

Performance Modeling

Didem Unat

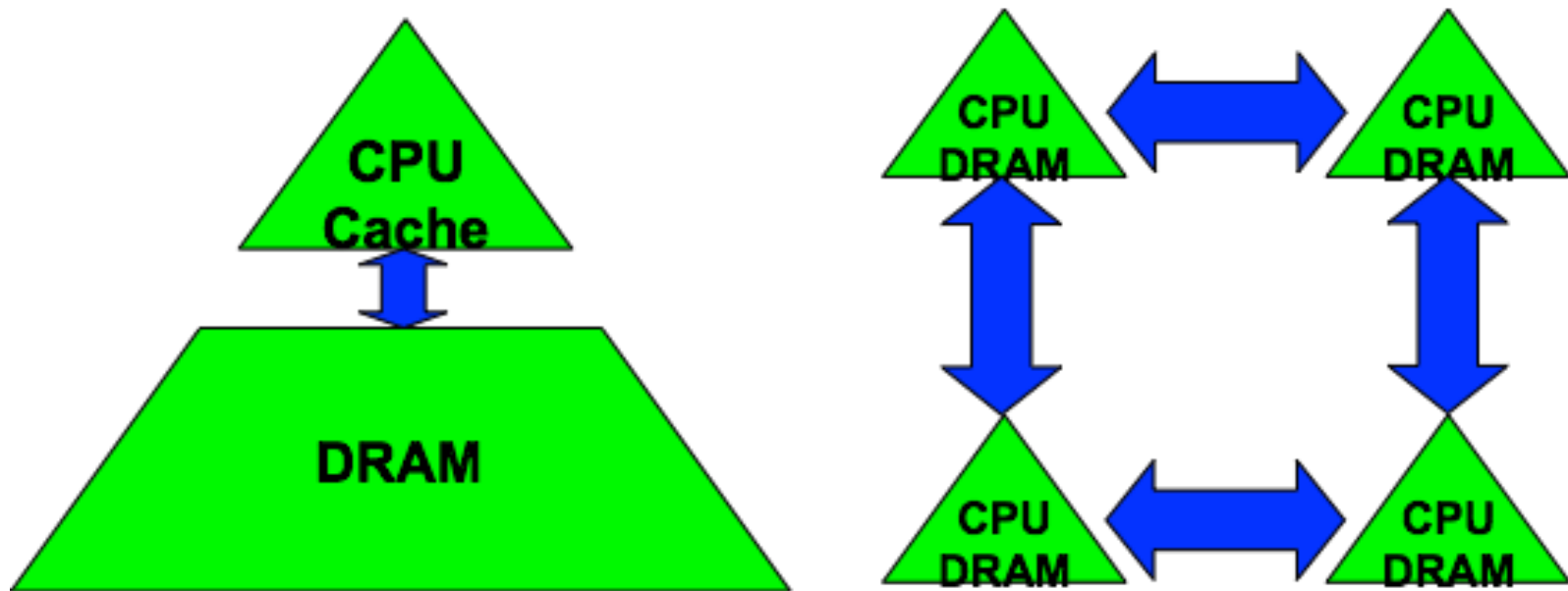
COMP 429/529 Parallel Programming

Why model performance?

- Identify bottlenecks in an application
- Focus on the most time-consuming regions of an application
- Reason about the capabilities of underlying architecture
- Remember, we are interested in performance (speedup) at the end of the day

Data Movement

- Algorithms have three costs (two of them can be classified under one)
 - Arithmetic (Flops)
 - Communication: moving data between levels of memory hierarchy and processors over a network



Modeling Performance

- At any given time, a processor can be busy with one of the following:
 - Computation
 - Communication
 - Data access (to memory or cache)
 - Communication over network
 - Disk I/O
- A simple model for total execution time (excluding IO)
 - $T_{\text{total}} = \text{Compute time} + \text{Memory time} + \text{Communication time}$
 $= T_F + T_M + T_C$

Performance Model

- $T_{\text{total}} = T_F + T_M + T_C$
- Definitions:
 - f = total # of floating point arithmetic (flop) operations
 - t_f = time per flop $\ll t_m$
 - m = total # of memory elements (words) moved between fast and slow memory
 - t_m = time per slow memory access
 - c = total # of bytes communicated between nodes
 - t_c = average time for communicating one byte
- $T_{\text{total}} = f \cdot t_f + m \cdot t_m + c \cdot t_c$

