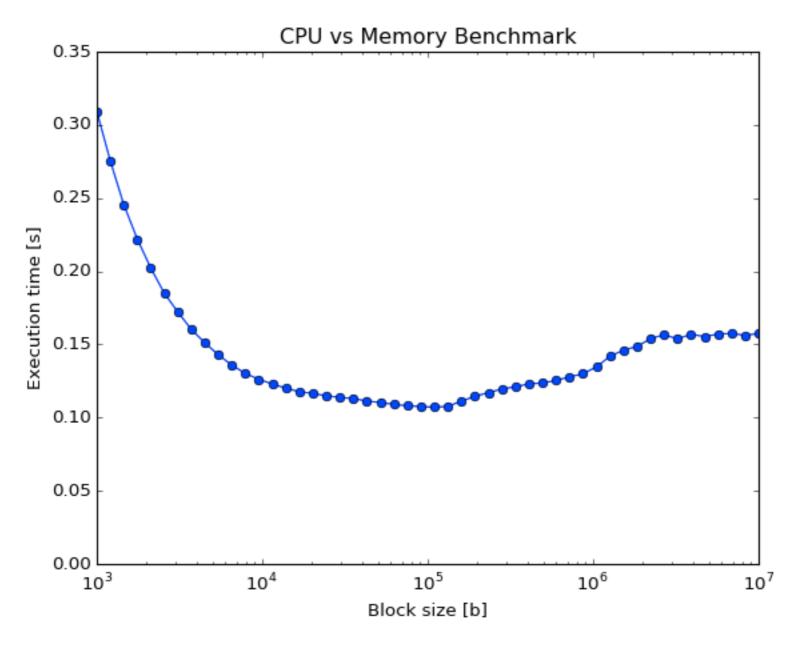
### The Blocking Technique

When accessing disk or memory, get a contiguous block that fits in CPU cache, operate upon it and reuse it as much as possible.



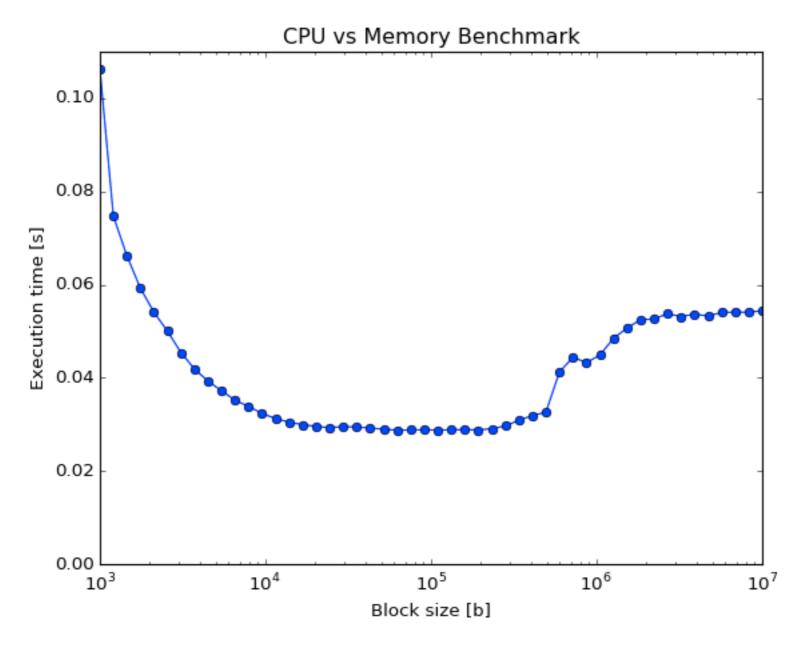
Use this extensively to leverage spatial and temporal localities

## The Blocking Technique in Action (Exercise 0)



CPU: Intel Xeon E312xx @ 2.00GHz (Sandy Bridge)

