# Optimizations

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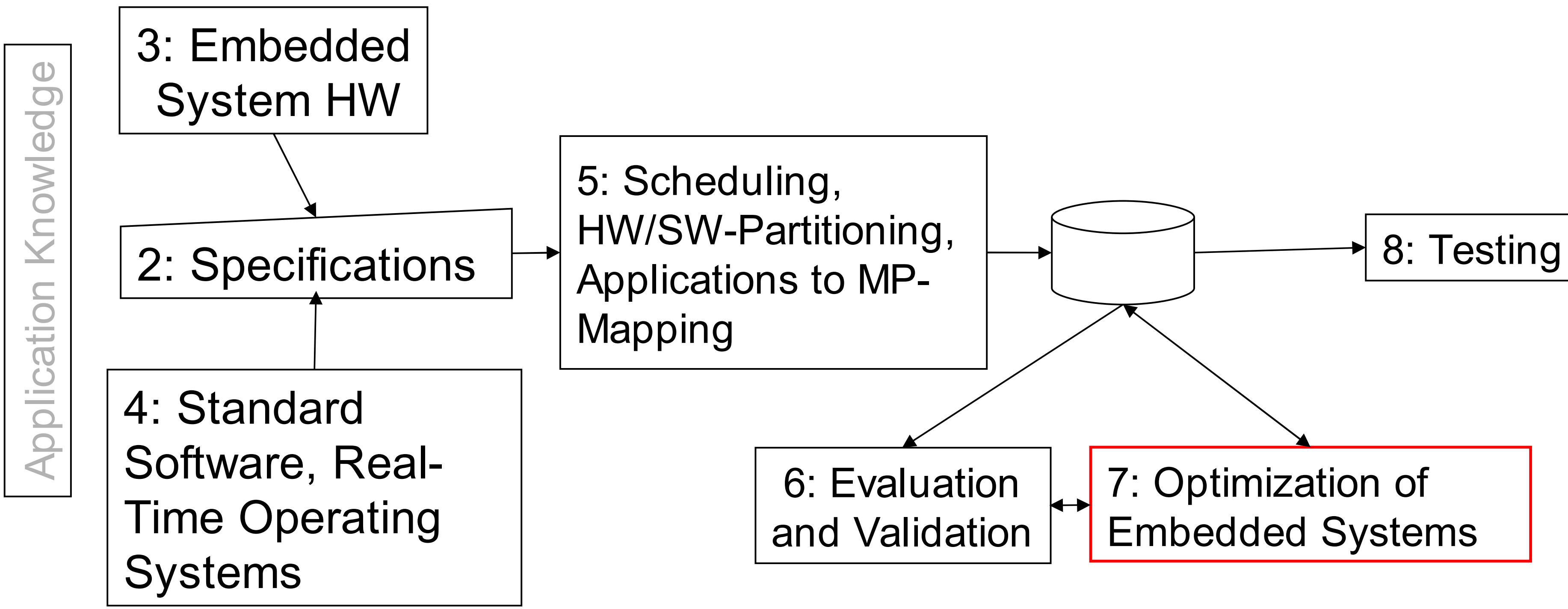
# Structure of this course



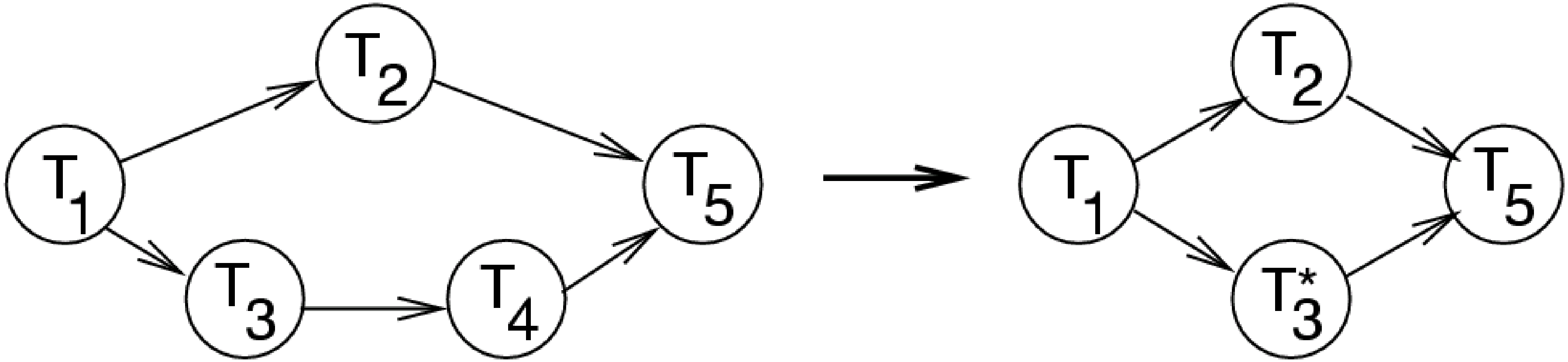
# Task-level concurrency management

*Granularity*: size of tasks (e.g. in instructions)

Readable specifications and efficient implementations can possibly require different task structures.

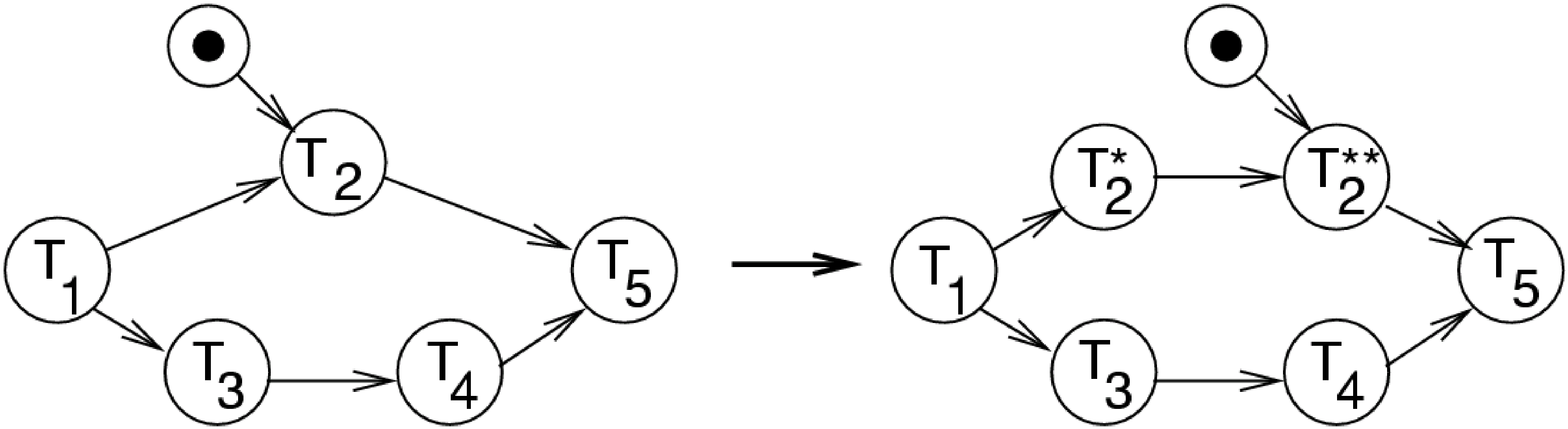
☞ Granularity changes

# Merging of tasks




Reduced overhead of context switches,
More global optimization of machine code,
Reduced overhead for inter-process/task communication.

# Splitting of tasks




No blocking of resources while waiting for input,
more flexibility for scheduling, possibly improved result.

# Merging and splitting of tasks

The most appropriate task graph granularity depends upon the context ☞ merging and splitting may be required.

Merging and splitting of tasks should be done automatically, depending upon the context.

# Automated rewriting of the task system
# - Example -

IN

```
PROCESS GetData
 (InPort IN, OutPort DATA){
float sample,sum; int i;
while (1)  {
 sum=0;
 for (i=0; i<N; i++){
  READ(IN,sample,1)
  sum+=sample;
  WRITE(DATA,sample,1)
 }
 WRITE(DATA,sum/N,1);
}}
```

