
Computations on Graphs: Partitioning, Load Balancing, and Algorithms

John Mellor-Crummey

**Department of Computer Science
Rice University**

johnmc@rice.edu

Topics for Today

- **Partitioning and load balancing of irregular problems**
—mostly about graphs, but applies more broadly
- **Computing on graphs**

Partitioning and Load Balancing

- Broad class of problems have irregular structure
- Map application data to processors for computing in parallel
- Apply to grid points, elements, matrix rows, particles

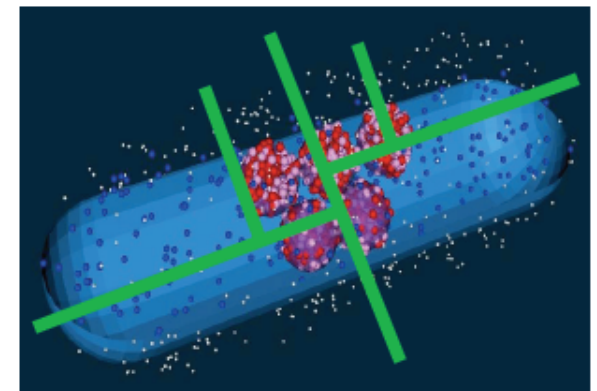
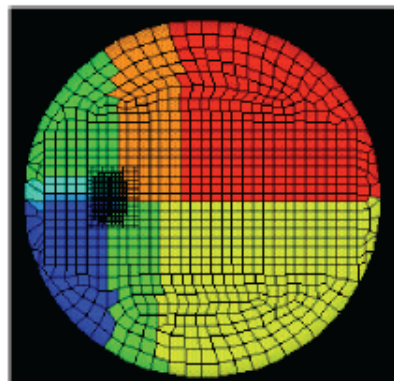
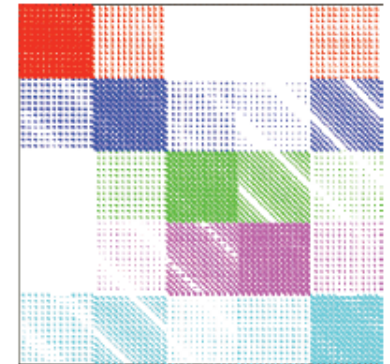
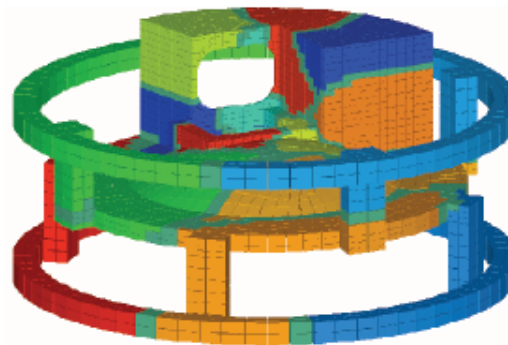
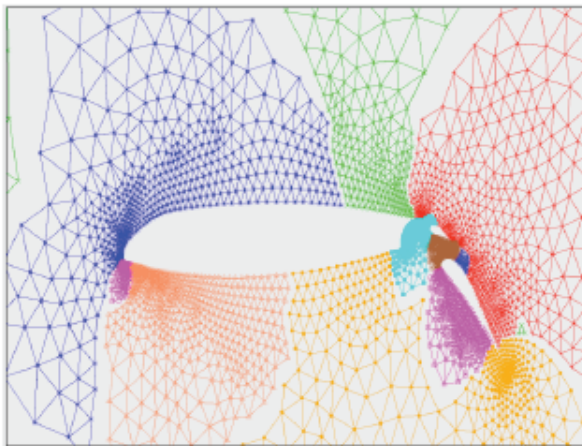


Figure credit: Erik Boman, Cedric Chevalier, Karen Devine. The Zoltan Toolkit – Partitioning, Ordering, and Coloring. Dagstuhl Tutorial. 2009.

Computational Approach

- **Distributed memory model**
- **Data decomposition + “owner computes”**
 - distribute data among the processors**
 - owner performs all computation on its data**
 - data distribution defines work assignment**
 - data dependencies among data items owned by different processors require communication**

Kinds of Partitionings

- **Static**

—all information available before computation starts



—alternatively, could be run as an off-line preprocessing step

- **Dynamic**

—information not known until runtime, work changes during computation (e.g., adaptive methods), or locality of objects changes (e.g., particles move)

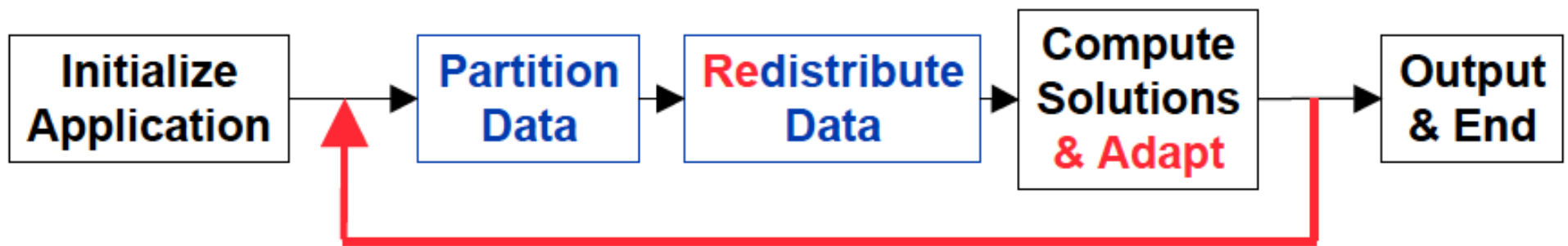
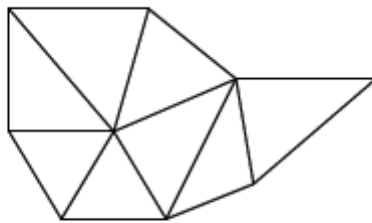


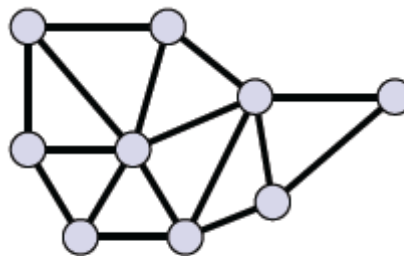
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Graph Models

