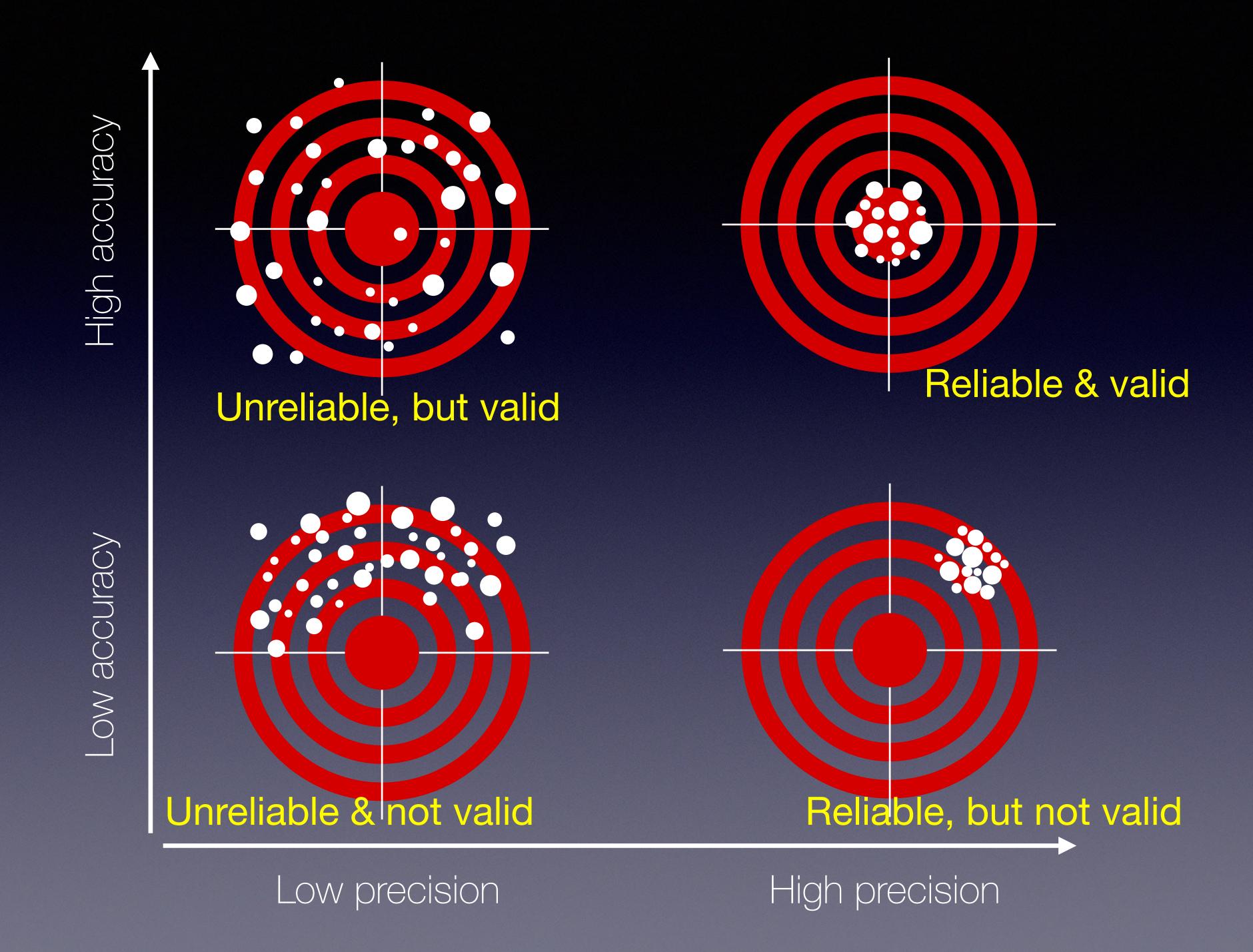
HPC IN LIFE SCIENCES: MOLECULAR DYNAMICS

- 1. CAVEATS FOR COMPLEX MODELS
- 2. PARALLELIZING & ACCELERATING REAL CODES
- 3. HETEROGENEOUS (CPU+GPU) ACCELERATION



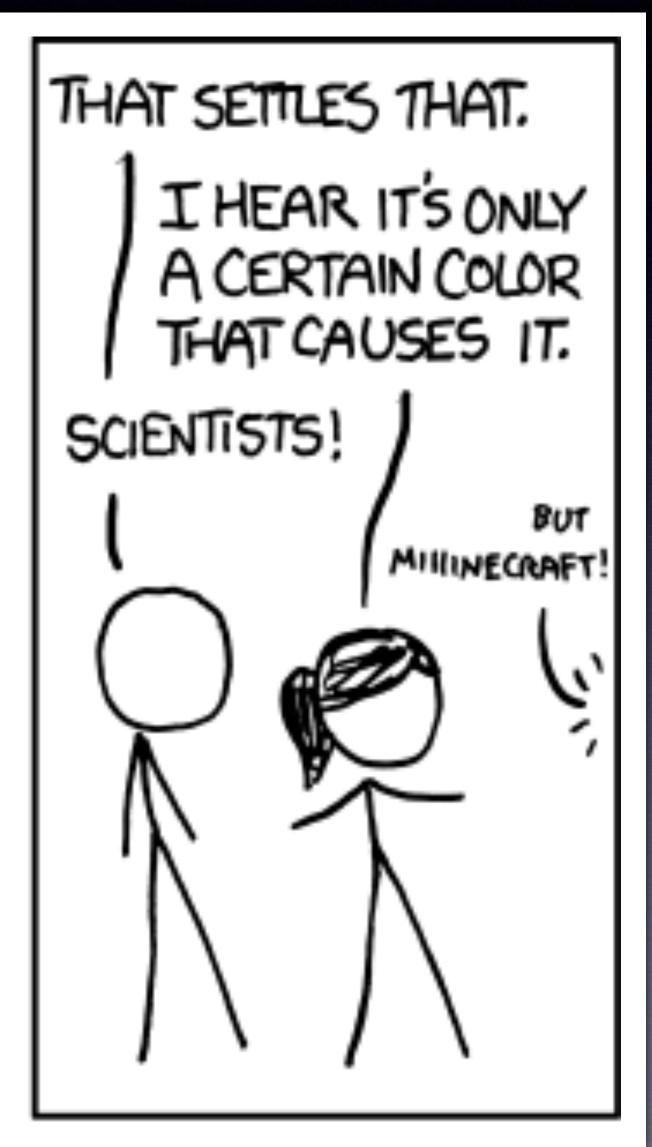


P-value hacking

https://www.xkcd.com/882/







WE FOUND NO LINK BETWEEN PURPLE JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN BROWN JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN PINK JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN BLUE JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN TEAL JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN SALMON JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN RED JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN TURQUOISE JELLY BEANS AND ACNE (P > 0.05).

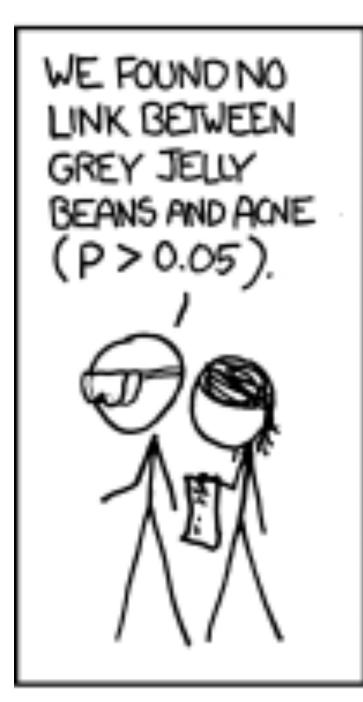


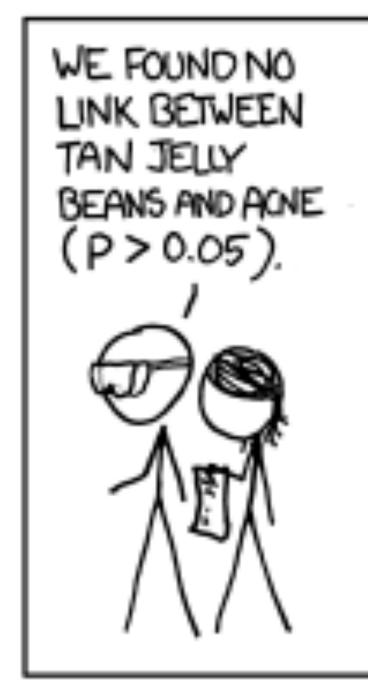
WE FOUND NO LINK BETWEEN MAGENTA JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN YELLOW JELLY BEANS AND ACNE (P > 0.05).

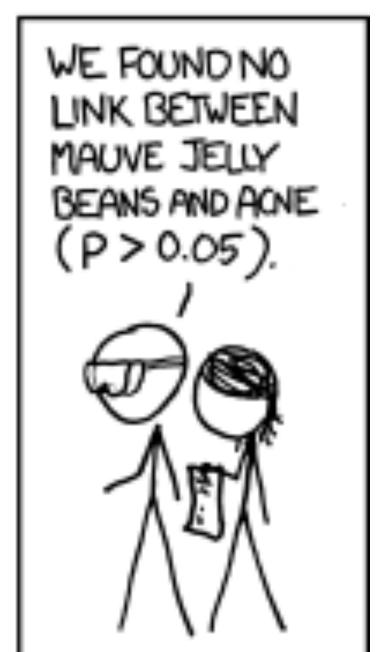


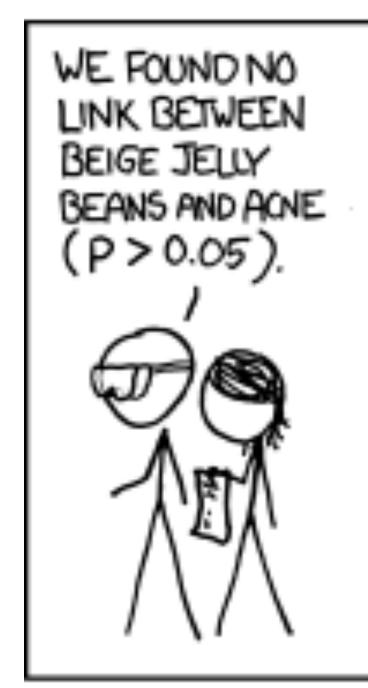


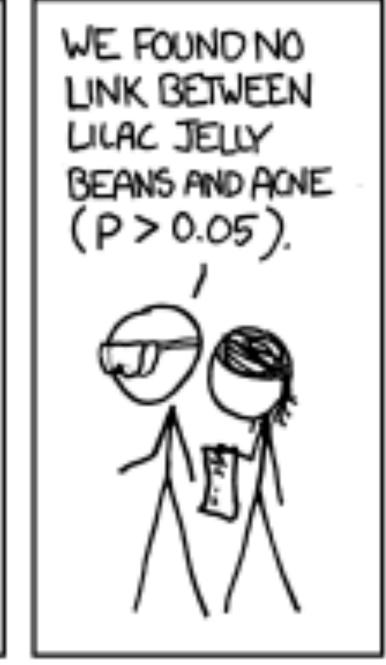


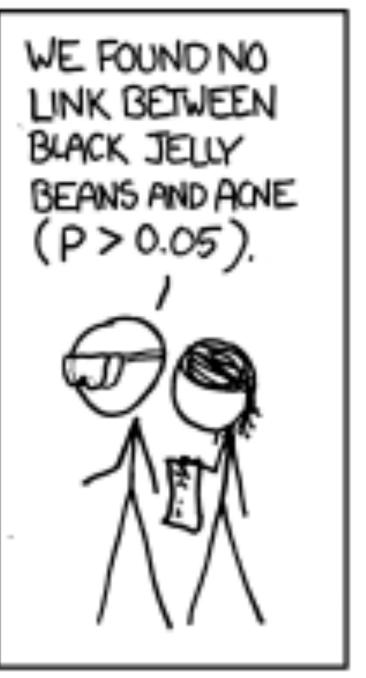


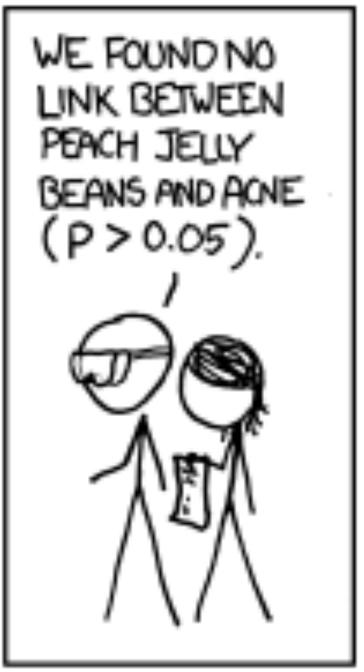


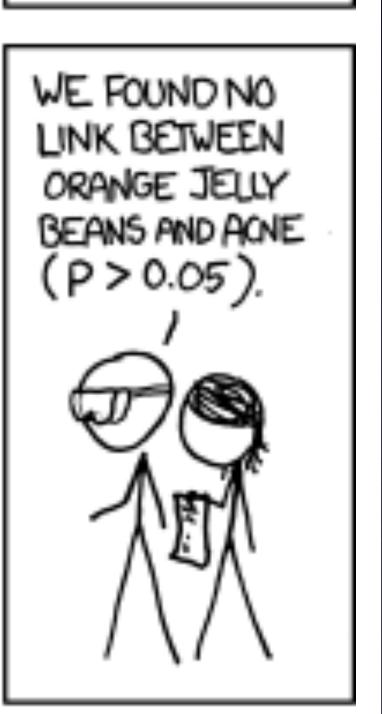


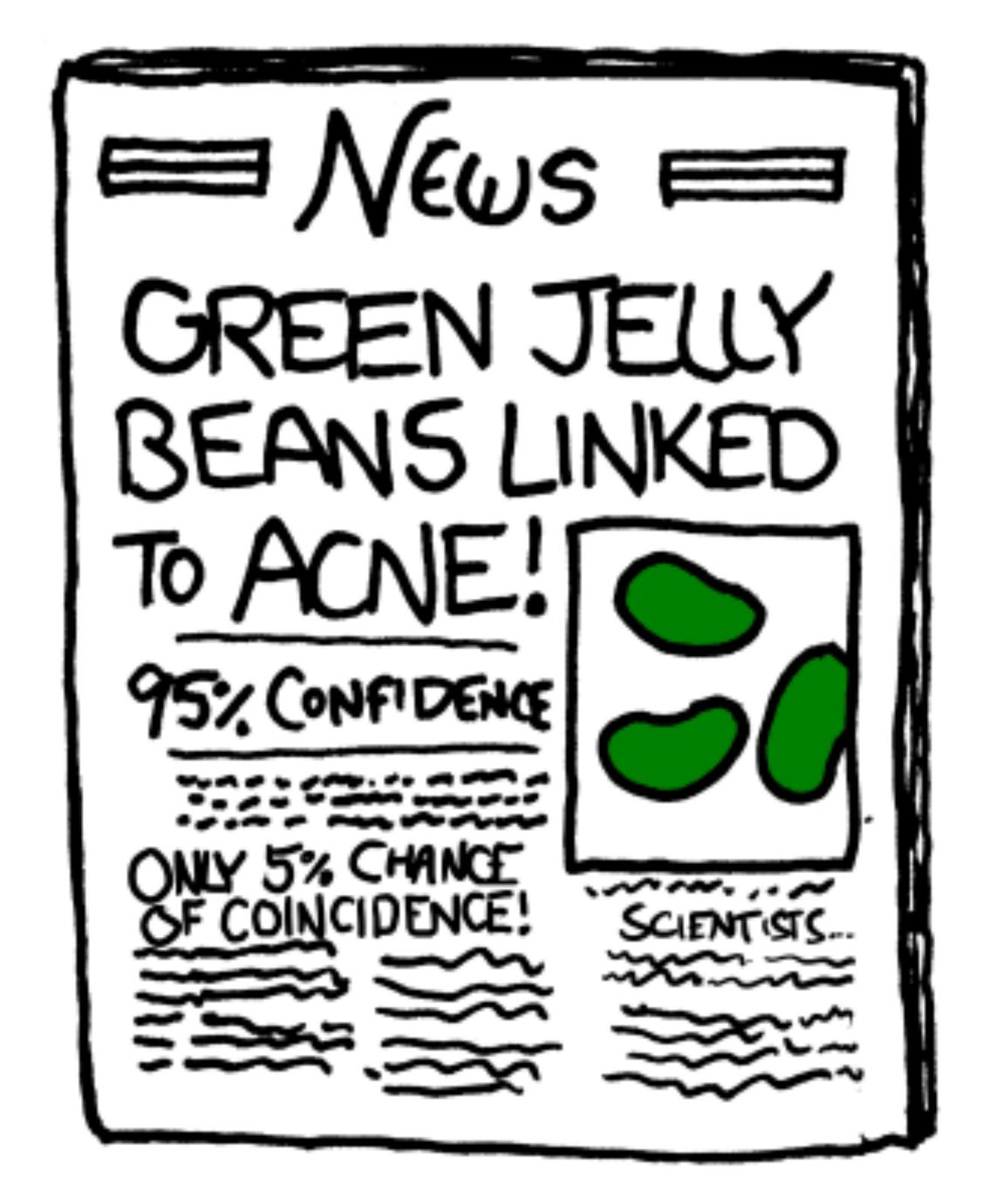












P-value hacking - for real

BMC Genetics 2014, **15**:12 http://www.biomedcentral.com/1471-2156/15/12



RESEARCH ARTICLE

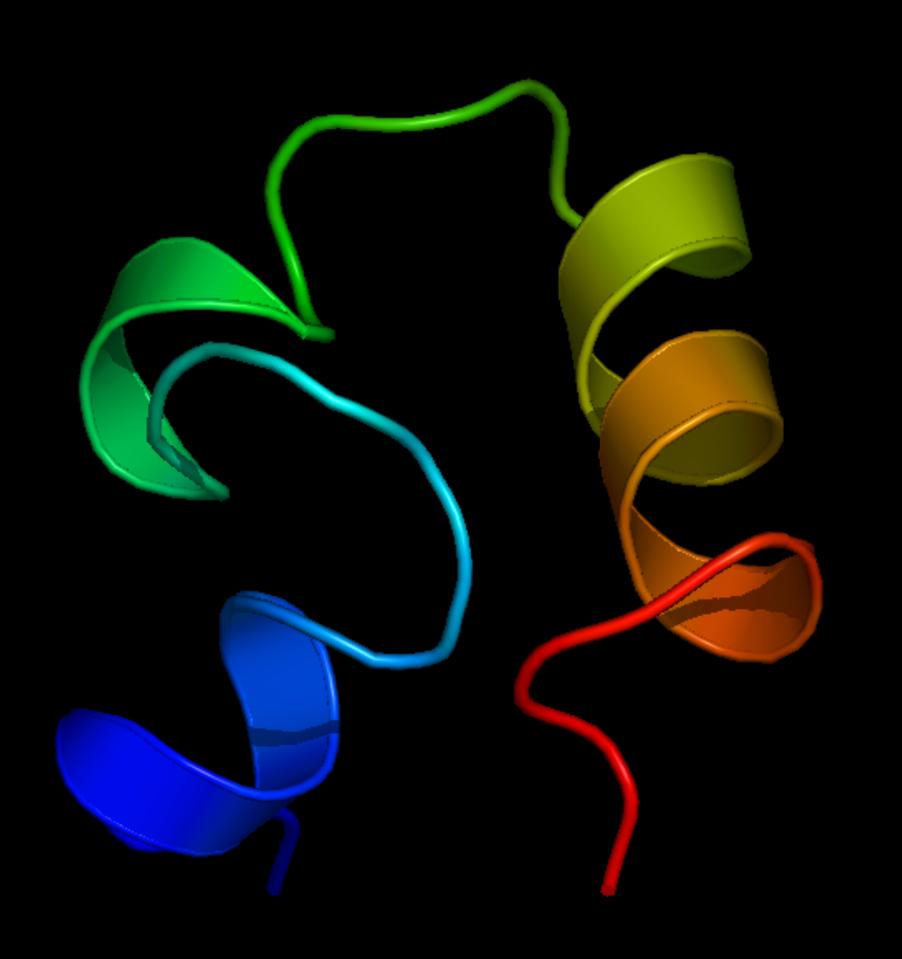
Open Access

Change in paternal grandmothers' early food supply influenced cardiovascular mortality of the female grandchildren