Overlaps

- Different operations can be overlapped with each other
- Prefetching:
 - overlapped computation and memory access
 - hardware/software prefetching
- Non-blocking communication primitives:
 - overlapped computation and communication
- Algorithmically overlapping computation/communication:
 - designate computation & communication threads
 - can still use blocking communication primitives

*-bound

- $T_{\text{total}} = f * t_f + m * t_m + c * t_c$
- If $T_{\text{total}} \approx c * t_c \Rightarrow$ performance is **communication-bound**
 - Performance improvements may be possible
 - Ex: graph traversals, sparse matrix computations
- If $T_{\text{total}} \approx m * t_m \Rightarrow$ performance is **memory-bound**
 - Data locality/access patterns may be improved
 - Ex: stencil applications
- If $T_{\text{total}} \approx f * t_f \Rightarrow$ performance is **CPU-bound**
 - CPU performing close to its peak – as good as one can get
 - Ex: dense matrix computations

Arithmetic Intensity

- How many flops performed per memory access in an application?
- Assumptions:
 - Only 2 levels in the memory hierarchy
fast (cache) and **slow** (memory)
 - All data are initially in the slow memory
- **Arithmetic Intensity: $q = f / m$**
 - average number of flops per slow memory access
 - also known as flop:byte ratio (flop to byte ratio)

FLOPS-to-Byte Ratio of a Machine

Also called **Machine Balance**=

$\text{Flops:Bytes} = \text{Peak Flop Rate} / \text{Peak Memory Bandwidth}$

- Here peak can be replaced with sustained (or measured values).
- Vendors like Intel or AMD usually announce the peak flop rate of a chip
 - e.g. 1 Teraflops etc.
- Memory bandwidth
 - e.g 200 GB/sec etc
- The machine is considered to be *imbalance* if the flops:bytes is too high or too low
 - Usually high these days because it is harder to provide more memory bandwidth (\$)
 - Performing computation is cheap

Memory Intensive or Compute Intensive?

- If Machine Balance > Arithmetic Intensity of an Application
 - Then the application is memory bandwidth limited
 - Otherwise the application is compute-bound
- Memory intensive
 - means that the application needs faster data transfer rate than the machine can provide thus memory hierarchy creates a performance bottleneck
 - If we had more bandwidth, our performance would increase
- Compute-intensive
 - means that the application needs faster compute rate than the machine can provide thus the CPU speed creates a performance bottleneck
 - If we had a higher clock rate, our performance would increase

GPU Tesla K40

- Peak double precision floating point performance
 - 1.43 Teraflops (base clock)
 - 1.66 Teraflops (GPU boost)
- Memory Bandwidth (Sustained)
 - ~184 GB/sec
 - Can achieve higher with tuning (or ECC off)
- Machine Balance
 - $184/1043 = 0.18$ (byte:flop ratio)
 - or the machine can perform ~5.6 flops per byte

Example Application

- A simulation performs 14 flops per data point
 - Note that some operations (e.g. division) are more expensive than other flops but let's ignore that for now
- Per data point, it performs 3 memory accesses at best
 - $3 * 8 \text{ bytes} = 24 \text{ bytes}$
- $q = f/m = 14/24 = 0.583$ (flop to byte ratio)