DATA

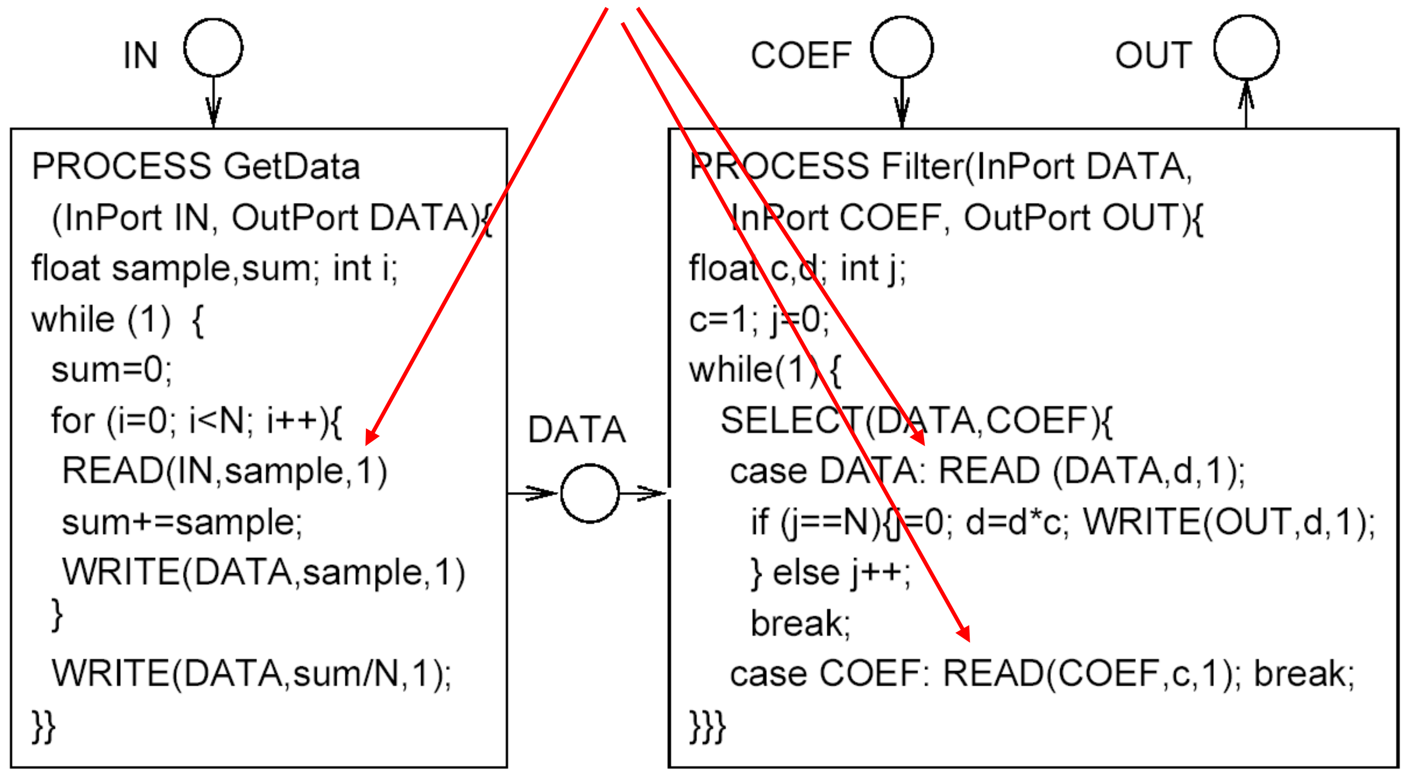
COEF

OUT

```
PROCESS Filter(InPort DATA,
    InPort COEF, OutPort OUT){
float c,d; int j;
c=1; j=0;
while(1) {
   SELECT(DATA,COEF){
    case DATA: READ (DATA,d,1);
      if (j==N){j=0; d=d*c; WRITE(OUT,d,1);
      } else j++;
      break;
    case COEF: READ(COEF,c,1); break;
}}}
```

# Attributes of a system that needs rewriting

Tasks blocking after they have already started running



# Work by Cortadella et al.

1. Transform each of the tasks into a Petri net,
2. Generate one global Petri net from the nets of the tasks,
3. Partition global net into “sequences of transition”
4. Generate one task from each such sequence

Mature, commercial approach not yet available

# Result, as published by Cortadella

Reads only at the beginning

Initialization task

IN

OUT

```
Init(){
  sum=0;i=0;c=1;j=0;
}
```

```
Tin(){
  READ(IN,sample,1);
  sum+=sample; i++;
  DATA=sample; d=DATA;
  if (j==N) {j=0; d=d*c; WRITE(OUT,d,1);
            }else j++;
L0: if (i<N) return;
  DATA=sum/N; d=DATA;
  if (j==N) {j=0; d=d*c; WRITE(OUT,d,1);
     }else j++;
  sum=0; i=0; goto L0
}
```

Never true

COEF

```
Tcoef(){
  READ(COEF,c,1);
}
```

Always true

# Optimized version of Tin

Never true

IN OUT

```
Tin(){
  READ(IN,sample,1);
  sum+=sample; i++;
  DATA=sample; d=DATA;
  if (j==N) {j=0; d=d*c; WRITE(OUT,d,1);
            }else j++;
L0: if (i<N) return;
  DATA=sum/N; d=DATA;
  if (j==N) {j=0; d=d*c; WRITE(OUT,d,1);
     }else j++;
  sum=0; i=0; goto L0
}
```

j==i-1

Always true

j ☞ i

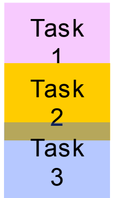
```
Tin () {
READ (IN, sample, 1);
sum += sample; i++;
DATA = sample; d = DATA;
L0: if (i < N) return;
DATA = sum/N; d = DATA;
d = d*c; WRITE(OUT,d,1);
sum = 0; i = 0;
return;
}
```

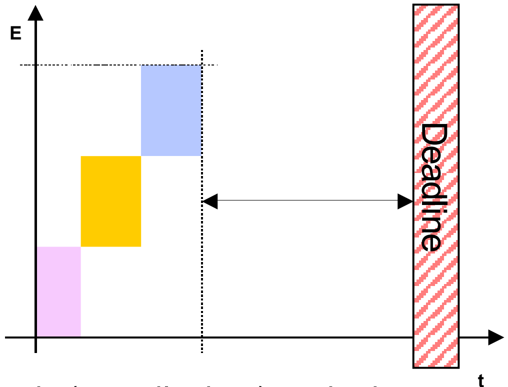
# Task-level concurrency management (2)

- The dynamic behavior of applications getting more attention.
- Energy consumption reduction is the main target.
- Some classes of applications (i.e. video processing) have a considerable variation in processing power requirements depending on input data.
- Static design-time methods becoming insufficient.
- Runtime-only methods not feasible for embedded systems.

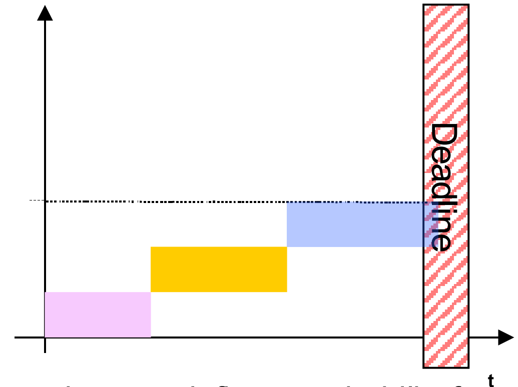
→ How about mixed approaches?

# Example of a mixed TCM

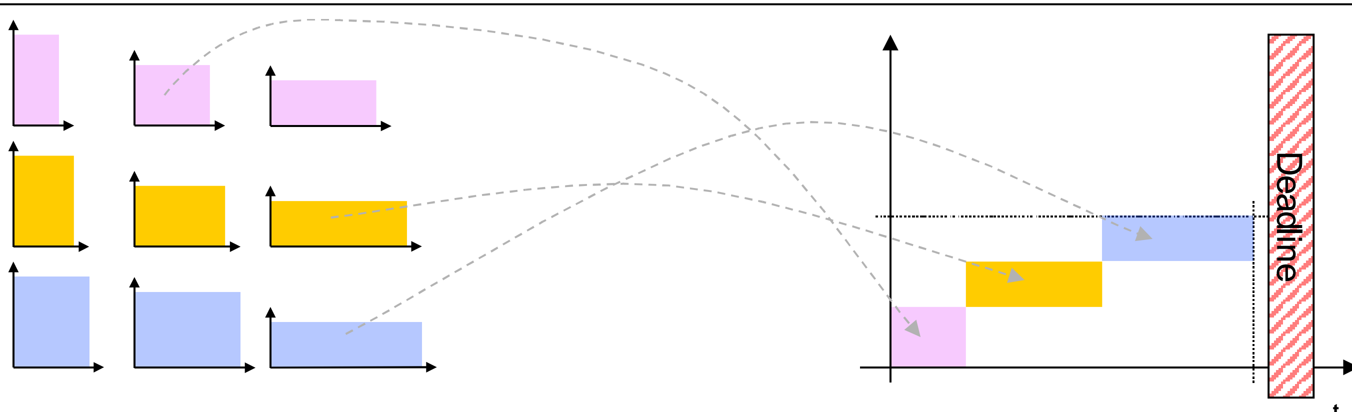



Static (compile-time) methods can ensure WCET feasible schedules, but waste energy in the average case.




…or they can define a probability for violating the deadline.




Mixed methods use compile-time analysis to define a set of possible execution parameters for each task.

Runtime scheduler selects the most energy saving, deadline preserving combination.

[IMEC, Belgium, http://www.imec.be/]

# Floating-point to fixed point conversion

Pros:

- Lower cost
- Faster
- Lower power consumption
- Sufficient SQNR, *if properly scaled*
- Suitable for portable applications

Cons:

- Decreased dynamic range
- Finite word-length effect, *unless properly scaled*
    - Overflow and excessive quantization noise
- Extra programming effort

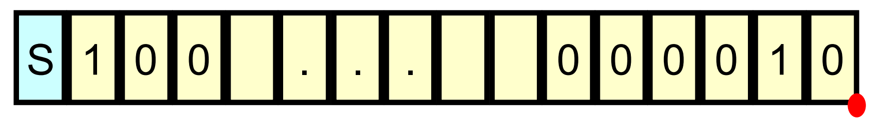
© *Ki-Il Kum, et al.* (Seoul National University): A Floating-point To Fixed-point C Converter For Fixed-point Digital Signal Processors, 2nd SUIF Workshop, 1996

# Fixed-Point Data Format

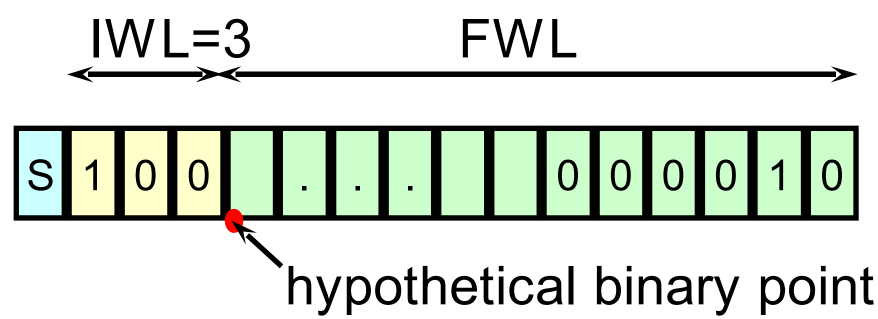
## • Floating-Point vs. Fixed-Point

- *exponent*, mantissa
- Floating-Point
  - automatic computation and update of each exponent at run-time
- Fixed-Point
  - implicit exponent
  - determined off-line