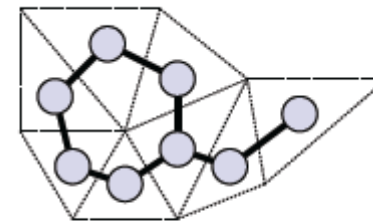
- Graphs model the structure of a problem
- Node graph (mesh nodes compute)
 - vertices = mesh nodes
 - edges = communication between nodes
- Dual graph (mesh elements compute)
 - vertices = mesh elements
 - edges = communication between mesh elements
 - exchanges take place for every face between adjacent elements



2D irregular mesh



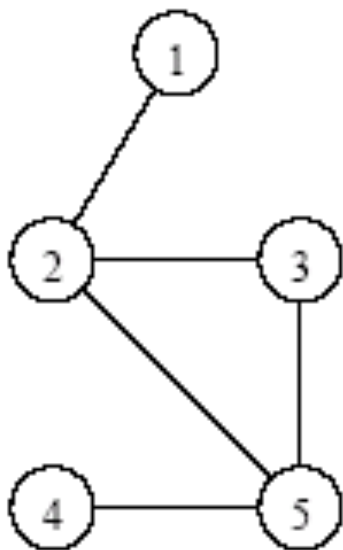
Node graph



Dual graph

Adjacency Matrix for Graph $G = (V, E)$

- $|V| \times |V|$ matrix
 - matrix element $a_{i,j} = 1$ if nodes i and j share an edge; 0 otherwise
 - for a weighted graph, $a_{i,j} = w_{i,j}$, the edge weight
- Requires $\Theta(|V|^2)$ space



$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

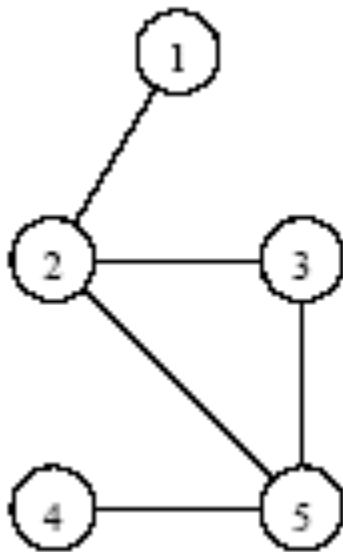
Adjacency matrix
representation

adjacency matrix is symmetric
about the diagonal for
undirected graphs

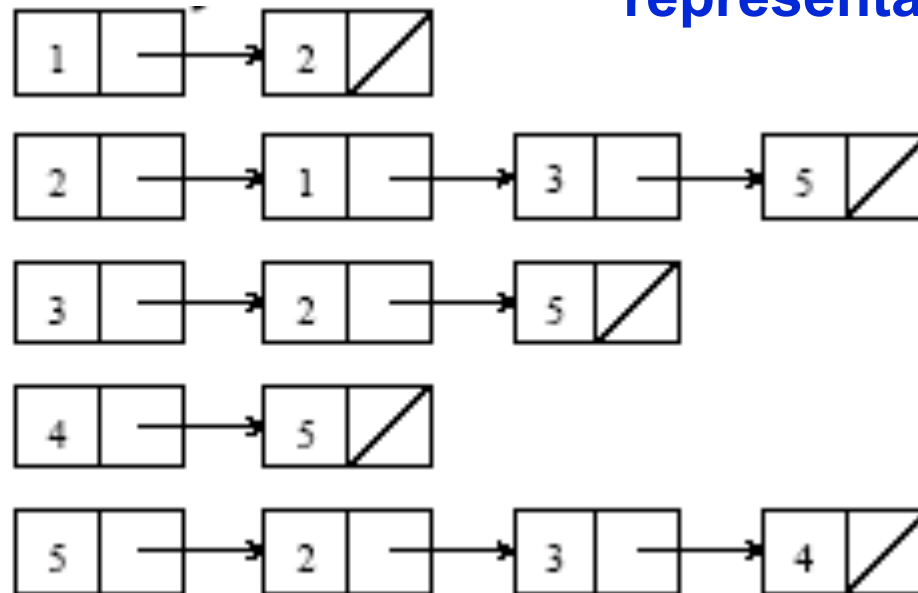
Undirected graph

Adjacency List for Graph $G = (V, E)$

- An array $Adj[1..|V|]$ of lists
 - each list $Adj[v]$ is a list of all vertices adjacent to v
- Requires $\Theta(|E|)$ space

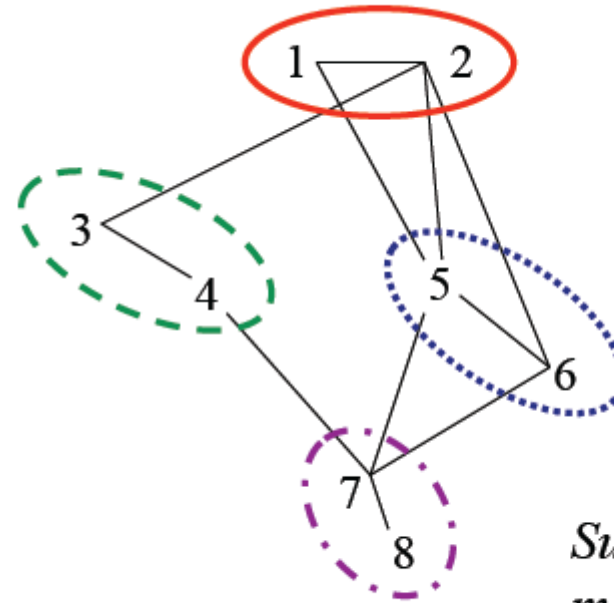


Adjacency list
representation



Partitioning using an Adjacency Matrix

	1	2	3	4	5	6	7	8
1	1	1			1			
2	1	1	1		1	1		
3		1	1	1				
4			1	1			1	
5	1	1			1	1	1	
6		1			1	1	1	
7				1	1	1	1	1
8							1	1



Subdomains are mapped to the processors

- Can reorder rows and columns of the matrix
 - non-zeros outside of blocks require communication
- An optimal partition of the graph for parallel computation has
 - equal number of vertices in subdomains
 - lowest number of edges between subdomains

