



Leibniz-Rechenzentrum  
der Bayerischen Akademie der Wissenschaften

# Performance Optimization of Smoothed Particle Hydrodynamics and Experiences on Many-Core Architectures

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Intel MIC Programming Workshop & Scientific Workshop "HPC for natural hazard assessment and disaster mitigation", LRZ, June 28<sup>th</sup>, 2017

# Work contributors



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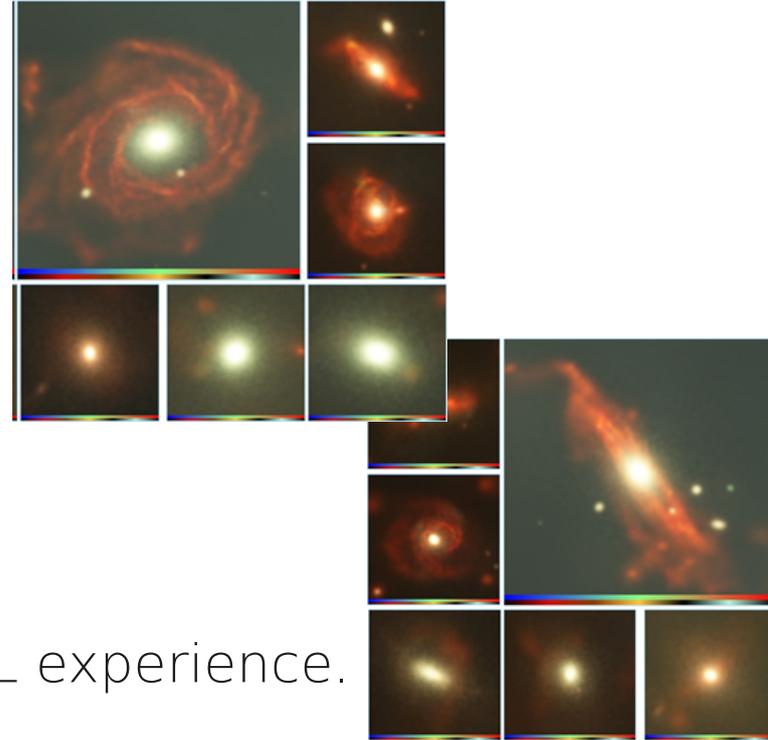
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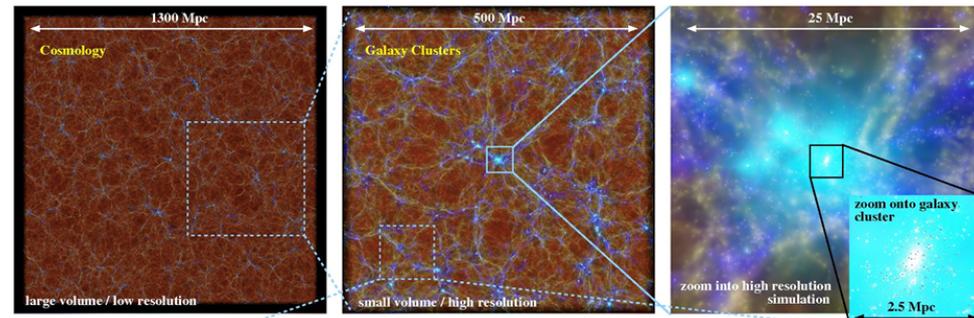
# Outline of the talk

- Overview of the code: P-Gadget3 and SPH.
- Challenges in code modernization approach.
- Multi-threading parallelism and scalability.
- Enabling vectorization through:
  - Data layout optimization (AoS  $\rightarrow$  SoA).
  - Reducing conditional branching.
- Performance results, takeaways from our KNL experience.



# Gadget intro

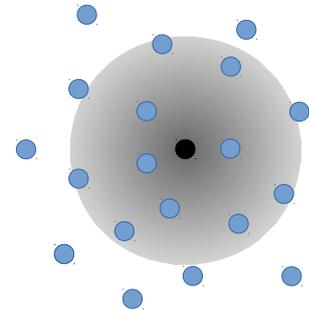
- Leading application for simulating the formation of the **cosmological** large-scale **structure** (galaxies and clusters) and of processes at sub-resolution scale (e.g. star formation, metal enrichment).
- Publicly available, cosmological TreePM N-body + **SPH** code.
- First developed in the late **90s** as **serial** code, later evolved as an MPI and a hybrid code.
- Good scaling performance up to  $O(100k)$  Xeon cores (SuperMUC@LRZ).



