

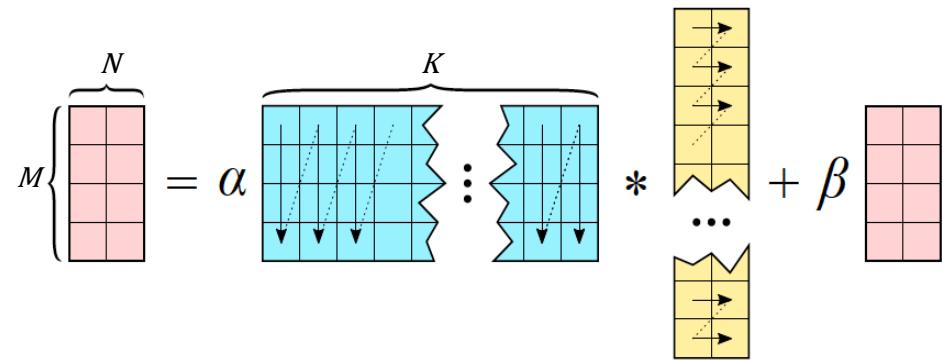


Erlangen Regional  
Computing Center



# Case study: tall & skinny matrix-matrix (TSMM) multiplication

- Block of vectors → Tall & Skinny Matrix (e.g.  $10^7 \times 10^1$  dense matrix)
- Row-major storage format (see SpMVM)
- Block vector subspace orthogonalization procedure requires, e.g. computation of scalar product between vectors of two blocks
- TSMM mutliplication



$$K \gg N, M$$

$$\alpha = 1; \beta = 0$$

$$C = \alpha A^T * B + \beta C$$

- General rule for dense matrix-matrix multiply: Use vendor-optimized GEMM, e.g. from Intel MKL<sup>1</sup>:

$$C_{mn} = \sum_{k=1}^K A_{mk}B_{kn}, \quad m = 1..M, n = 1..N$$

double

System	P <sub>peak</sub> [GF/s]	b <sub>S</sub> [GB/s]	Size	Perf.	Efficiency
Intel Xeon E5 2660 v2 10c@2.2 GHz	176 GF/s	52 GB/s	SQ	160 GF/s	91%
			TS	16.6 GF/s	6%
Intel Xeon E5 2697 v3 14c@2.6GHz	582 GF/s	65 GB/s	SQ	550 GF/s	95%
			TS	22.8 GF/s	4%

Matrix sizes:

Square (SQ): M=N=K=15,000

Tall&Skinny (TS): M=N=16 ; K=10,000,000

complex double

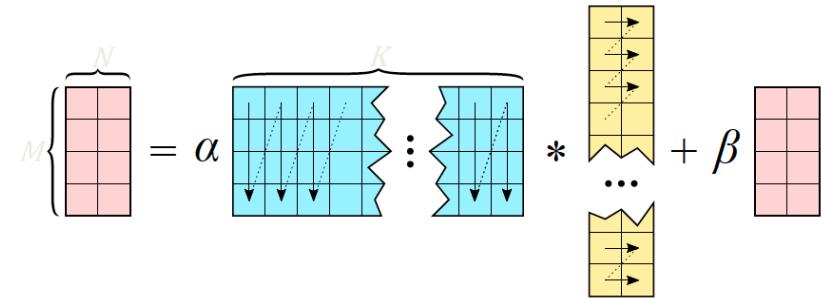
TS@MKL:  
Good or bad?