Limitations to Performance

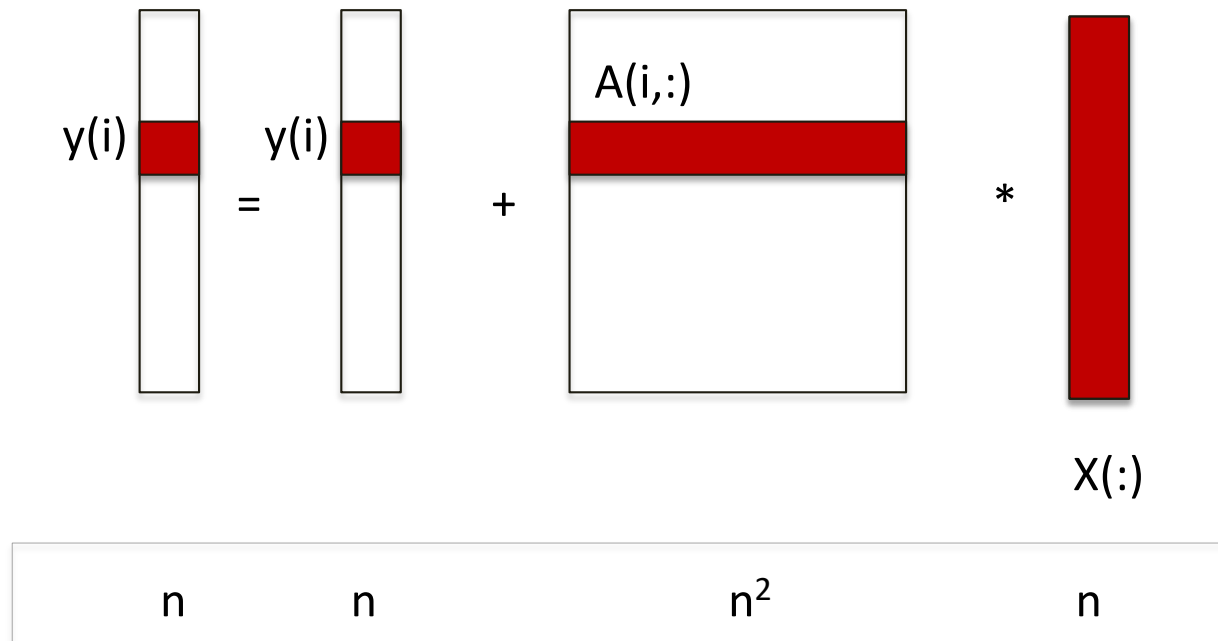
- Compare flops:byte
 - Tesla K40 can perform 5.6 flops per byte.
 - The application only needs $14/24 = 0.583$ flops per byte
- or bytes:flop
 - The application needs $24/14 = 1.71$ bytes per flop
 - Tesla K40 can only bring 0.18 bytes per flop
- This application is clearly memory bandwidth-limited. If we had more bandwidth, the app will perform better!

Case Study with Matrix-Vector Multiply

Case Study: Matrix-Vector Multiply

```
{implements  $y = y + A*x$ }  
for i = 1:n  
    for j = 1:n  
         $y(i) = y(i) + A(i,j)*x(j)$ 
```

- how many bytes accessed at best?
- how many flops performed?



Case Study: Matrix-Vector Multiply

```
{read x(1:n) into fast memory}
{read y(1:n) into fast memory}
for i = 1:n
    {read row i of A into fast memory}
    for j = 1:n
        y(i) = y(i) + A(i,j)*x(j)
    {write y(1:n) back to slow memory}
```

- m = number of bytes accessed on slow memory = $3n + n^2$ doubles
- f = number of arithmetic operations = $2n^2$
- $q = f / m \approx 2 / 8$ (in double precision)

=> Matrix-vector multiplication limited by the slow memory speed, because in general $t_f \ll t_m$

Case Study: Matrix-Vector Multiply

```
{read x(1:n) into fast memory}
{read y(1:n) into fast memory}
for i = 1:n
    {read row i of A into fast memory}
    for j = 1:n
         $y(i) = y(i) + A(i,j) * x(j)$ 
    {write y(1:n) back to slow memory}
```

- **Important assumptions:**
 - Fast memory is large enough to hold $3n$ doubles
 - Time to access data in fast memory costs nothing!