Abstract

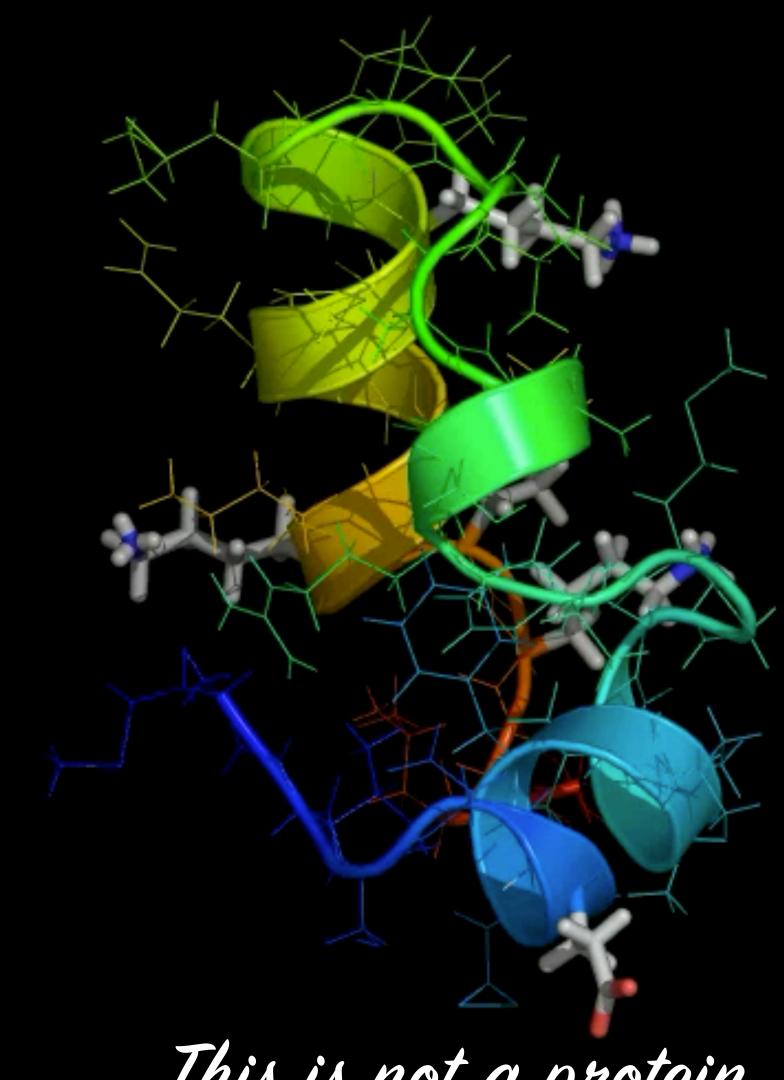
Background: This study investigated whether large fluctuations in food availability during grandparents' early development influenced grandchildren's cardiovascular mortality. We reported earlier that changes in availability of food - from good to poor or from poor to good - during intrauterine development was followed by a double risk of sudden death as an adult, and that mortality rate can be associated with ancestors' childhood availability of food. We have now studied transgenerational responses (TGR) to sharp differences of harvest between two consecutive years' for ancestors of 317 people in Överkalix, Sweden.

Results: The confidence intervals were very wide but we found a striking TGR. There was no response in







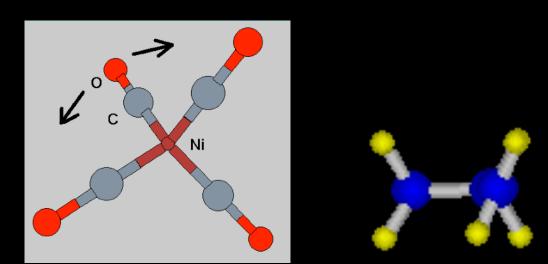


This is not a protein

$$\left[\frac{-\hbar^2}{2m}\nabla^2 + V\right]\Psi = i\hbar\frac{\partial}{\partial t}\Psi$$

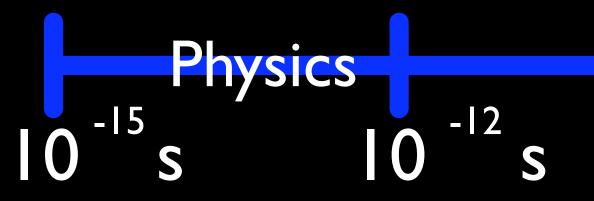
F=ma

Experiments



Efficient averaging

Less detail





Where we need to be
Biology
10 -3 S

Simulations

Where we are

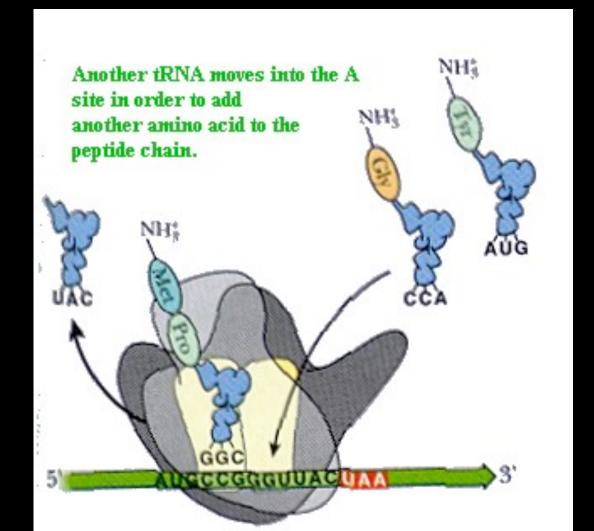
Where we want to be

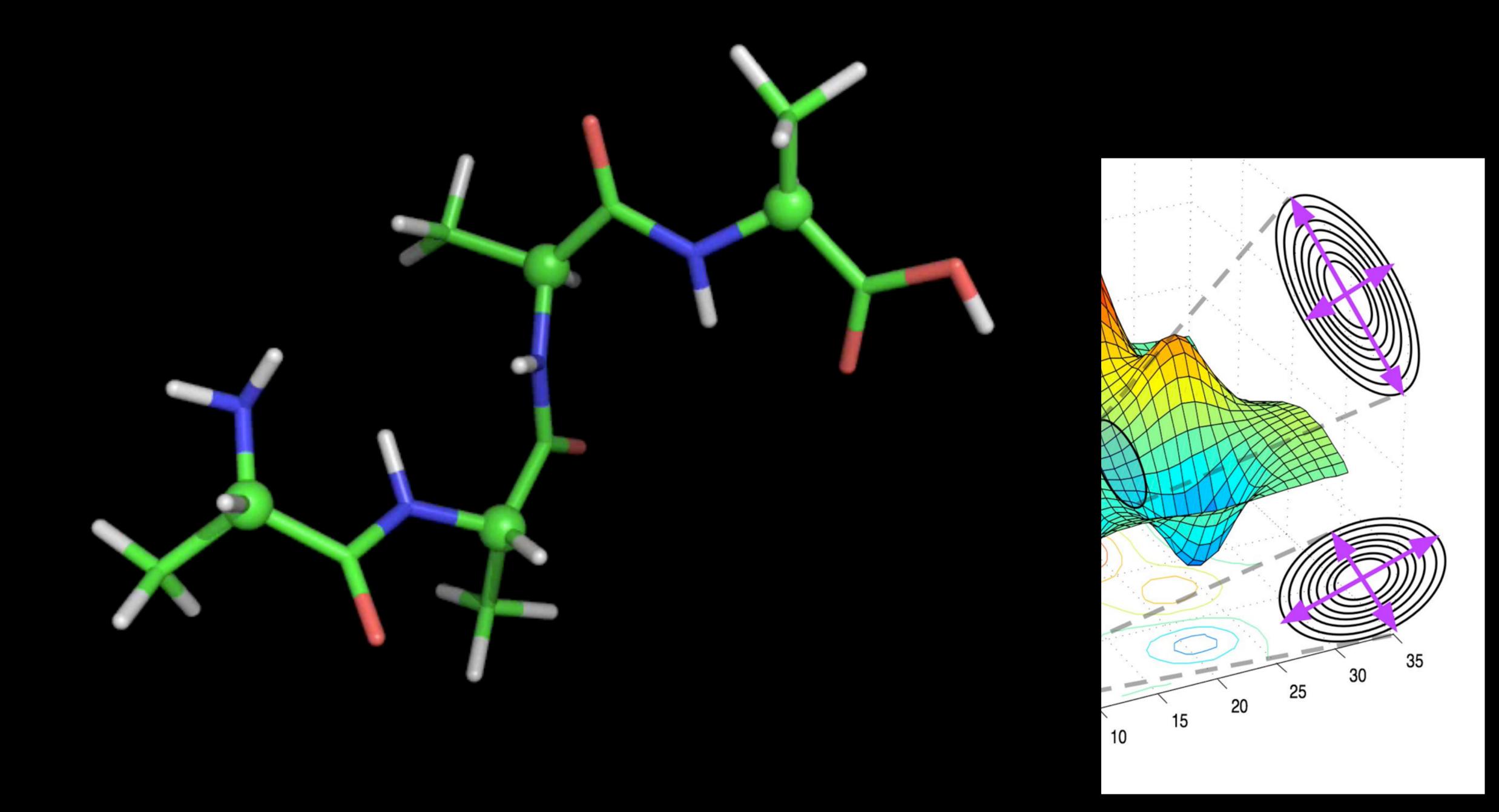
Extreme detail

Sampling issues?

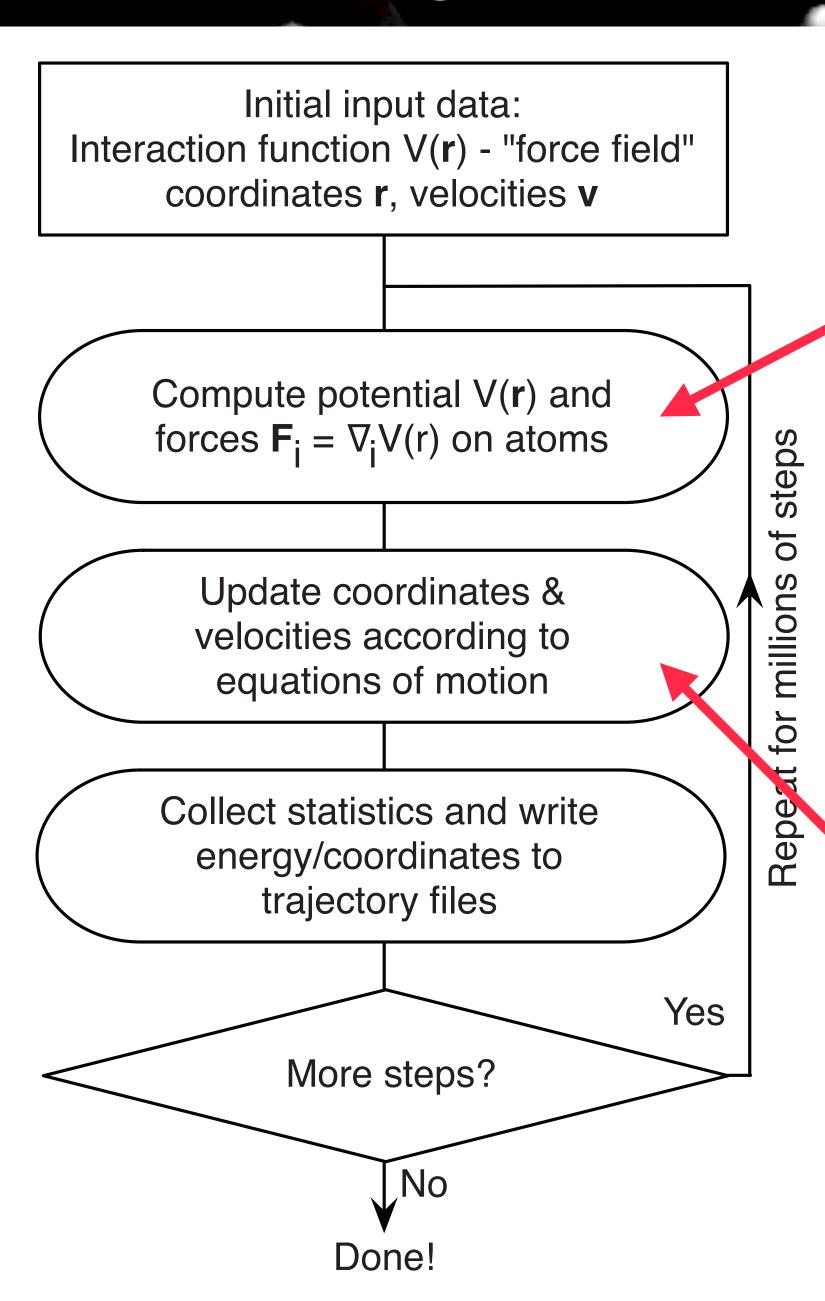
Parameter quality?







Challenge: MD is intrinsically a sequential problem

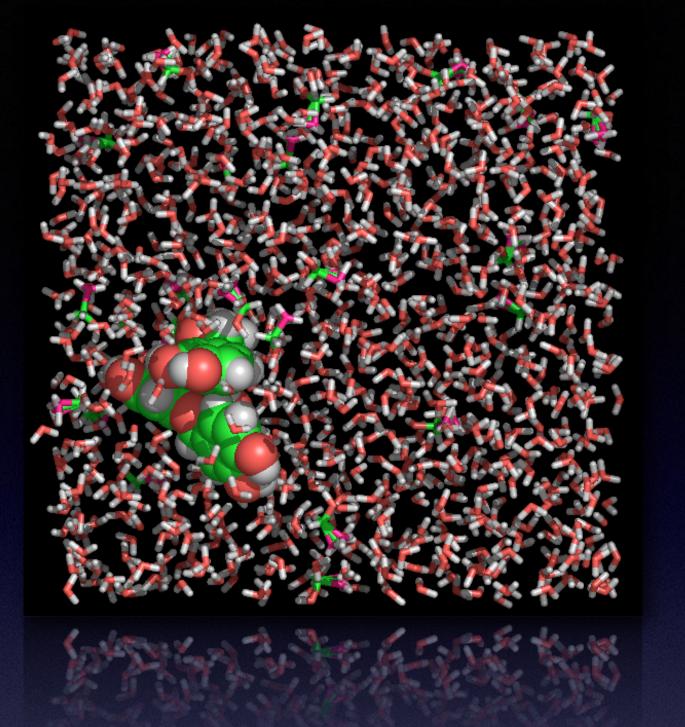


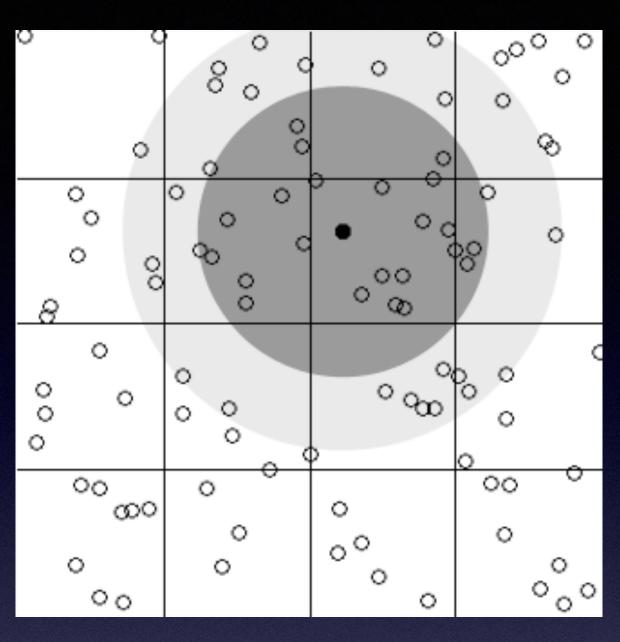
$$\begin{split} V(r) &= \sum_{bonds} \frac{1}{2} k_{ij}^{b} \left(r_{ij} - r_{ij}^{0} \right)^{2} \\ &+ \sum_{angles} \frac{1}{2} k_{ijk}^{\theta} \left(\theta_{ijk} - \theta_{ijk}^{0} \right)^{2} \\ &+ \sum_{torsions} \left\{ \sum_{n} k_{\theta} \left[1 + \cos \left(n\phi - \phi_{0} \right) \right] \right\} \\ &+ \sum_{torsions} k_{\xi} \left(\xi_{ijkl} - \xi_{ijkl}^{0} \right) \\ &+ \sum_{impropers} k_{\xi} \left(\xi_{ijkl} - \xi_{ijkl}^{0} \right) \\ &+ \sum_{i,j} \frac{q_{i}q_{j}}{4\pi\varepsilon_{0}r_{ij}} \\ &+ \sum_{i,j} \left[\frac{C_{12}}{r_{ij}^{12}} - \frac{C_{6}}{r_{ij}^{6}} \right] \end{split}$$

Costly, because these terms involve all pairs

$$m_i \frac{\partial^2 r_i}{\partial t^2} = F_i \quad i = 1..N$$
 $F_i = -\frac{\partial V(r)}{\partial r_i}$

With $\Delta t \sim 1 \text{fs}$ and μs to s timescales of interest, we need $10^9 \text{-} 10^{15}$ steps.





