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# The Multigrid Method

# Review of Last Lecture and Outline

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- Review Poisson equation
  - Overview of Methods for Poisson Equation
  - Jacobi's method
  - Red-Black SOR method
  - Conjugate Gradients
- } Reduce to sparse-matrix-vector multiply  
Need them to understand Multigrid
- Multigrid
  - Comparison of methods

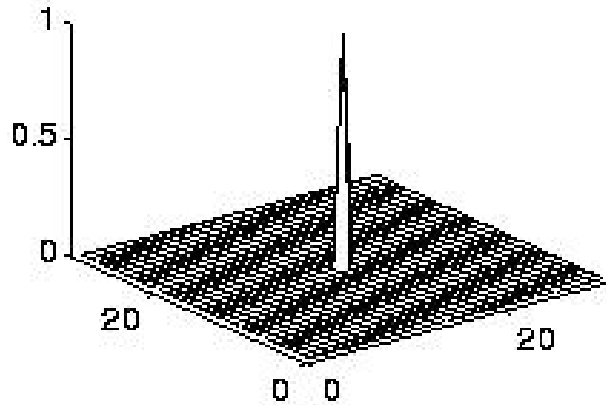
## Motivation for Multigrid

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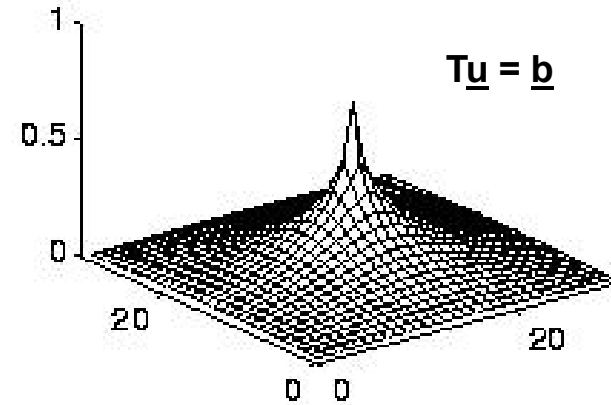
- Recall that Jacobi, SOR, CG, or any other sparse-matrix-vector-multiply-based algorithm can only move information **one grid-cell** at a time, due to local structure of stencil → It takes  $O(N^{1/2})$  steps to get information across the grid
- Faster convergence in  $O(1)$  steps requires moving information across grid faster than to one neighboring grid cell per step.
- Can be shown that decreasing error by fixed factor  $c < 1$  and takes  $\Omega(\log n)$  steps → Convergence to a fixed error  $\varepsilon < 1$  takes  $\Omega(\log n)$  steps

# Multigrid Motivation

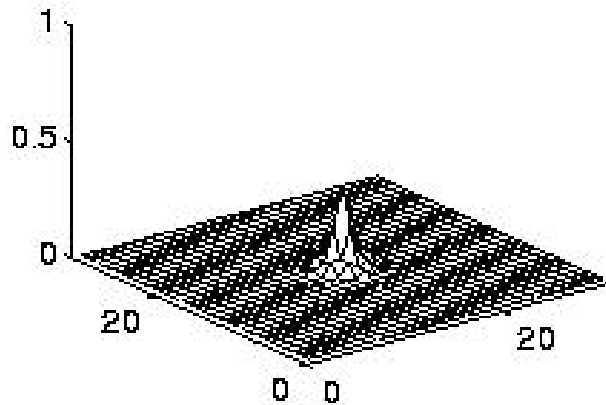
Right Hand Side



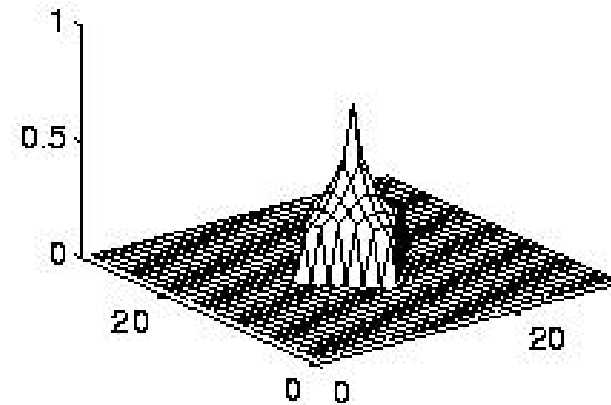
True Solution



5 steps of Jacobi



Best 5 step solution (with optimal  $\omega$ )



Takes  $O(n)$  steps to propagate information across an  $n \times n$  grid

# Multigrid Overview

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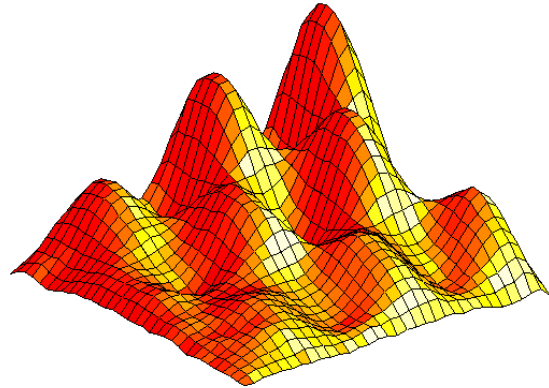
## ◦ Basic Algorithm:

- Replace problem on fine grid by an approximation on a coarser grid
- Solve the coarse grid problem approximately, and use the solution as a starting guess for the fine-grid problem, which is then iteratively updated
- Solve the coarse grid problem **recursively**, i.e. by using a still coarser grid approximation, etc.

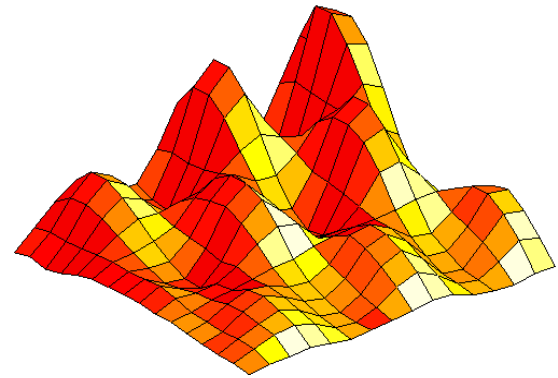
## ◦ Success depends on coarse grid solution being a good approximation to the fine grid

# Fine and Coarse Approximations

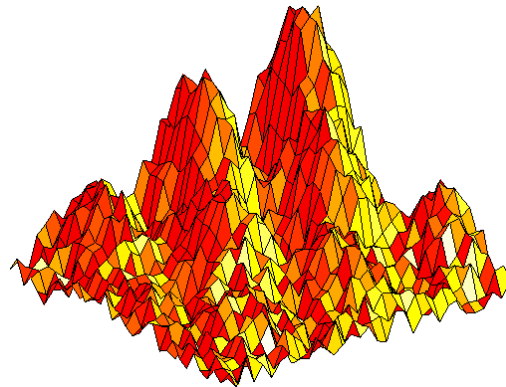
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Fine



Coarse



# Multigrid Sketch, continued

- $P^{(m)}, P^{(m-1)}, \dots, P^{(1)}$  is sequence of problems from finest to coarsest