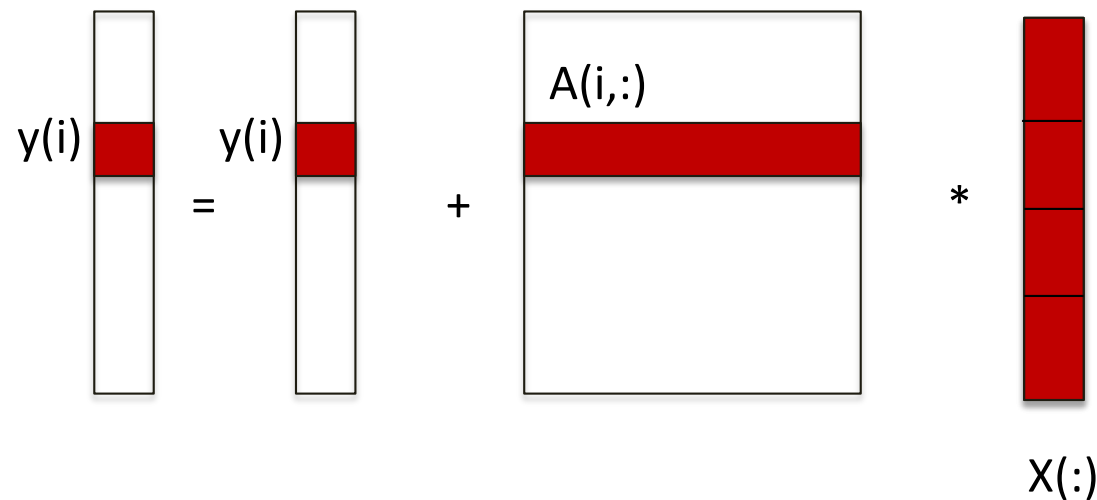
Case Study: Matrix-Vector Multiply

- How many cache misses would such an implementation incur on x , if the **cache size was** $< n$ and Least Recently Used replacement policy is used?

n^2/w w :cache-line width

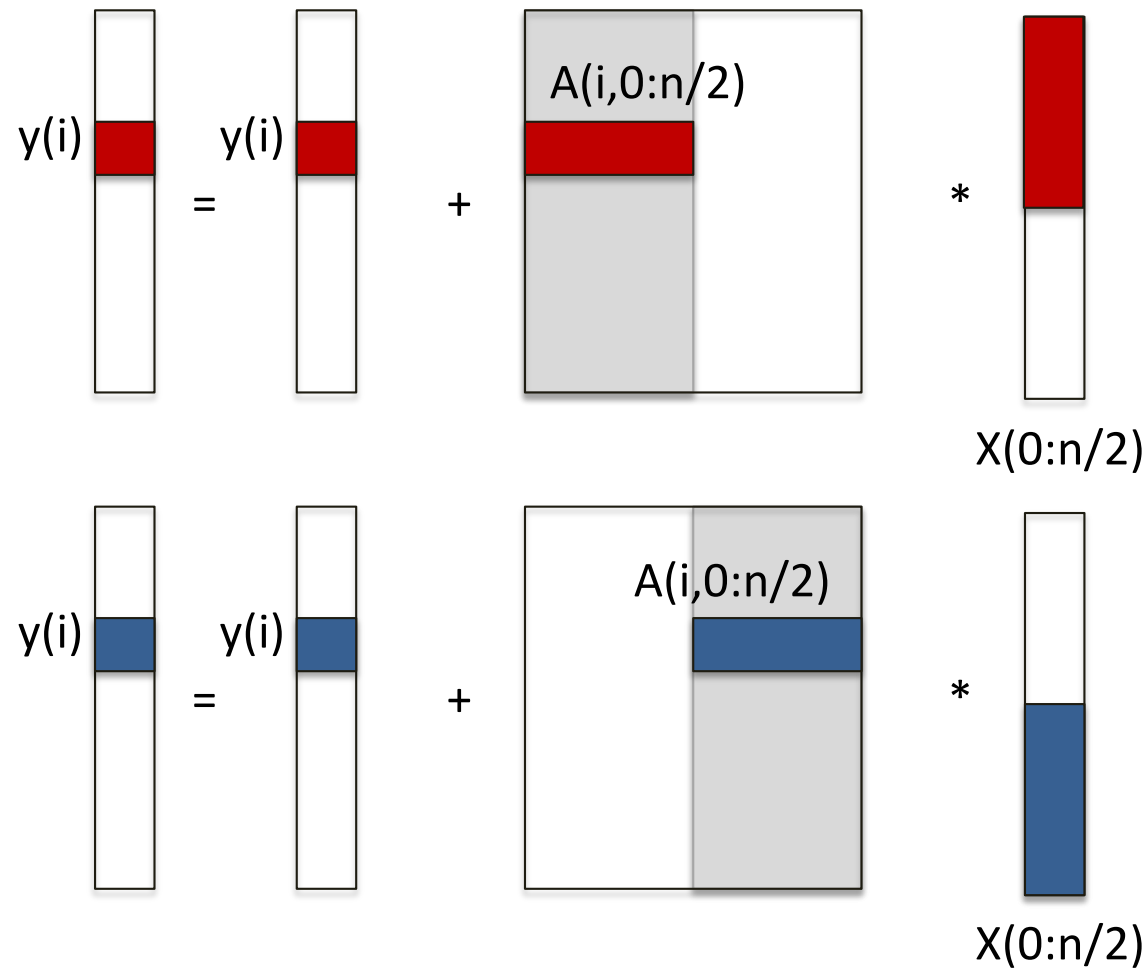
For every row of A , n/w misses occur

Is it possible to do better?