The challenge:

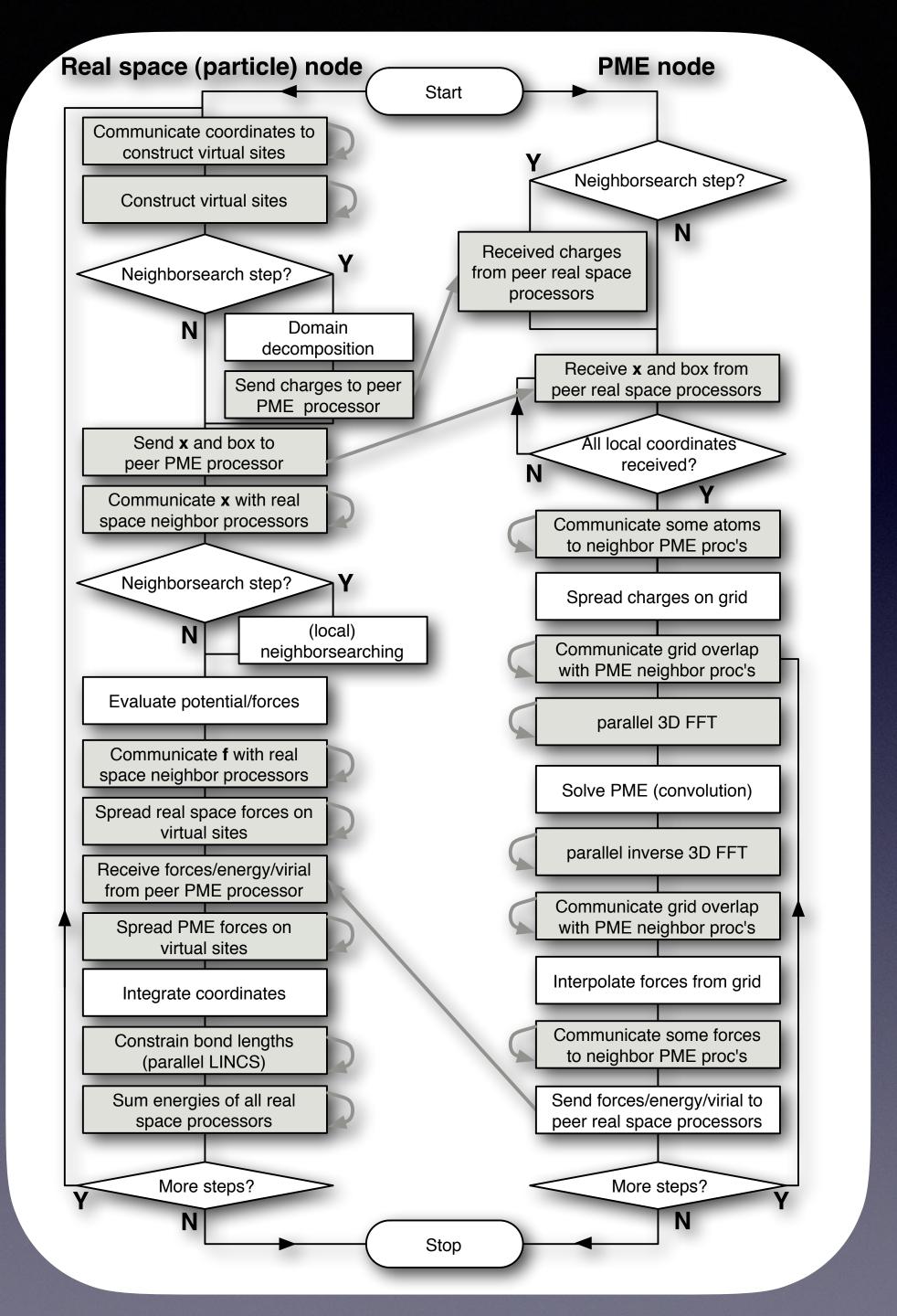
- ~100,000 atoms
- Each has ~500 neighbors
 - Maintain a list of them, update ea 10 steps
- ~50M interactions/step
- ~2B FLOPS per step
- ~1ms real time per step

```
for(k=nj0; (k<nj1); k++)
   /* Get j neighbor index. and coordinate index */
                   = jjnr[k];
   /* load j atom coordinates */
                     = pos[j3+0];
                     = pos[j3+1];
                     = pos[j3+2];
    /* Calculate distance */
                     = ix1 - jx1;
   dy11
                     = iy1 - jy1;
                     = iz1 - jz1;
   dz11
                     = dx11*dx11+dy11*dy11+dz11*dz11;
    rsq11
                     and 1/r2 */
    /∗ Calculate 1
                     = 1.0/sqrt(rsq11);
    rinv11
    /* Load paramete.
                     = iq*charqe[inr];
                     = nti+2*type[jnr];
                     = vdwparam[tj];
                     = vdwparam[tj+1];
                     = rinv11*rinv11;
   rinvsq
    /* Coulomb interaction */
                     = qq*rinv11;
   vcoul
   vctot
                     = vctot+vcoul;
    /* Lennard-Jones interaction */
   rinvsix
                     = rinvsq*rinvsq*rinvsq;
   Vvdw6
                     = c6*rinvsix;
   Vvdw12
                     = c12*rinvsix*rinvsix;
   Vvdwtot
                     = Vvdwtot+Vvdw12-Vvdw6;
                     = (vcoul+12.0*Vvdw12-6.0*Vvdw6)*rinvsq;
   fscal
   /* Calculate temporary vectorial force */
                     = fscal*dx11;
                     = fscal*dy11;
                     = fscal*dz11;
    /* Increment i atom force */
   fix1
                     = fix1 + tx;
   fiy1
                     = fiy1 + ty;
   fiz1
                     = fiz1 + tz;
   /* Decrement j atom force */
   faction[j3+0]
                     = faction[j3+0] - tx;
   faction[j3+1]
                     = faction[j3+1] - ty;
   faction[j3+2]
                     = faction[j3+2] - tz;
   /* Inner loop uses 38 flops/iteration */
```

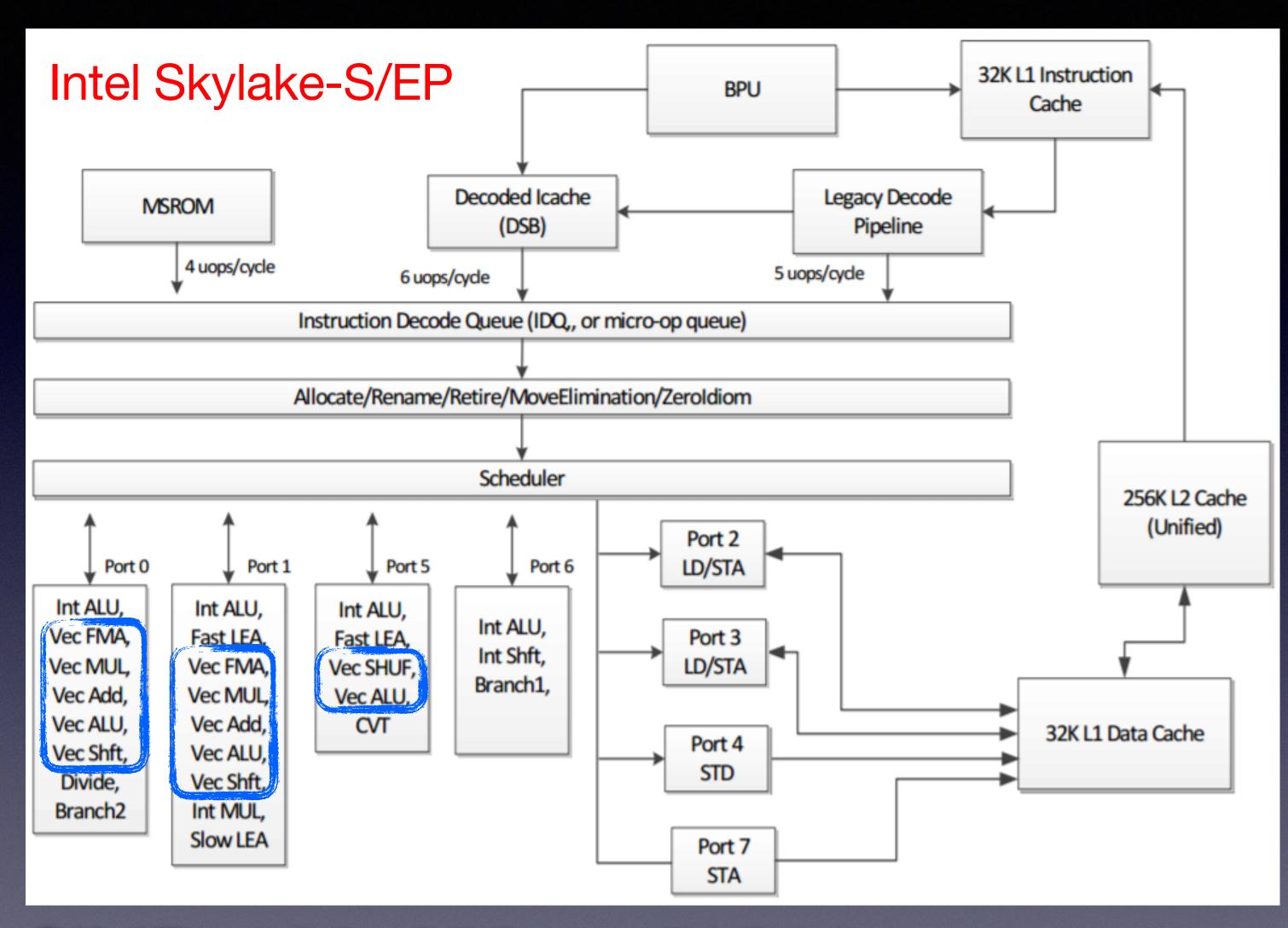
The things we do every ~100 µs

To-Do Monday 09:15:48.004.100 (simple version) Adjust domain decomposition [communicate] Communicate coordinates to/from 26 neighbor nodes Find atoms in proximity [communicate] Change charges or parameters for free energy Create local virtual particles [communicate] Send coordinates to GPU Calculate short-range electrostatics & VdW Calculate bonds Calculate angles Calculate torsions Perform long-range lattice summation [communicate] Apply external fields/forces Get forces back from GPU Send forces to 26 neighbors [communicate] Integrate new positions Constrain bonds [communicate] Update stats. (temperature, energy) [communicate] Write coordinates/forces if necessary A fairly typical HPC application - complex & fast

<u>S</u>



What does a modern CPU core look like?



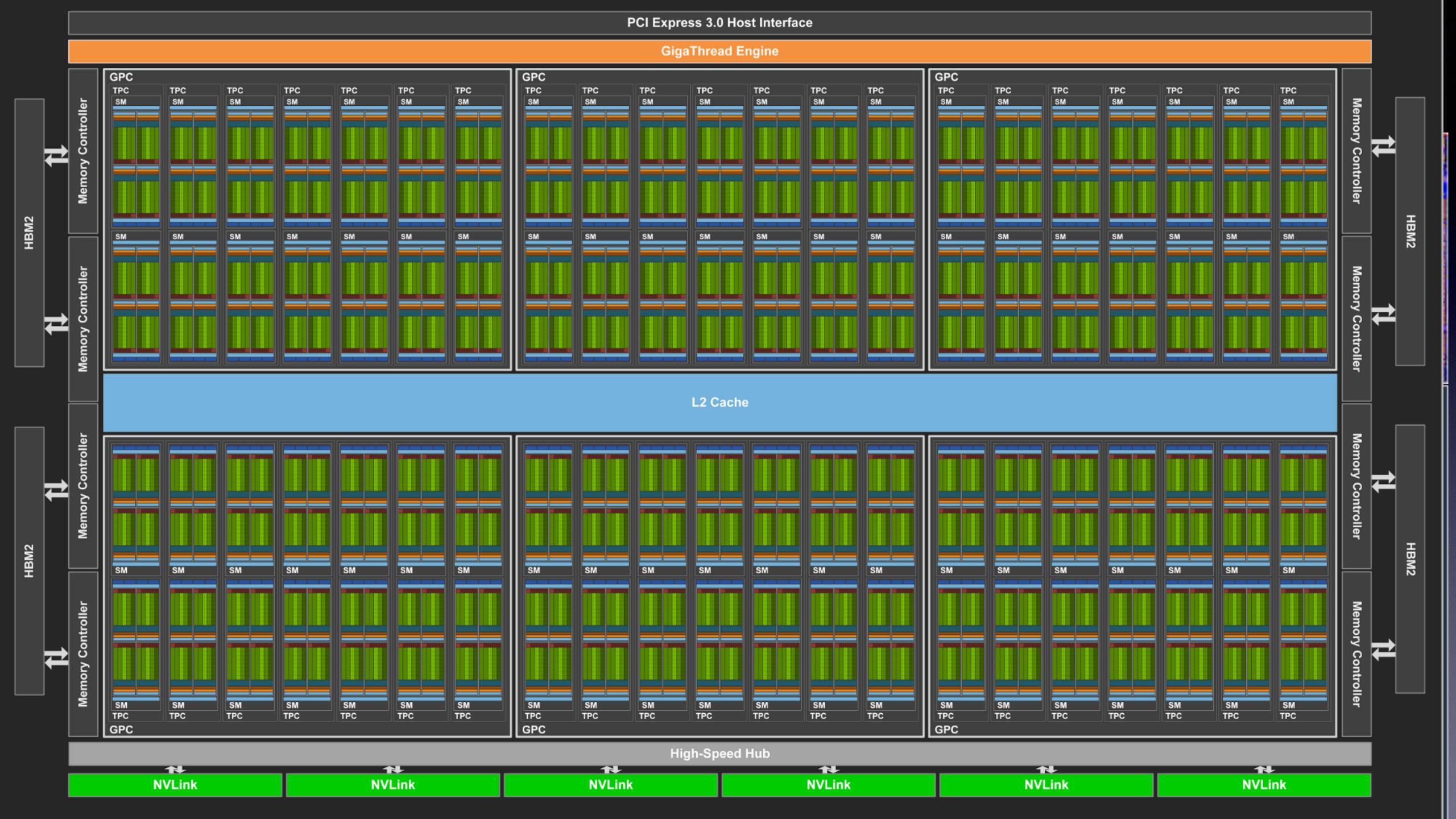
SIMD: 128, 256, or 512 bit vectors

5 μops/core each cycle SIMD + FMA: 64 flops @ single prec.

Up to 32 cores per chip
2 sockets per node

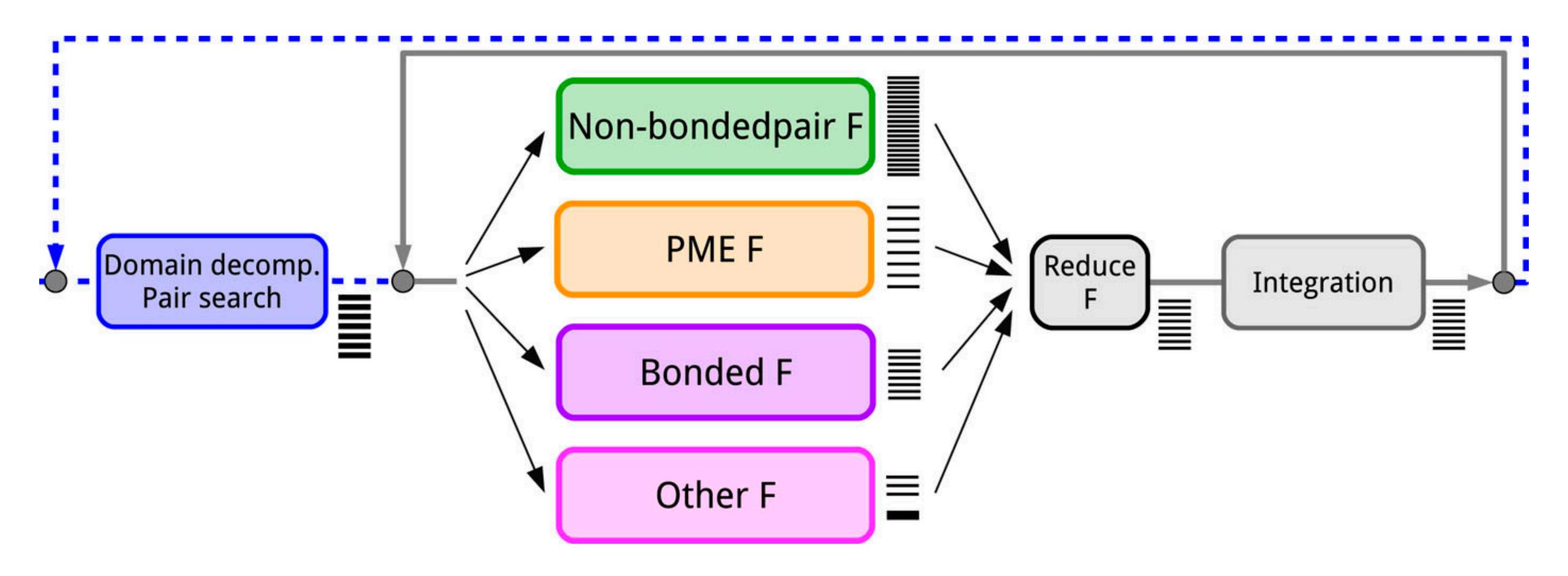
Theoretically: 320 instructions or 4096 flops per *cycle* on each node.

latency is ~4 cycles on Skylake. You need 256 independent FMA flops (128 FMA operations) to saturate just a single core

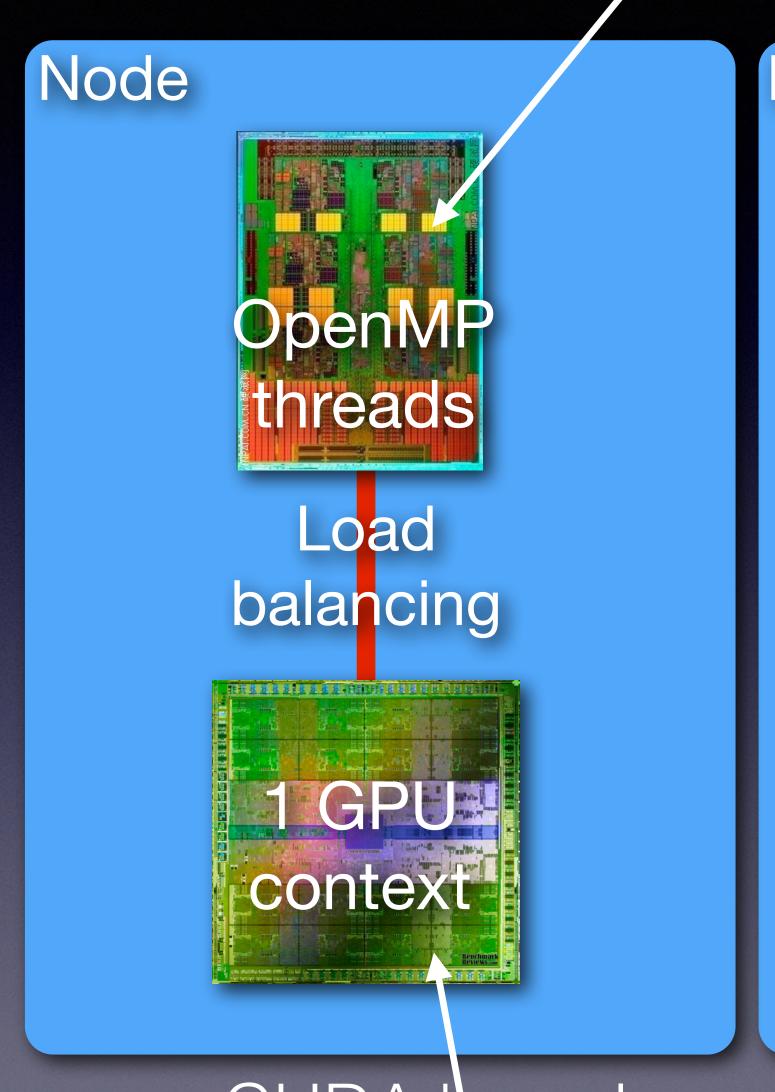


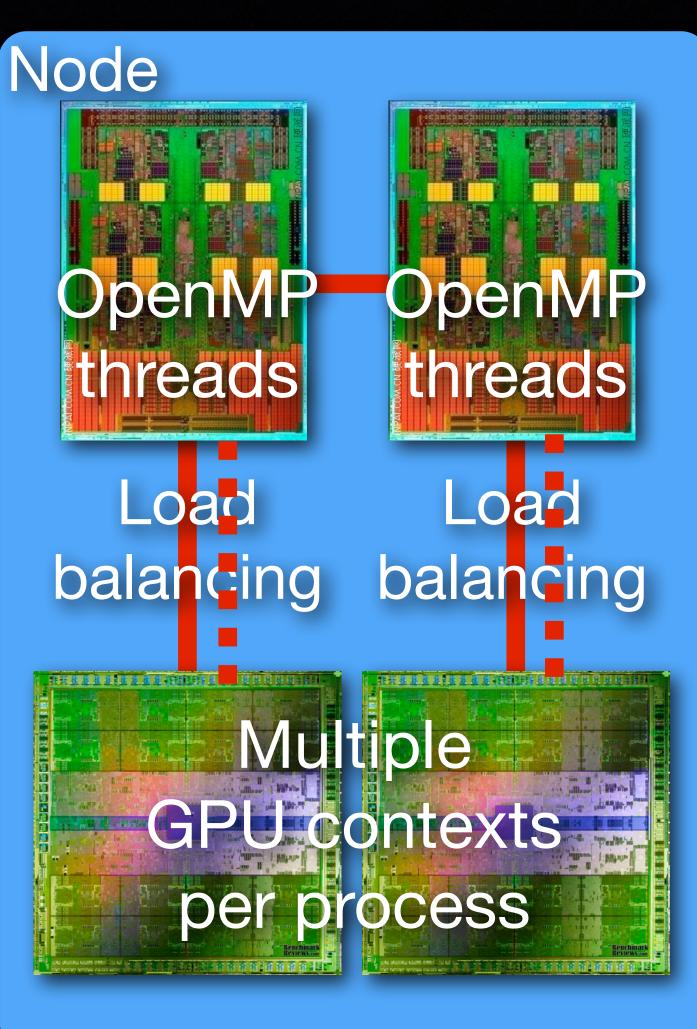
Acceleration Approaches

	GPU libraries	OpenAcc	Pure CUDA	Heterogeneous CPU/GPU
Initial effort / Expertise req.				
Generality / Portability				
Performance				
Code maintainability				
	Works if your code offloads to libraries	Always works, but success depends on you & compiler	Lots of work, assumes impl. can run entirely on GPU	Even more work, less CUDA, can use both CPU & GPU