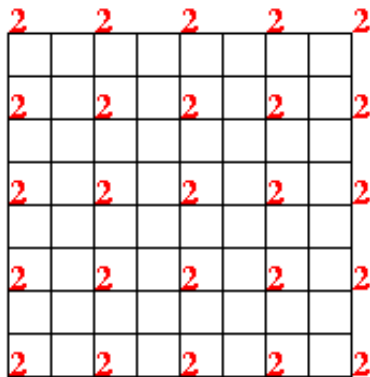
$P^{(3)}$ : 1D grid of 9 points  
7 unknowns  
Points labeled **2** are  
part of next coarser grid



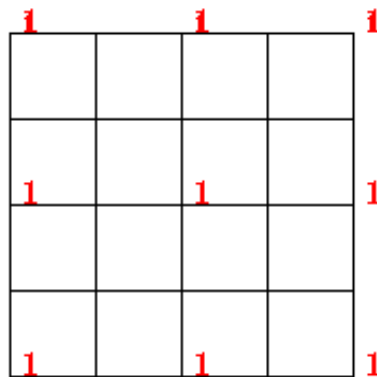
$P^{(2)}$ : 1D grid of 5 points  
3 unknowns  
Points labeled **1** are  
part of next coarser grid



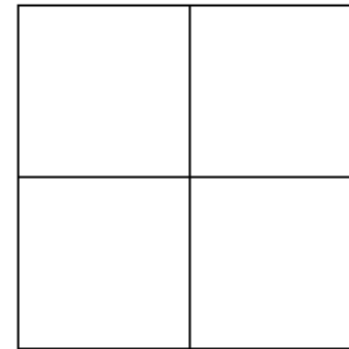
$P^{(1)}$ : 1D grid of 3 points  
1 unknown



$P^{(3)}$ : 9 by 9 grid of points  
7 by 7 grid of unknowns  
Points labeled **2** are  
part of next coarser grid



$P^{(2)}$ : 5 by 5 grid of points  
3 by 3 grid of unknowns  
Points labeled **1** are  
part of next coarser grid



$P^{(1)}$ : 3 by 3 grid of points  
1 by 1 grid of unknowns

# Multigrid Operators (1)

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- For problem  $P^{(i)}$  solve  $T_i x_i = b_i$  :
  - $b_i$  is the RHS and
  - $x_i$  is the current estimated solution
  - $T_i$  is implicit in the operators below.

} both live on grids of size  $2^{i-1}$
- All the following operators (next slide) just **average** values on neighboring grid points
  - Neighboring grid points on coarse problems are far away in fine problems, so **information moves quickly** on coarse problems
  - Levels will be constructed explicitly
  - (→ next slide gives an overview of the operators)



## Multigrid Operators (2)

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- The **restriction operator  $R_i$**  maps  $P^{(i)}$  to  $P^{(i-1)}$ 
  - Restricts problem on fine grid  $P^{(i)}$  to coarse grid  $P^{(i-1)}$  by sampling or averaging
  - $b_{i-1} = R_i(b_i)$
- The **interpolation operator  $In_{i-1}$**  maps an approximate solution  $x_{i-1}$  to an  $x_i$ 
  - Interpolates solution on coarse grid  $P^{(i-1)}$  to fine grid  $P^{(i)}$
  - $x_i = In_{i-1}(x_{i-1})$
- The **solution operator  $S_i$**  takes  $P^{(i)}$  and computes an improved solution  $x(i)$  on same grid
  - Uses “weighted” Jacobi or SOR
  - $x_{i, \text{improved}} = S_i(b_i, x_i)$
- Details of these operators follow after describing overall algorithm

# Multigrid V-Cycle Algorithm (recursive)

Function MGV (  $b_i$  ,  $x_i$  )

... Solve  $T_i x_i = b_i$  given  $b_i$  and an initial guess for  $x_i$

... return an improved  $x_i$

if (  $i = 1$  )

    compute exact solution  $x_1$  of  $P^{(1)}$

    return  $x_1$

else

$x_i = S_i(b_i, x_i)$

$r_i = T_i x_i - b_i$

$d_i = \text{In}_{i-1}(\text{MGV}(R_i(r_i), 0))$

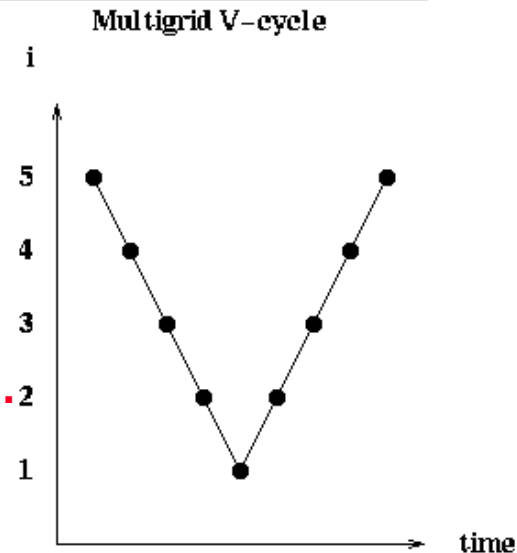
$x_i = x_i - d_i$

$x_i = S_i(b_i, x_i)$

    return  $x_i$

only 1 unknown.

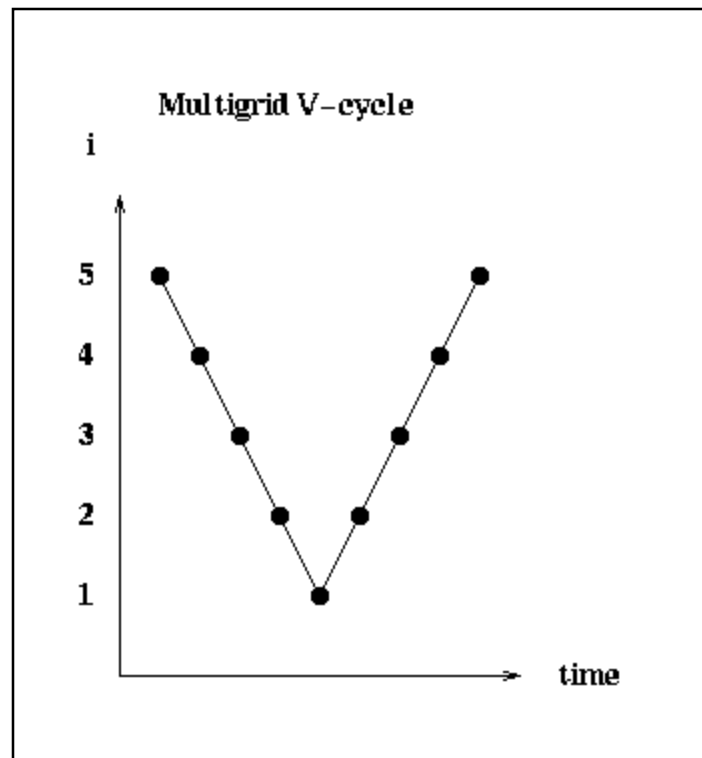
improve solution by  
damping high frequency error,  
compute residual,  
solve  $T_i d_i = r_i$  recursively,  
correct fine grid solution,  
improve solution again.