Finite Element Mesh Example

NASA airfoil finite-element mesh, 4253 grid points

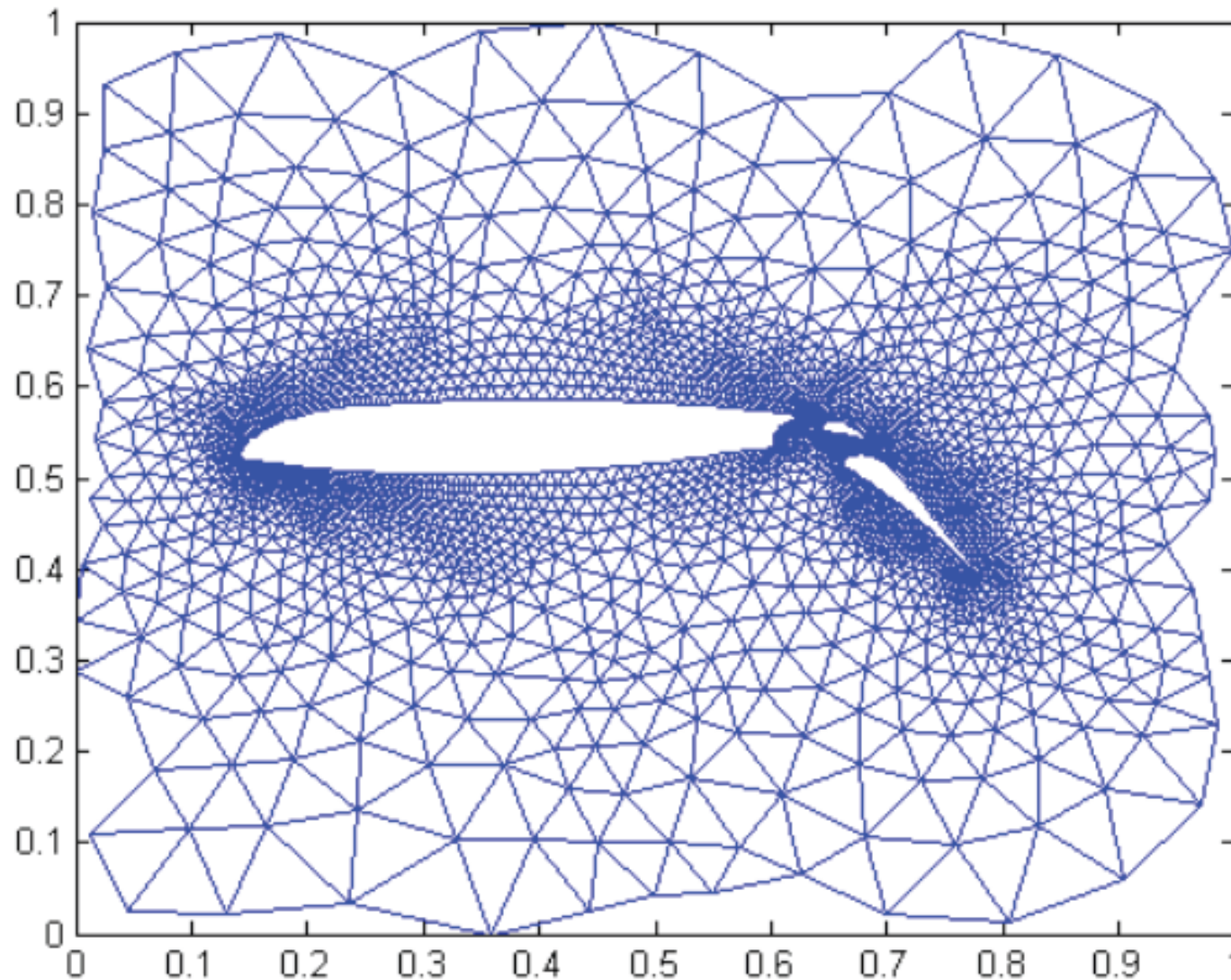


Image source: MATLAB 7.5 NASA airfoil demo

Adjacency Matrix and Reverse Cuthill-McKee Reordering

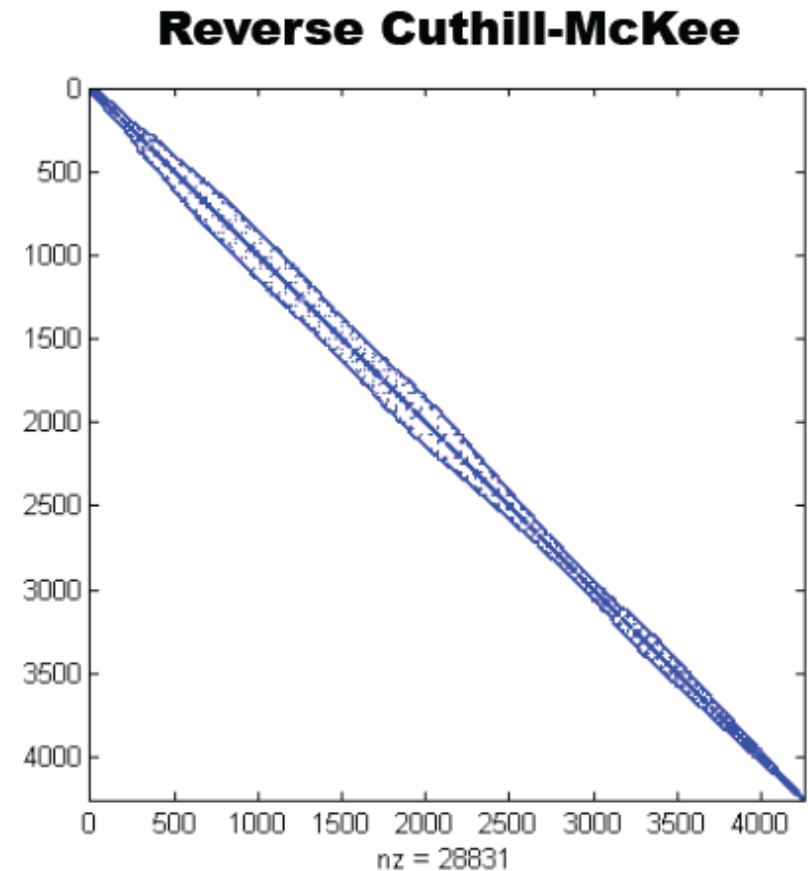
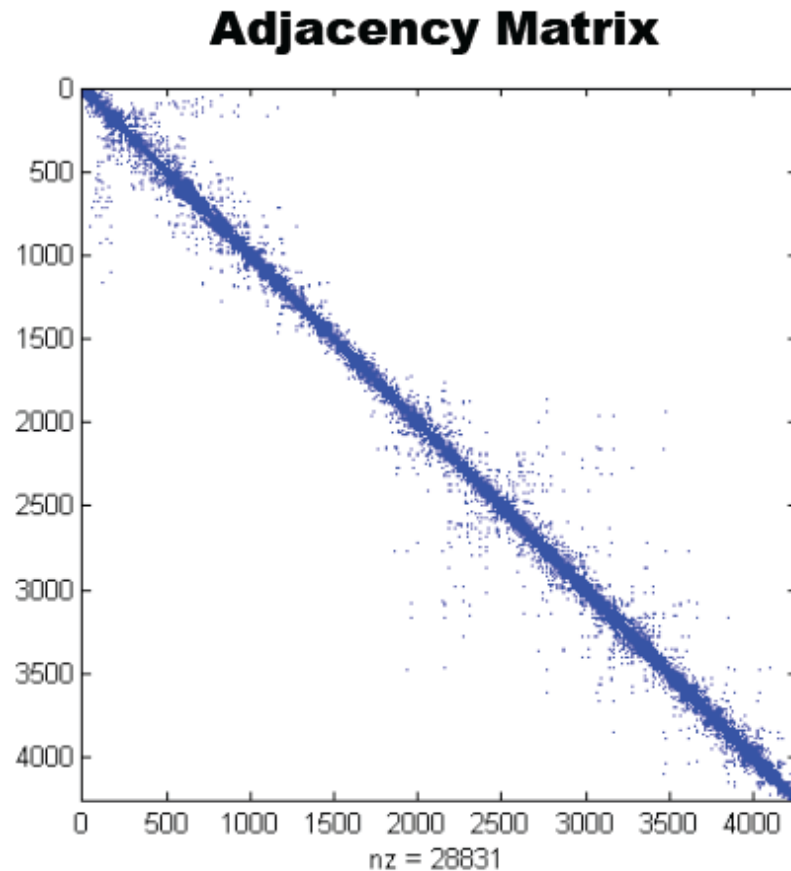