## • Integer vs. Fixed-Point



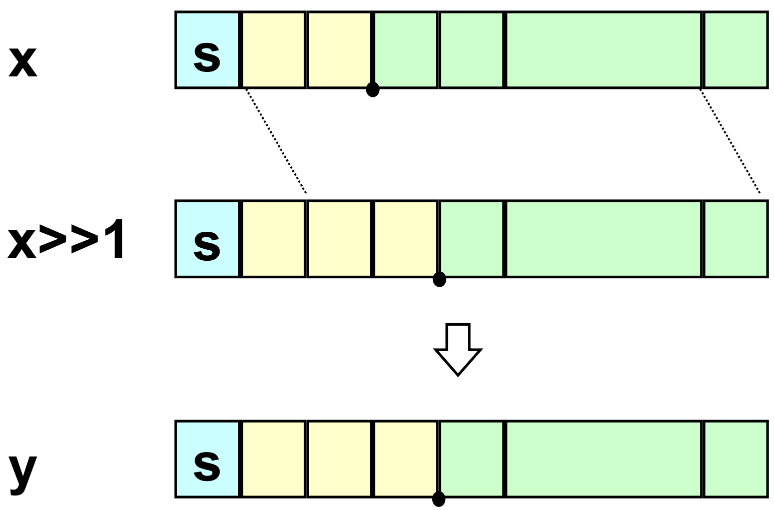

(a) Integer



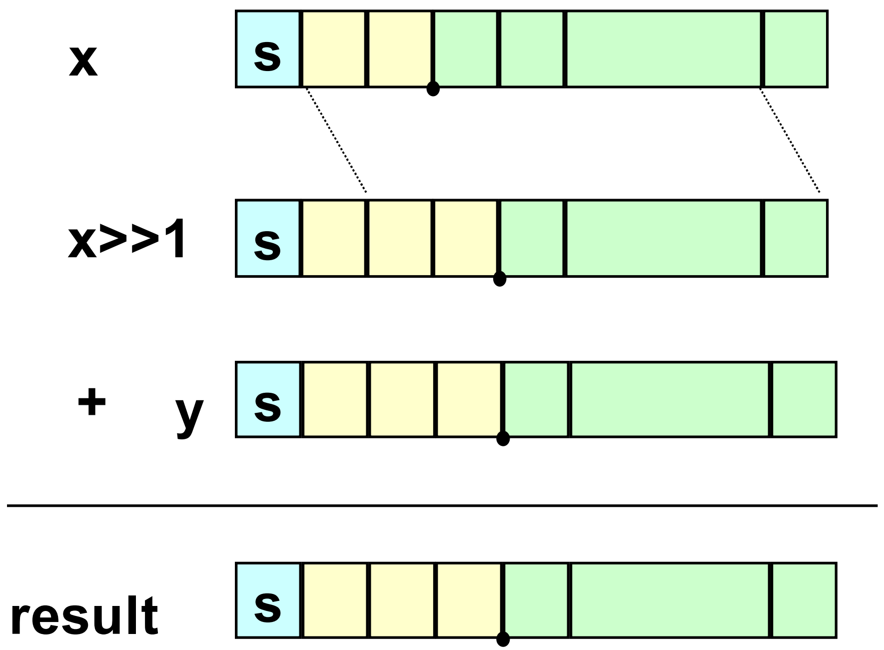

(b) Fixed-Point

# Assignment and Addition/Subtraction

Assume y = x, with
-x (IWL=2) and
-y (IWL=3):