Case Study: Matrix-Vector Multiply

- A blocked algorithm should do better



Case study: Matrix-Vector multiply

Tiling (Cache Blocking)

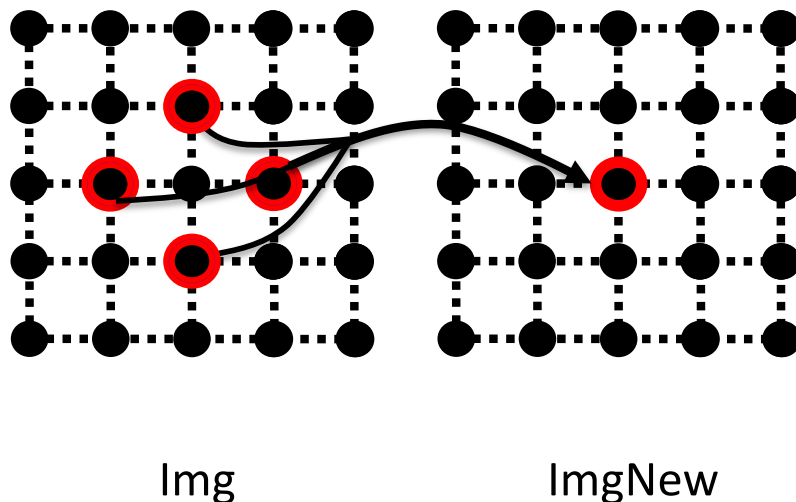
- Tiling or cache blocking is a well-known cache optimization to reduce cache misses
- Block the data into tiles and process each tile before computing the next tiles

With cache-blocking (tiling):

- read each element of **A** once from slow memory
- read each element of **x** once from slow memory
- read & write each element of **y** twice from/to memory
 - Twice because they are two blocks (in this example)
- total cache misses on x: n/w
- total cache misses on y: $2n/w$

Case Study: 5-point Stencil

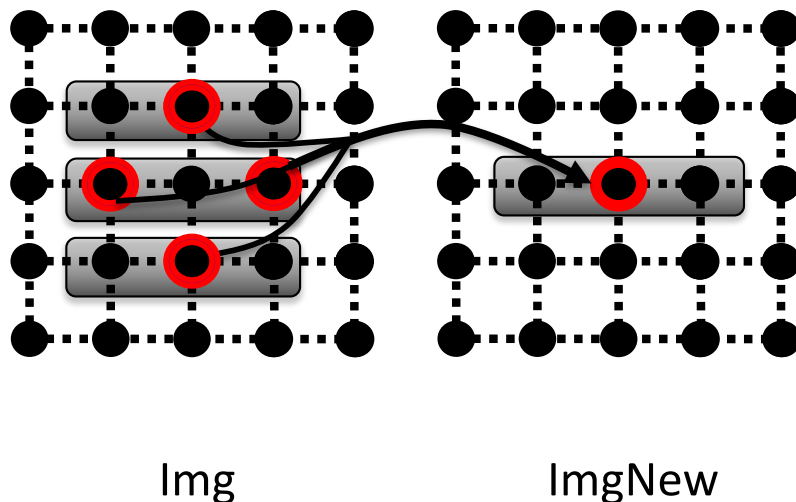
```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
    for (i,j) in (0:N-1, 0:N-1)
        Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
    Swap(Imgnew,Img)
```



- Four loads and one store from/to memory
 - 5 accesses per element
- 3 Adds + 1 MUL
 - 4 flops per element

5-point Stencil

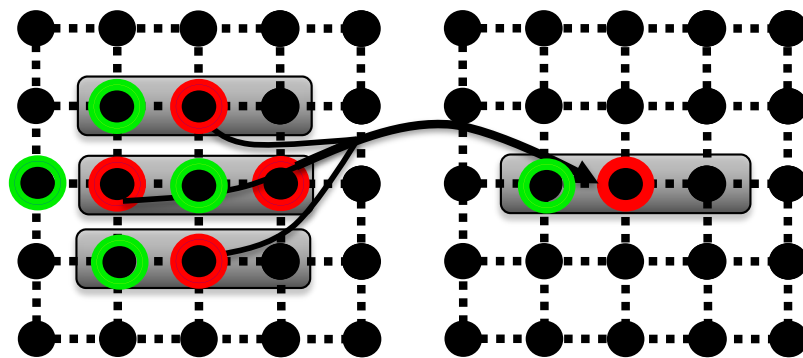
```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
    for (i,j) in (0:N-1, 0:N-1)
        Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
    Swap(Imgnew,Img)
```