Image source: MATLAB 7.5 NASA airfoil demo

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J. A. George and J. W-H. Liu, *Computer Solution of Large Sparse Positive Definite Systems*, Prentice-Hall, 1981

Reverse Cuthill-McKee

- **Cuthill-McKee**
 - begin with a peripheral vertex
 - partition vertices into levels until all nodes are exhausted
 - level set K contains all vertices adjacent to all nodes in level $K-1$
 - list nodes in each level in increasing degree
 - only difference with conventional breadth-first search
- **Reverse order of the above**
 - reduces fill-in when using GE

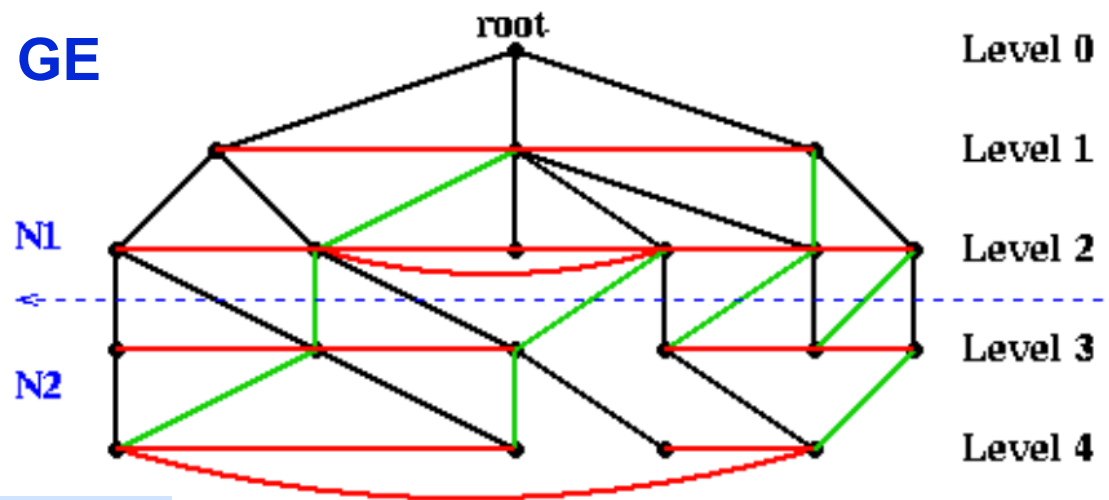


Figure credit: Marsha Berger and Andreas Klöckner. Lecture 12: Load balancing and partitioning. G63.2011.002/G22.2945.001. NYU. November 16, 2010.

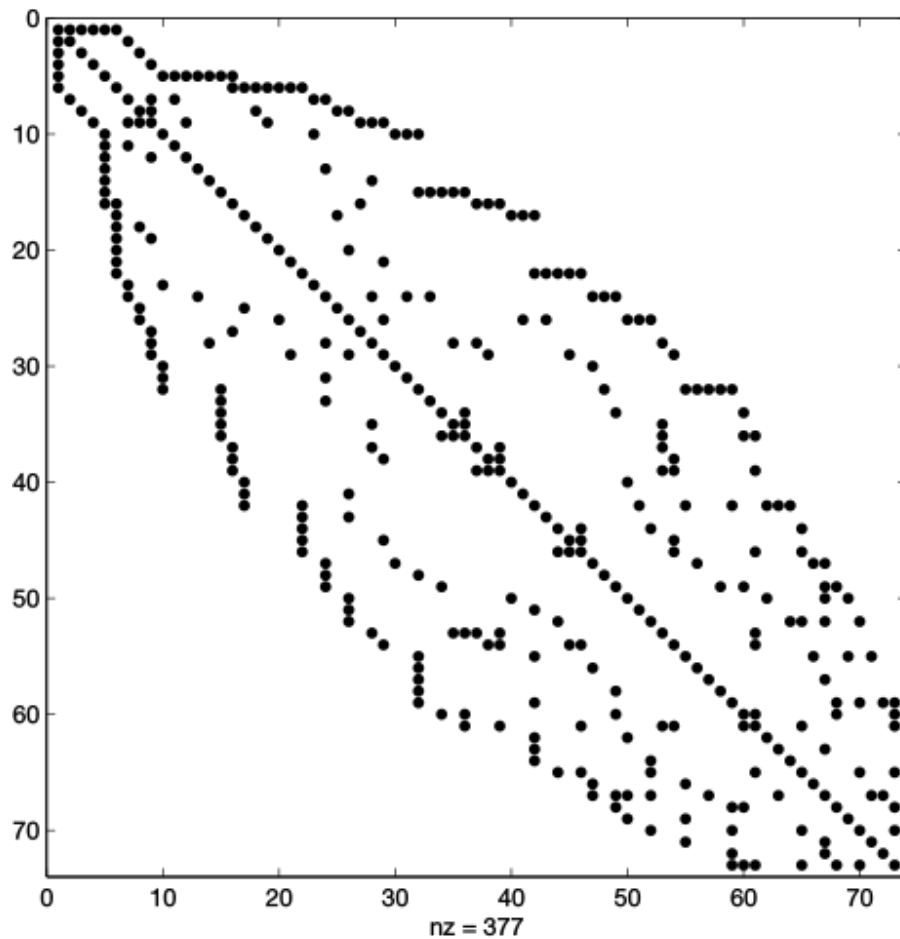
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Tree Edges ———
Horizontal Edges ———
Interlevel Edges ———