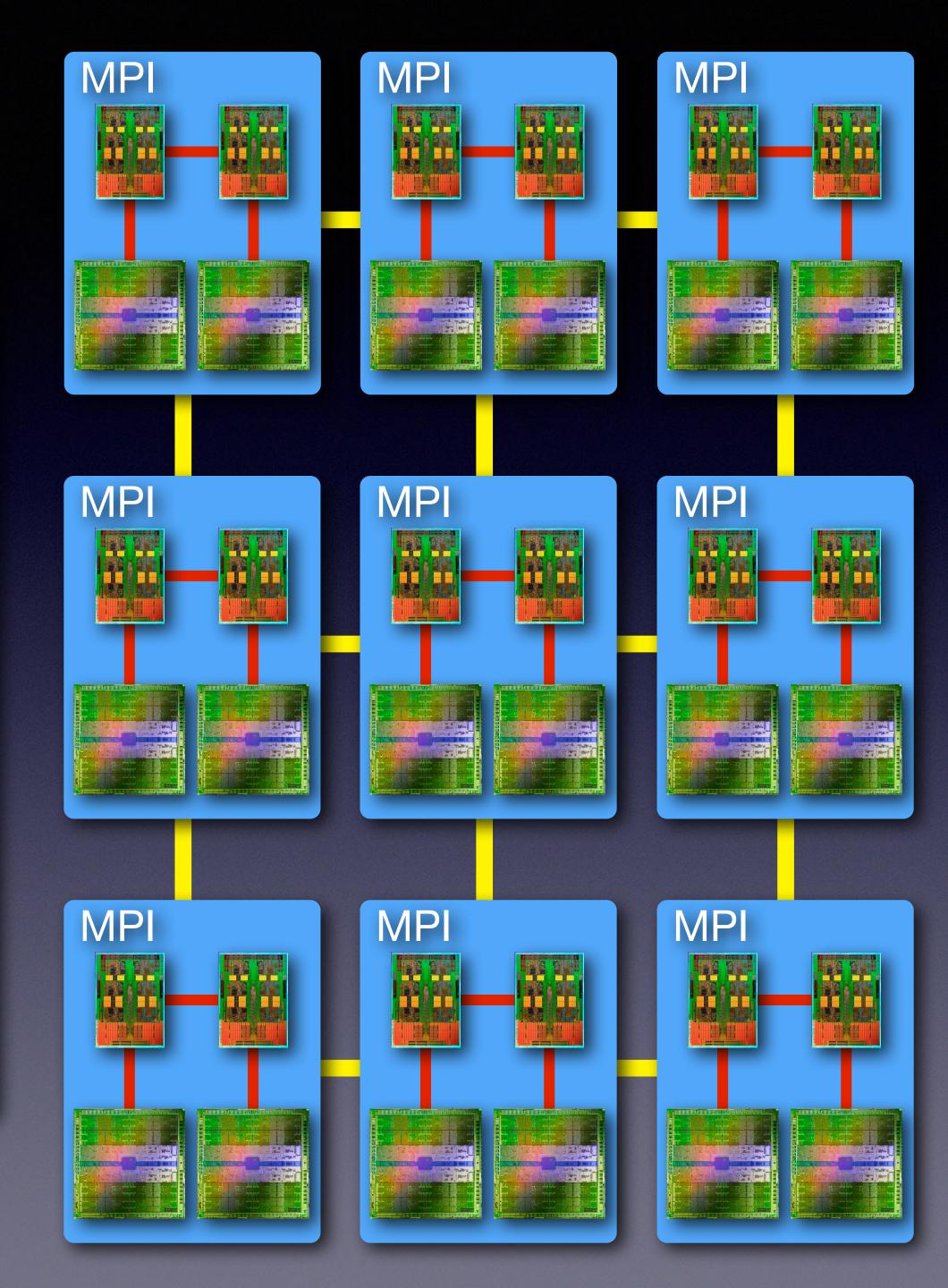


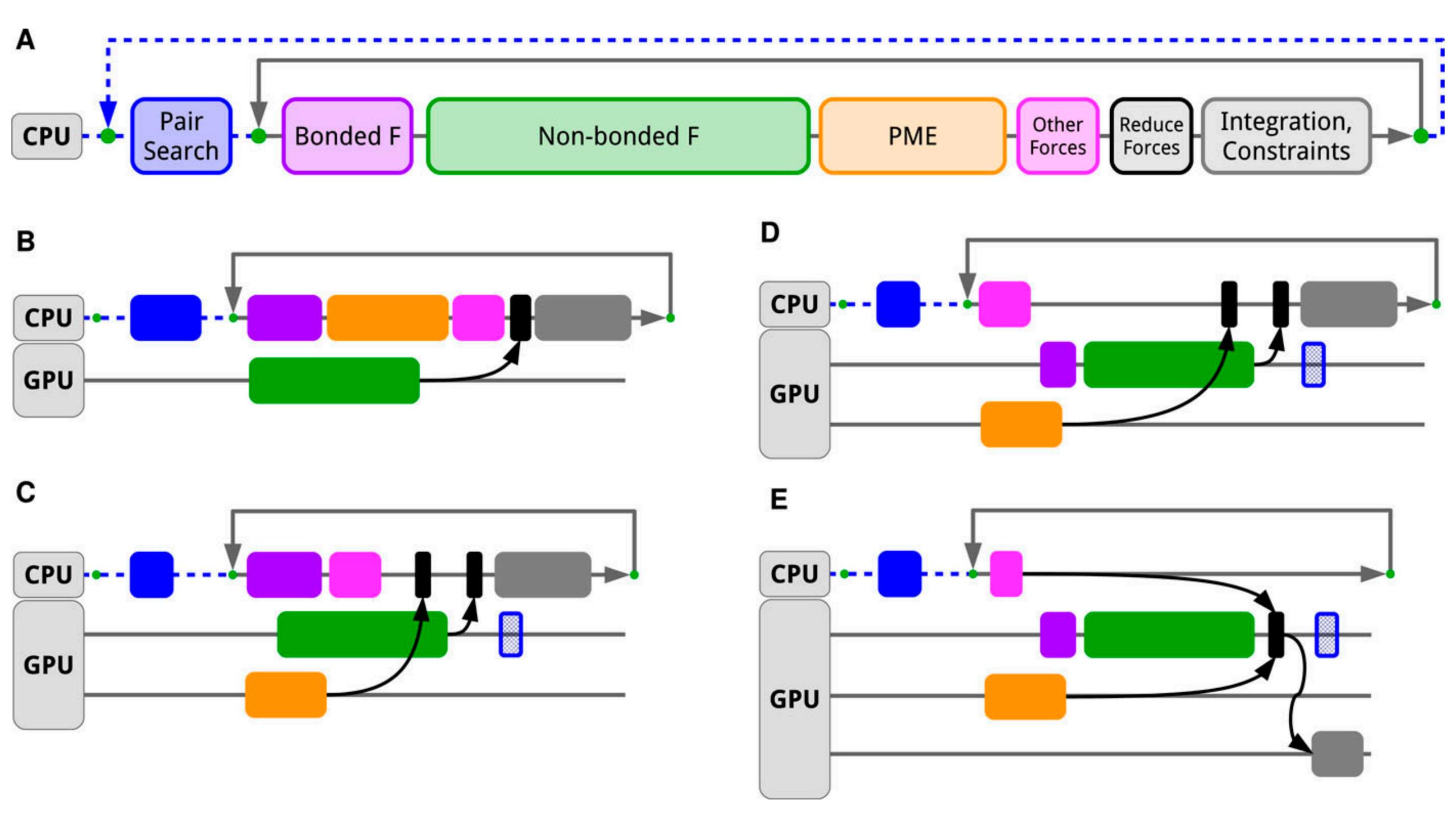
Explicit SIMD instructions on CPUs & Xeon Phi; each instruction does up to 32 flops



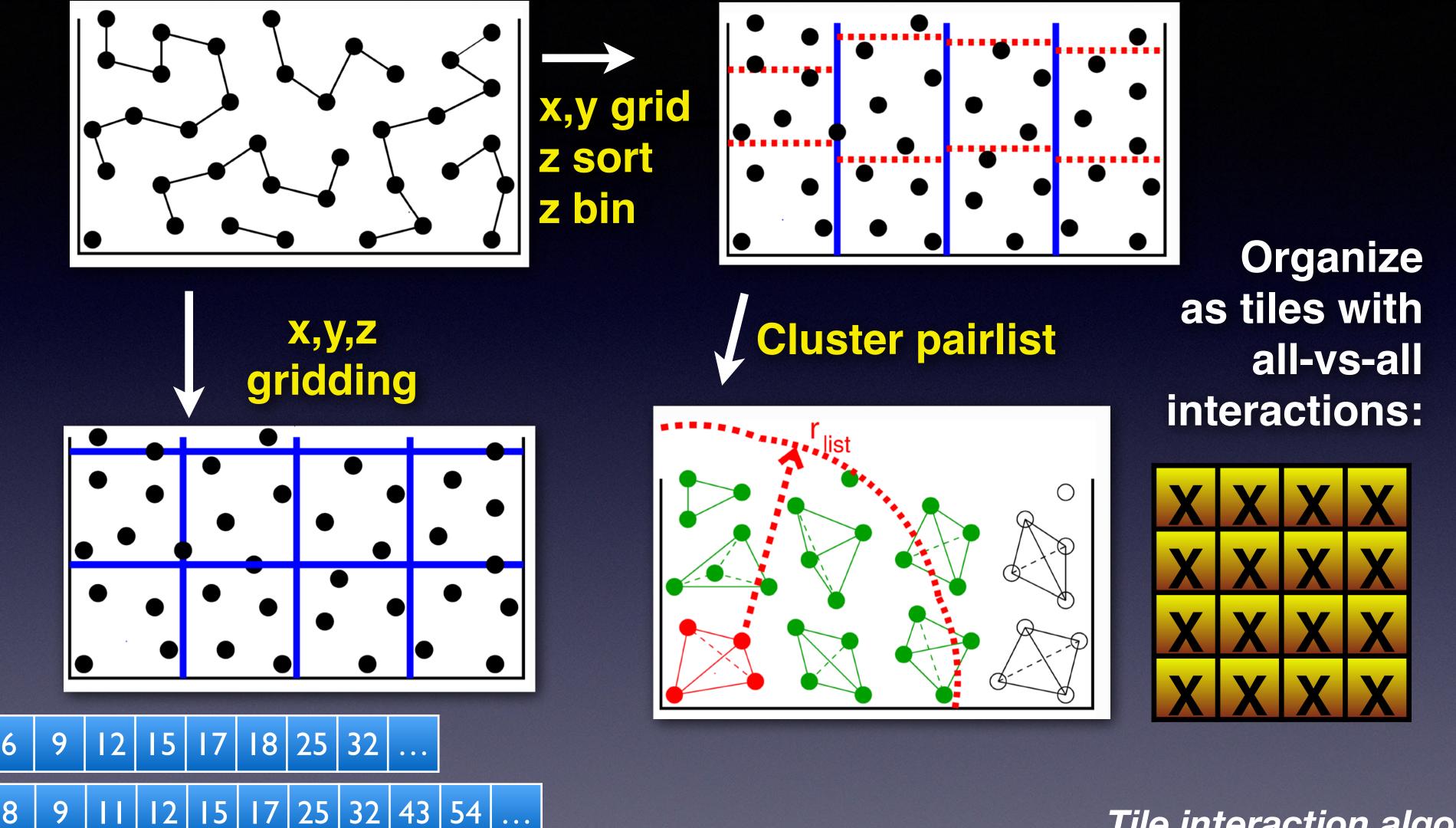


CUDA kernels on NVIDIA GPUs, OpenCL for AMD/Intel GPUs





From neighborlists to cluster proximity lists: Revisit algorithms



Tile interaction algorithms: Load N atoms, compute N^2 forces

The Link-cell algorithm: Load 1 atom, calculate 1 interaction Verlet, Phys Rev 159, 98-103 (1967)

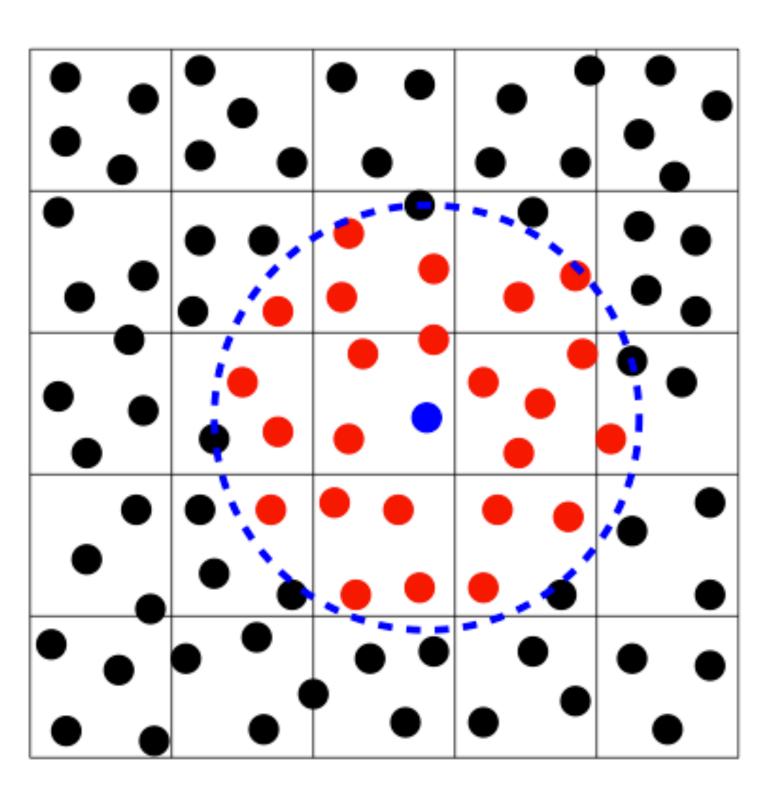
9 | 10 | 11 | 12 | 13 | 19 | 20 | ...

i=3:

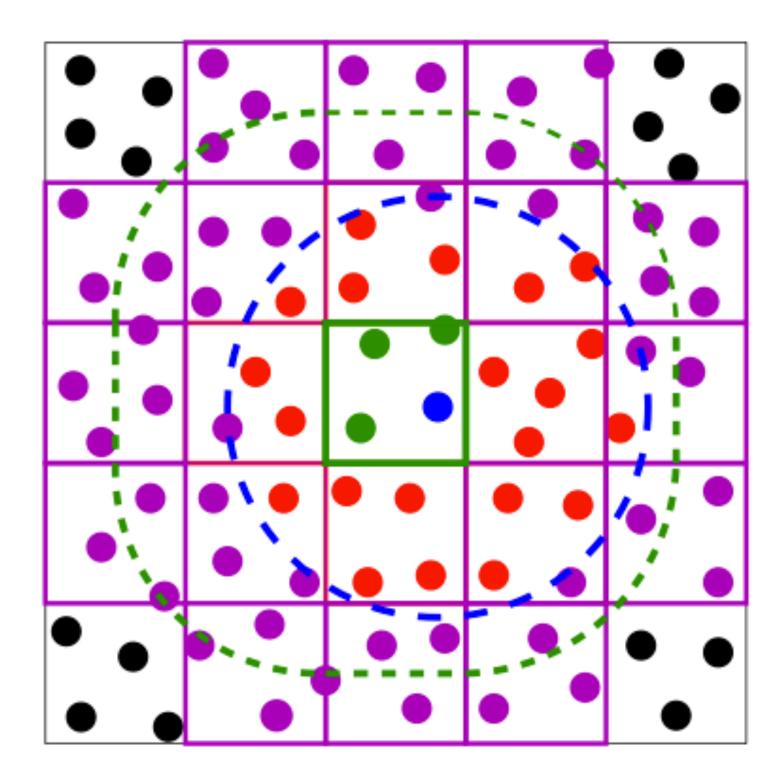
This creates a new problem: Tiling circles is difficult

You want to calculate interactions with red neighbors

serial computing



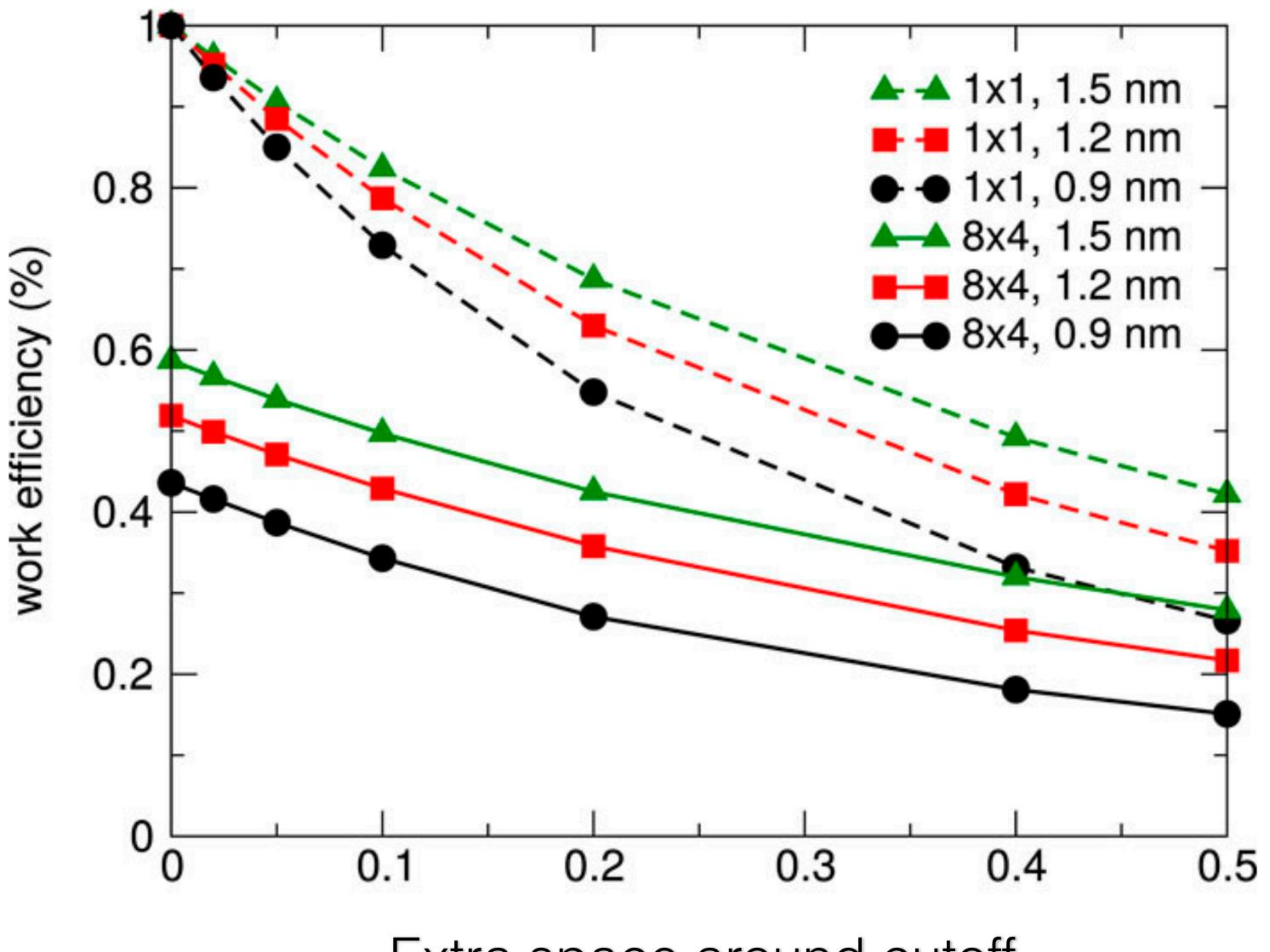
stream computing



Lots of wasted FLOPS!