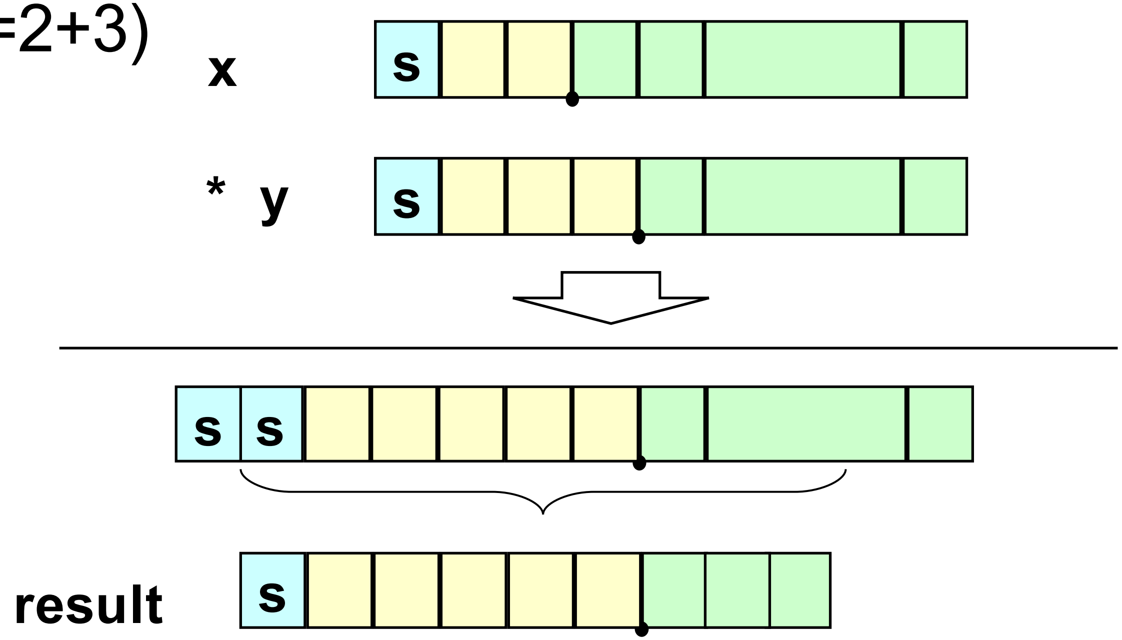

Let result = x + y:
equalizing each IWL



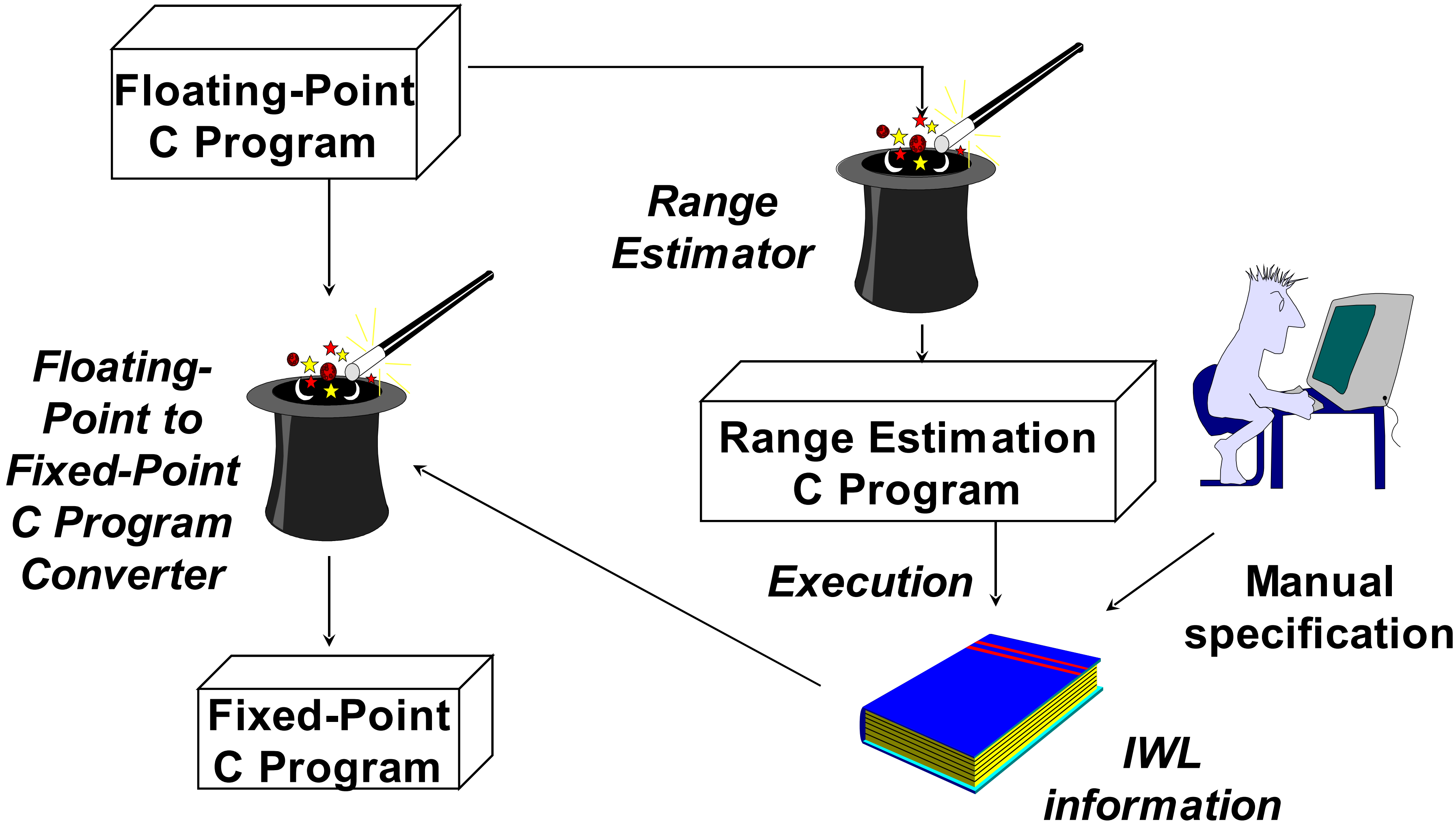

© *Ki-Il Kum, et al*

# Multiplication

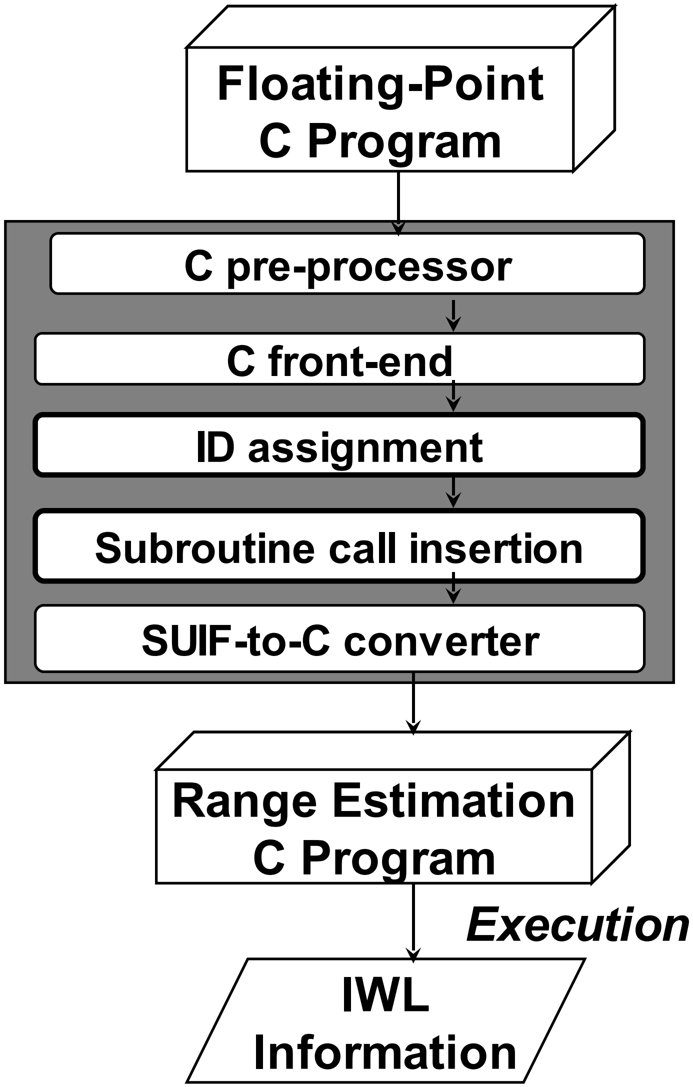
Assume result = x * y, with
-x (IWL=2) and
-y (IWL=3)
-> result (IWL=2+3)



# Development Procedure



# Range Estimator




SUIF Compiler System

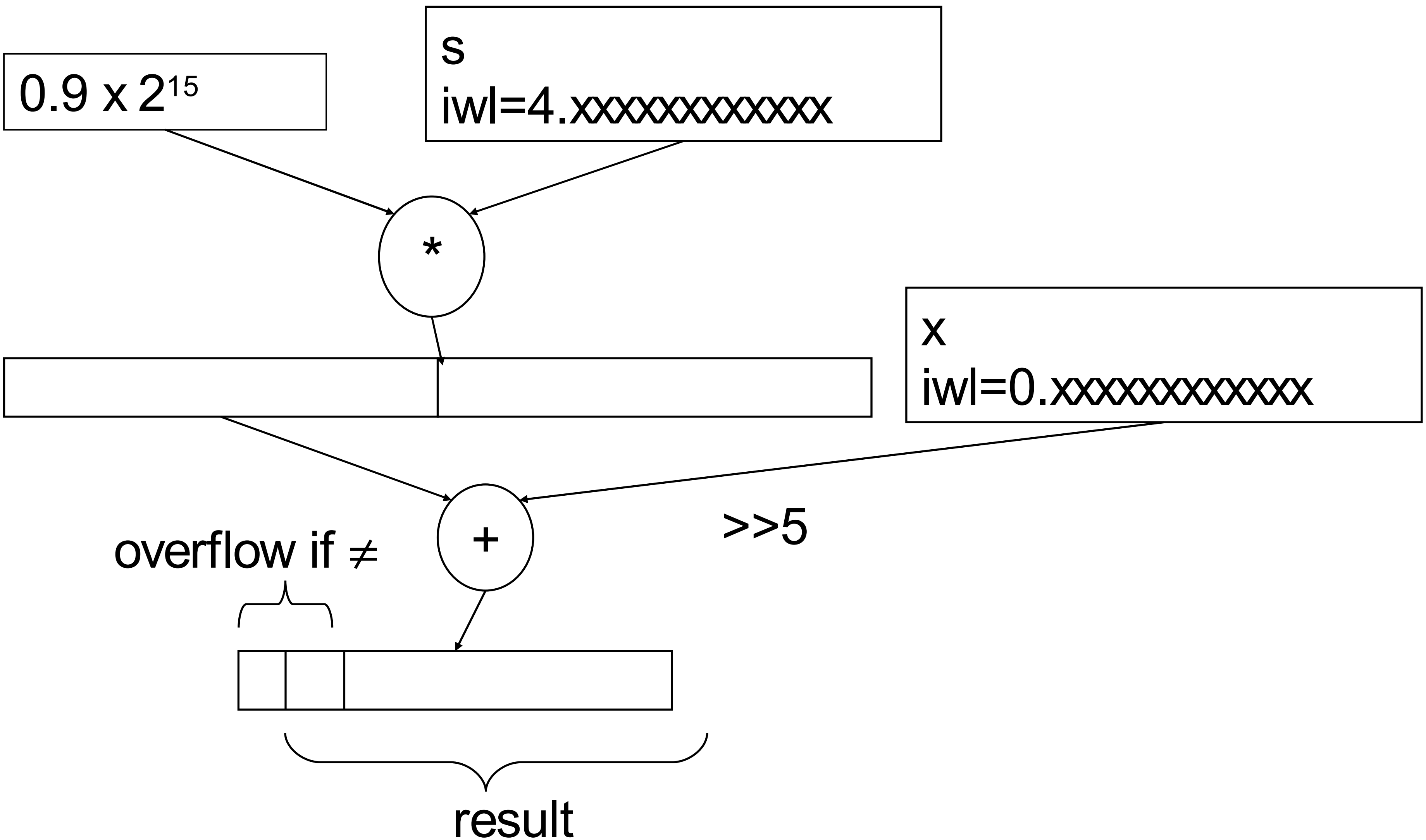
## Range Estimation C Program

```
float iir1(float x)
{
    static float s = 0;
    float y;

    y = 0.9 * s + x;
    range(y, 0);
    s = y;
    range(s, 1);

    return y;
}
```

# Operations in fixed point program



# Floating-Point to Fixed-Point Program Converter

Fixed-Point C Program

```
int iir1(int x)
{
 static int s = 0;
 int y;
 y=sll(mulh(29491,s)+ (x>> 5),1);
 s = y;
 return y;
}
```

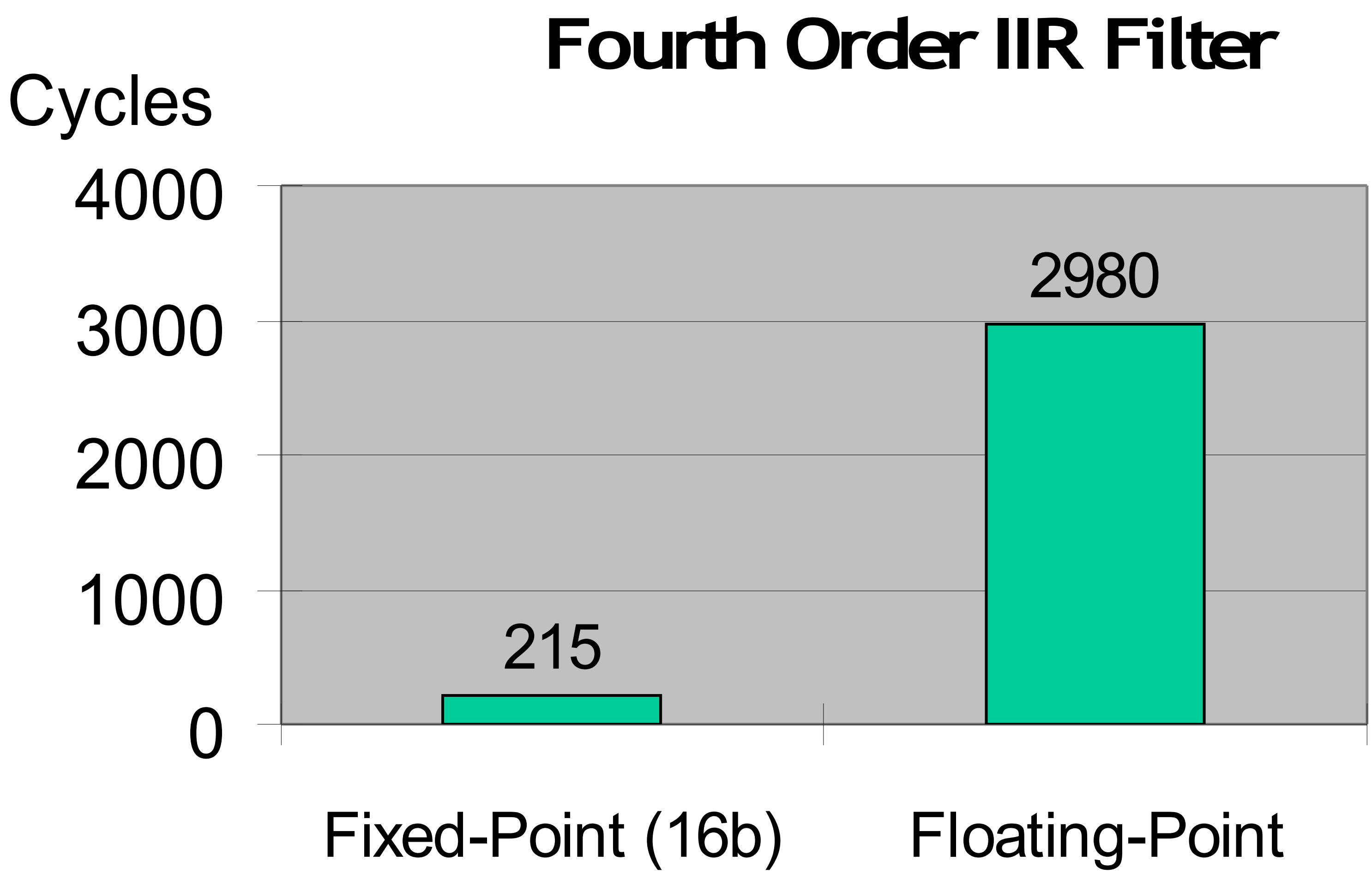
*mulh*

- to access the upper half of the multiplied result
- target dependent implementation