# Smoothed particle hydrodynamics (SPH)

- **SPH** is a Lagrangian particle method for solving the equations of fluid dynamics, widely used in astrophysics.
- It is a **mesh-free** method, based on a **particle discretization** of the medium.
- The local estimation of gas density (and all other derivation of the governing equations) is based on a **kernel-weighted summation** over neighbor particles:

$$\rho_i = \rho(\mathbf{r}_i) = \sum_j m_j W(|\mathbf{r}_i - \mathbf{r}_j|, h_j)$$



# Optimization strategy

- We isolate the representative code kernel `subfind_density` and run it in as a stand-alone application, avoiding the overhead from the whole simulation.
- As most code components, it consists of two sub-phases of nearly equal execution time (40 to 45% for each of them), namely the `neighbour-finding phase` and the remaining `physics computations`.
- Our physics workload: ~ 500k particles. This is a typical workload per node of simulations with moderate resolution.
- We focus on `node-level performance`, through `minimally invasive` changes.
- We use tools from the Intel® Parallel Studio XE (`VTune Amplifier` and `Advisor`).

# Target architectures for our project



Intel® Xeon processor

- E5-2650v2 Ivy-Bridge (**IVB**) @ 2.6 GHz, 8-cores / socket.  
TDP: 95W, RCP (03/2017): \$1116.
- AVX.



Intel® Xeon Phi™ coprocessor  
*1<sup>st</sup> generation*

- Knights Corner (**KNC**) coprocessor 5110P @ 1.1GHz, 60 cores.  
TDP: 225W, RCP: N/D.
- **Native** / offload computing.
- Directly login via ssh.
- SIMD 512 bits.

# Further tested architectures



## Intel® Xeon processors

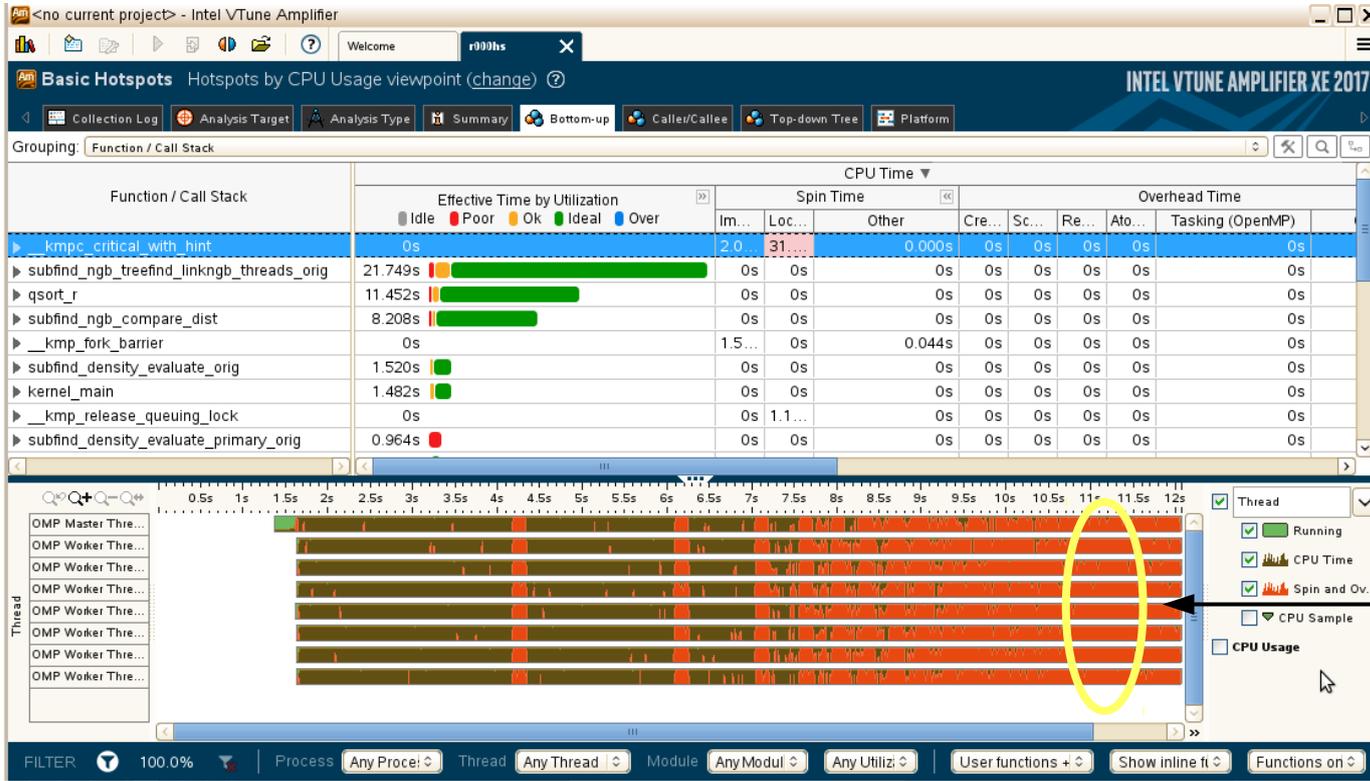
- E5-2697v3 Haswell (**HSW**) @ 2.3 GHz, 14-cores / socket.  
TDP: 145W, RCP (03/2017): \$2702.
- AVX2, FMA.
- E5-2699v4 Broadwell (**BDW**) @ 2.2 GHz, 22-cores / socket.  
TDP: 145W, RCP (03/2017): \$4115.
- AVX2, FMA.