## Why is this called a V-Cycle?

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- ° Just a picture of the call graph
- ° In time a V-cycle looks like the following



# Complexity of a V-Cycle

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## ◦ On a serial machine

- Work at each “dot” in the V-cycle is  $O(\text{the number of unknowns})$
- Cost of level  $i$  is  $(2^i - 1)^2 = O(4^i)$  (for a 2D grid)
- If finest grid level is  $m$ , **total time is:**

$$\sum_{i=1}^m O(4^i) = O(4^m) = \text{O(\# unknowns)}$$

## ◦ On a parallel machine (PRAM)

- with one processor per grid point and free communication, each step in the V-cycle takes constant time,  **$O(1)$**
- Total V-cycle time is  $O(m) = \text{O(log \#unknowns)}$

# Full Multigrid (FMG)

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## ◦ Intuition:

- improve solution by doing multiple V-cycles
- avoid expensive fine-grid (high frequency) cycles
- analysis of why this works is beyond the scope of this class

**Function FMG ( $b_m, x_m$ )**

**... return improved  $x_m$  given initial guess**

**compute the exact solution  $x_1$  of  $P^{(1)}$**

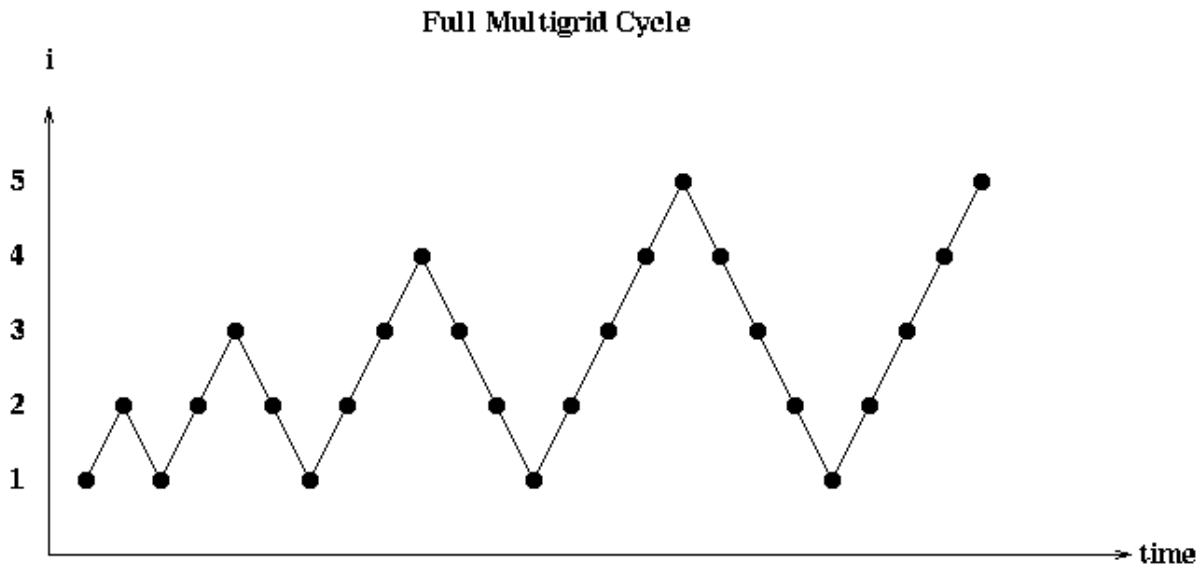
**for  $i=2$  to  $m$**

**$x_i = \text{MGV} ( b_i, \text{In}_{i-1} (x_{i-1}) )$**

## ◦ In words:

- Solve the problem with 1 unknown
- Given a solution to the coarser problem,  $P^{(i-1)}$ , map it to starting guess for  $P^{(i)}$
- Solve the finer problem using the Multigrid V-cycle

# Full Multigrid Cost Analysis



- **One V for each call to FMG**
  - one also use “W”s and other compositions
- **Serial time:**  $\sum_{i=1}^m O(4^i) = O(4^m) = O(\# \text{ unknowns})$
- **PRAM time:**  $\sum_{i=1}^m O(i) = O(m^2) = O(\log^2 \# \text{ unknowns})$

# Complexity of Solving Poisson's Equation

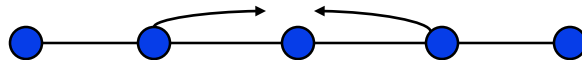
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- Theorem: error  $\varepsilon$  after one FMG call is  $\leq c$  times the error before, where  $c < 1/2$ , and **independent of # unknowns**
- $x^k = \text{FMG}(b, x^{k-1}) \implies \varepsilon(x^k) < 1/2 \varepsilon(x^{k-1})$  (i.e., at least 1 bit per FMG iteration.  $x^k$  = solution after  $k^{\text{th}}$  FMG iteration)
- Corollary: We can make the error  $\varepsilon < \text{tol}$ , for any fixed tolerance in a fixed number of steps, **independent of size of the finest grid**
- This is the most important convergence property of MG, distinguishing it from other methods, which converge more slowly for large grids
- Total complexity is just proportional to the cost of one FMG call

## The Solution Operator $S_i$ - Details

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- The solution operator  $S_i$ , is a weighted Jacobi op.
- Consider the 1D problem



- At level  $i$ , pure Jacobi replaces:

$$x(j) := 1/2 (x(j-1) + x(j+1) + b(j) )$$

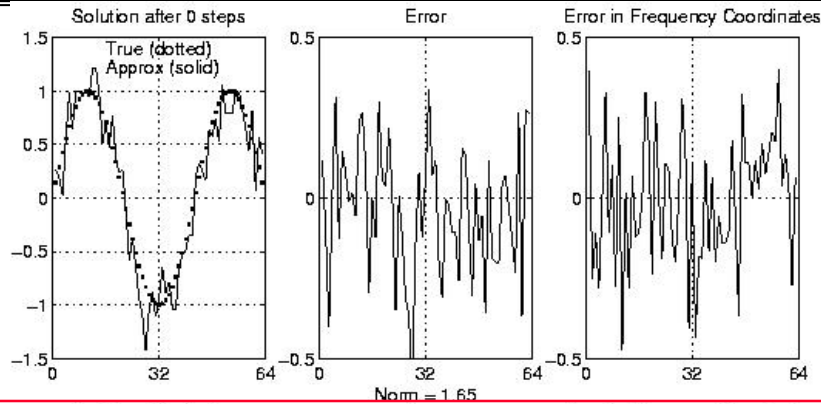
- Weighted Jacobi uses:

$$x(j) := 1/3 (x(j-1) + x(j) + x(j+1) + b(j) )$$

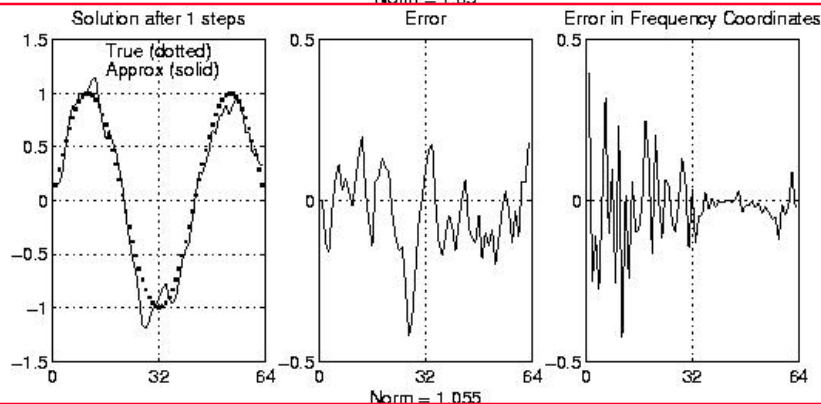
- In 2D, similar average of nearest neighbors