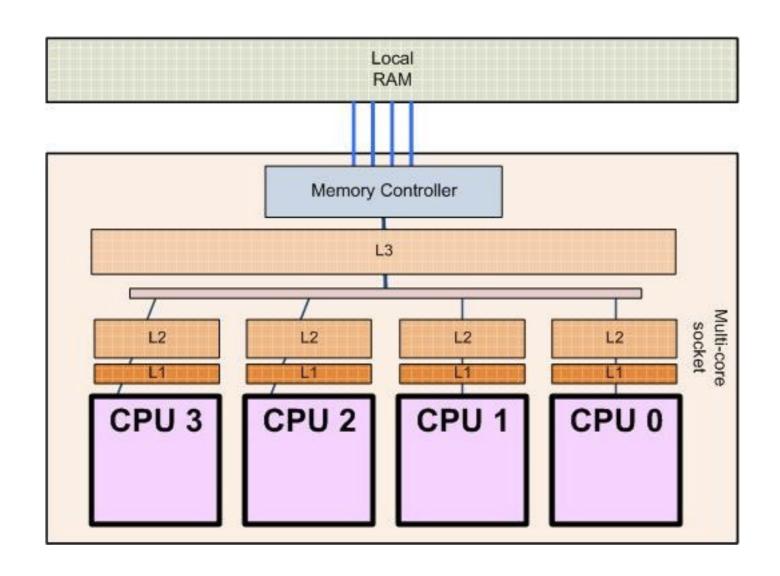
## The Blocking Technique in Action (Exercise 0)



CPU: Intel Xeon(R) CPU E3-1245 v5 @ 3.50GHz (Skylake)

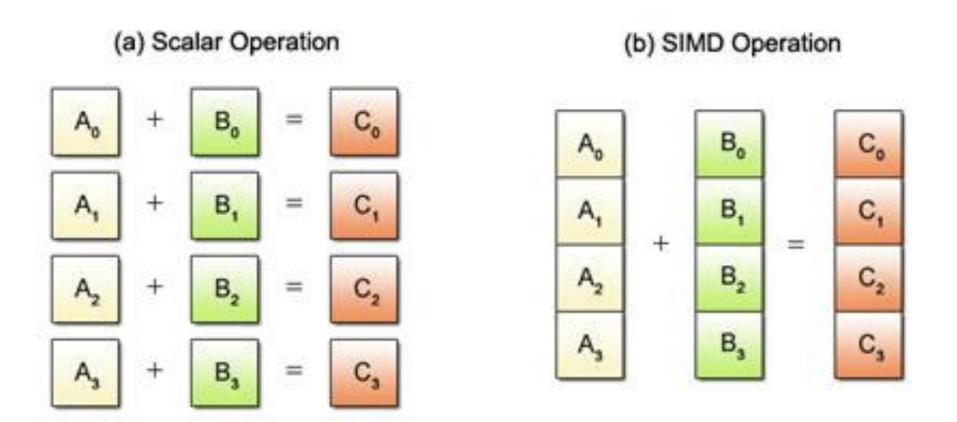
# Trends in Computer Architecture

#### We Are In A Multicore Age



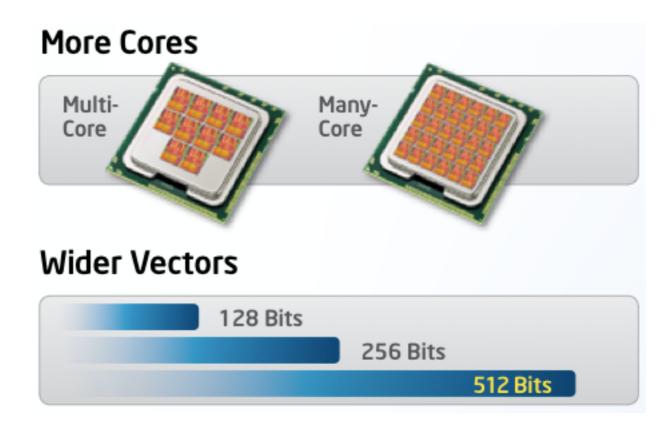
 This requires special programming measures to leverage all its potential: threads, multiprocessing

## SIMD: Single Instruction, Multiple Data

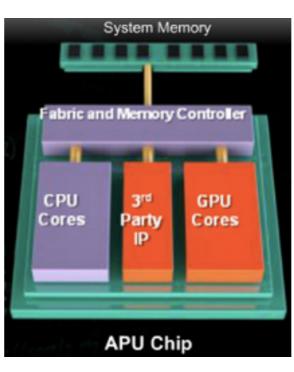


More operations in the same CPU clock

#### Forthcoming Trends in CPU



**CPU+GPU Integration** 



#### Hierarchy of Memory By 2018 (Educated Guess)

HDD (persistent)