- So only three of the four loads count for the bytes move
 - In the middle row, two accesses are in the same cache-line
- Bytes:flops ratio then
 - 4 words / 4 flops = 1 word

5-point Stencil

```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
  for (i,j) in (0:N-1, 0:N-1)
    Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
  Swap(Imgnew,Img)
```



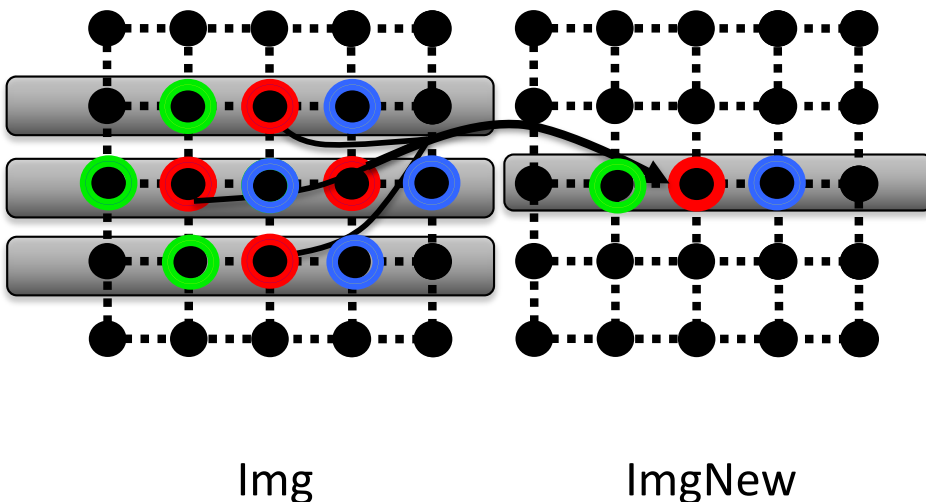
Img

ImgNew

- Row can stay in the cache for three successive row traversals if the cache is large enough to hold more than two rows

5-point Stencil

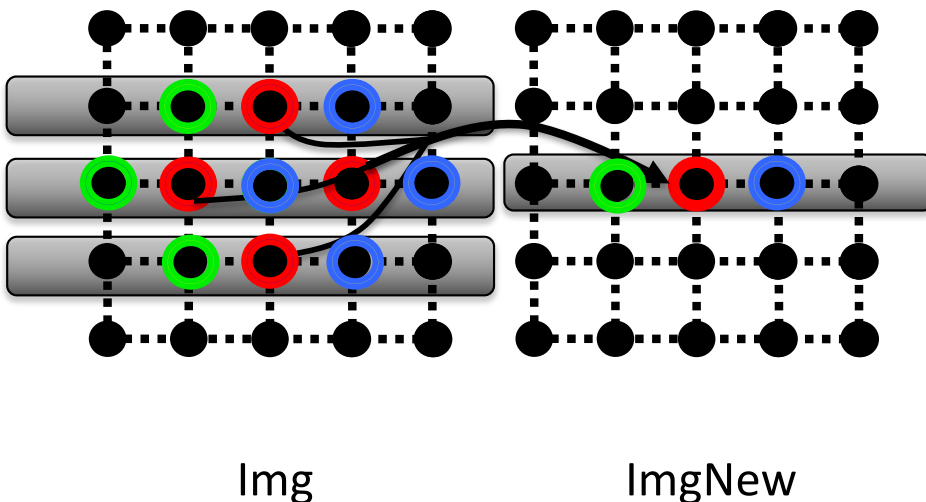
```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
    for (i,j) in (0:N-1, 0:N-1)
        Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
    Swap(Imgnew,Img)
```



- Row can stay in the cache for three successive row traversals if the cache is large enough to hold more than two rows