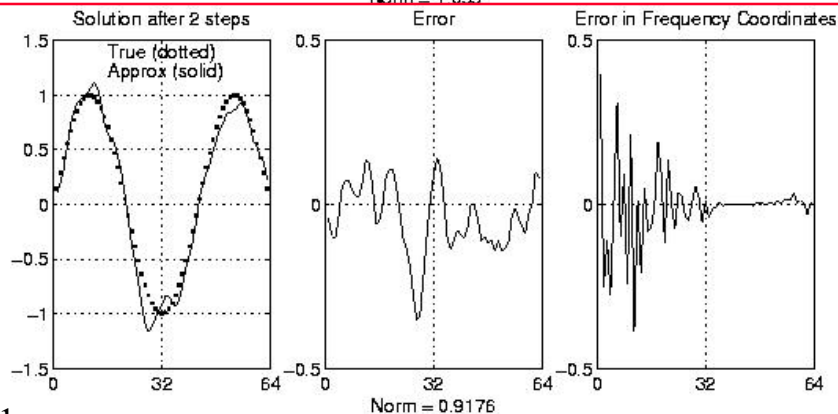
# Weighted Jacobi chosen to damp high frequency error



**Initial error**  
**“Rough”**  
**Lots of high frequency components**  
**Norm = 1.65**



**Error after 1 Jacobi step**  
**“Smoother”**  
**Less high frequency component**  
**Norm = 1.055**

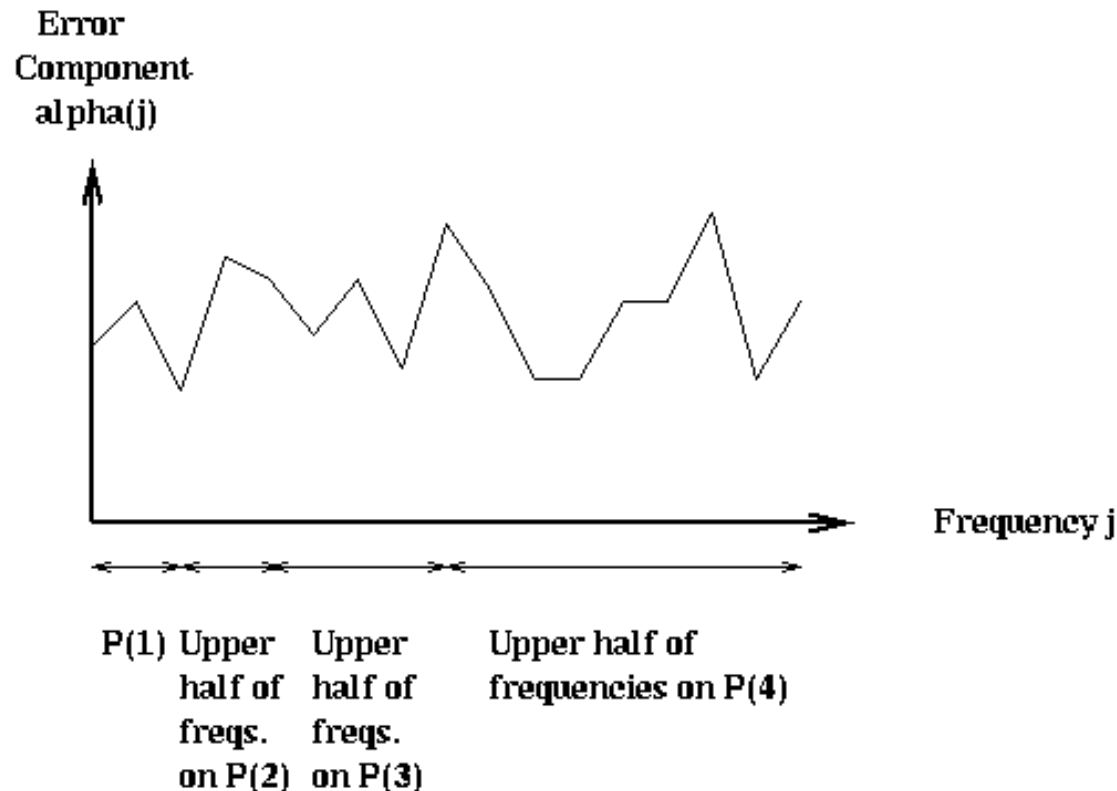


**Error after 2 Jacobi steps**  
**“Smooth”**  
**Little high frequency component**  
**Norm = .9176,**  
**won't decrease much more**

# Multigrid as Divide and Conquer Algorithm

- ° Each level in a V-Cycle reduces the error in one part of the frequency domain