*sll*

- to remove 2nd sign bit
- opt. overflow check

# Performance Comparison
# - Machine Cycles -

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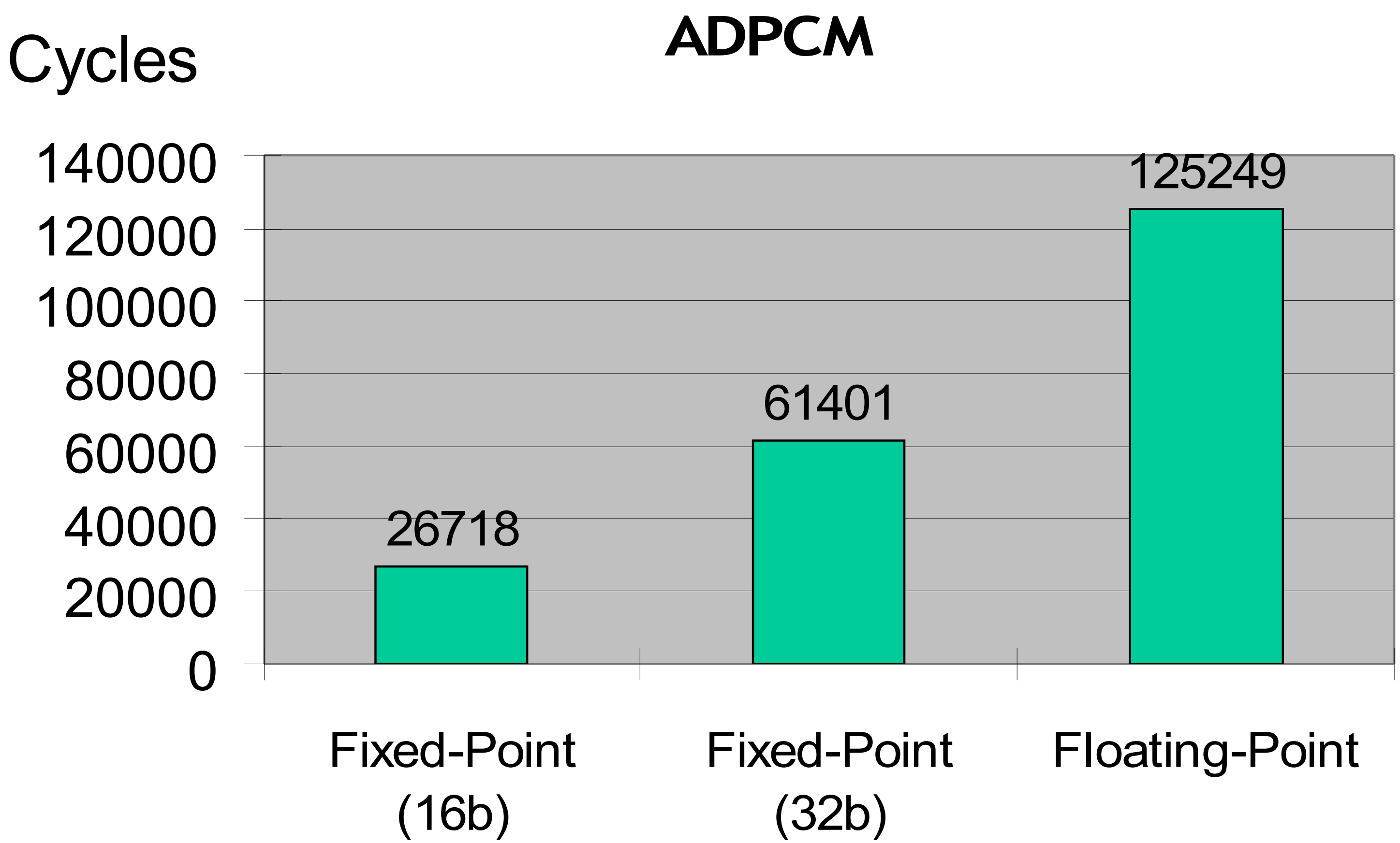
# Performance Comparison - Machine Cycles -

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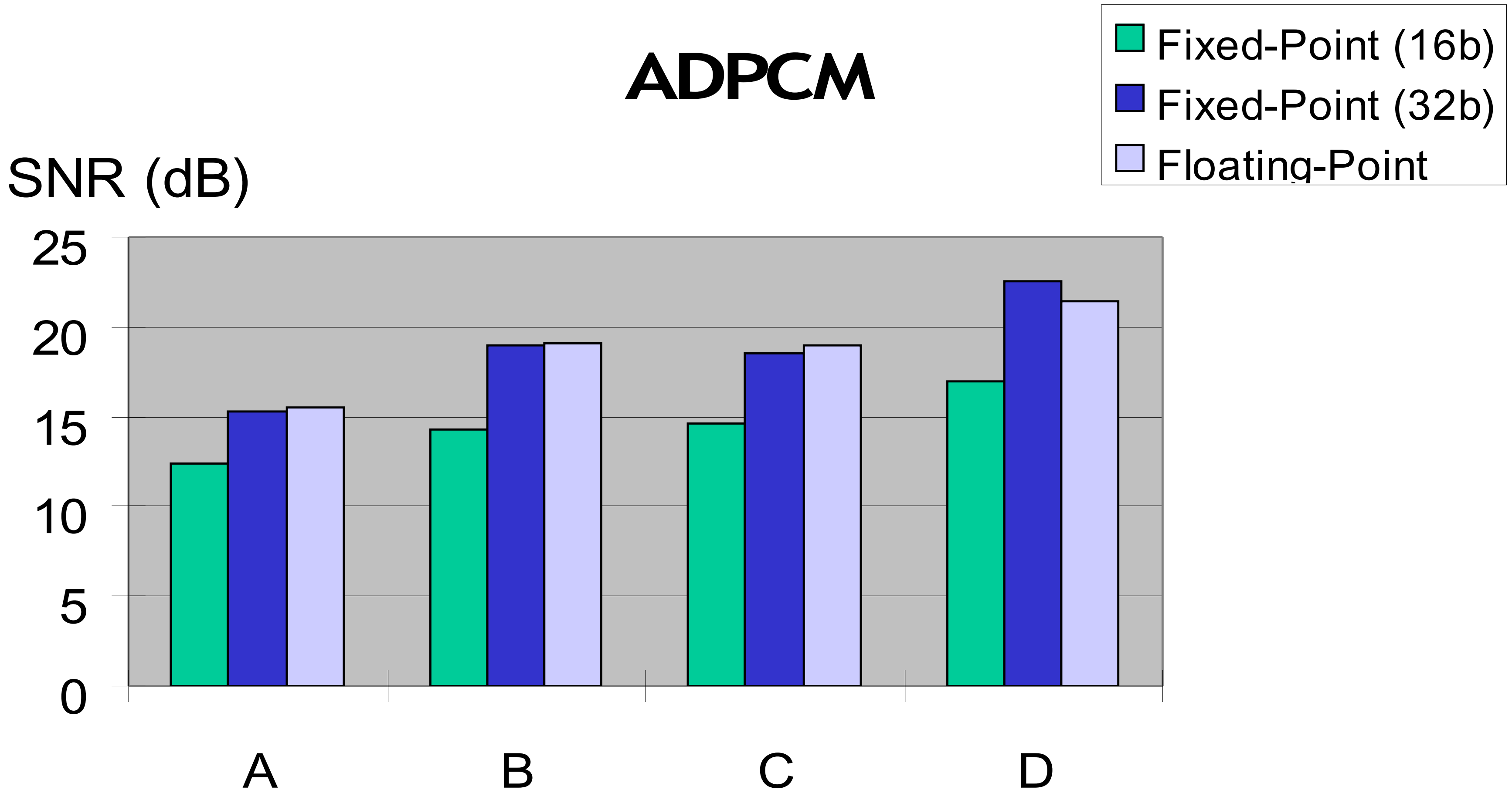
# Performance Comparison
# - SNR -

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# High-level software transformations

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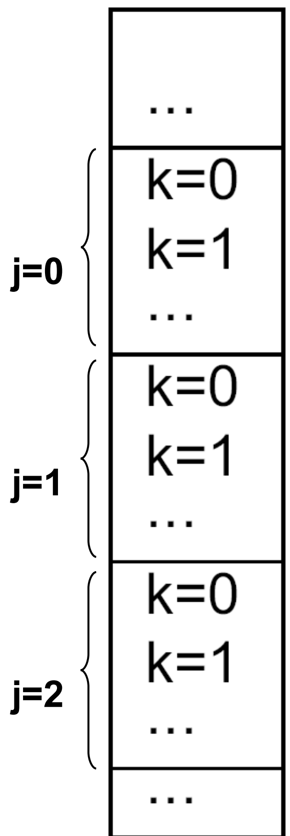
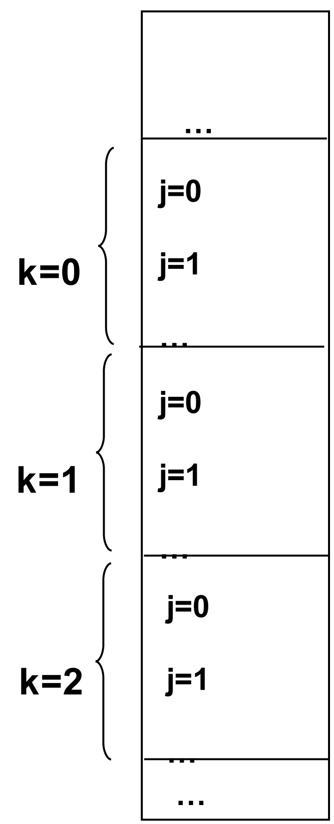
# Impact of memory allocation on efficiency