SSD SATA (persistent)

SSD PCIe (persistent)

XPoint (persistent)

RAM (addressable)

\_4

3

L2

L1

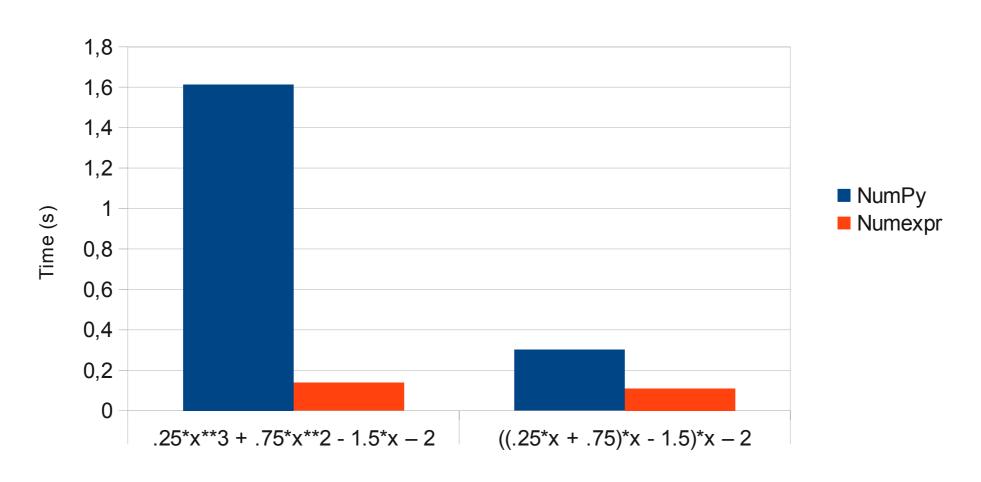
9 levels will be common!

#### numexpr

- It is a computational engine for NumPy that makes a sensible use of the memory hierarchy for better performance
- It can use multi-core (via multi-threading) and SIMD (via Intel's MKL) for better CPU usage.
- PyTables, pandas and bcolz (among others) can all leverage numexpr automatically if installed

#### Computing with numexpr

Time to evaluate polynomial (1 thread)



### Power Expansion

Numexpr expands expression:

$$0.25*x**3 + 0.75*x**2 + 1.5*x - 2$$

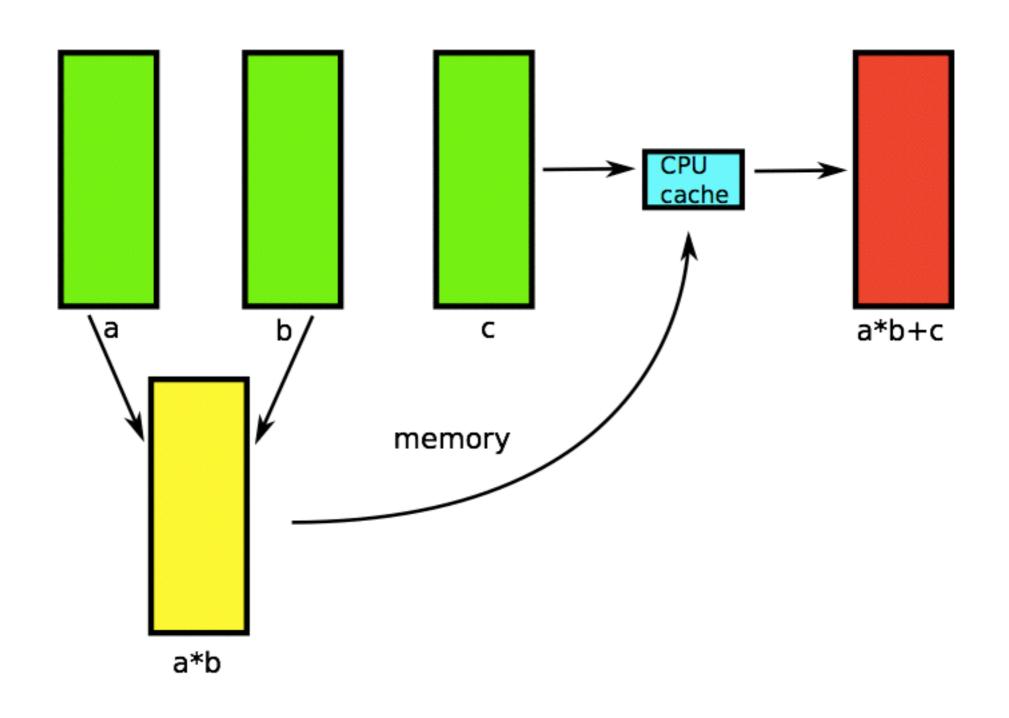
to:

$$0.25*x*x*x + 0.75*x*x + 1.5*x - 2$$

so, no need to use the expensive pow()

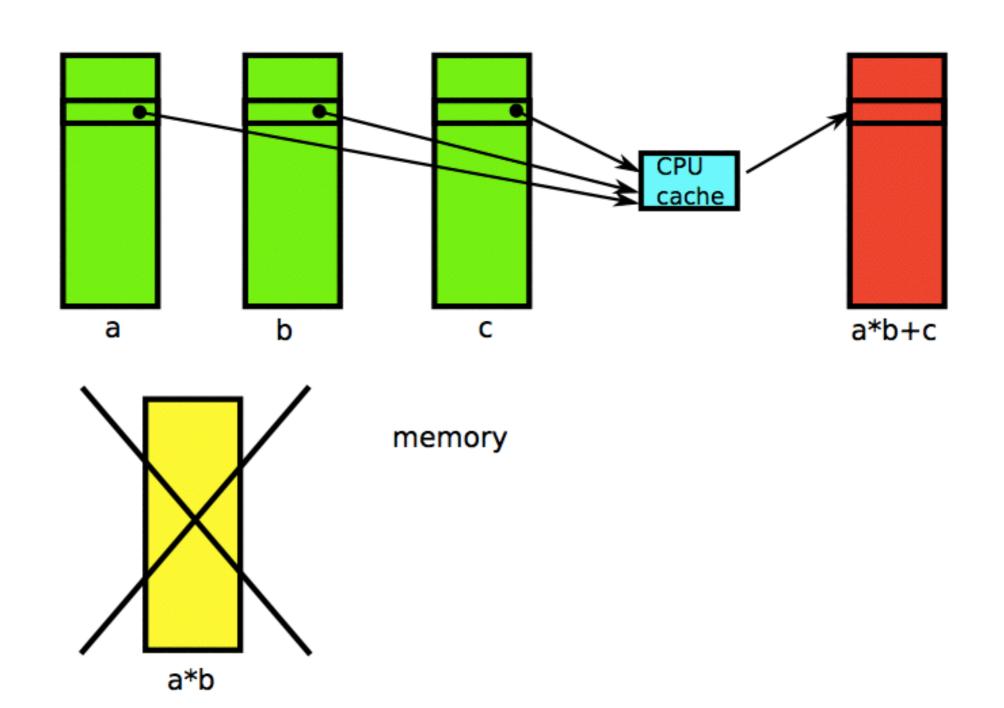
#### Computing with NumPy

Temporaries go to memory