Schematic Description of Multigrid

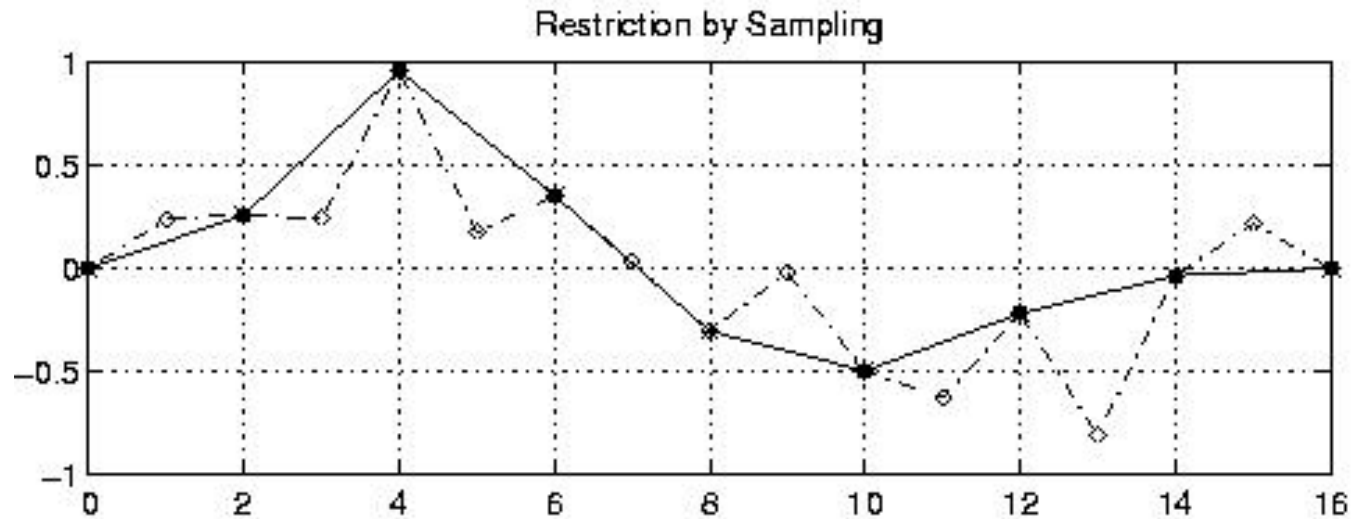


## The Restriction Operator $R_i$ - Details

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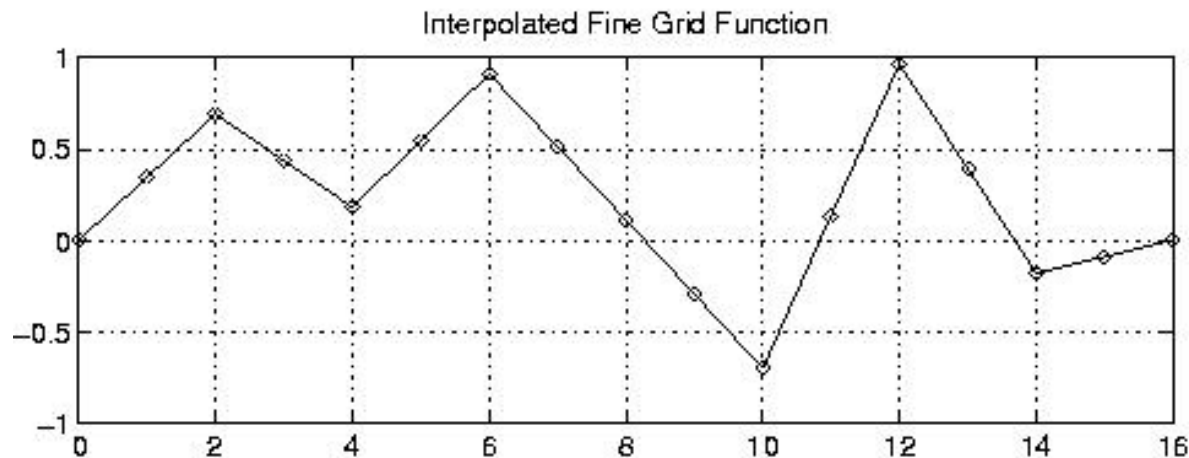
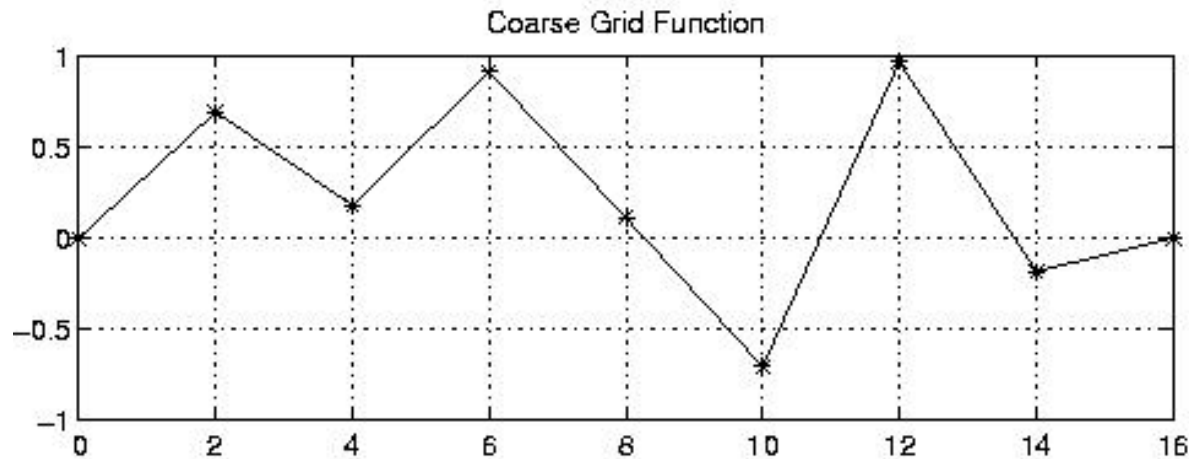
- The restriction operator  $R_i$  takes
  - a problem  $P^{(i)}$  with RHS  $b_i$  and
  - maps it to a coarser problem  $P^{(i-1)}$  with RHS  $b_{i-1}$
- In 1D, average values of neighbors
  - $x_{\text{coarse}}(j) = 1/4 * x_{\text{fine}}(j-1) + 1/2 * x_{\text{fine}}(j) + 1/4 * x_{\text{fine}}(j+1)$

# The Restriction Operator $R_i$ - Details

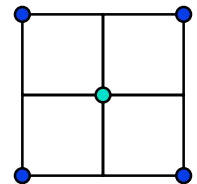


° In 2D, average with all 8 neighbors (N,S,E,W,NE,NW,SE,SW)