## Intel® Xeon Phi™ processor *2<sup>nd</sup> generation*

- Knights Landing (**KNL**) Processor 7250 @ 1.4 GHz, 68 cores.  
TDP: 215W, RCP (03/2017): \$4876.
- Available as bootable processor.
- Binary-compatible with x86.
- High bandwidth memory.
- New AVX512 instructions set.

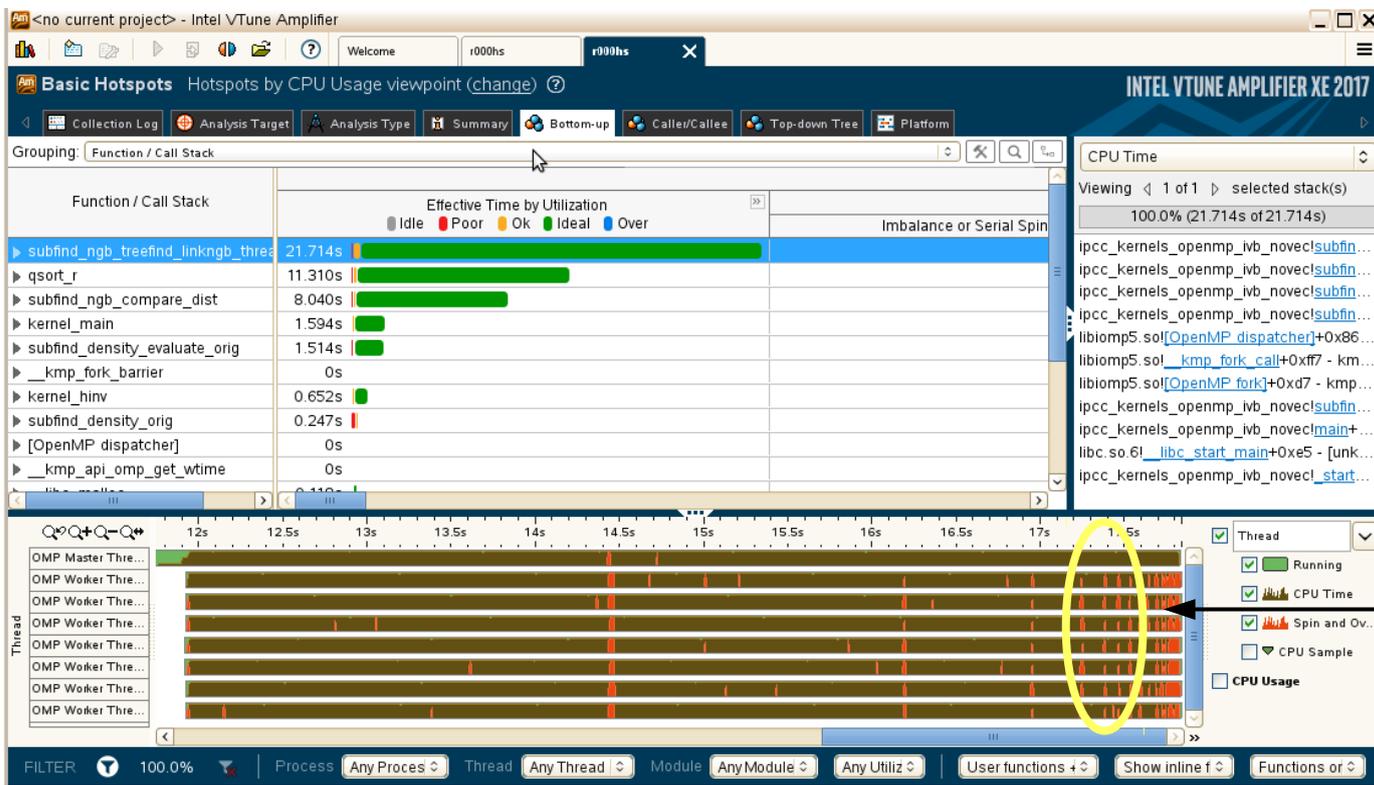
# Initial profiling



- Severe shared-memory parallelization **overhead**
- At later iterations, the particle list is **locked** and **unlocked** constantly due to the recomputation
- Spinning time **41%**