5-point Stencil

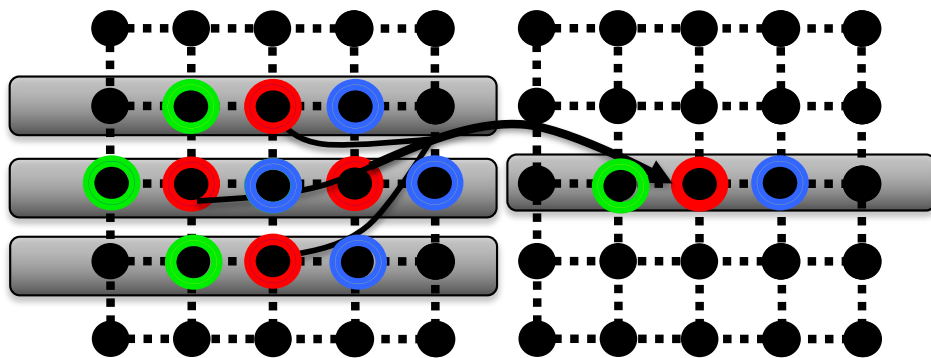
```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
    for (i,j) in (0:N-1, 0:N-1)
        Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
    Swap(Imgnew,Img)
```



- Under this condition, we can assume that loading the neighbors at row $i-1$ and $i+1$ comes at no cost
- We have already loaded $i-1$ while computing previous row and $i+1$ will be reused when we compute the next row.

5-point Stencil

```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
  for (i,j) in (0:N-1, 0:N-1)
    Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
  Swap(Imgnew,Img)
```



Img

ImgNew

We require only one load
and one store

Bytes:Flops = 2 words/4
flops= 0.5 words

However, when the image is large and three
successive rows cannot fit into cache, then
we are back to 1 words/flop

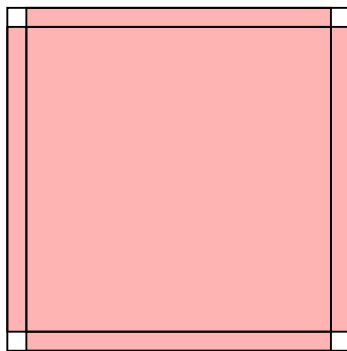
5-point Stencil

```
//image smoothing example using 5-point stencil
for iter = 1 : nSmooth
    for (i,j) in (0:N-1, 0:N-1)
        Imgnew [i,j] = (Img[i-1,j]+Img[i+1,j]+Img[i,j-1]+Img[i, j+1])*.25
    Swap(Imgnew,Img)
```

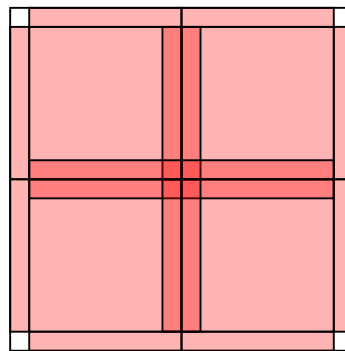
- If image size is N , each element is 4 bytes, then **at best**, we move (in reality, it might be worse)
 - Bytes_Moved = $N*N*2*4$ bytes
 - Sustained Memory Bandwidth = Bytes_Moved/Running Time
 - Compare this with the machine bandwidth rate (Stream benchmark) to see how good or bad you are doing
- If the data doesn't fit into cache, then apply tiling

Cache Blocking (Tiling)

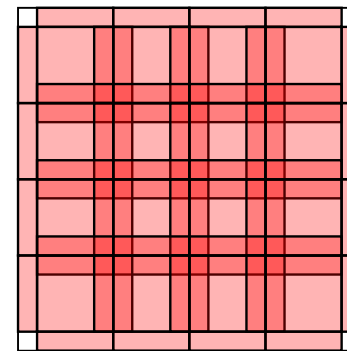
- Cache blocking exposes trade-off between cache size and memory bandwidth:
 - PRO: Smaller working set –allows working set to fit into cache, enabling reuse
 - CON: Redundant memory traffic –pulls overlapping ghost zones in from memory
 - Important parameter to tune: tile size (cache block size)