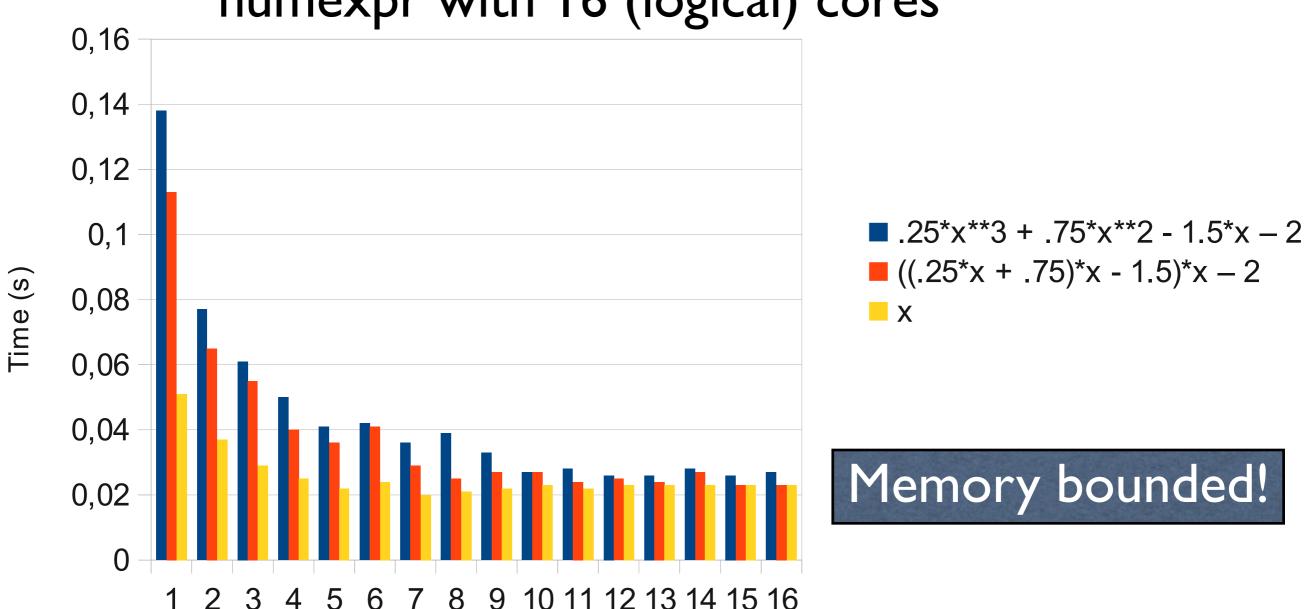
#### Computing with numexpr

Temporaries stay in cache



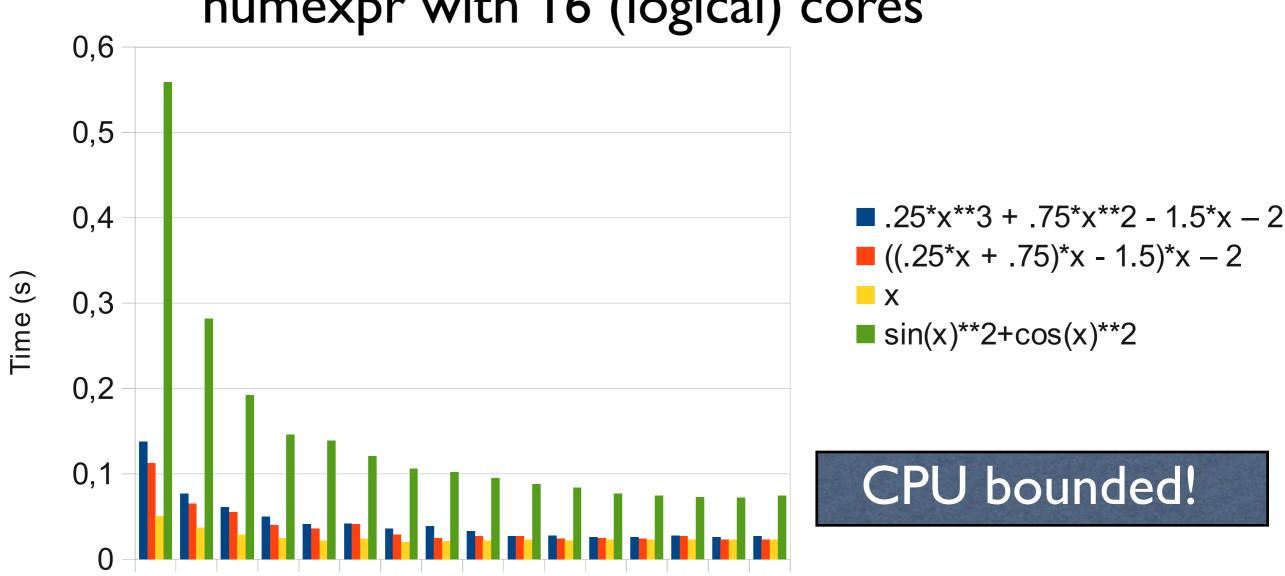
#### numexpr Allows Multithreading for Free