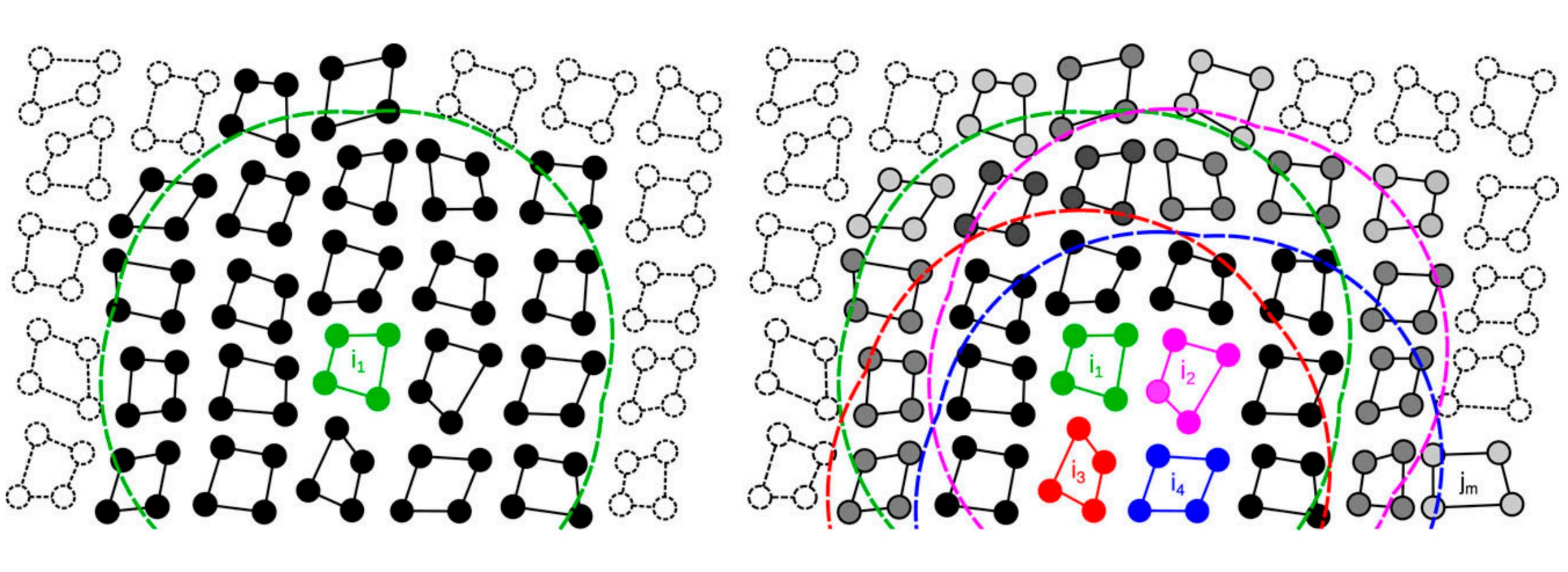
- You need a lot of cubes to cover a sphere
- All interactions beyond cutoff need to be zero





Extra space around cutoff

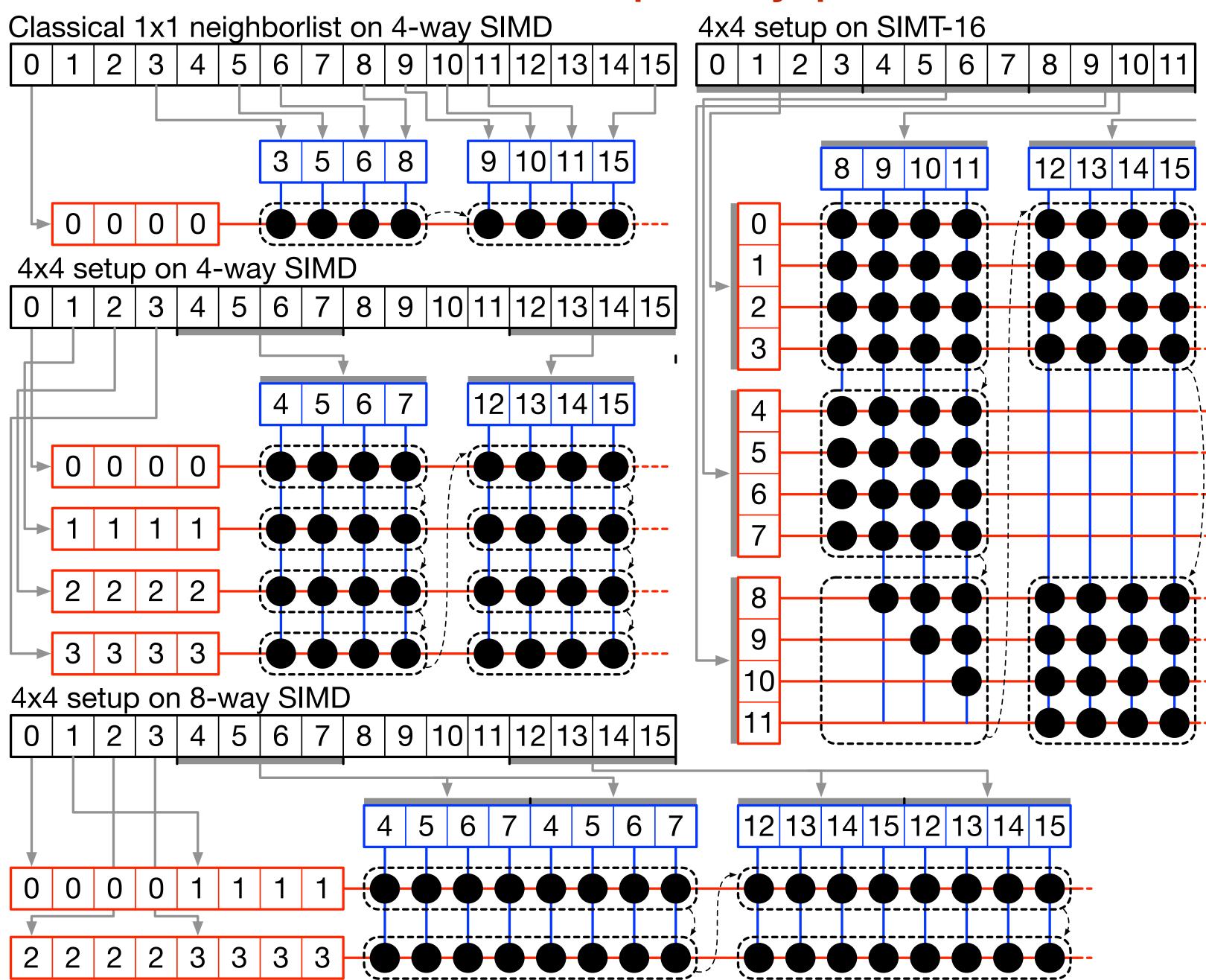
Clusters on CPUs, Superclusters on GPUs



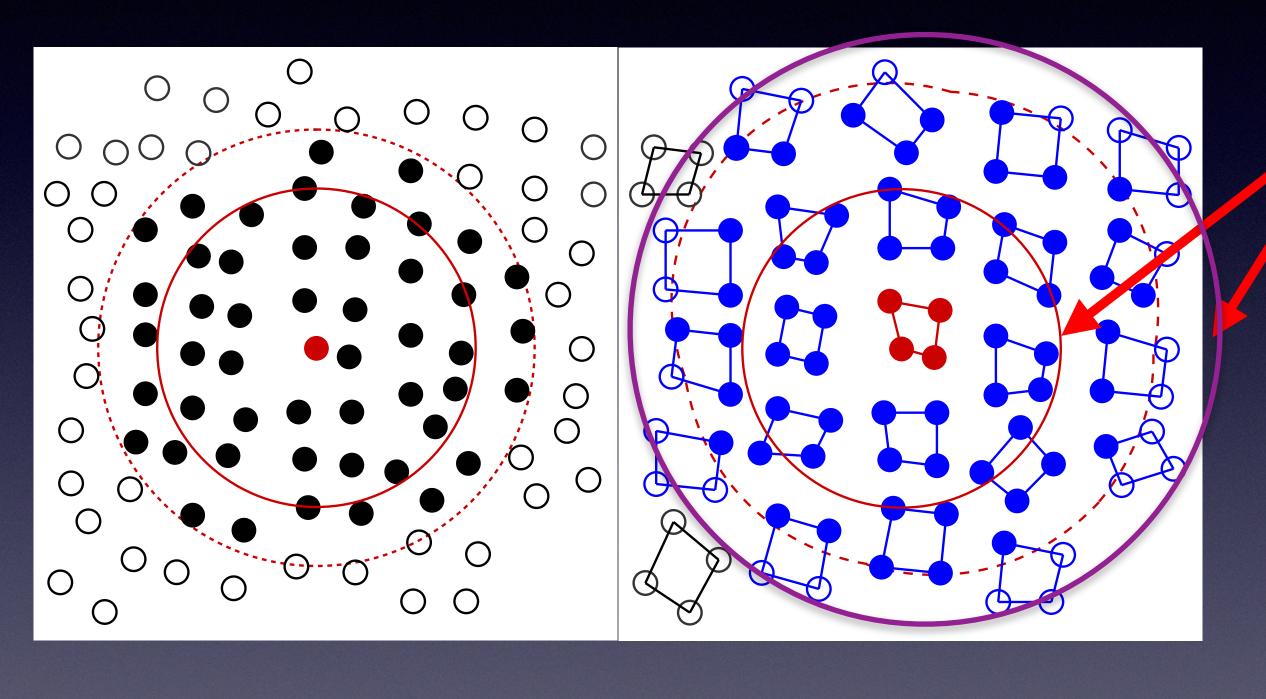
Bringing the Performace back to the CPU

Unified GPU/CPU architecture - completely portable

CUDA **OpenCL** Intel MIC x86 SSE2 x86 SSE4.1 x86 AVX x86 AVX-128-FMA **x86 AVX2** x86 AVX2_128 x86 AVX-512F x86 AVX-512ER Arm Neon Arm64 Asimd IBM QPX IBM VMX IBM VSX Fujitsu HPC-ACE



Atom clustering and pair list buffering

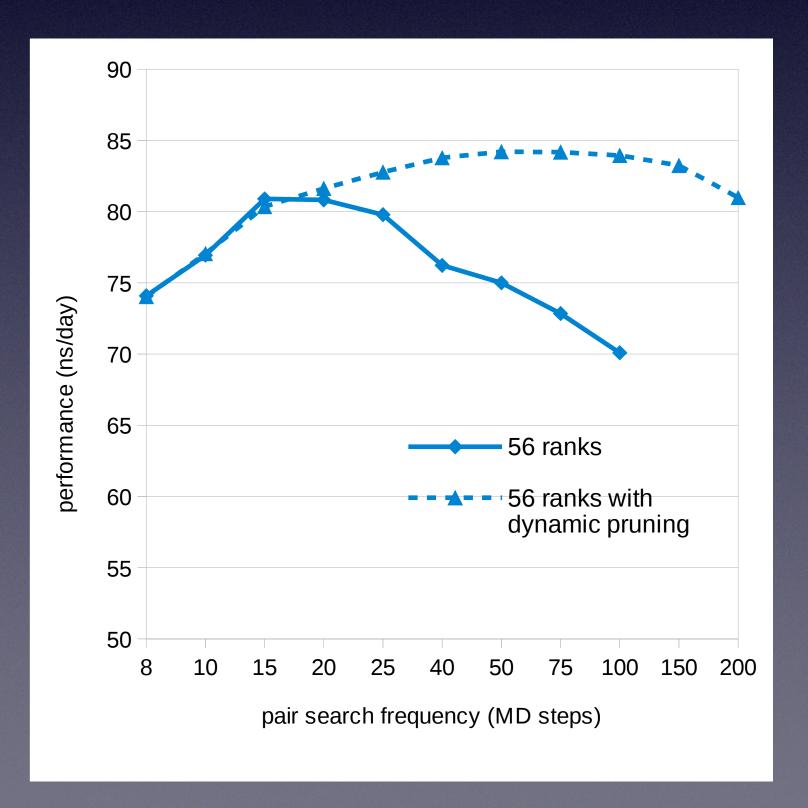


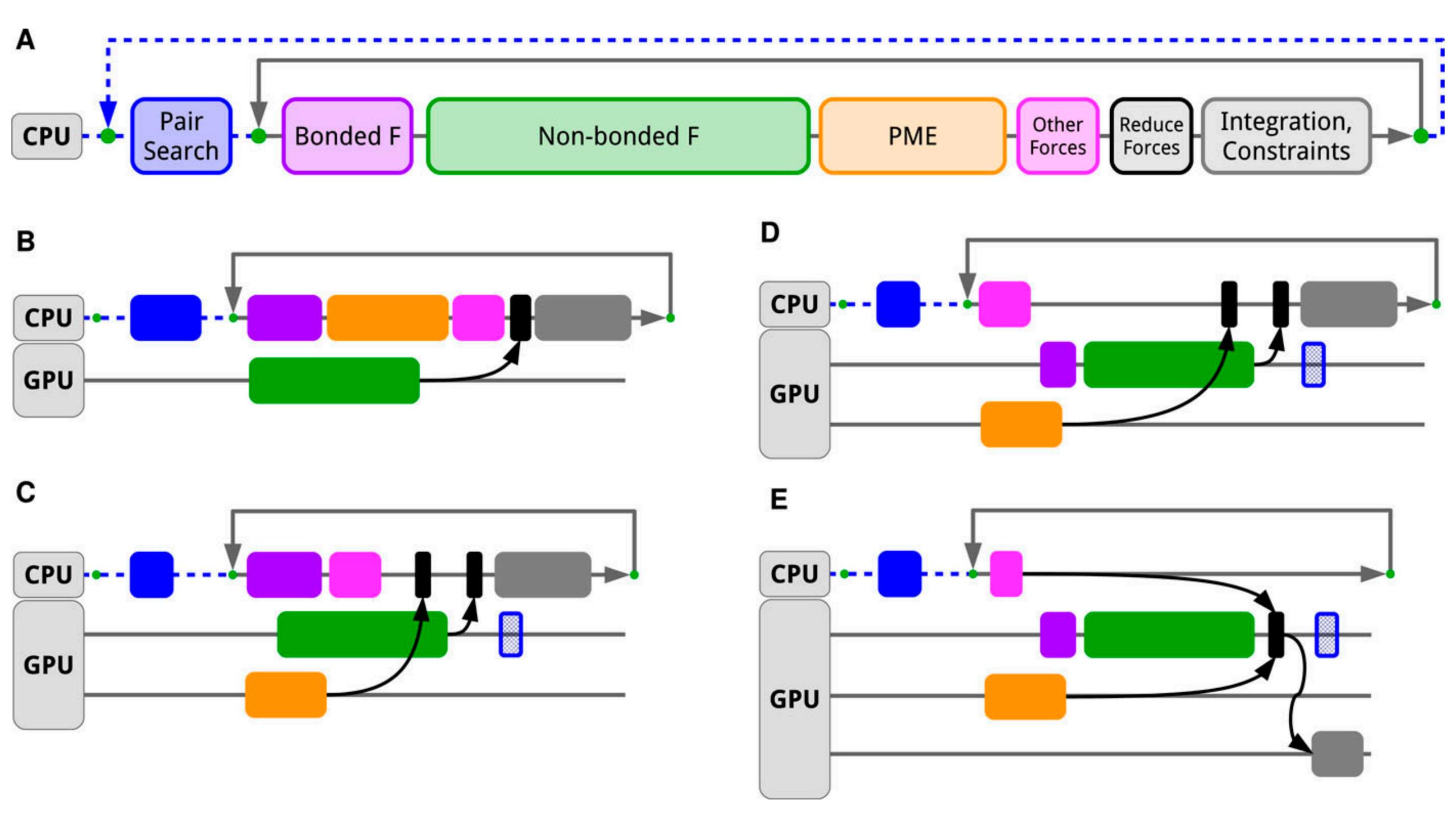
We can
Adjust the
size of this buffer

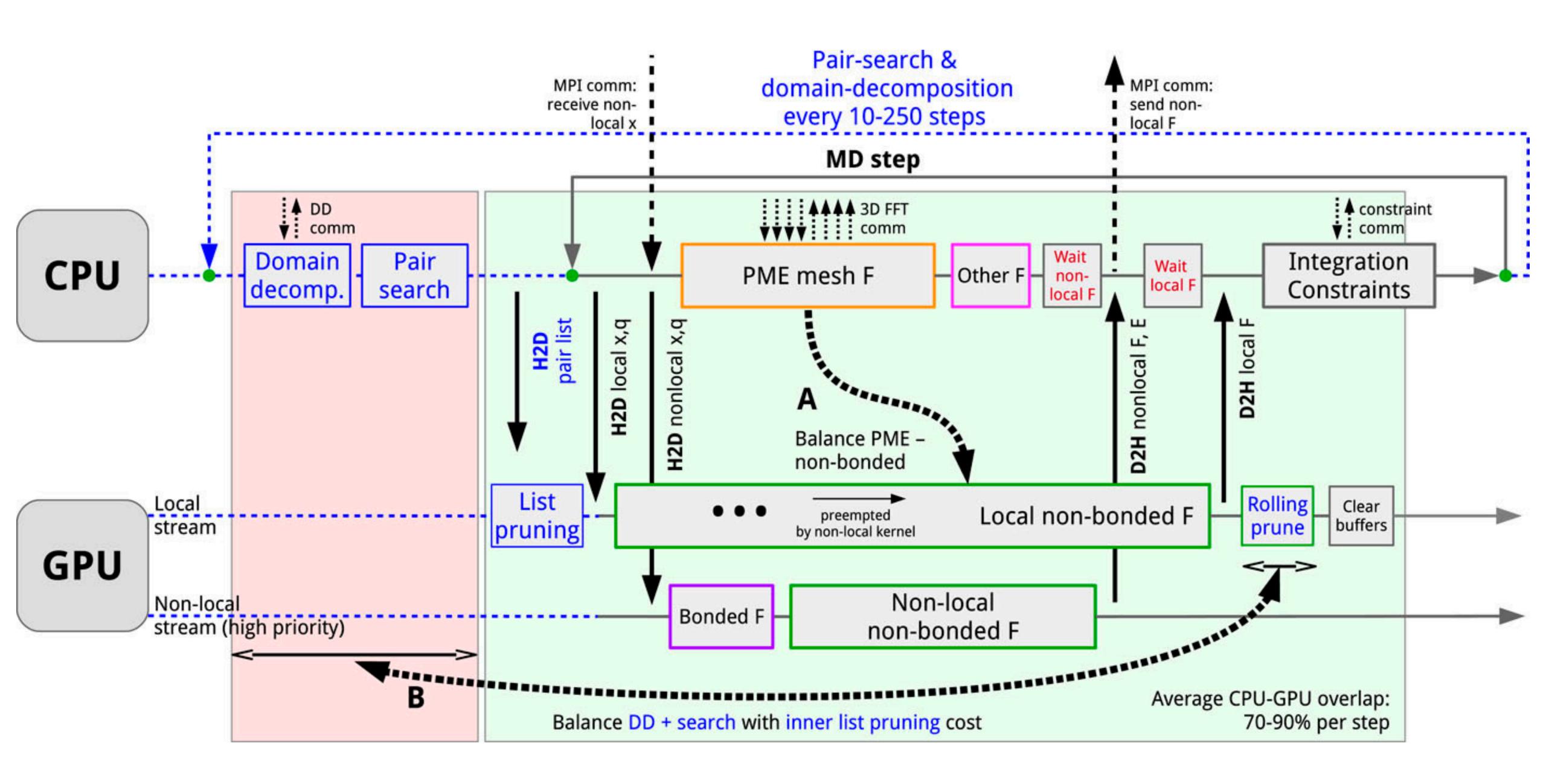
Larger buffer means more calculations, but we can update the neighbor list less frequently