Cuthill-McKee vs. Reverse Cuthill-McKee Ordering

Cuthill-McKee



Reverse Cuthill-McKee

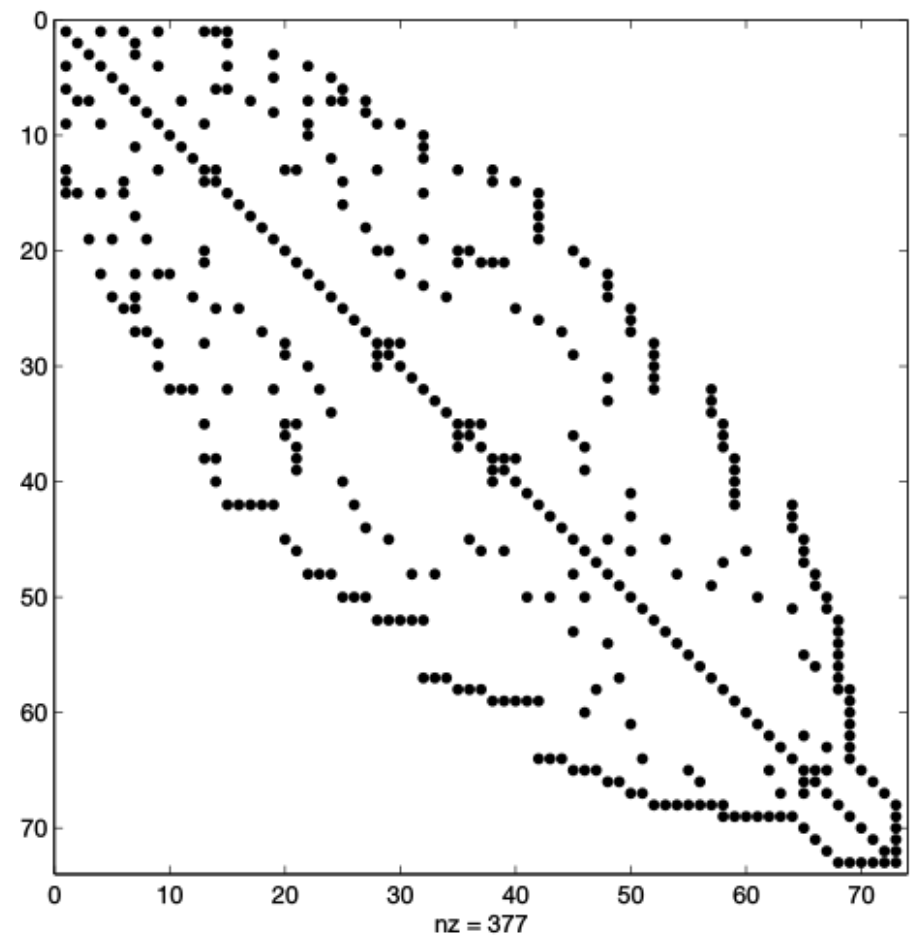
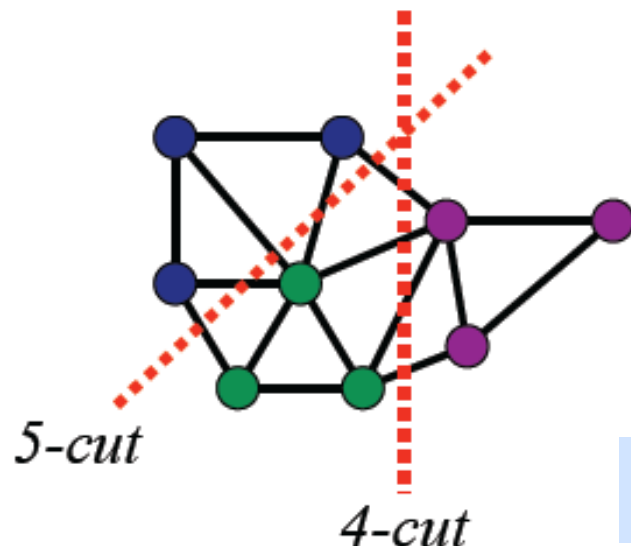


Figure credit: https://en.wikipedia.org/wiki/Cuthill-McKee_algorithm

Goals of Partitioning

- **Balance constraint**
 - balance computational load such that each processor has the same execution time
 - balance storage such that each processor has the same storage requirements
- **Minimum edge cut**
 - minimize communication volume between subdomains, along edges of the mesh
- **Note: communication to computation ratio comes from both partitioning and the algorithm**



*Example 3-way partition
with edge-cut = 9*

Figure credit: Robert Van Engelen. Graph Partitioning for High Performance Scientific Simulations. Slides. Spring 2009.