#### Transcendental Functions





10 11 12 13 14 15 16

### Multithreaded numexpr and Beyond: Numba

#### Numexpr Limitations

 Numexpr only implements element-wise operations, i.e. 'a\*b' is evaluated as:

```
for i in range(N):
    c[i] = a[i] * b[i]
```

In particular, it cannot deal with things like:

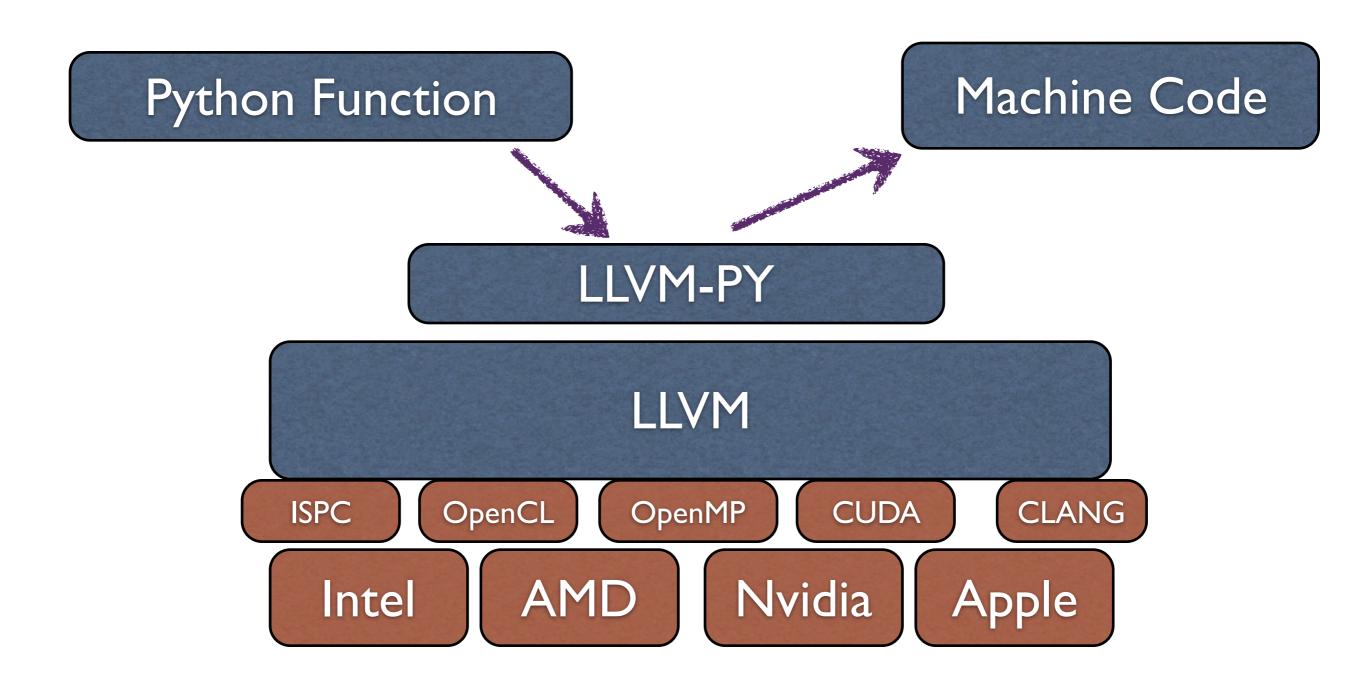
```
for i in range(N):

c[i] = a[i-1] + a[i] * b[i]
```

## Numba: Overcoming numexpr Limitations

- Numba is a JIT that can translate a subset of the Python language into machine code
- It uses LLVM infrastructure behind the scenes
- Can achieve similar or better performance than numexpr, but with more flexibility

#### How Numba works



#### Take-away Messages

- When you have to optimize, have in mind the starving CPU problem.
- Do not always try to parallelize blindly. Give optimization a try first.
- Use proper tools when you need speed. Using one single tool for everything is not going to work well.

#### Eskerrik Asko!