**Array p[j][k]**

Row major order (C)




Column major order (FORTRAN)



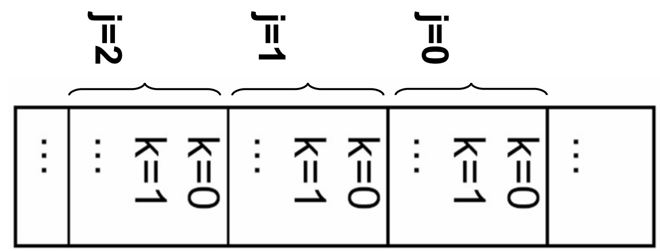
# Best performance if innermost loop corresponds to rightmost array index

**Two loops, assuming row major order (C):**

```
for (k=0; k<=m; k++)          for (j=0; j<=n; j++)
  for (j=0; j<=n; j++) )        for (k=0; k<=m; k++)
    p[j][k] = ...                 p[j][k] = ...
```

Same behavior for homogenous memory access, but:

For row major order




↑ Poor cache behavior    Good cache behavior ↑

☞ memory architecture dependent optimization

# ☞ Program transformation “Loop interchange”

☞ Improved locality

```
Example:
…#define iter 400000
int a[20][20][20];
void computeijk() {int i,j,k;
   for (i = 0; i < 20; i++) {
       for (j = 0; j < 20; j++) {
             for (k = 0; k < 20; k++) {
                   a[i][j][k] += a[i][j][k];}}}}
void computeikj() {int i,j,k;
   for (i = 0; i < 20; i++) {
       for (j = 0; j < 20; j++) {
             for (k = 0; k < 20; k++) {
                   a[i][k][j] += a[i][k][j] ;}}}}…
start=time(&start);for(z=0;z<iter;z++)computeijk();
   end=time(&end);
   printf("ijk=%16.9f\n",1.0*difftime(end,start));
```

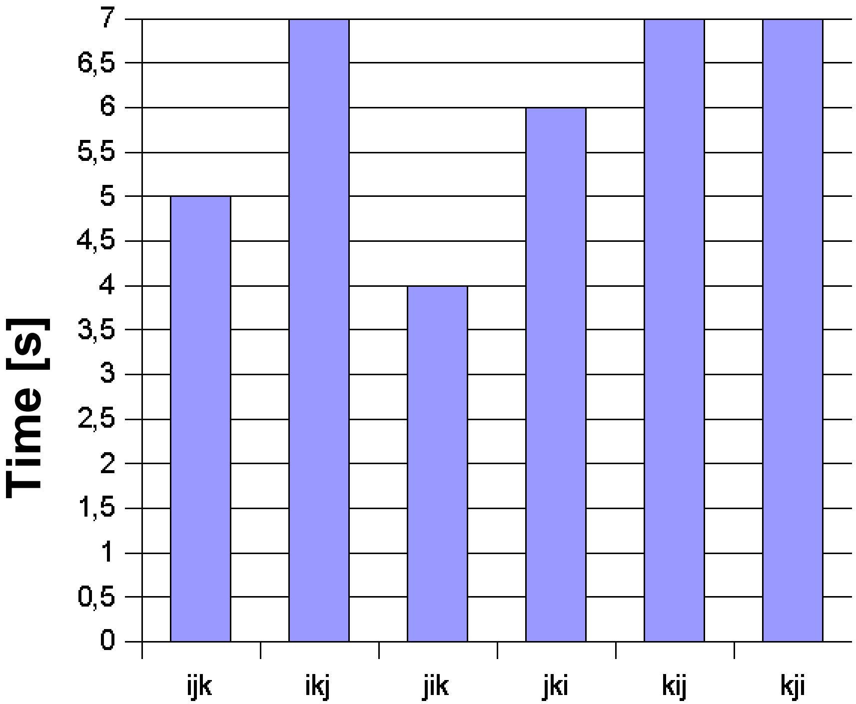
(SUIF interchanges array indexes instead of loops)

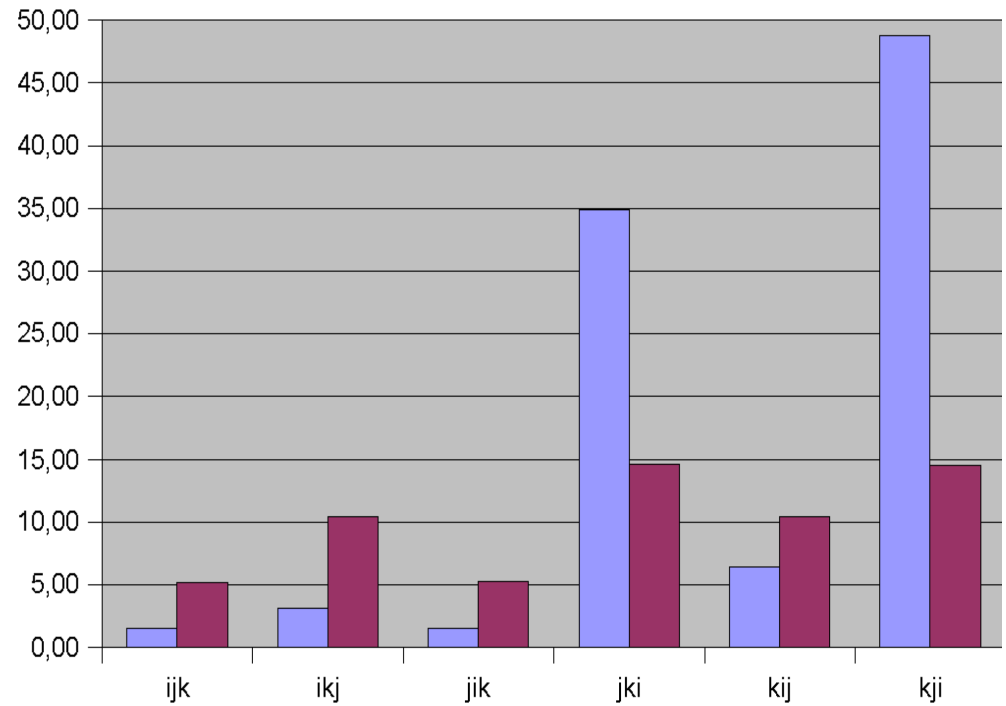
# Results:
# strong influence of the memory architecture

Loop structure: i j k

Dramatic impact of locality

| Processor | Ti C6xx | Sun SPARC | Intel Pentium |
|---|---|---|---|
| reduction to [%] | ~ 57% | 35% | 3.2 % |




Not always the same impact ..

[Till Buchwald, Diploma thesis, Univ. Dortmund, Informatik 12, 12/2004]

# Transformations
# “Loop fusion” (merging), “loop fission”

```
for(j=0; j<=n; j++)
  p[j]= ... ;
for (j=0; j<=n; j++) ,
  p[j]= p[j] + ...
```

```
for (j=0; j<=n; j++)
  {p[j]= ... ;
       p[j]= p[j] + ...}
```

Loops small enough to allow zero overhead Loops

Better locality for access to p.
Better chances for parallel execution.

Which of the two versions is best?
Architecture-aware compiler should select best version.

# Example: simple loops

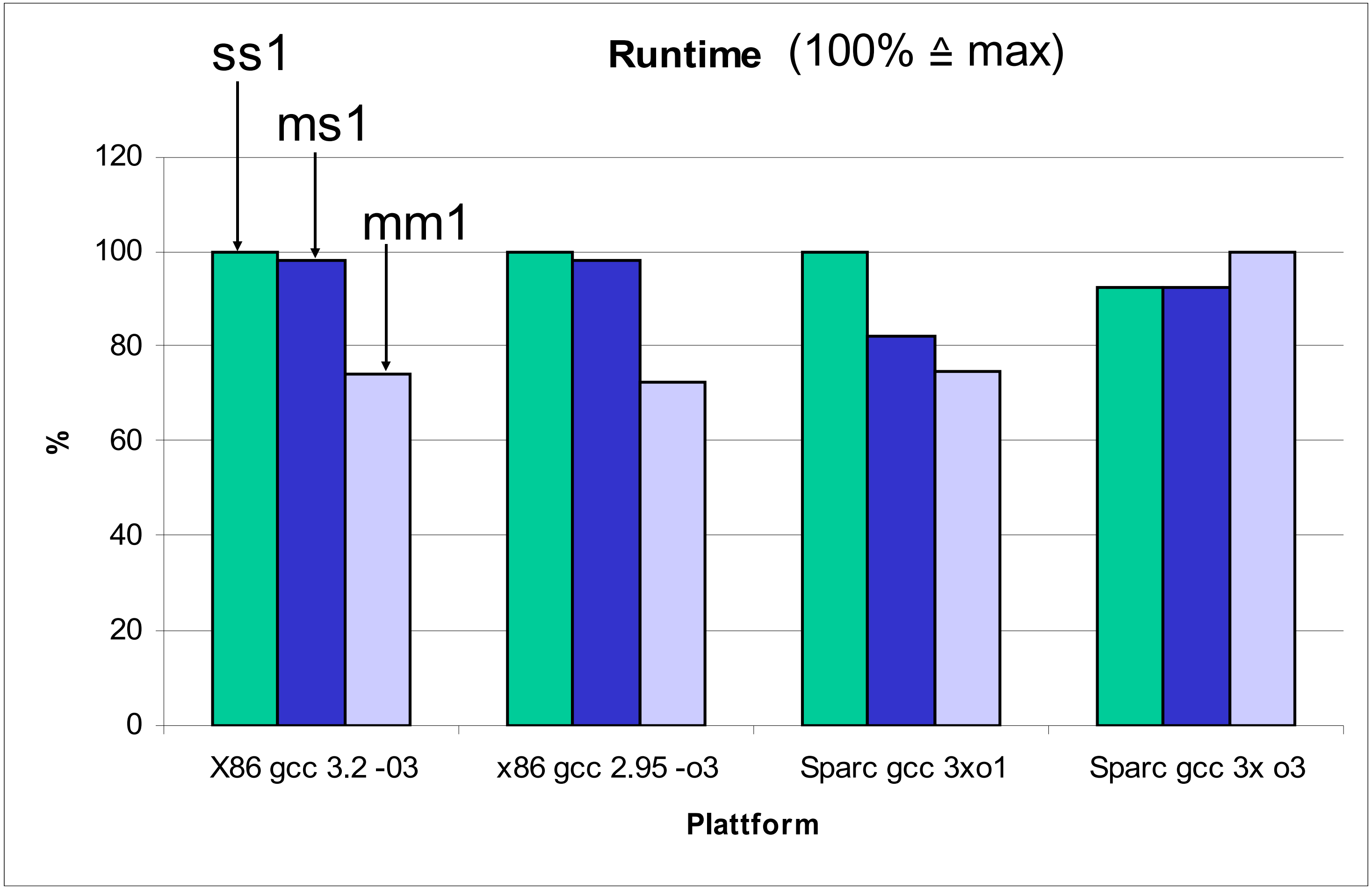
```
#define size 30
#define iter 40000
int a[size][size];
float b[size][size];
```

```
void ss1() {int i,j;
 for (i=0;i<size;i++){
  for (j=0;j<size;j++){
   a[i][j]+= 17;}}
 for(i=0;i<size;i++){
  for (j=0;j<size;j++){
   b[i][j]-=13;}}}
```

```
void ms1() {int i,j;
 for (i=0;i< size;i++){
  for (j=0;j<size;j++){
   a[i][j]+=17;    }
  for (j=0;j<size;j++){
   b[i][j]-=13; }}}
```

```
void mm1() {int i,j;
 for(i=0;i<size;i++){
  for(j=0;j<size;j++){
   a[i][j] += 17;
   b[i][j] -= 13;}}}
```