**thread spinning**

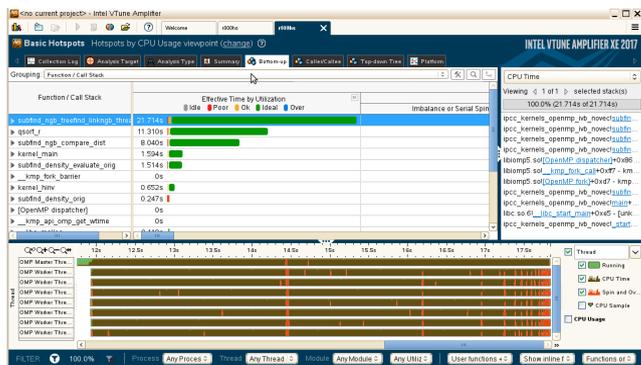
# Improved performance



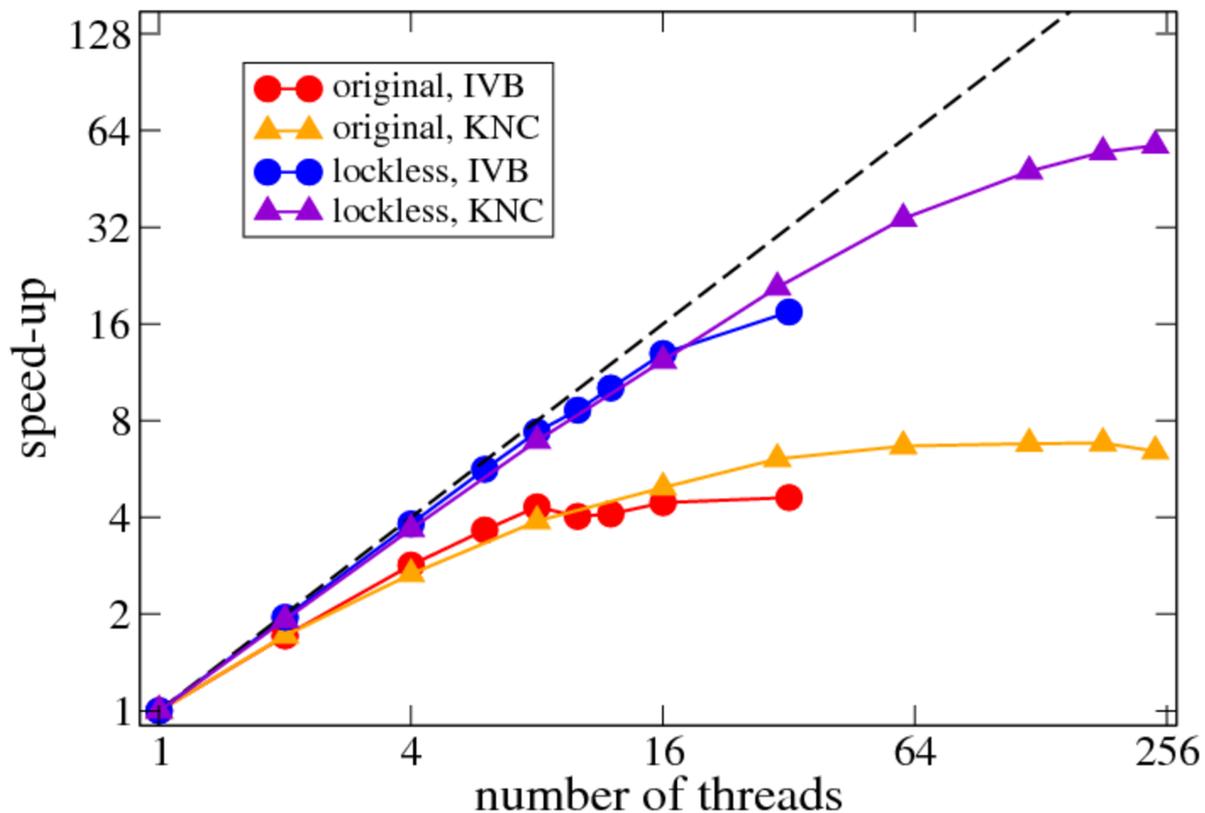
- Lockless scheme: lock contention removed through "todo" particle list and OpenMP dynamic scheduling.
- Time spent in spinning only 3%