New dual-pair list buffer:

- Use very large buffers, and prune it every few steps
- reduces overhead
- less sensitive to parameters







The big gain of heterogeneous acceleration:

Very little CUDA required

c cuda kernel.c

= tex1Dfetch<float>(nbparam.nbfp_texobj, 2 * (ntypes * typei + typej));

E_lj_p = int_bit * (c12 * (inv_r6 * inv_r6 + nbparam.repulsion_shift.cpot)*ONE_TWELVETH_F -

c6 * (inv_r6 + nbparam.dispersion_shift.cpot)*ONE_SIXTH_F);

= tex1Dfetch(nbfp_texref, 2 * (ntypes * typei + typej)); = tex1Dfetch(nbfp_texref, 2 * (ntypes * typei + typej) + 1);

calculate_force_switch_F_E(nbparam, c6, c12, inv_r, r2, &F_invr, &E_lj_p);

calculate_force_switch_F(nbparam, c6, c12, inv_r, r2, &F_invr);

calculate_force_switch_f(nbparam, c6, c12, inv_r, r2, &F_invr);

+= (1.0f - int_bit) * NBNXN_AVOID_SING_R2_INC;

/* load the rest of the i-atom parameters */

= atib[i * CL_SIZE + tidxi];

/* avoid NaN for excluded pairs at r=0 */

 $inv_r6 = inv_r2 * inv_r2 * inv_r2;$

/* We could mask inv_r2, but with Ewald

* masking both inv_r6 and F_invr is faster */

 $F_{invr} = inv_r6 * (c12 * inv_r6 - c6) * inv_r2;$

= xqbuf.w;

typei = atom_types[ai];

/* LJ 6*C6 and 12*C12 */

/* USE_TEXOBJ */

inv_r = rsqrt(r2); $inv_r^2 = inv_r * inv_r;$

inv_r6 *= int_bit; /* EXCLUSION_FORCES */

 $\Theta \Theta \Theta$

#else

#endif

#else

#endif

#endif

#else

352

c cuda_kernel.c > No Selection

#ifdef IATYPE_SHMEM

#ifdef USE_TEXOBJ

#if defined EXCLUSION_FORCES

#ifdef LJ_FORCE_SWITCH #ifdef CALC_ENERGIES

#endif /* CALC_ENERGIES */ #endif /* LJ_FORCE_SWITCH */

#endif /* LJ_FORCE_SWITCH */ #endif /* CALC_ENERGIES */

#if defined CALC_ENERGIES || defined LJ_POT_SWITCH

```
n_cuda lindahl$ ls -ltar
                                   lindahl
                                                   13012 Apr 18 15:10 nbnxn_cuda_types.h
                                                    9155 Apr 18 15:10 nbnxn_cuda_kernels.cuh
                                   lindahl
                                            staff
                                                   21576 Apr 18 15:10 nbnxn_cuda_kernel_utils.cuh
                                   lindahl
                                            staff
                                                   20945 Apr 18 15:10 nbnxn_cuda_kernel.cuh
                                   lindahl
                                            staff
                                   lindahl
                                                    1965 Apr 18 15:10 CMakeLists.txt
                                            staff
                                   lindahl
                                                   39049 Apr 18 15:10 nbnxn_cuda_data_mgmt.cu
                                            staff
                                                    3667 Apr 18 15:10 nbnxn_cuda.h
                                    inalahl
                                            staff
                                            staff
                                                   30920 May 22 09:13 nbnxn_cuda.cu
                                       lahl
                                                    2686 May 22 09:13 ..
                                      lahl
                                            staff
                                                     340 May 22 09:13 .
                                            staff
                                          A total of ~3000 lines of CUDA,
= tex1Dfetch<float>(nbparam.nbfp_texobj, 2 * (ntypes * typei + typej) + 1);
                                           compared to ~2M lines of C++
```

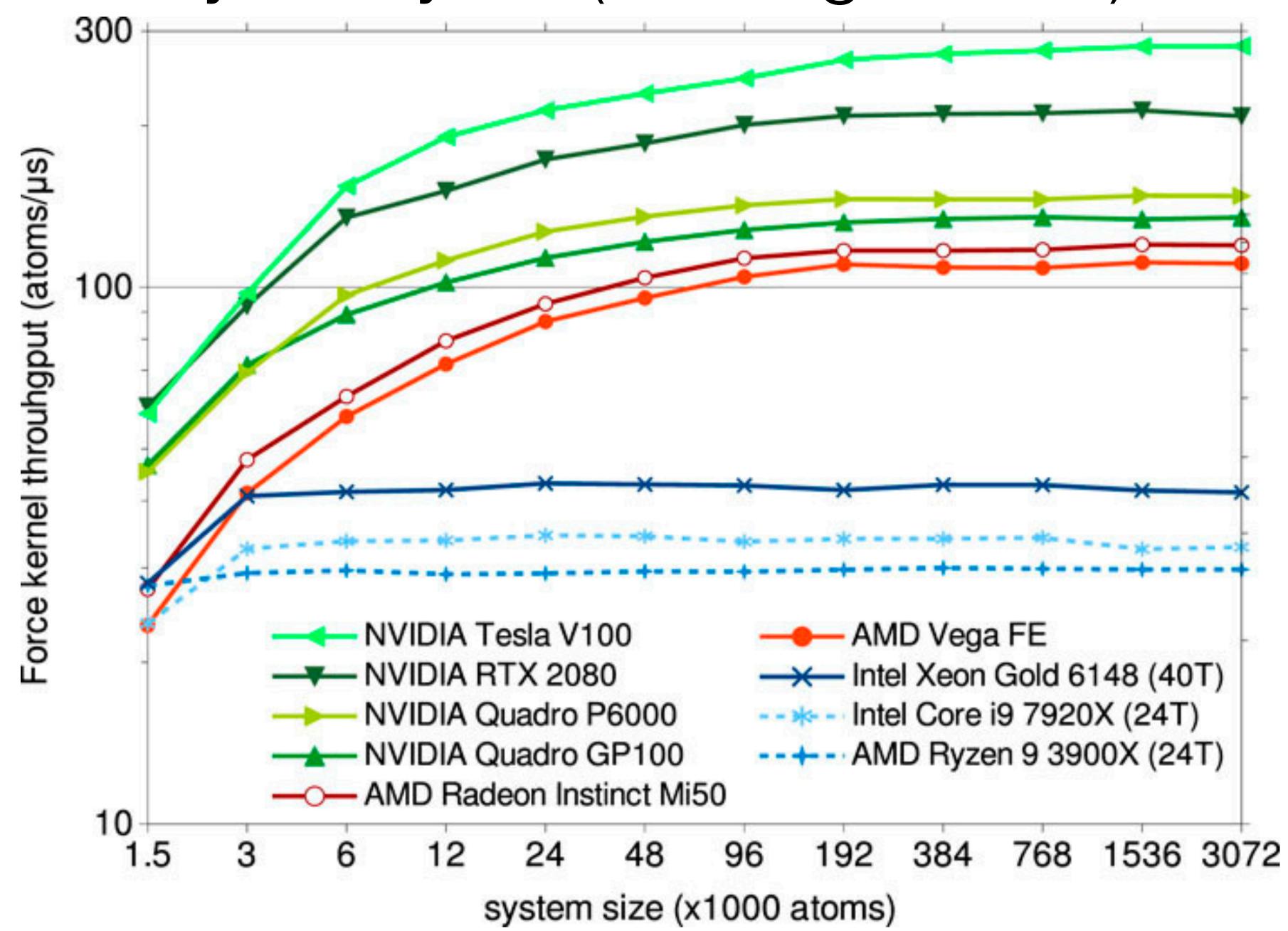
so we wrote OpenCL kernels too!

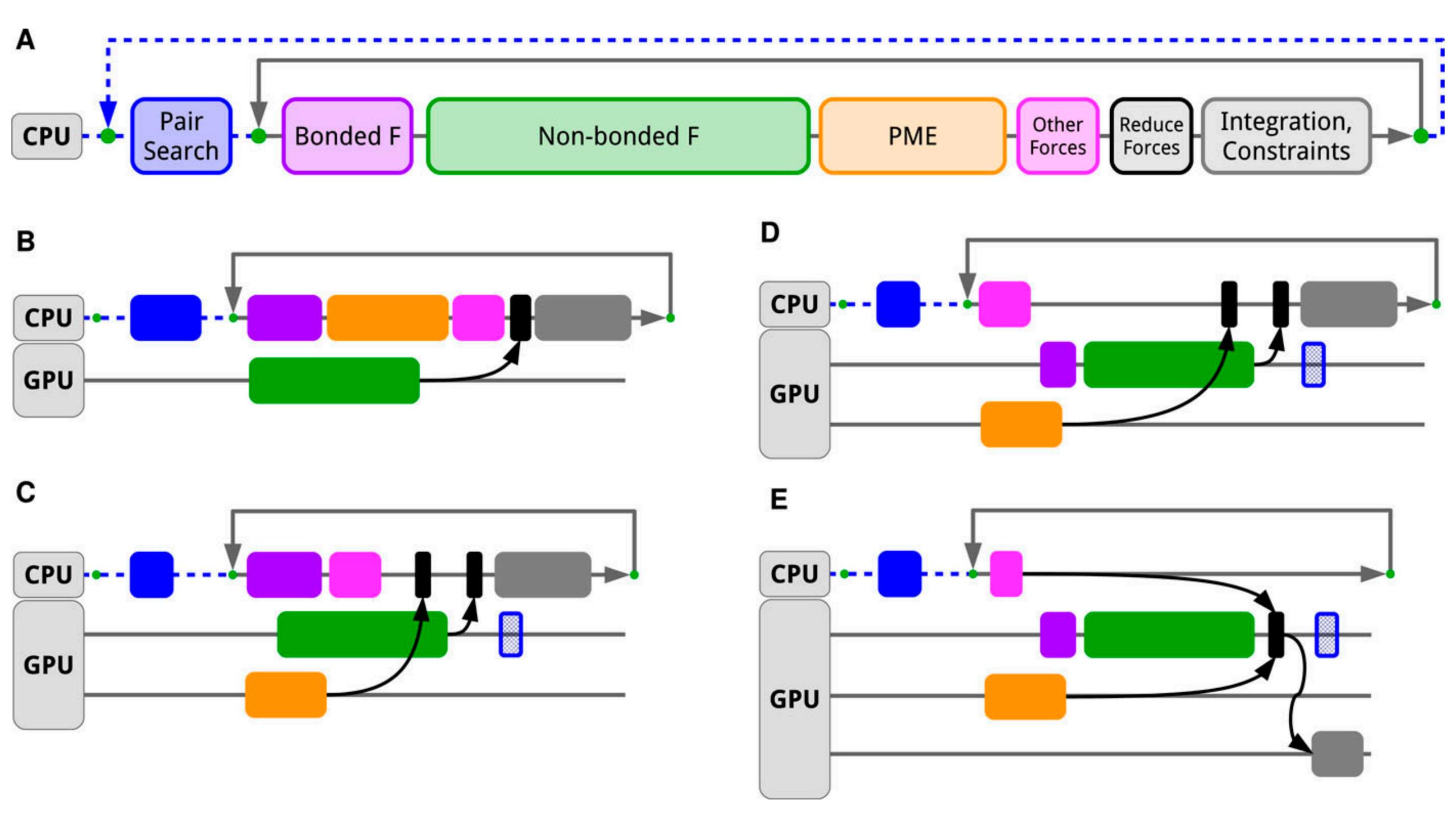
Make good use of both GPU & CPU

- Use the CPU to pre-calculate or optimize data structures, so there is less work for the GPU to do in your kernels
- Easier to implement more complex optimization on CPU
- Advanced multi-node domain decomposition easier on CPU
- Run some parts of the algorithm on the CPU (avoid wasting flops)
- 1. It's important to keep the GPU busy
- 2. ... but it doesn't have to be busy 100% of the time!
- 3. A CUDA GPU running at 100% will get hot, and clock down
- 4. NVML "application clocks" effectively overclock the GPU on-the-fly when you have less than 100% utilization

Think of a node as a collection of compute & communication devices - use them all!

Kernel latency is key for (heterogeneous) acceleration





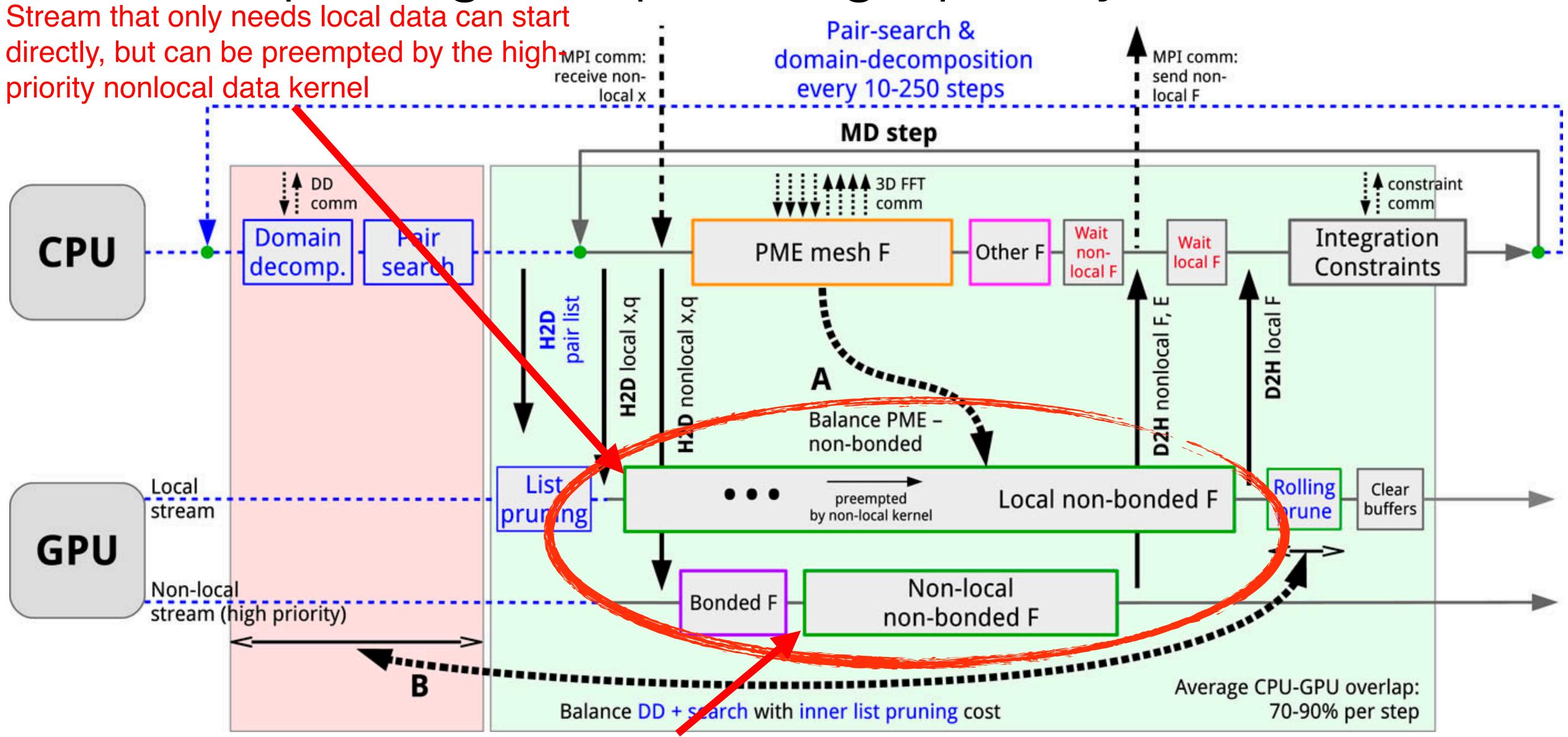
Exploiting multiple & high-priority streams

Stream that only needs local data can start directly, but can be preempted by the high-priority nonlocal data kernel

CUDA
Non-local
stream (high priority)

When remote data is delivered, handle it immediately so it can be returned faster

Exploiting multiple & high-priority streams



When remote data is delivered, handle it immediately so it can be returned faster