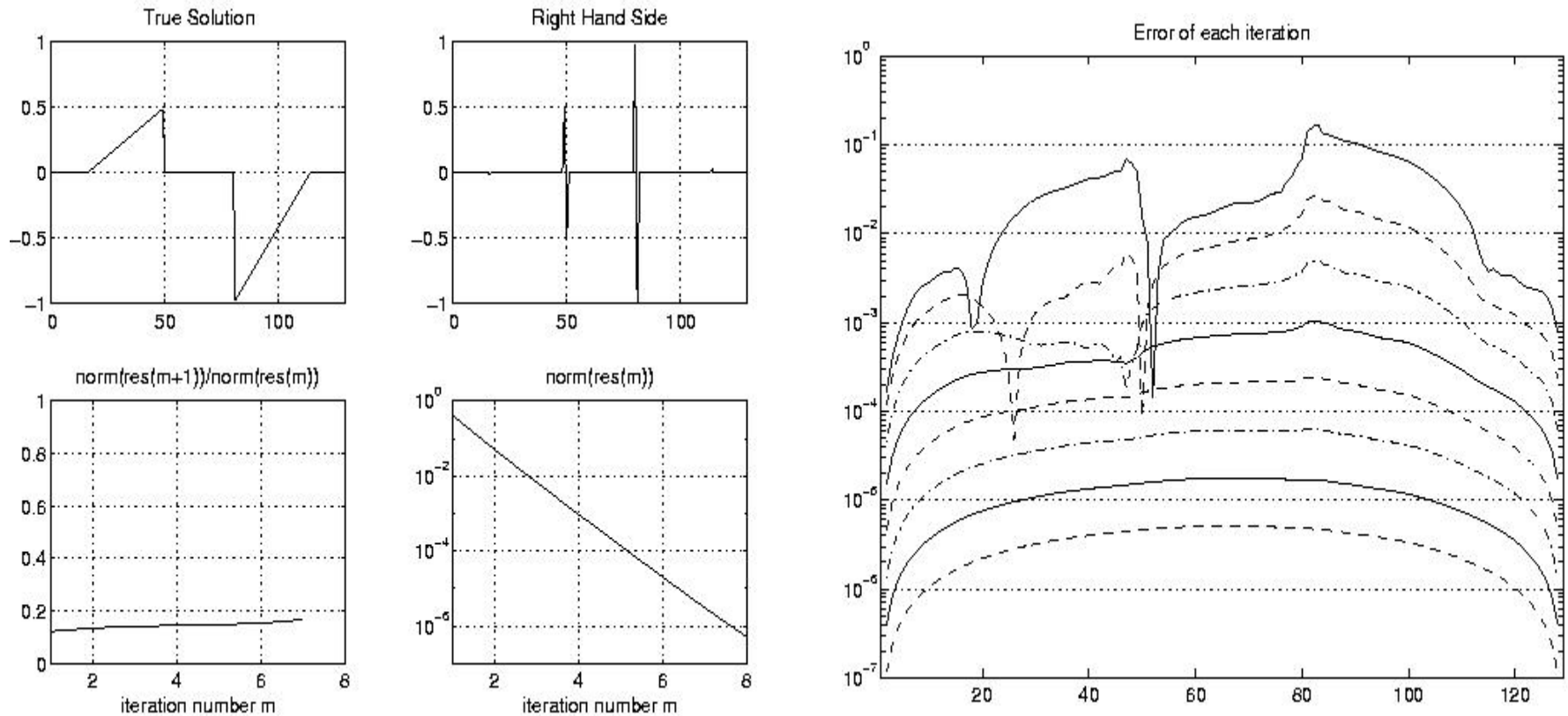
# Interpolation Operator $In_i$



- ° In 2D, interpolation requires averaging with 4 nearest neighbors (NW,SW,NE,SE)



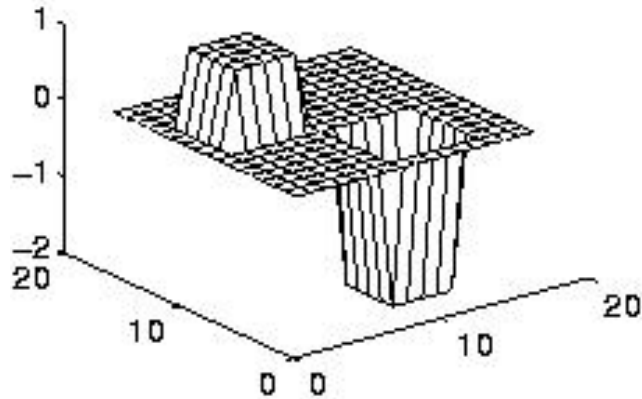
# Convergence Picture of Multigrid in 1D



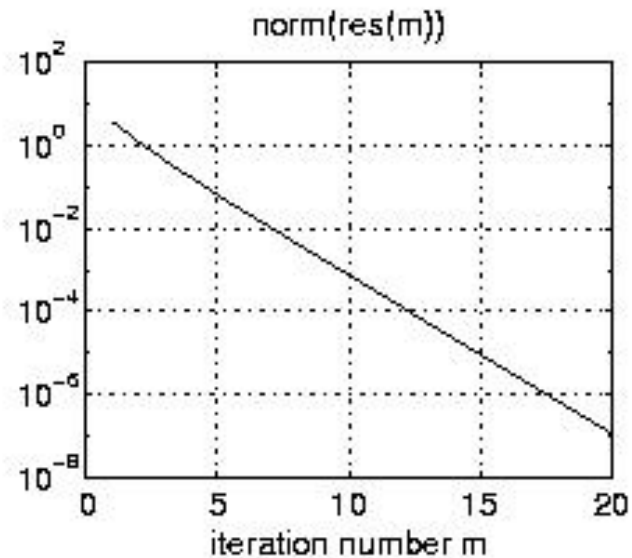
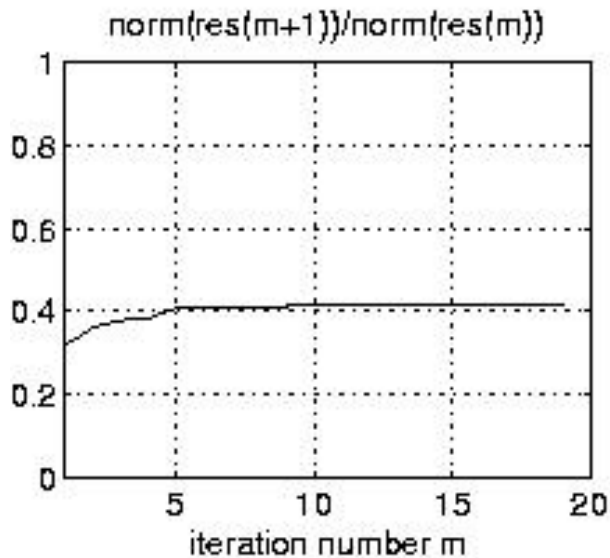
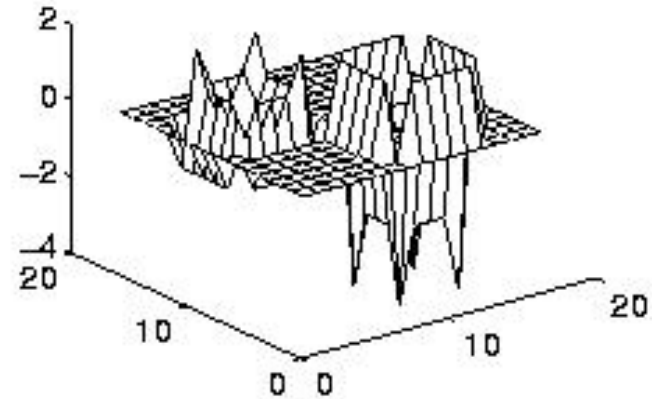
- Full Multigrid on each iteration
- Error decreases by a factor  $>5$  on each iteration