Graph Partitioning Problem

- Let $G = (V, E)$ be a weighted undirected graph with weight functions $w_V: V \rightarrow \mathbb{R}^+$, $w_E: E \rightarrow \mathbb{R}^+$
- K-way graph partitioning problem
 - split V into K disjoint subdomains S_j $j = 1, \dots, k$ such that
 - balance constraint
$$\sum_{v \in S_j} w_V(v) \text{ is roughly equal, for all } j = 1, \dots, k$$
 - minimum edge cut
$$\sum_{(u,v) \in E \text{ such that } u \in S_i \text{ and } v \in S_j} w_E((u,v)) \text{ is minimal}$$
- Weight functions are defined that
 - w_V models computational work
 - w_E models communication
- Can add subdomain weights to improve mapping to heterogeneous nodes or processors

Static Graph Partitioning

- **Geometric techniques**
 - recursive coordinate bisection
 - recursive inertial bisection
 - space filling curves
- **Combinatorial techniques**
 - Kernighan-Lin
- **Multi-level schemes**
 - multilevel recursive bisection
 - multilevel k-way partitioning

Geometric Partitioning Techniques

- **Goal:** group together vertices that are nearby in space
- **When are these methods applicable**
 - when coordinate system exists or can be constructed
- **How:**
 - partition based on coordinate information
 - may consider vertex weights as well
 - recursively bisect mesh into increasingly smaller subdomains
- **Properties**
 - typically fast
 - have no concept of edge cut, so no communication optimization
 - may suffer from disconnected meshes in complex subdomains

Recursive Coordinate Bisection (RCB)

- **Geometric method**
 - compute centers of mass of mesh elements
 - project onto axis of longest dimension
 - bisect the list of centers
 - repeat recursively
- **Strength: fast, easy to parallelize**
- **Weakness: low quality partitionings**

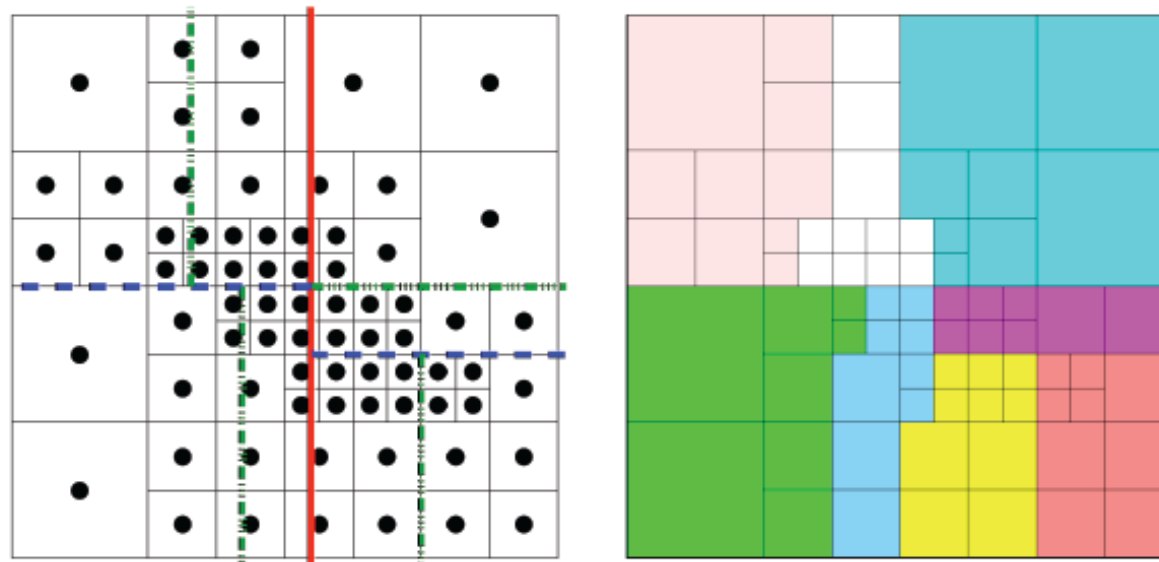
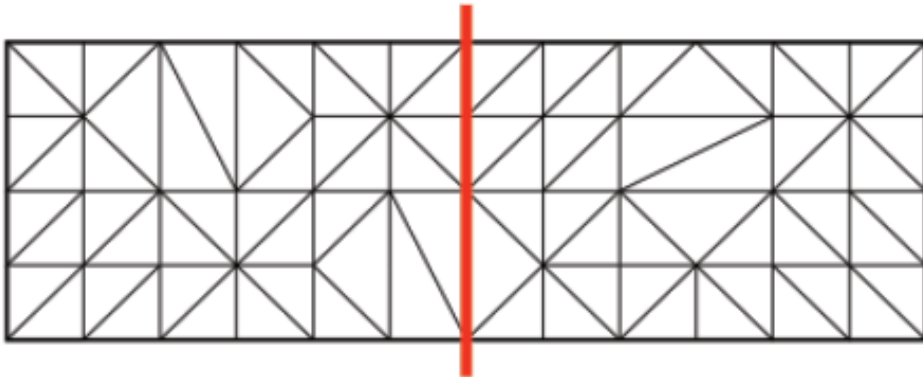


Figure Credit: K. Schloegel, et al. Graph Partitioning for High Performance Scientific Simulations. In CRPC Parallel Computing Handbook. Morgan Kauffman, 2000.

Recursive Coordinate Bisection (RCB)

- **Bisect mesh normal to the longest dimension**
 - yields smaller subdomain boundaries
 - typically reduces communication volume

Bisected normal to the x-axis



Bisected normal to the y-axis

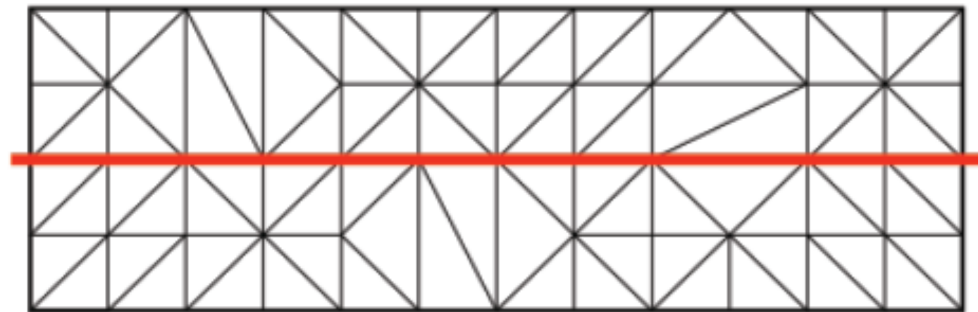


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Recursive Inertial Bisection (RIB)

- Orient bisection to minimize the subdomain boundary
- Mesh elements are converted into point masses
 - compute principal inertial axis of the mass distribution
 - bisect orthogonal to the principal inertial axis
 - repeat recursively
- Fast and better quality than recursive coordinate bisection