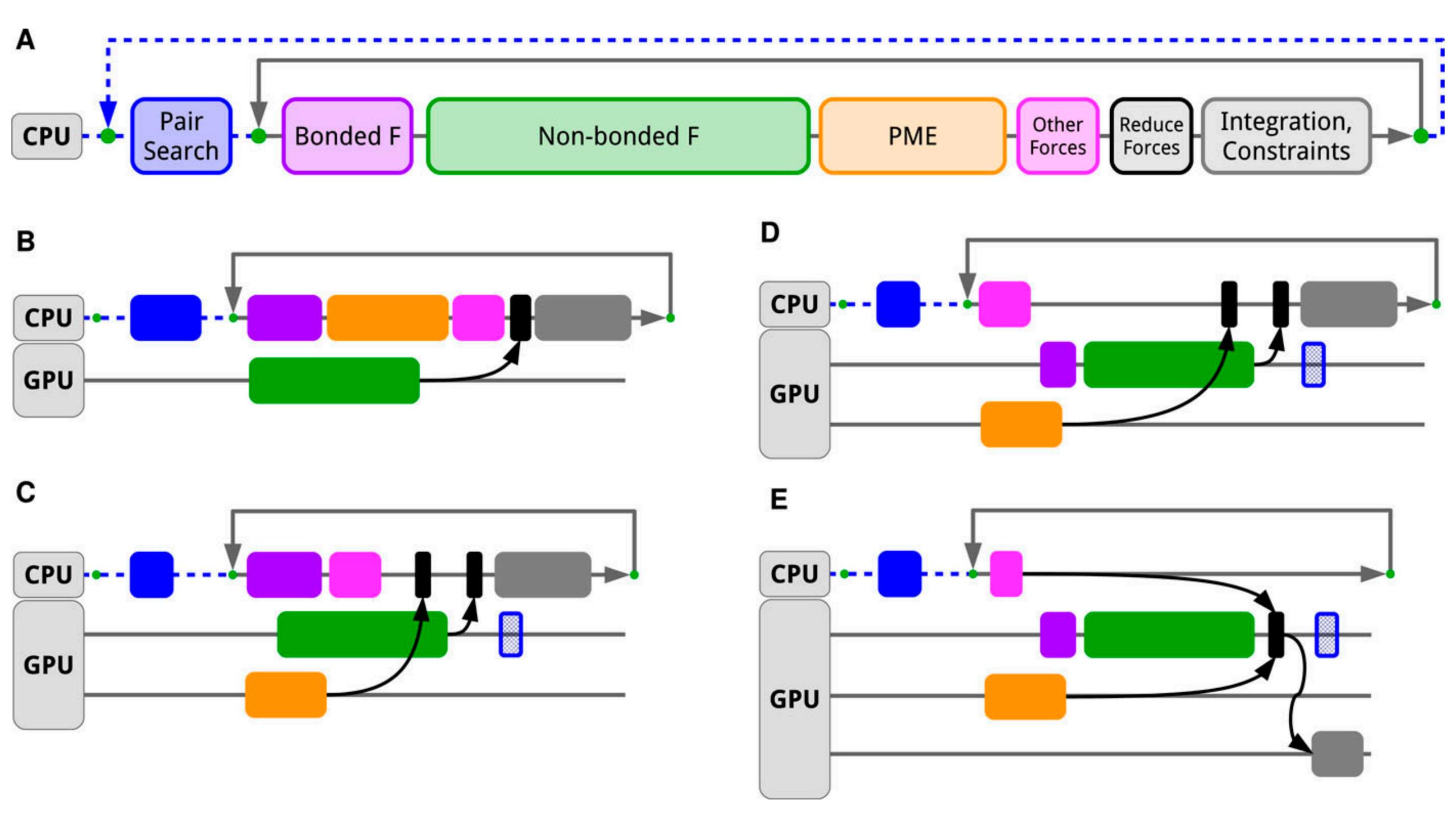
Revisiting Amdahl's law - give GPU more work

The least parallel part of the code (or at least slowest piece of hardware) will eventually dominate execution completely and limit scaling

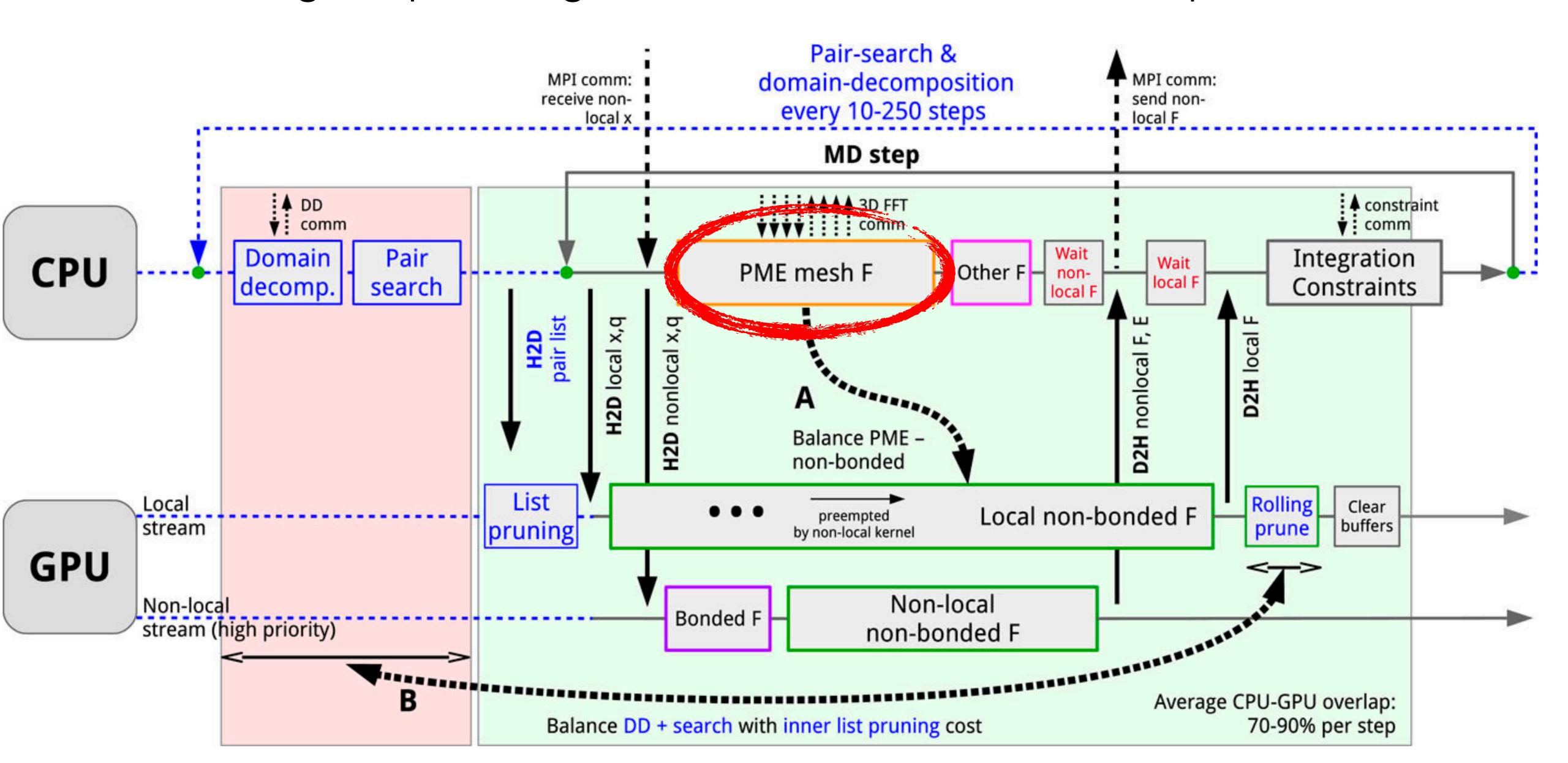
Thanks to heterogeneous parallelism and efficient CPU-side algorithms, GROMACS frequently outperforms GPU-only implementations - and yet we only need a few thousand lines of CUDA.

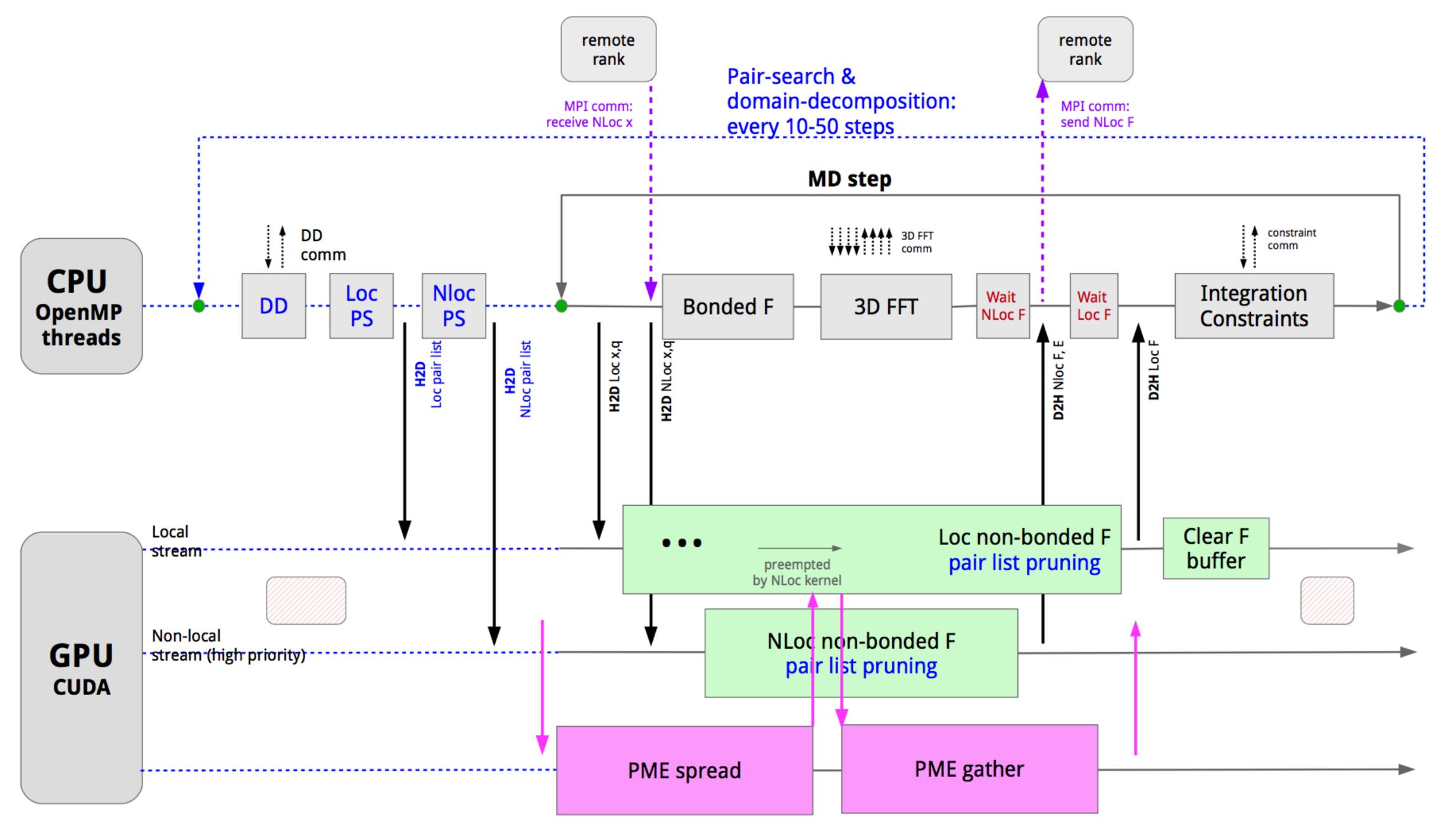
But... GPU performance grows faster than CPU performance, and sometimes we want to put a high-end GPU in an old low-end CPU box

Our CPUs used to wait for the GPUs, now it's often the opposite



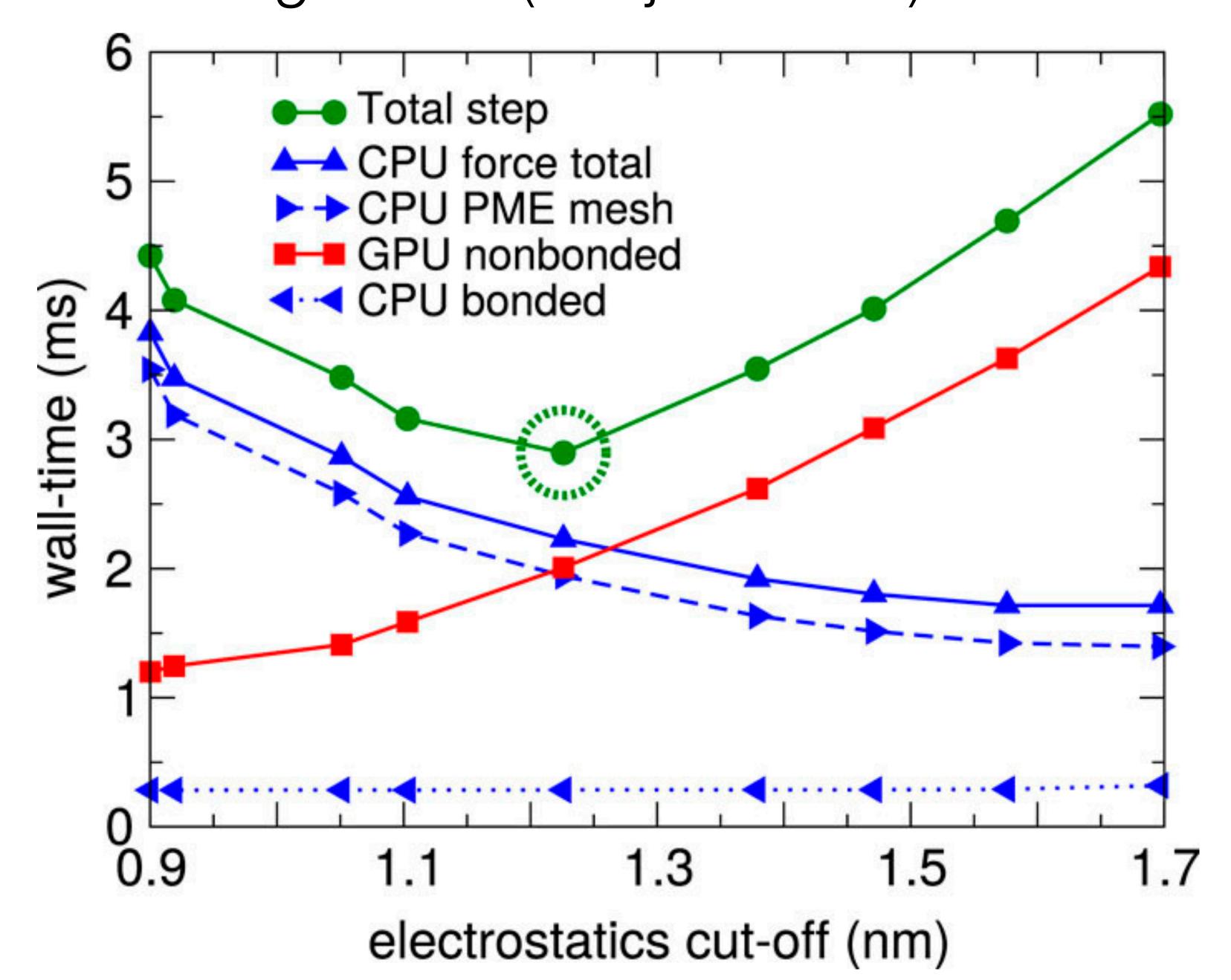
The new bottleneck (for slow CPUs) is the PME algorithm 3D grid spreading, FFTs, convolution, iFFT, interpolation



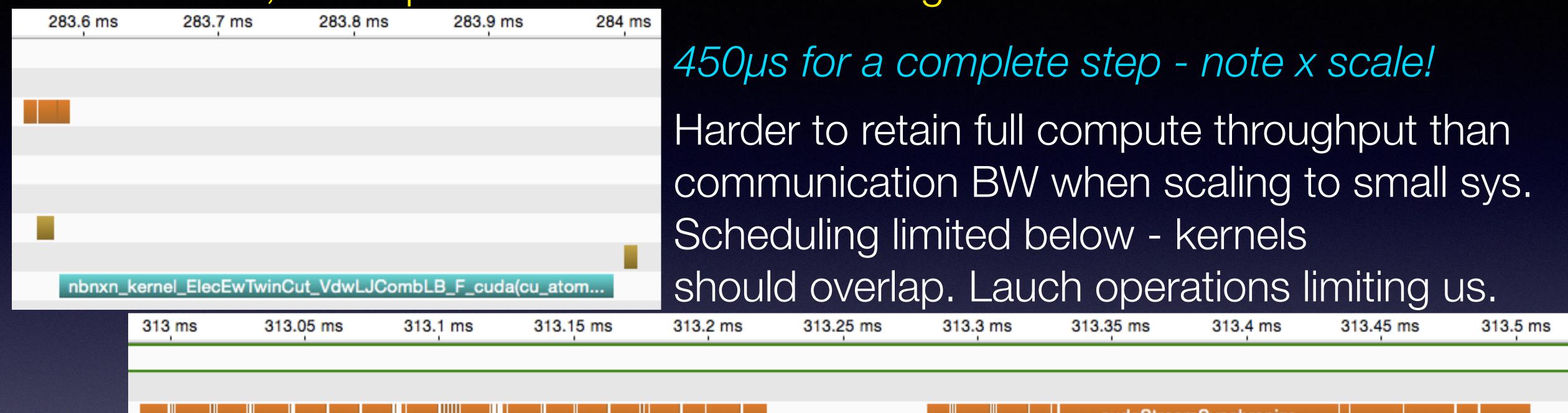


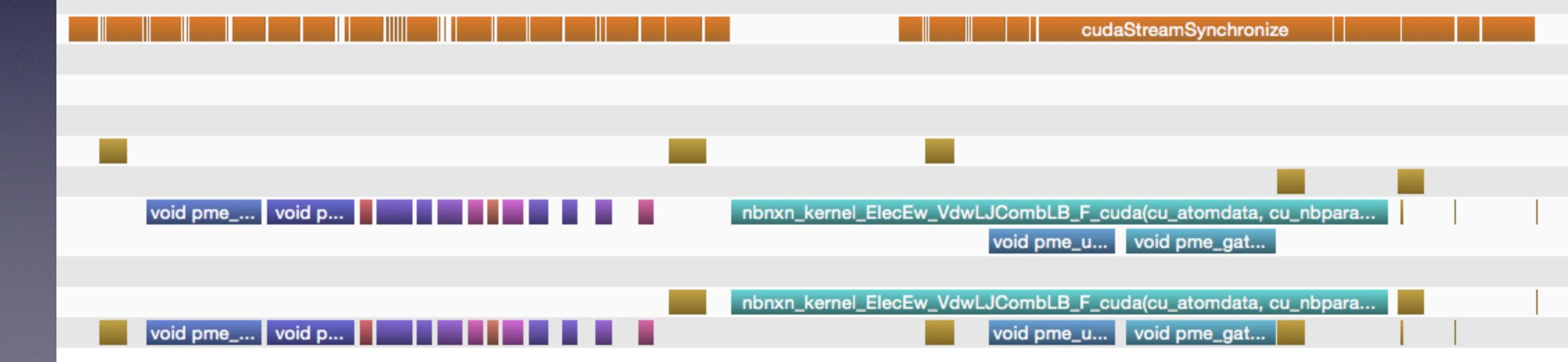
PME offload into separate stream

Load-balance the algorithm (not just work) between CPU & GPU

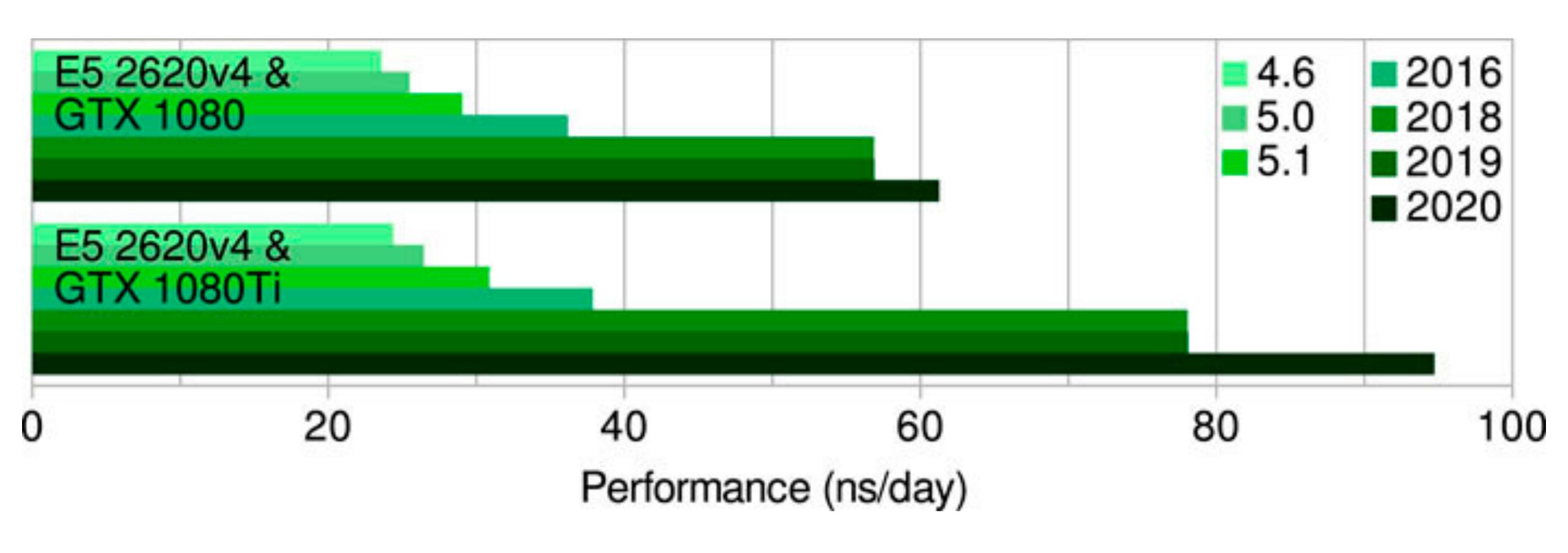


GPU Timestep profile before/after PME offload (P100) Highly challenging small system (25k atoms), very fast iterations. Much harder, but important for multi-GPU scaling