# Results: simple loops




☞ Merged loops superior; except Sparc with –o3

# Loop unrolling

```
for (j=0; j<=n; j++)
p[j]= ... ;
```

⇒

```
for (j=0; j<=n; j+=2)
    {p[j]= ... ; p[j+1]= ...}
```

factor = 2

Better locality for access to p.
Less branches per execution of the loop. More opportunities for optimizations.
Tradeoff between code size and improvement.
Extreme case: completely unrolled loop (no branch).

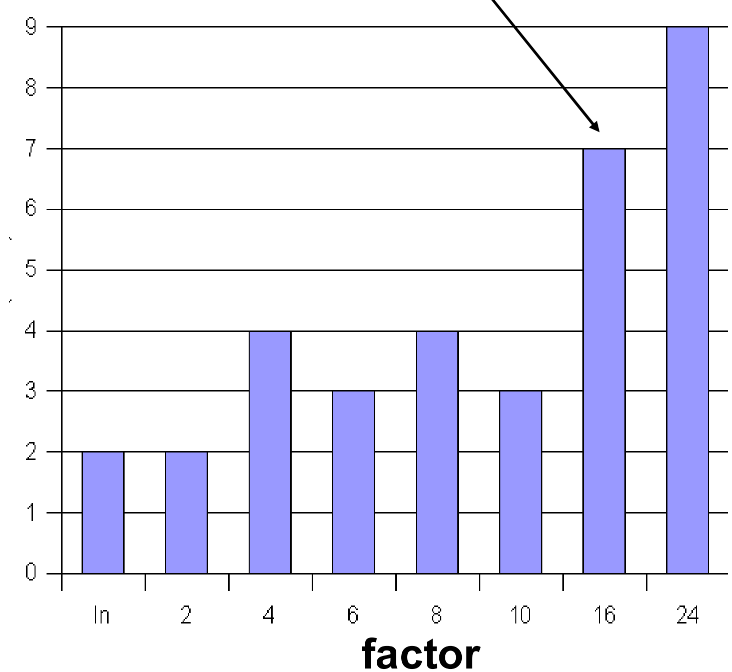
# Example: matrixmult

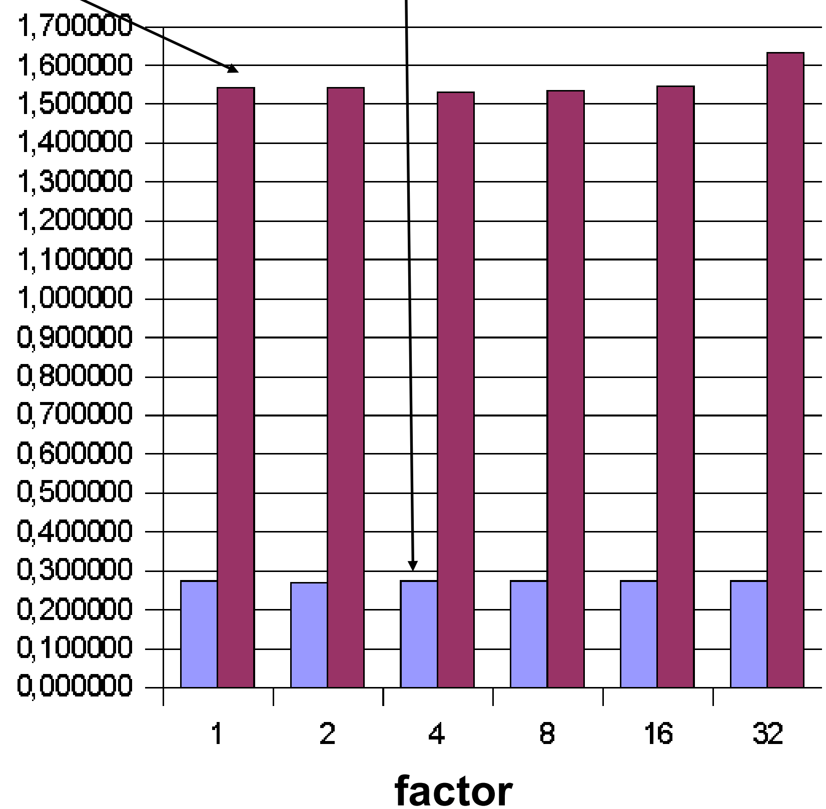
```
#define s 30
#define iter 4000
int
a[s][s],b[s][s],c[s]
[s];
void compute(){int
i,j,k;
 for(i=0;i<s;i++){
  for(j=0;j<s;j++){
   for(k=0;k<s;k++){
    c[i][k]+=
    a[i][j]*b[j][k];
}}}}
```

```
extern void compute2()
 {int i, j, k;
  for (i = 0; i < 30; i++) {
   for (j = 0; j < 30; j++)  {
    for (k = 0; k <= 28; k += 2)
     {{int *suif_tmp;
     suif_tmp = &c[i][k];
     *suif_tmp=
     *suif_tmp+a[i][j]*b[j][k];}
     {int *suif_tmp;
     suif_tmp=&c[i][k+1];
     *suif_tmp=*suif_tmp
            +a[i][j]*b[j][k+1];
  }}}}
 return;}
```

# Results

| Processor | Ti C6xx | Sun SPARC | Intel Pentium |
|---|---|---|---|
| | | | |



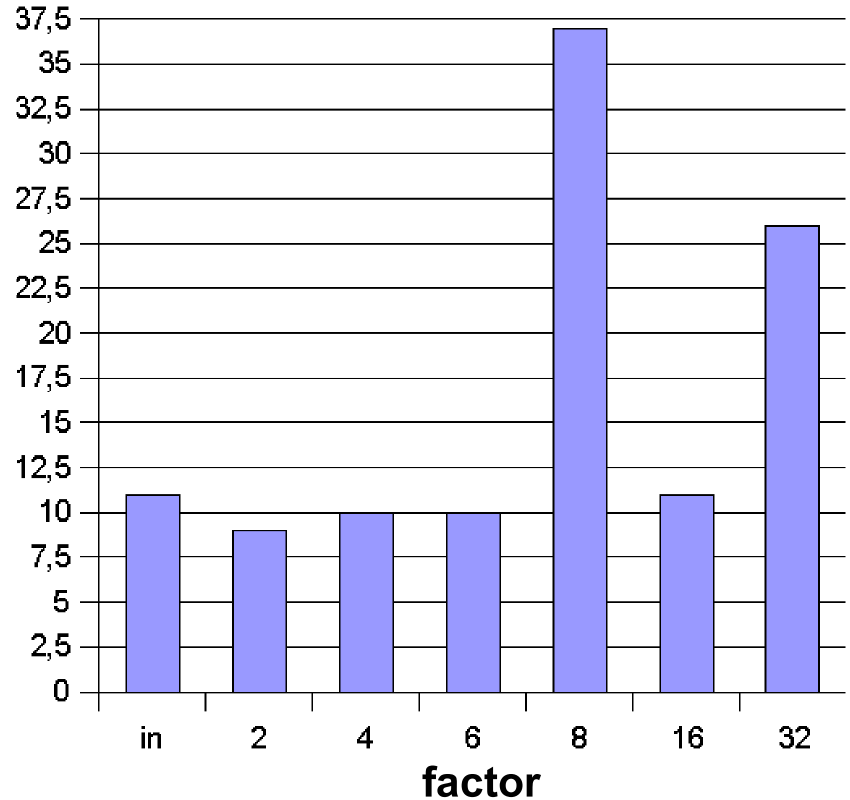

Benefits quite small; penalties may be large

[Till Buchwald, Diploma thesis, Univ. Dortmund, Informatik 12, 12/2004]

# Results: benefits for loop dependences

| Processor | Ti C6xx |
|---|---|
| reduction to [%] | |

```
#define s 50
#define iter 150000
int a[s][s], b[s][s];
void compute() {
 int i,k;
  for (i = 0; i < s; i++) {
   for (k = 1; k < s; k++) {
    a[i][k] = b[i][k];
    b[i][k] = a[i][k-1];
}}}
```