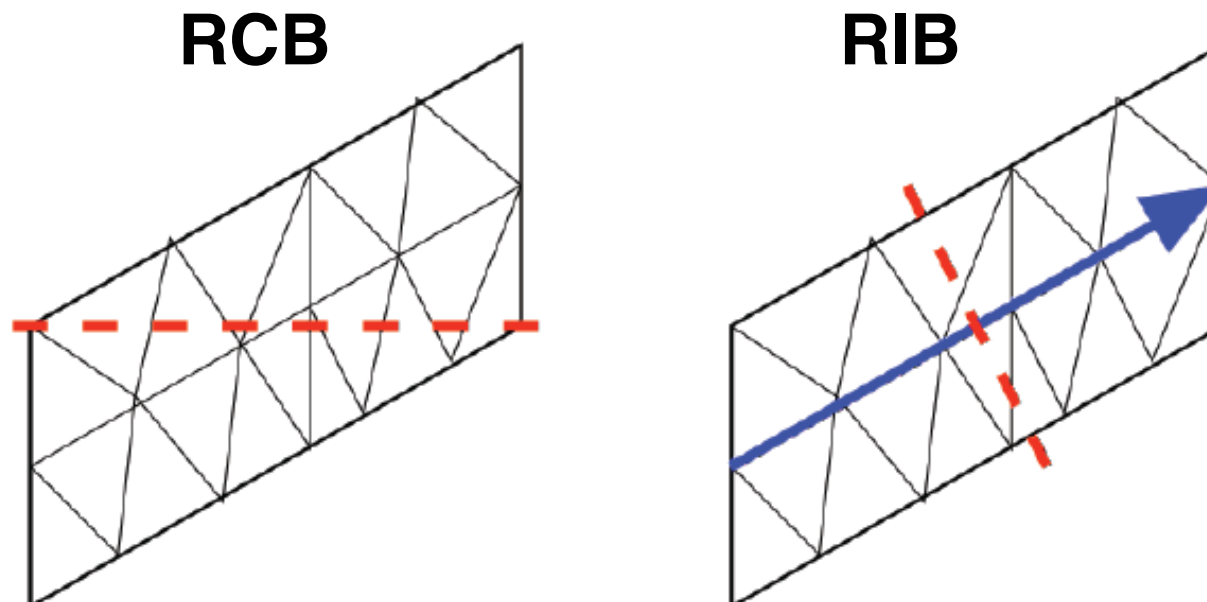
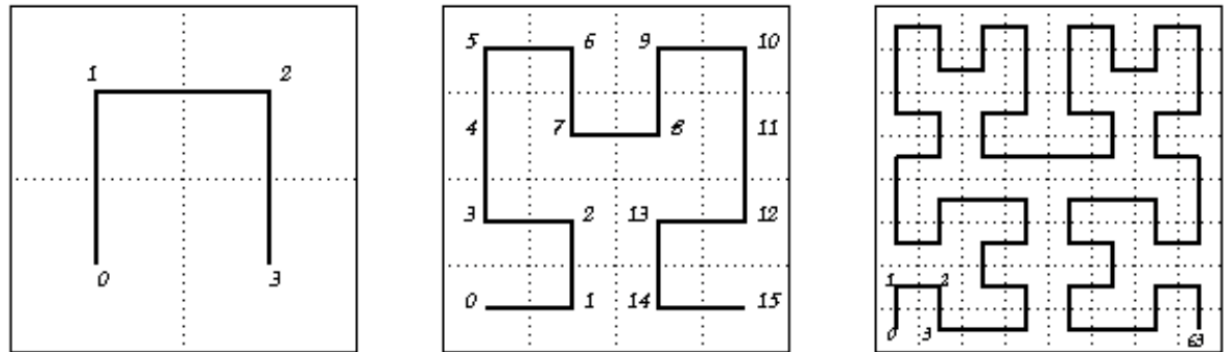


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Space-filling Curves

- RCB and RIB only consider a single dimension at a time
- Space-filling curve techniques linearly order a multidimensional mesh (nested hierarchically, preserves locality)

Peano-Hilbert curve



Morton / Z-order curve

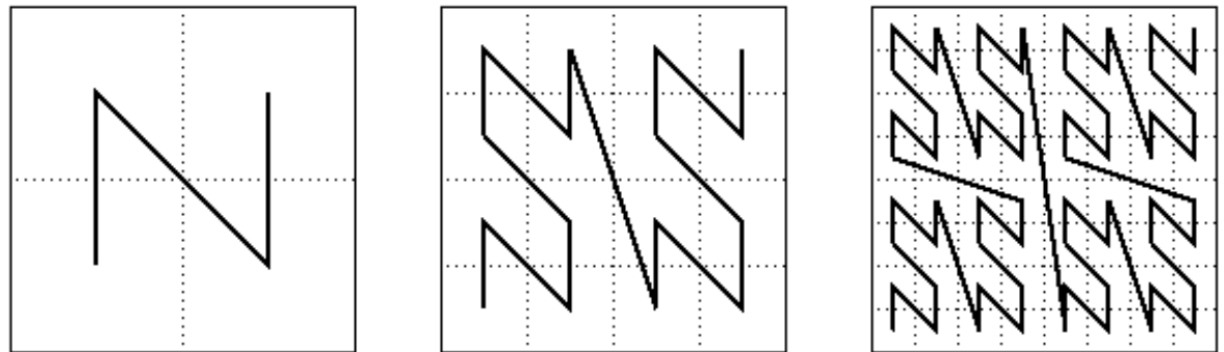
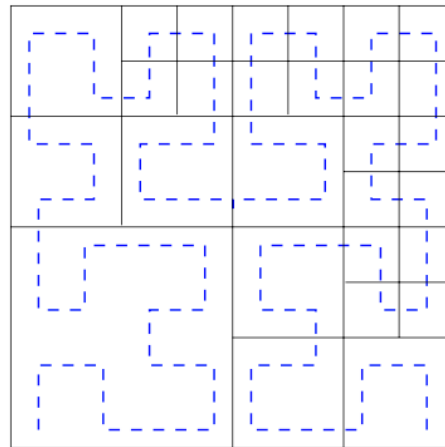
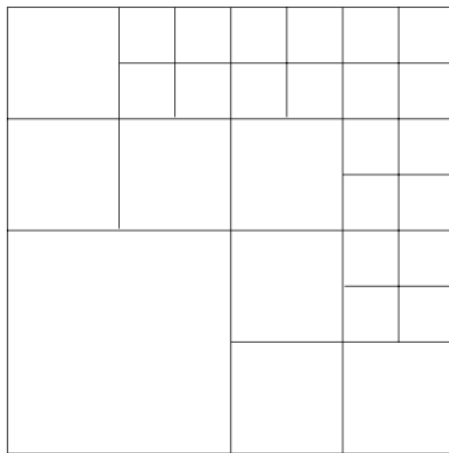