**no spinning**

# Improved speed-up



- On IVB @ 8 threads
  - speed-up: 1.8x
  - parallel efficiency: 92%
- On KNC @ 60 threads
  - speed-up: 5.2x
  - parallel efficiency: 57%



# Obstacles to efficient auto-vectorization

```
for(n = 0, n < neighboring_particles, n++ ) {  
    j = ngblist[n];  
  
    if (particle n within smoothing_length) {  
  
        inlined_function1(..., &w);  
        inlined_function2(..., &w);  
  
        rho    += P_AoS[j].mass*w;  
        vel_x += P_AoS[j].vel_x;  
        ...  
        v2 += vel_x*vel_x + ... vel_z*vel_z;  
    }  
}
```

← for loop over neighbors

← check for computation

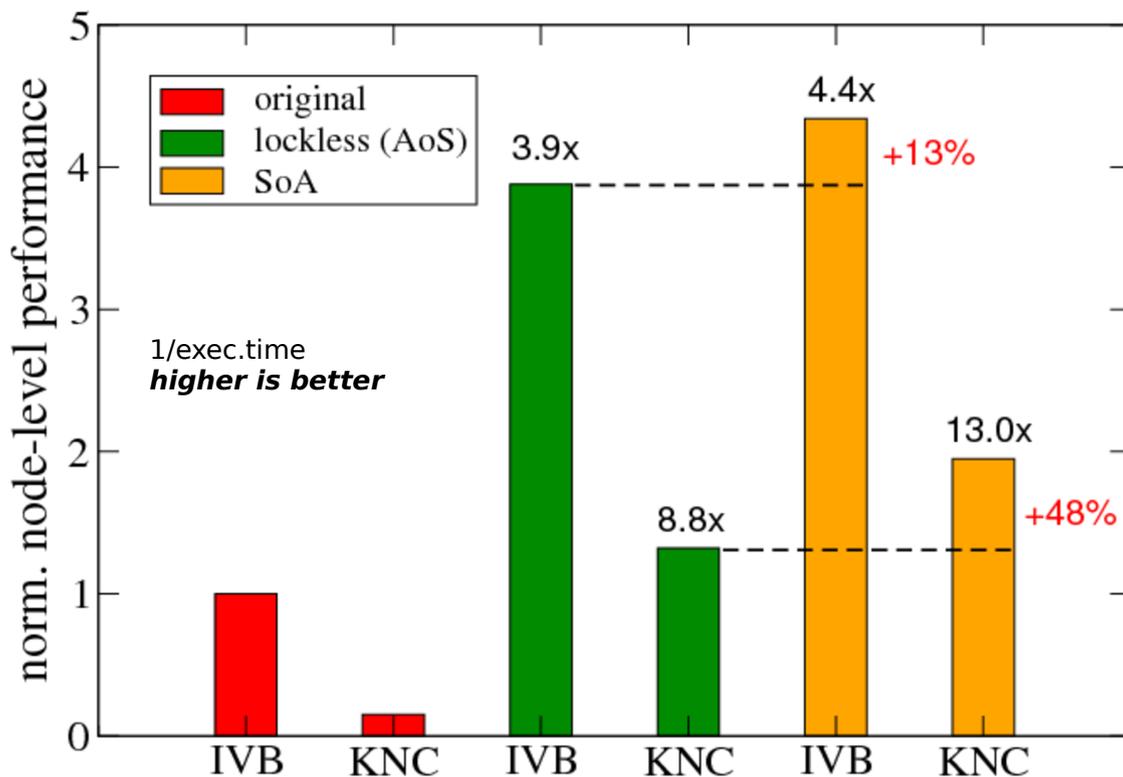
← computing physics

← Particles properties via  
**AoS** (cache unfriendly!)

$$\rho_i = \rho(\mathbf{r}_i) = \sum_j m_j W(|\mathbf{r}_i - \mathbf{r}_j|, h_j)$$

# AoS to SoA: performance outcomes

- Gather+scatter **overhead** at most **1.8%** of execution time.  
→ intensive **data-reuse**
- Performance improvement:
  - on **IVB**: **13%**, on **KNC**: **48%**
- Xeon/Xeon Phi performance ratio: from 0.15 to 0.45.
- The data structure is now **vectorization-ready**.