# Convergence Picture of Multigrid in 2D

True Solution

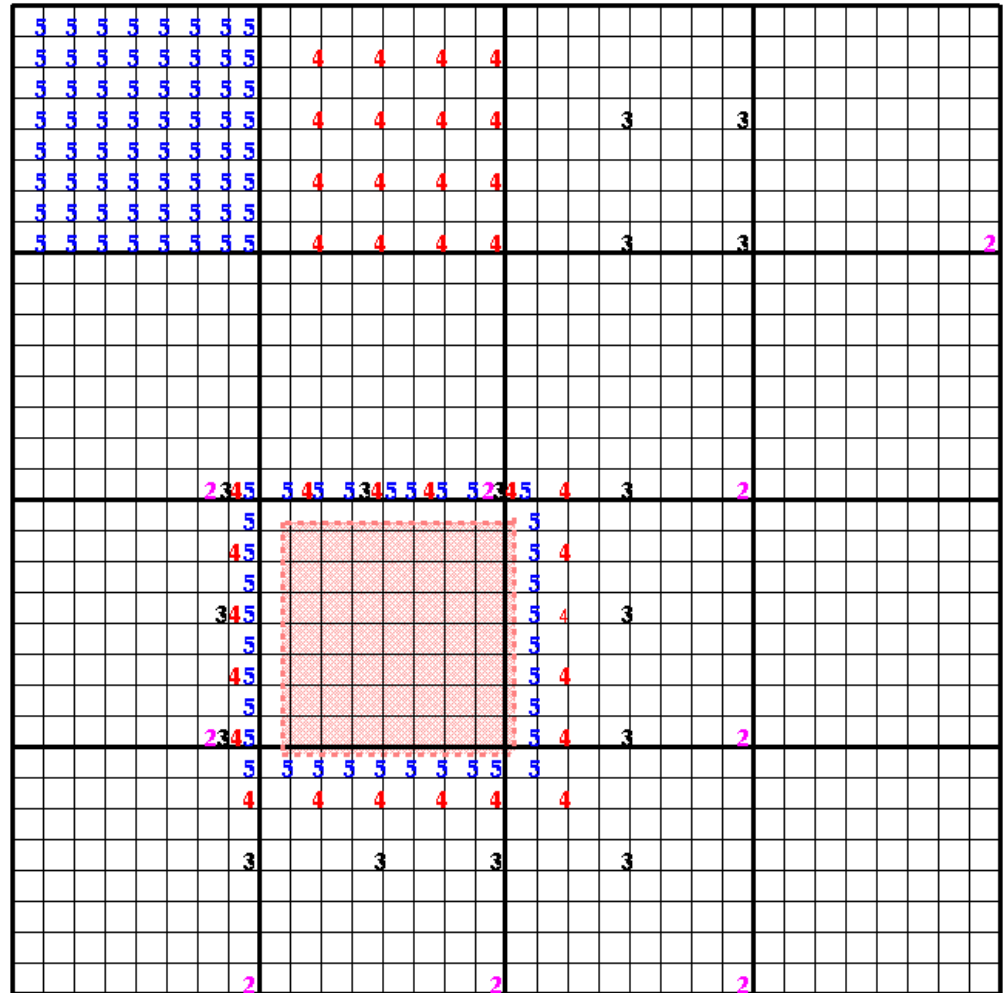


Right Hand Side



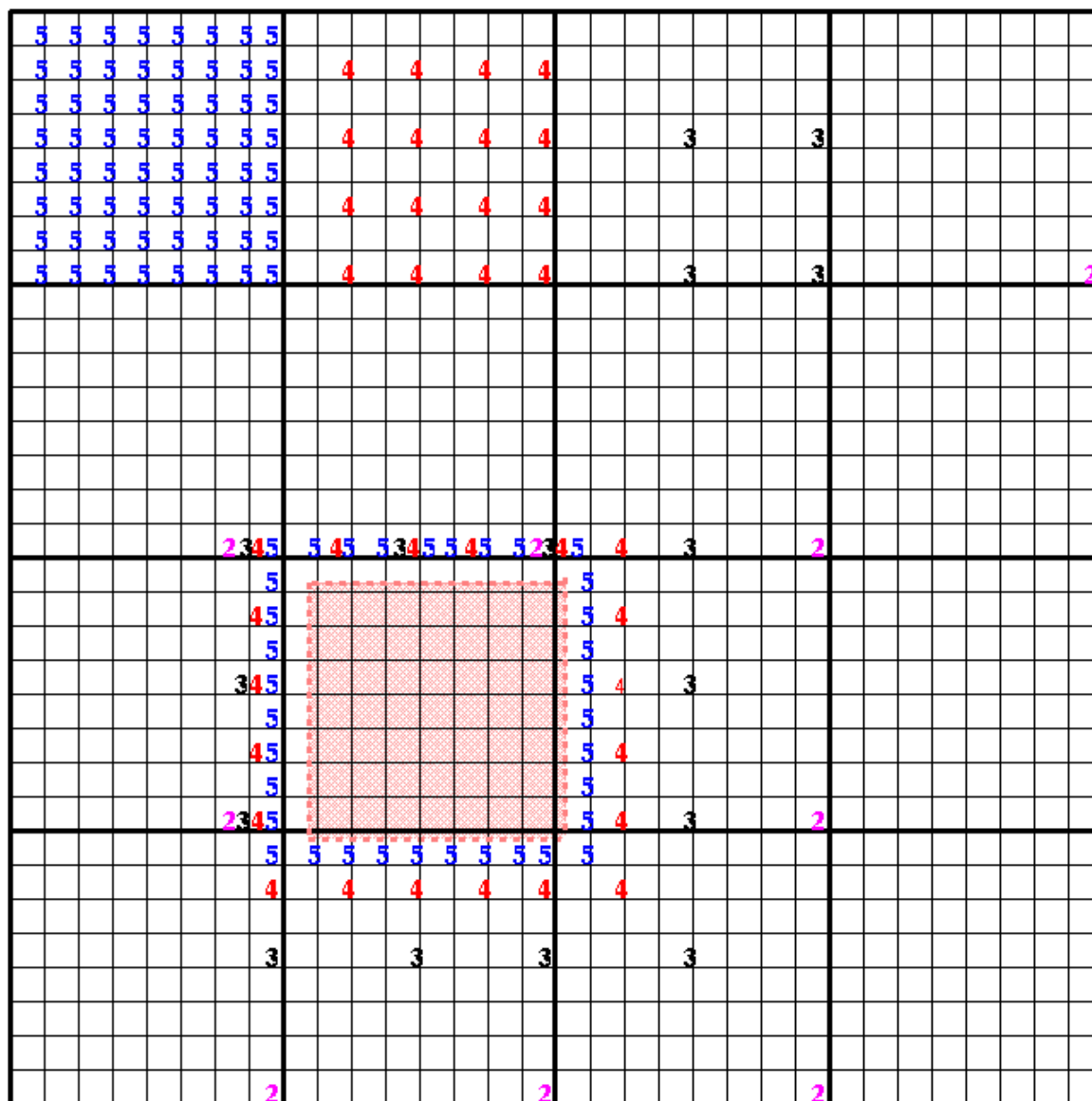
# Parallel 2D Multigrid

- Multigrid on 2D requires nearest neighbor (up to 8) computation at each level of the grid
- Start with  $n=2^m+1$  by  $2^m+1$  grid (here  $m=5$ )
- Use an  $s$  by  $s$  processor grid (here  $s=4$ )



Communication pattern for Multigrid on 33 by 33 mesh with 4 by 4 processor grid  
 In top processor row, grid points labeled  $m$  are updated in problem  $P(m)$  of multigrid  
 Pink processor owns grid points inside pink box  
 In lower half of graph, grid points labeled  $m$  need to be communicated to pink processor  
 in problem  $P(m)$  of multigrid





Communication pattern for Multigrid on 33 by 33 mesh with 4 by 4 processor grid

In top processor row, grid points labeled m are updated in problem  $P(m)$  of multigrid

Pink processor owns grid points inside pink box

In lower half of graph, grid points labeled m need to be communicated to pink processor in problem  $P(m)$  of multigrid

# Performance Model of parallel 2D Multigrid

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- Assume  $2^m+1$  by  $2^m+1$  grid of unknowns,  $n = 2^m+1$ ,  $N = n^2$
- Assume  $p = 4^k$  processors, arranged in  $2^k$  by  $2^k$  grid
  - Each processor starts with  $2^{m-k}$  by  $2^{m-k}$  subgrid of unknowns
- Consider V-cycle starting at level  $m$ 
  - At levels  $m$  through  $k$  of V-cycle, each processor does some work
  - At levels  $k-1$  through  $1$ , **some processors are idle**, because a  $2^{k-1}$  by  $2^{k-1}$  grid of unknowns cannot occupy each processor