No blocking



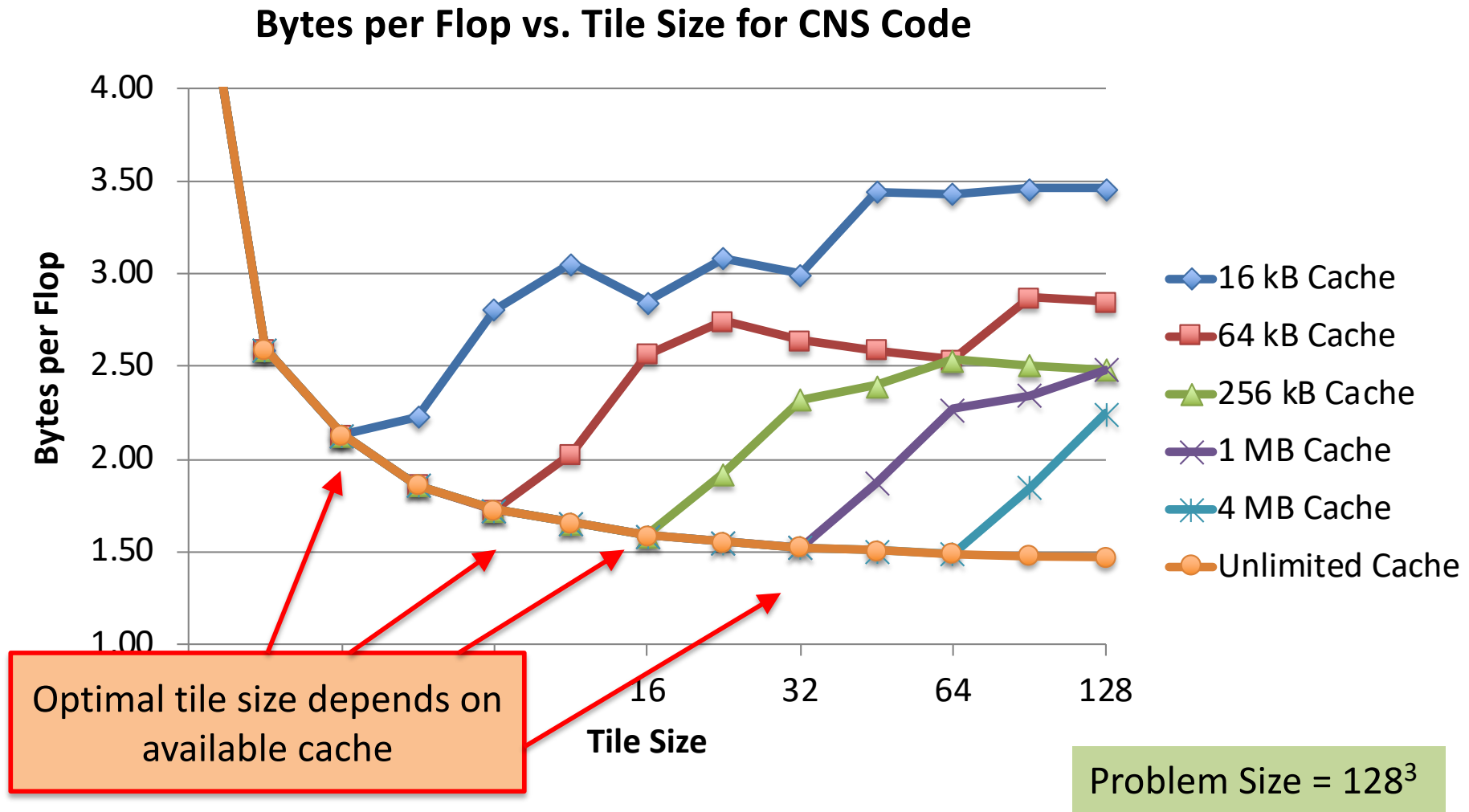
2x blocking



4x blocking

Cache and Tile Size Effects on Memory Traffic

An Example application: Choosing block size based on your cache size and working set



Acknowledgments

- These slides are inspired and partly adapted from
 - Metin Aktulga (Michigan State Univ.)
 - Scott Baden (UCSD)
 - Jim Demmel from UC Berkeley
 - Cy Chan, Didem Unat (ExaSAT journal)
 - The course book (Pacheco)
 - Didem Unat, Cy Chan, Weiqun Zhang, Samuel Williams, John Bachan, John Bell, John Shalf, "ExaSAT: An Exascale Co-Design Tool for Performance Modeling", International Journal of High Performance Computing Applications (IJHPCA), February, 2015