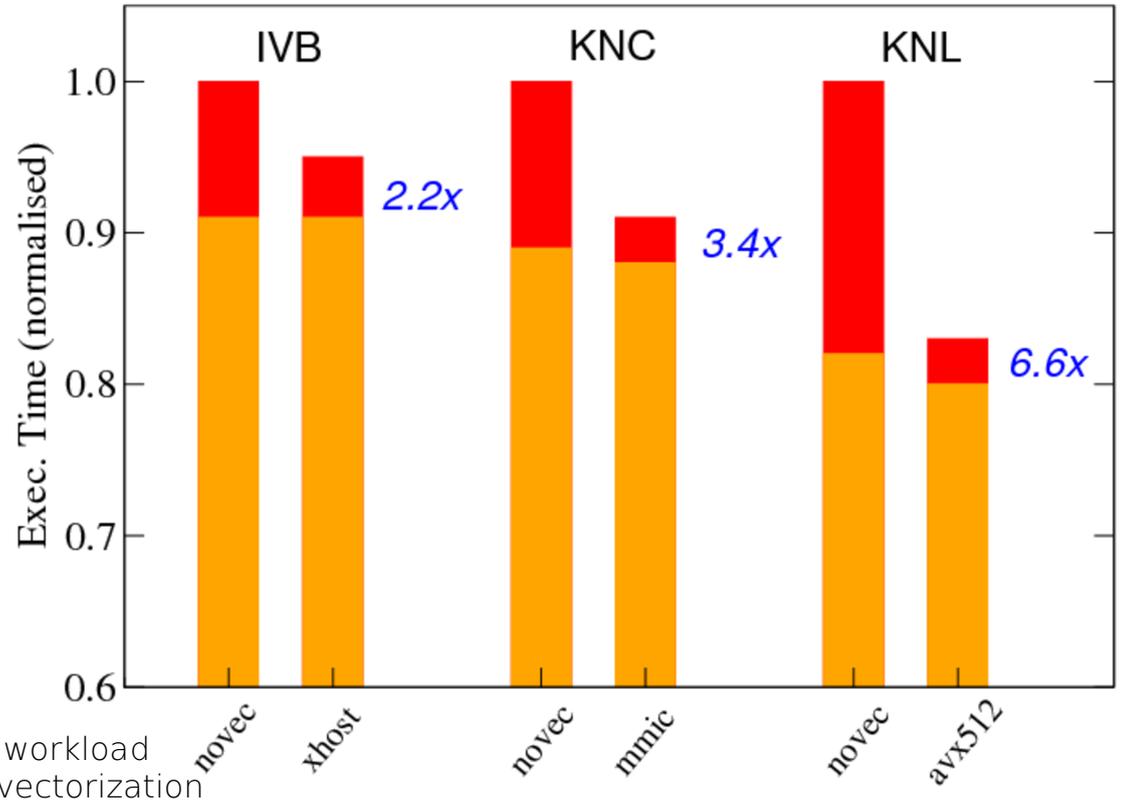
# Vectorization: improvements from IVB to KNL

- Vectorization through localized masking (*if-statement* moved inside the inlined functions).
- Vector efficiency:  
perf. gain / vector length

on IVB: 55%

on KNC: 42%

on KNL: 83%



- Yellow + red bar: kernel workload  
- Red bar: target loop for vectorization

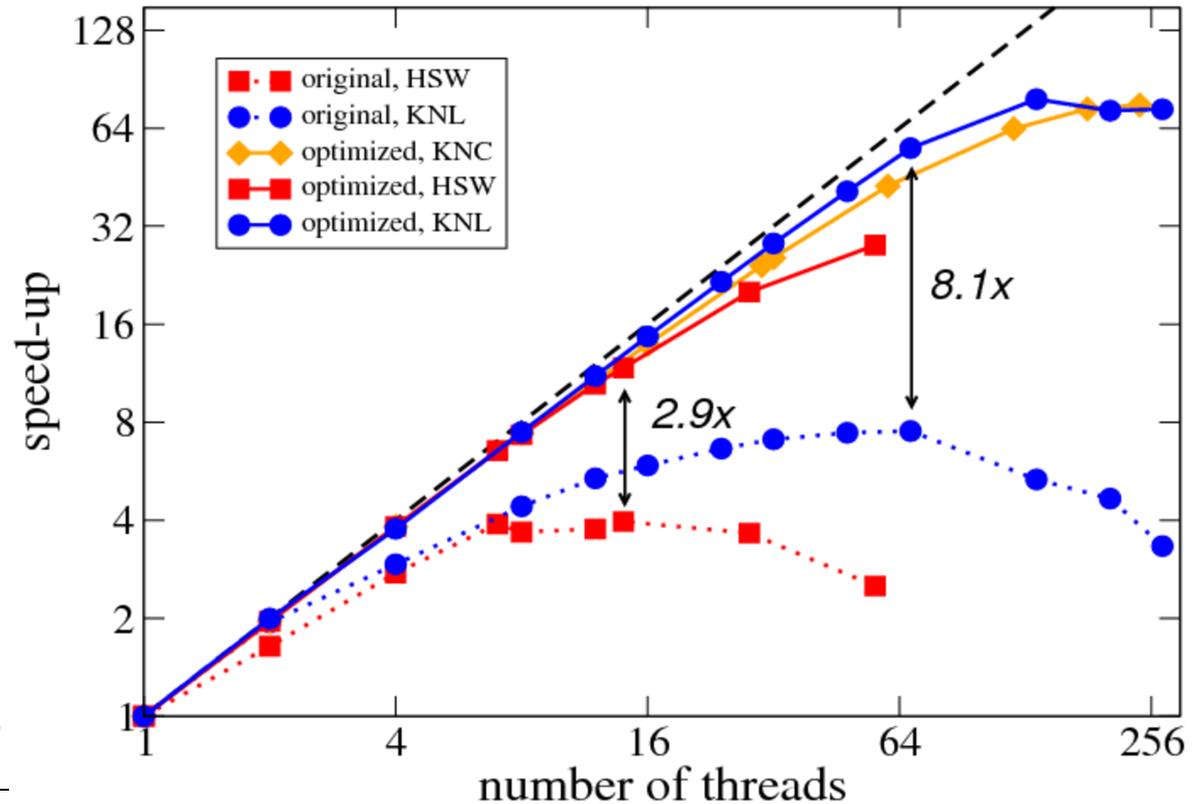
# Node-level performance comparison between HSW, KNC and KNL