# Performance Model of parallel 2D Multigrid (2)

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## ◦ Cost of one level (j) or $P^{(j)}$ in V-cycle

- If level  $j \geq k$ , then cost =

$O(4^{j-k})$  .... Flops, proportional to the number of grid points/processor  
+  $O(1) \alpha$  .... Send a constant # messages to neighbors  
+  $O(2^{j-k}) \beta$  .... Number of words sent

- If level  $j < k$ , then cost =

$O(1)$  .... Flops, proportional to the number of grid points/processor  
+  $O(1) \alpha$  .... Send a constant # messages to neighbors  
+  $O(1) \beta$  .... Number of words sent

## ◦ Sum over all levels in all V-cycles in FMG to get complexity

## Comparison of Methods (using $p$ processors)

	# Flops	# Messages	# Words sent
<b>MG</b>	$N/p + \log p * \log N$	$(\log N)^2$	$(N/p)^{1/2} + \log p * \log N$
<b>FFT</b>	$N \log N / p$	$p^{1/2}$	$N/p$
<b>SOR</b>	$N^{3/2}/p$	$N^{1/2}$	$N/p$

- **SOR is slower than others on all counts**
- Flops for MG and FFT depends on accuracy of MG
- **MG communicates less total data (bandwidth)**
- **Total messages (latency) depends ...**
  - This coarse analysis can't say whether MG or FFT is better when  $\alpha \gg \beta$

# Practicalities

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- In practice, we don't go all the way to  $P^{(1)}$
- In sequential code, the coarsest grids are negligibly cheap, but on a parallel machine they are not.
  - Consider 1000 points per processor
  - In 2D, the surface to communicate is  $4 \cdot \sqrt{1000} \approx 128$ , or 13%
  - In 3D, the surface is  $1000 - 8^3 \approx 500$ , or 50%
  - Data locality ratio  $\alpha$  (large  $\alpha$  is preferred):

$$\alpha = \frac{\text{computation time between two communication steps}}{\text{communication time}}$$

- Apply communication avoiding Jacobi iterations!
- Dealing with coarse meshes efficiently
  - Should we switch to using fewer processors on coarse meshes?
  - Should we switch to another solver on coarse meshes?

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## Quiz 4

Deadline: Tuesday, November 16, 8:45AM

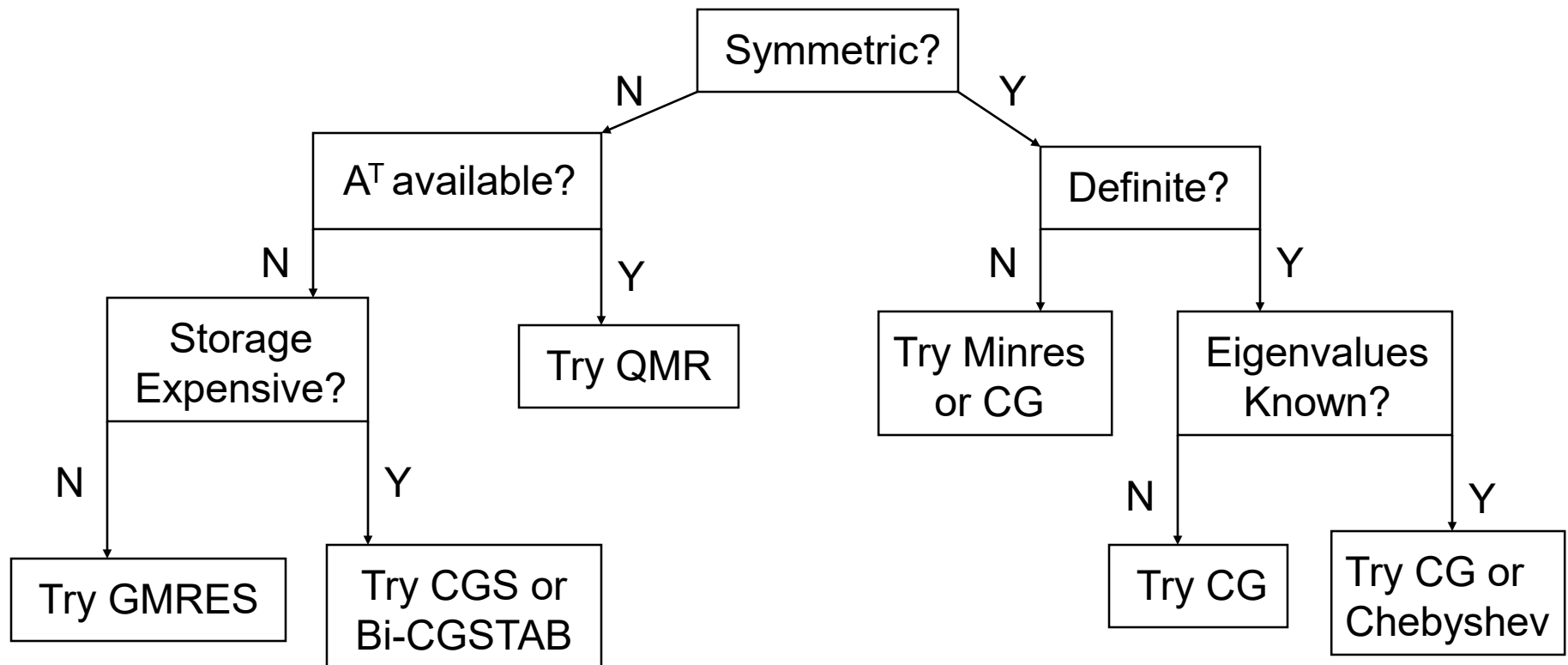
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# Extra Slides

(Not a part of discussions of the lecture)

# Templates for choosing an iterative algorithm for $Ax=b$

- Use only matrix-vector-multiplication, dot, saxpy, ...
- [www.netlib.org/templates](http://www.netlib.org/templates)





## Summary of Jacobi, SOR and CG

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- **Jacobi, SOR, and CG all perform sparse-matrix-vector multiply**
- **For Poisson, this means nearest neighbor communication on an  $n$ -by- $n$  grid**
- **It takes  $n = N^{1/2}$  steps for information to travel across an  $n$ -by- $n$  grid**
- **Since solution on one side of grid depends on data on other side of grid faster methods require faster ways to move information**
  - **FFT**
  - **Multigrid**

# Multigrid Methods

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- **We studied several iterative methods**
  - Jacobi, SOR, Gauss-Seidel, Red-Black variations, Conjugate Gradients (CG)
  - All use sparse matrix-vector multiply (nearest neighbor communication on grid)
- **Key problem with iterative methods is that:**
  - detail (short wavelength) is correct
  - convergence controlled by coarse (long wavelength) structure
- **In simple methods one needs of order  $N^2$  iterations to get good results**
  - Ironically, one goes to large  $N$  (fine mesh) to get detail
  - If all you wanted was coarse structure, a smaller mesh would be fine
- **Basic idea in multigrid is key in many areas of science**
  - Solve a problem at multiple scales
- **We get coarse structure from small  $N$  and fine detail from large  $N$** 
  - Good qualitative idea but how do we implement?