<sup>1</sup>Intel Math Kernel Library (MKL) 11.3

- Computational intensity

- $I = \frac{\text{#flops}}{\text{\#bytes (slowest data path)}}$

$$C_{mn} = \sum_{k=1}^K A_{mk} B_{kn}, \quad m = 1..M, n = 1..N$$



$$C = \alpha A^T * B + \beta C$$

$$K \gg N, M$$

$$\alpha = 1; \beta = 0$$

- Optimistic model (minimum data transfer) with  $M = N \ll K$

double precision:  $I_d \approx \frac{2KMN}{8(KM+KN)} \frac{F}{B} = \frac{M}{8} \frac{F}{B}$

complex double:  $I_z \approx \frac{8KMN}{16(KM+KN)} \frac{F}{B} = \frac{M}{4} \frac{F}{B}$

Now choose  $M = N = 16 \rightarrow I_d \approx \frac{16}{8} \frac{F}{B}$  and  $I_z \approx \frac{16}{4} \frac{F}{B}$ , i.e.  $B_d \approx 0.5 \frac{B}{F}$ ,  
 $B_z \approx 0.25 \frac{B}{F}$

Intel Xeon E5 2660 v2 ( $b_S = 52 \frac{GB}{s}$ )  $\rightarrow P = 104 \frac{GF}{s}$  (double)

Measured (MKL):  $16.6 \frac{GF}{s}$

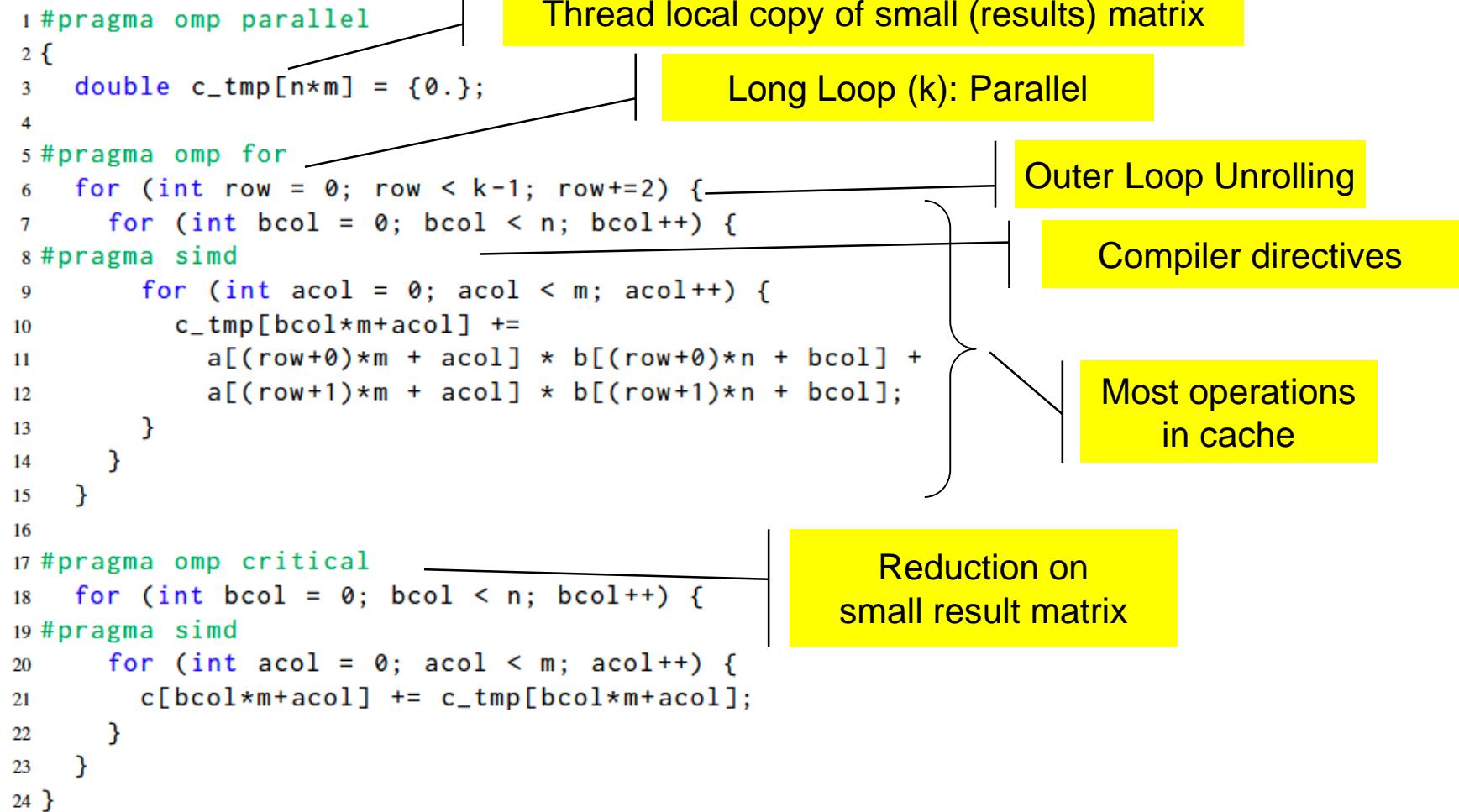
Intel Xeon E5 2697 v3 ( $b_S = 65 \frac{GB}{s}$ )  $\rightarrow P = 240 \frac{GF}{s}$  (double complex)