## Features of the KNL tests:

- KMP Affinity: scatter;
- Memory mode: Flat;
- MCDRAM via numactl;
- Cluster mode: Quadrant.

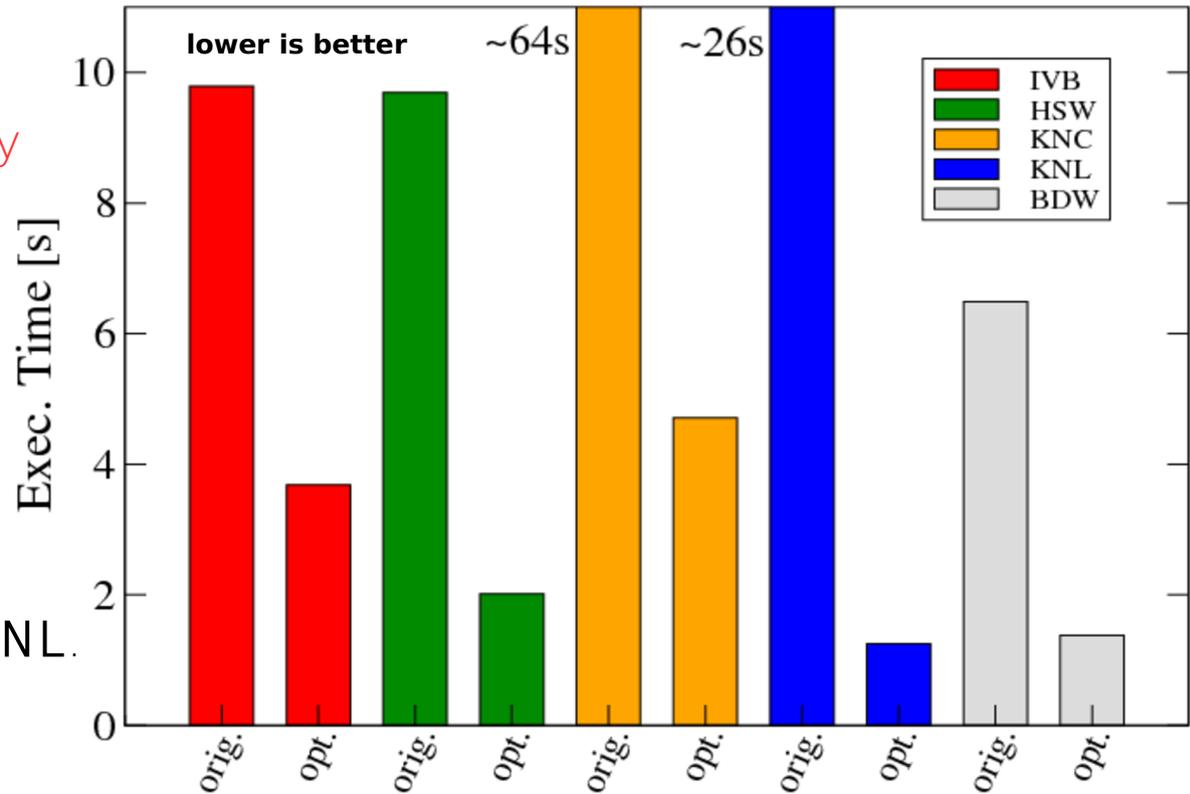
## Results:

- Our optimization improves the speed-up on all systems.
- Better threading scalability up to 136 threads on KNL.
- Hyperthreading performance is different between KNC and KNL



# Performance comparison: first results including KNL and Broadwell

- Initial vs. optimized including all optimizations for `subfind_density`
- IVB, HSW, BDW: 1 socket w/o hyperthreading.  
KNC: 1 MIC, 240 threads.  
KNL: 1 node, 136 threads.
- Performance gain:
  - Xeon Phi: **13.7x** KNC, **19.1x** KNL.
  - Xeon: **2.6x** IVB, **4.8x** HSW, **4.7x** BDW.



# Code optimization on KNL: lessons learnt (so far...)

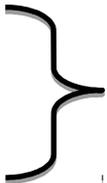
Optimization for KNL as a three-step process:

Step	Effort	Expected performance
Compilation "out of the box"	1 hour	Lower than Haswell (~ 1.5x)
Optimization without coding (use of AVX512, explore configuration, MCDRAM, MPI/OpenMP)	1 week	Up to 2x over previous step
Optimization with coding (this project and beyond)	1-3 months (IPCC: 2 years)	Up to the level of Broadwell

## Some more KNL wisdom

- Quad-cache is a good starting point, quad-flat with allocation on MCDRAM is worth being tested, SNC modes are for very advanced developers.
- It is unlikely to gain performance with more than 2 threads/core.
- Vectorize whenever possible, use compiler reports and tools to exploit low-hanging fruits.
- Know where your data are located and how they move.
- If optimizations are portable, the effort pays off!

# Summary and outlook

- Code modernization as the iterative process for improving the performance of an HPC application.
- Our IPCC example: P-Gadget3.
  - Threading parallelism
  - Data layout
  - Vectorization

Key points of our work, guided by analysis tools.
- This effort is (mostly) portable! Good performance found on new architectures (KNL and BDW) basically out-of-the-box.
- For KNL, architecture-specific features (MCDRAM, large vector registers and NUMA characteristics) are currently under investigation for different workloads.
- Investment on the future of well-established community applications, and crucial for the effective use of forthcoming HPC facilities.

# Acknowledgements

- Research supported by the Intel® Parallel Computing Center program.
- Project coauthors: Nicolay J. Hammer (LRZ), Vasileios Karakasis (CSCS).
- P-Gadget3 developers: Klaus Dolag, Margarita Petkova, Antonio Ragagnin.
- Research collaborator at Technical University of Munich (TUM): Nikola Tchipev.
- TCEs at Intel: Georg Zitzlsberger, Heinrich Bockhorst.
- Thanks to the IXPUG community for useful discussion.
- Special thanks to Colfax Research for granting access to their computing facilities.

# Back-up: removing lock contention

```
todo_partlist = partlist;
```



creating a **todo** particle list

```
while(partlist.length) {
```

```
    error=0;
```

```
    #pragma omp parallel for schedule(dynamic)
```

```
    for(auto p:todo_partlist) {
```



iterations over the **todo** list  
(*private ngblist*)

```
        if(something_is_wrog) error=1;
```

```
        ngblist = find_neighbours(p);
```

```
        sort(ngblist);
```

```
        for(auto n:select(ngblist,K))
```

```
            compute_interaction(p,n);
```



actual computation

**No-checks** for computation

```
//...check for any error
```

```
    todo_particles = mark_for_recomputation(partlist);
```

```
}
```

# Back-up: SoA implementation details

```
struct ParticleAoS
{
    float pos[3], vel[3], mass;
}
Particle_AoS *P_AoS;
P_AoS = malloc(N*sizeof(Particle_AoS));
```

```
struct ParticleSoA
{
    float *pos_x, ... , *vel_x, ..., mass;
}
Particle_SoA P_SoA;
P_SoA.pos_x = malloc(N*sizeof(float));
...
```

```
void gather_Pdata(struct Particle_SoA *dst, struct Particle_AoS *src, int N )
for(int i = 0, i < N, i++ ){
    dst -> pos_x[i] = src[i].pos[1]; dst -> pos_y[i] = src[i].pos[2]; ...
}
```

```
...
rho    += P_AoS[j].mass*w;
vel_x += P_AoS[j].vel_x;
...
```

```
...
rho    += P_SoA.mass[j]*w;
vel_x += P_SoA.vel_x[j];
...
```