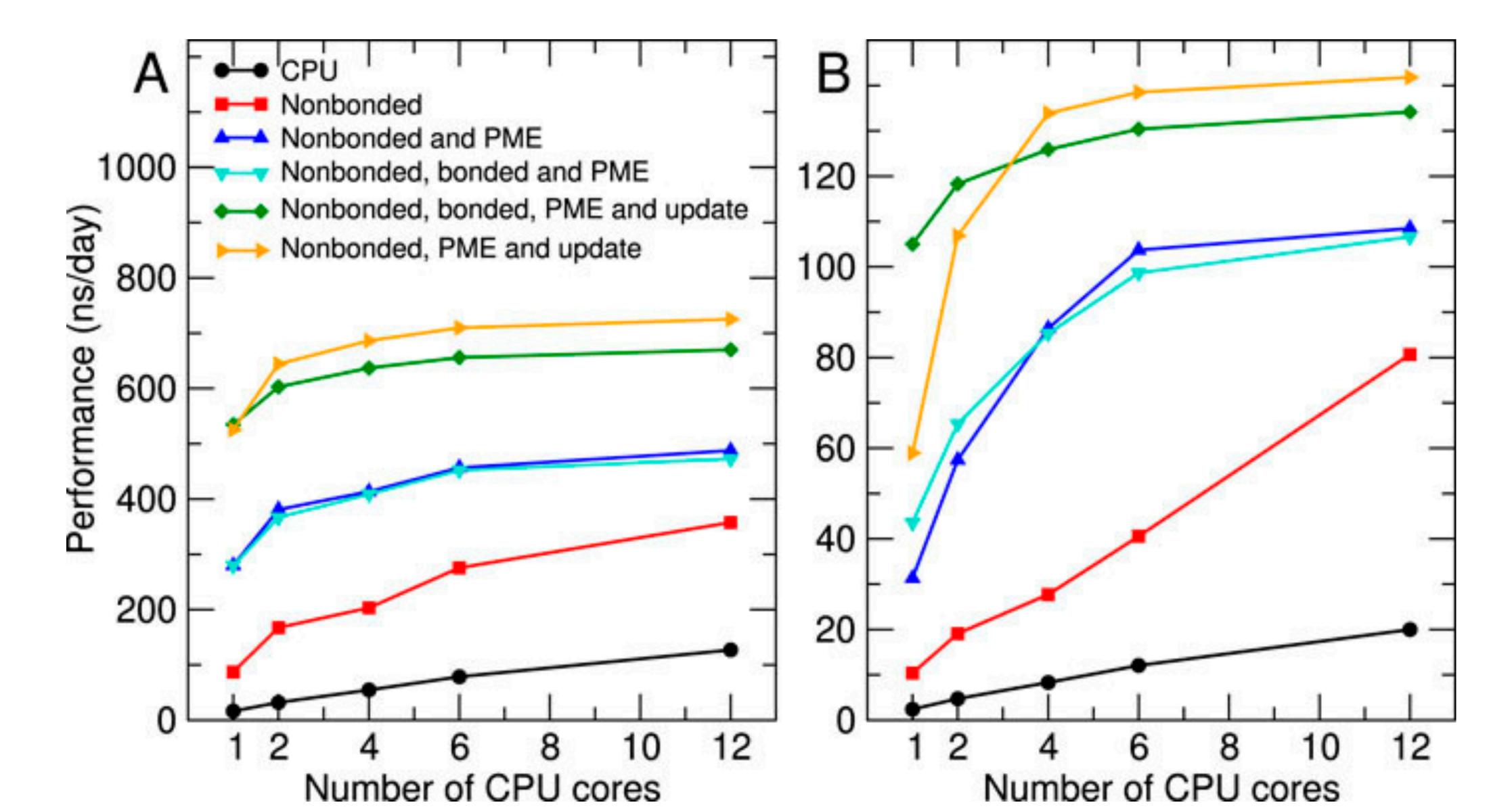




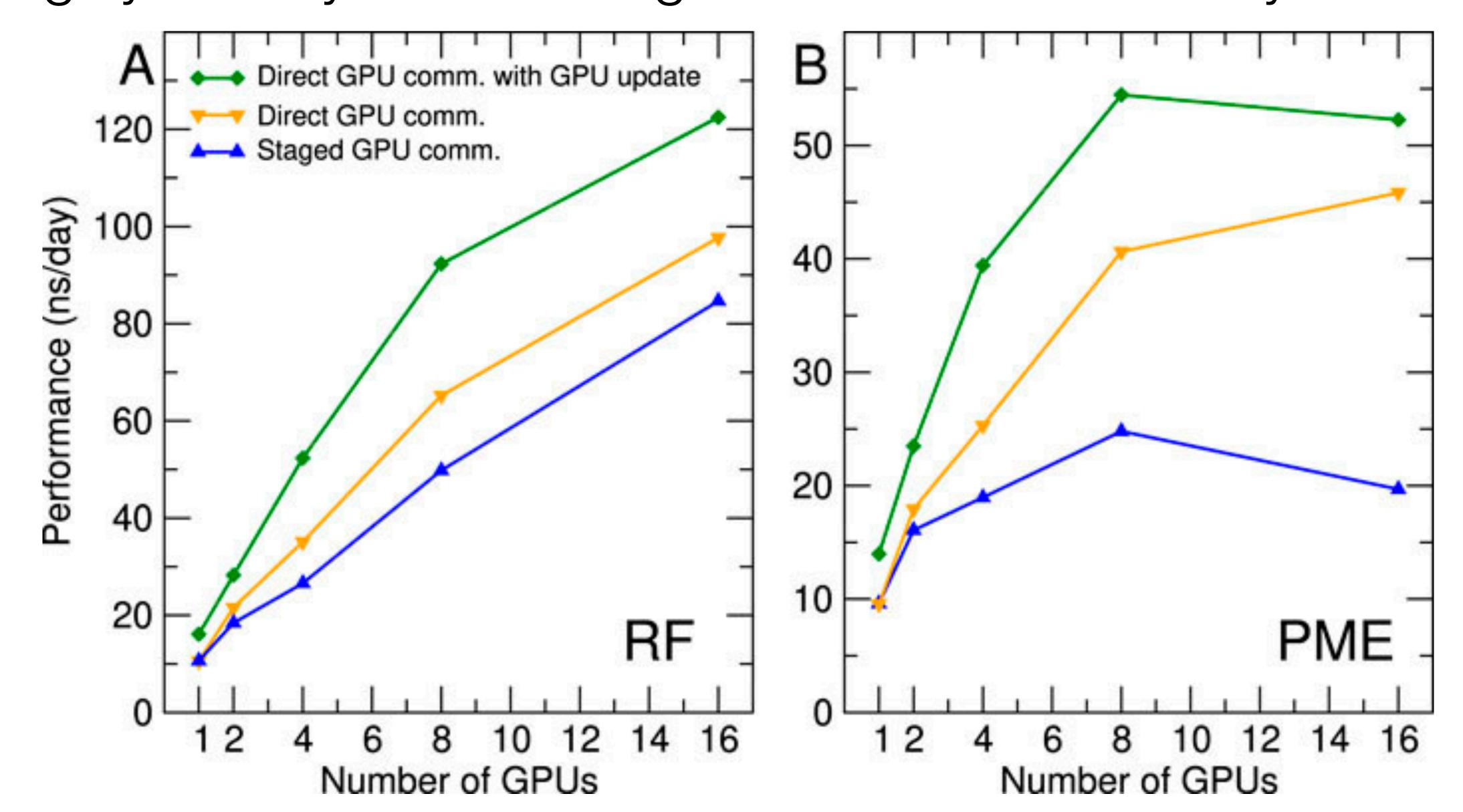
Even codes that have been tuned for ~20 years on CPUs and ~10 years on GPUs can get great performance gains just from better algorithms & implementations



We solved our issue of fast-CPU-dependency: Fast with a single core per GPU, even faster with many



Heterogeneous parallelisation provides good scaling even for the highly latency-sensitive algorithms in molecular dynamics



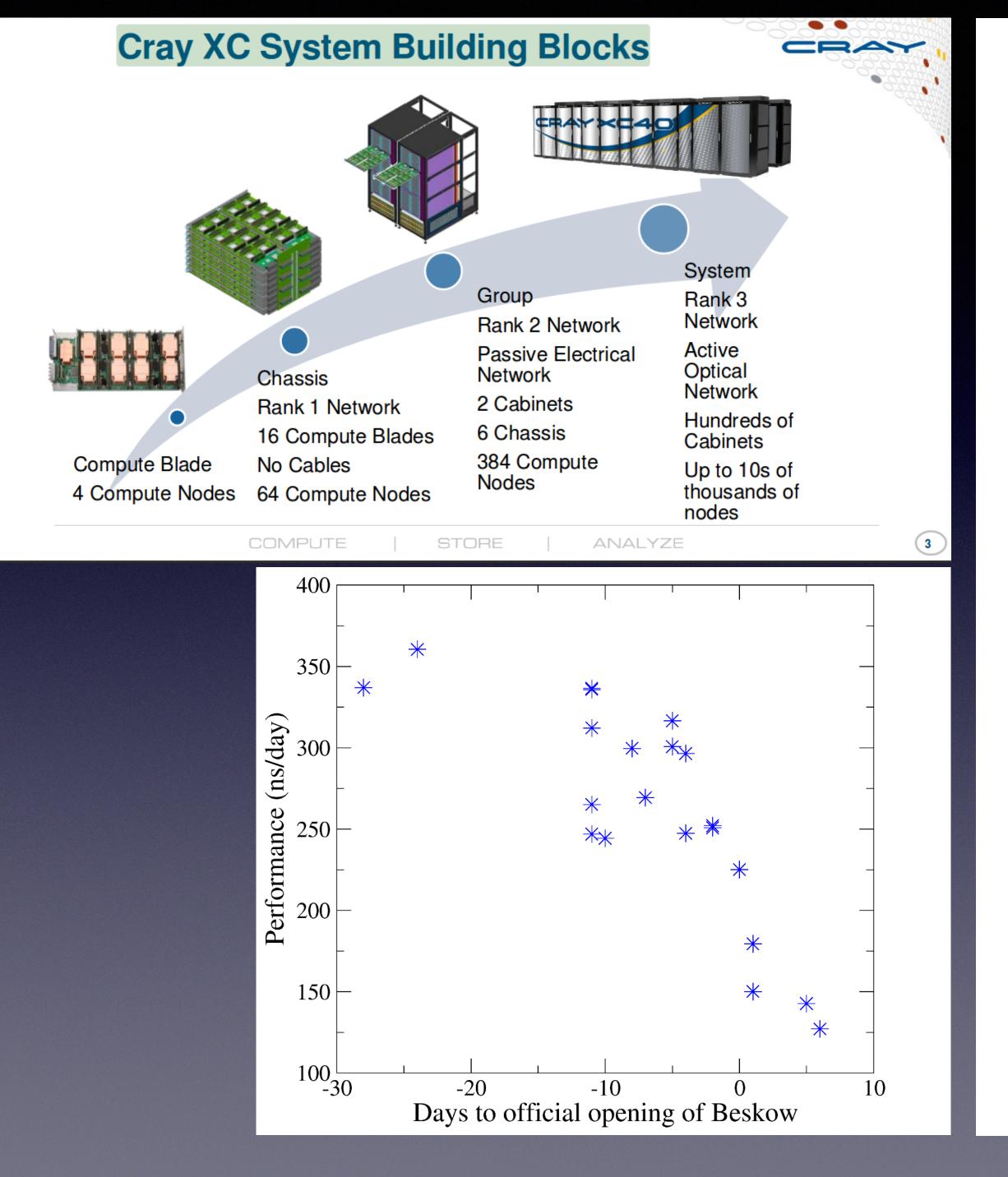
Strong caling issues - challenges at 100µs per iteration

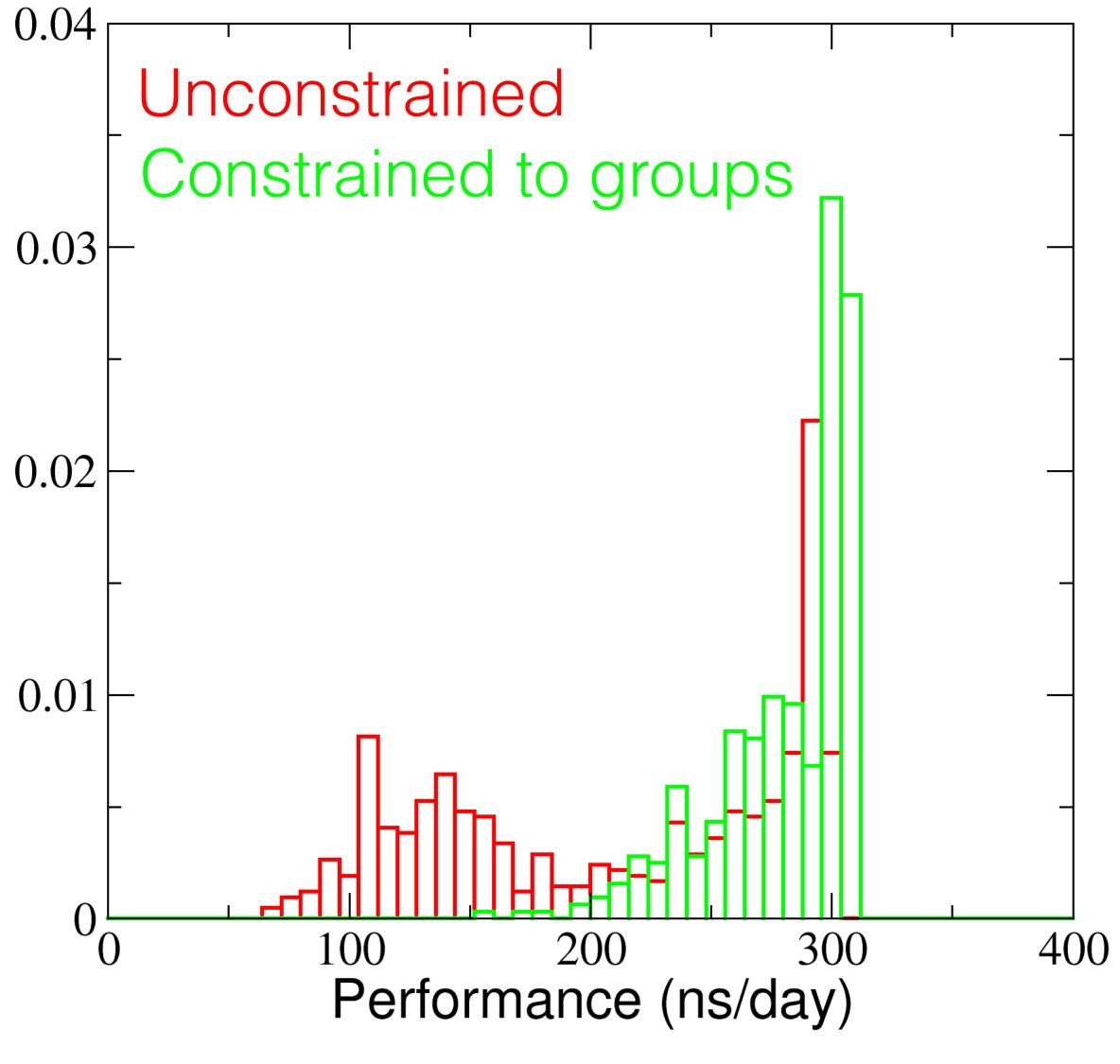
- The 3D-FFT in PME
- MPI overhead we need MPI_Put_notify()
- OpenMP barriers take significant time

- Load imbalance
- CUDA API overhead can be 50% of CPU time
- Too many GROMACS options to tweak manually

Large performance loss due to imbalance and network speed variation on Cray XC (interference from other jobs on the "smart" network)







Intra-rank parallelisation: OpenMP today, future?

Efficient current parallelization of all algorithms using MPI + OpenMP

OpenMP is (performance) portable, but limited:

- No way to run parallel tasks next to each other
- No binding of threads to cores (cache locality)

Need for a better threading model, requirements:

- Extremely low overhead barriers (all-all, all-1, 1-all)
- Binding of threads to cores
- Portable

We are convinced we are moving to a world where latency- and throughputoptimized units converge into the same chip - the future is heterogeneous!

Urgent need for better, standardized and portable HPC-focused task parallelism frameworks. We are looking into both ArgoBots and home-grown solutions.

Spend time with your algorithms, not just code tuning.

A single Skylake-EP node has 4096-fold parallelism. Your code likely doesn't.

Think accelerators - because a modern CPU looks like an accelerator, and they will likely converge to multiple units on one die in the future.

Heterogeneous parallelism uses all resources and provides architecture portability.

Fast-iteration codes are very sensitive to node placement, and they need task parallelism sooner rather than later.

Fast-iteration coding for CUDA/AVX512/OpenCL/SYCL isn't hard - but new algorithms are.

You can accomplish miracles with more codes than you think, but it takes 6-12 months - not an afternoon.

Theory & Computation is the new experiment!

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