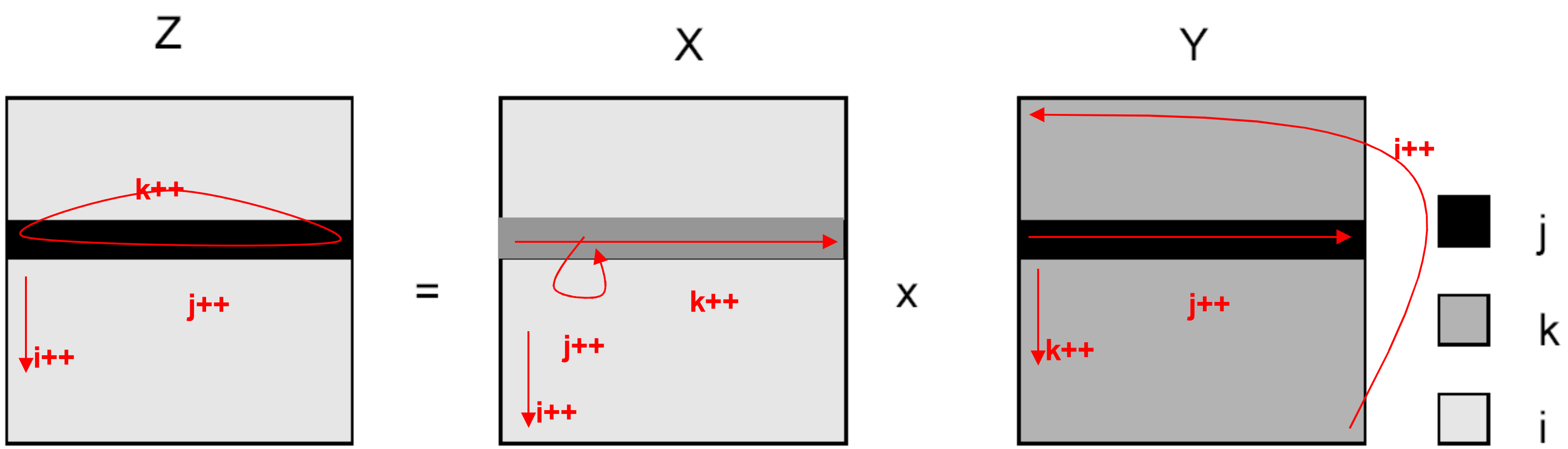



Small benefits;

[Till Buchwald, Diploma thesis, Univ. Dortmund, Informatik 12, 12/2004]

# Program transformation
# Loop tiling/loop blocking: - Original version -

```
for (i=1; i<=N; i++)
  for(k=1; k<=N; k++){
      r=X[i,k]; /* to be allocated to a register*/
      for (j=1; j<=N; j++)
          Z[i,j] += r* Y[k,j]
} % Never reusing information in the cache for Y and Z if N
  is large or cache is small (2 N³ references for Z).
```



# Loop tiling/loop blocking - tiled version -

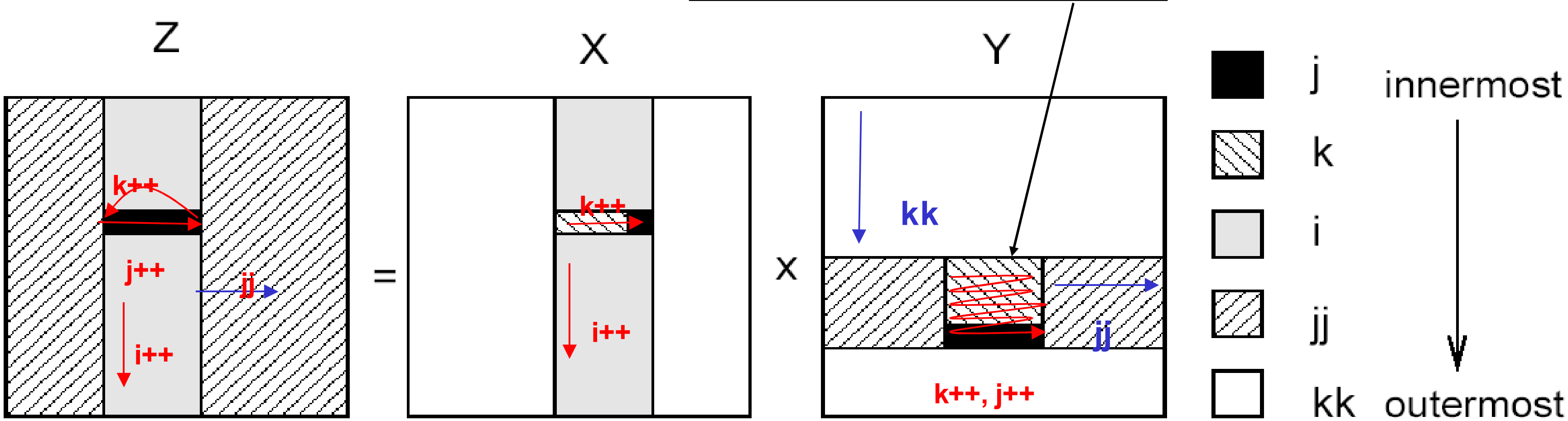
```
for (kk=1; kk<= N; kk+=B)
 for (jj=1; jj<= N; jj+=B)
  for (i=1; i<= N; i++)
   for (k=kk; k<= min(kk+B-1,N); k++){
    r=X[i][k]; /* to be allocated to a register*/
    for (j=jj; j<= min(jj+B-1, N); j++)
     Z[i][j] += r* Y[k][j]
    }
```

**Reuse factor of B for Z, N for Y**

**$O(N^3/B)$ accesses to main memory**

*Compiler should select best option*

*Same elements for next iteration of i*

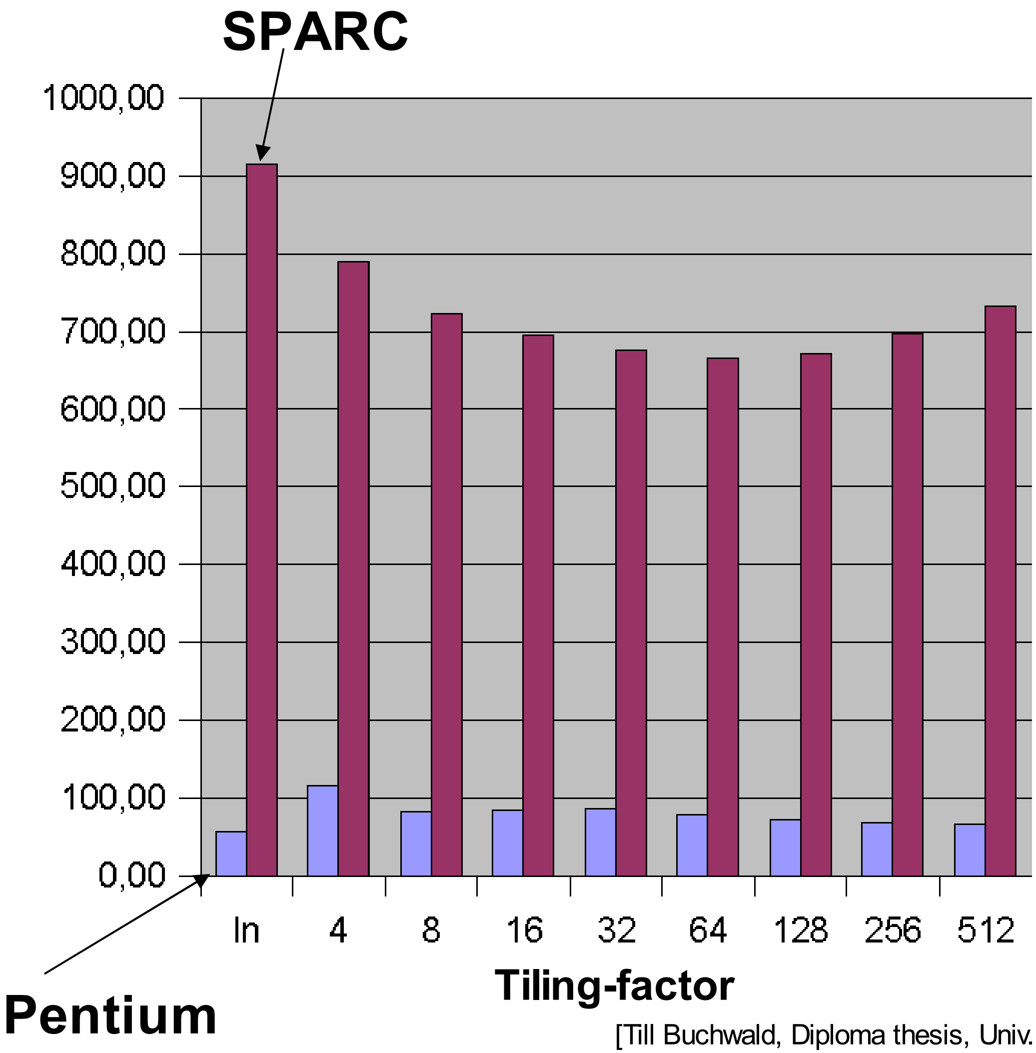





Monica Lam: The Cache Performance and Optimization of Blocked Algorithms, ASPLOS, 1991

# Example

In practice, results by Buchwald are disappointing.
One of the few cases where an improvement was achieved:
Source: similar to matrix mult.




[Till Buchwald, Diploma thesis, Univ. Dortmund, Informatik 12, 12/2004]

# Summary

- Task concurrency management
  - Re-partitioning of computations into tasks
  - Dynamic exploitation of slack
- Floating-point to fixed point conversion
  - Range estimation
  - Conversion
  - Analysis of the results
- High-level loop transformations
  - Fusion
  - Unrolling
  - Tiling