Measured (MKL):  $22.8 \frac{GF}{s}$

→ Potential speedup: 6–10x vs. MKL

```

1 #pragma omp parallel
2 {
3     double c_tmp[n*m] = {0.};
4
5 #pragma omp for
6     for (int row = 0; row < k-1; row+=2) {
7         for (int bcol = 0; bcol < n; bcol++) {
8 #pragma simd
9             for (int acol = 0; acol < m; acol++) {
10                 c_tmp[bcol*m+acol] +=
11                     a[(row+0)*m + acol] * b[(row+0)*n + bcol] +
12                     a[(row+1)*m + acol] * b[(row+1)*n + bcol];
13             }
14         }
15     }
16
17 #pragma omp critical
18     for (int bcol = 0; bcol < n; bcol++) {
19 #pragma simd
20         for (int acol = 0; acol < m; acol++) {
21             c[bcol*m+acol] += c_tmp[bcol*m+acol];
22         }
23     }
24 }
```



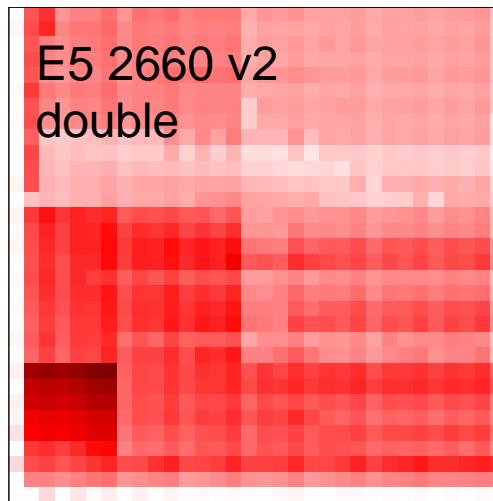
The diagram highlights several performance optimization techniques used in the code:

- Thread local copy of small (results) matrix**: Points to the declaration of `c_tmp` in line 3.
- Long Loop (k): Parallel**: Points to the outermost loop structure starting at line 6.
- Outer Loop Unrolling**: Points to the nested loops from line 6 to line 15.
- Compiler directives**: Points to the `#pragma` directives used throughout the code.
- Most operations in cache**: Points to the memory access pattern in lines 11 and 12, which access elements in a 2x2 block pattern.
- Reduction on small result matrix**: Points to the reduction operation in line 21, where the results are summed up.

Not shown: Inner Loop boundaries ( $n,m$ ) known at compile time (kernel generation)  
 $k$  assumed to be even

TS: M=N=16 ; K=10,000,000

System	P <sub>peak</sub> / b <sub>s</sub>	Version	Performance	RLM Efficiency
Intel Xeon E5 2660 v2 10c@2.2 GHz	176 GF/s 52 GB/s	TS OPT	98 GF/s	94 %
		TS MKL	16.6 GF/s	16 %
Intel Xeon E5 2697 v3 14c@2.6GHz	582 GF/s 65 GB/s	TS OPT	159 GF/s	66 %
		TS MKL	22.8 GF/s	9.5 %



Speedup  
vs. MKL:  
5x – 25x