Figure credit: <http://www.dcs.bbk.ac.uk/~jkl/BNCOD2000/img1.gif>

Space-filling Curves (SFC)

Applies even to adaptively refined meshes and particles



3	5	6	11	12	15	16
	4	7	10	13	14	17
2	8	9	19	18		
			20	21		
1			26	25	22	
				24	23	
			27	28		

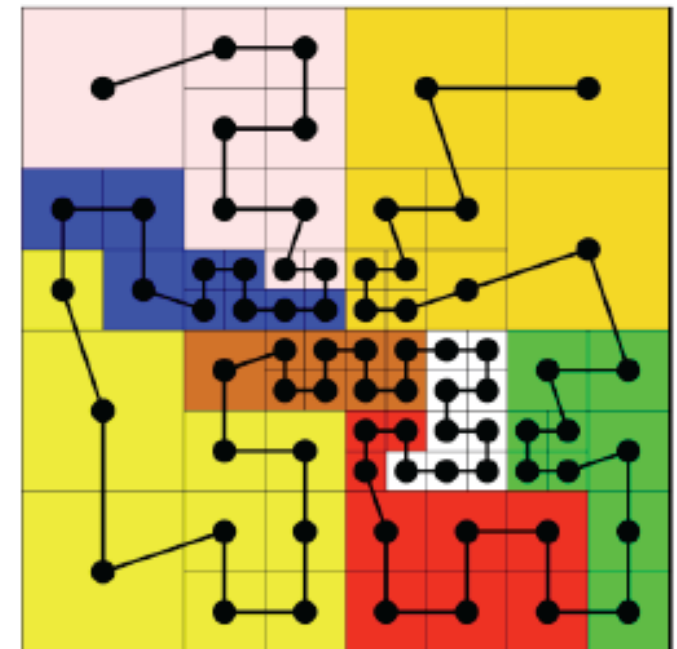
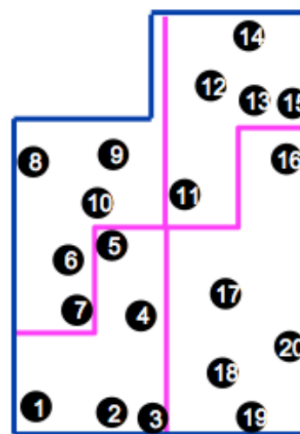
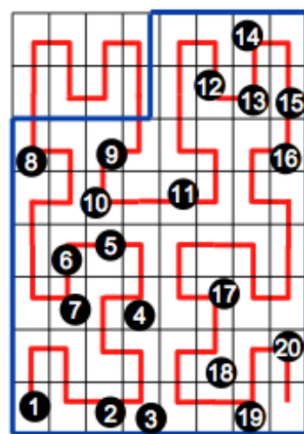
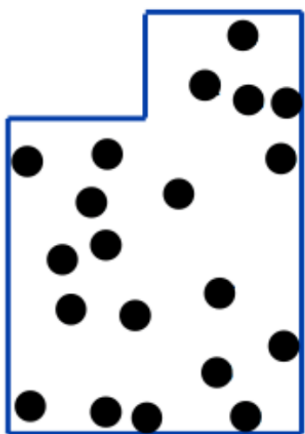


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Space-filling Curve Properties

- **Strengths**
 - broadly applicable: particles, adaptive mesh refinement, ...
 - generalizes to uneven workloads - incorporate weights
 - dynamic on-the-fly partitioning for any number of nodes
 - good for cache performance
- **Weaknesses**
 - need coordinates
 - partitions may not be compact

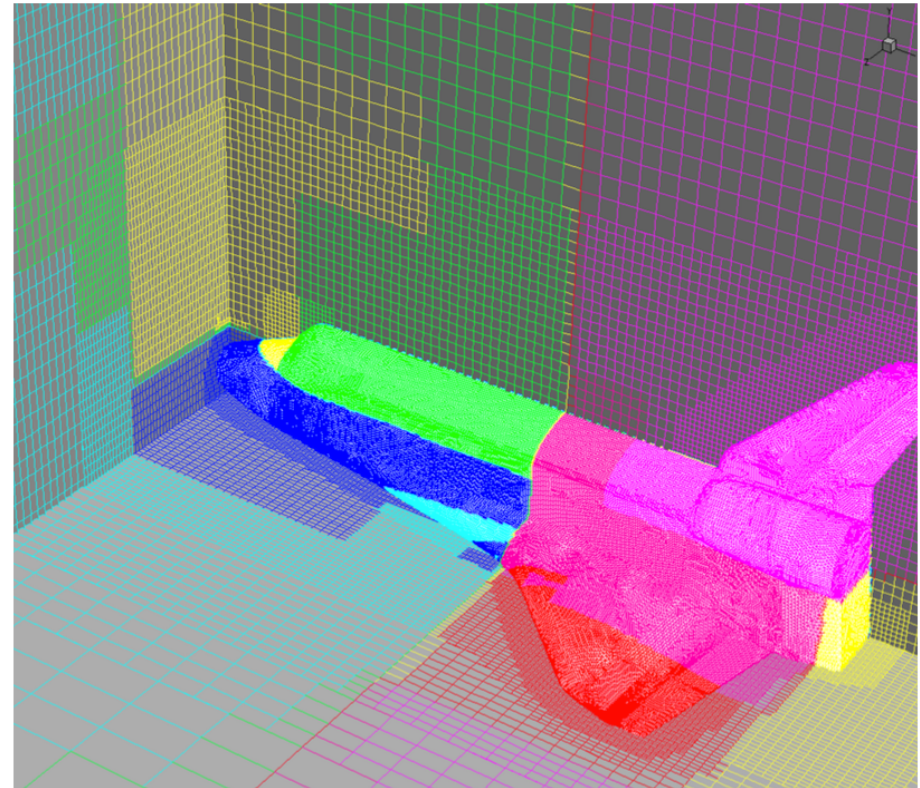


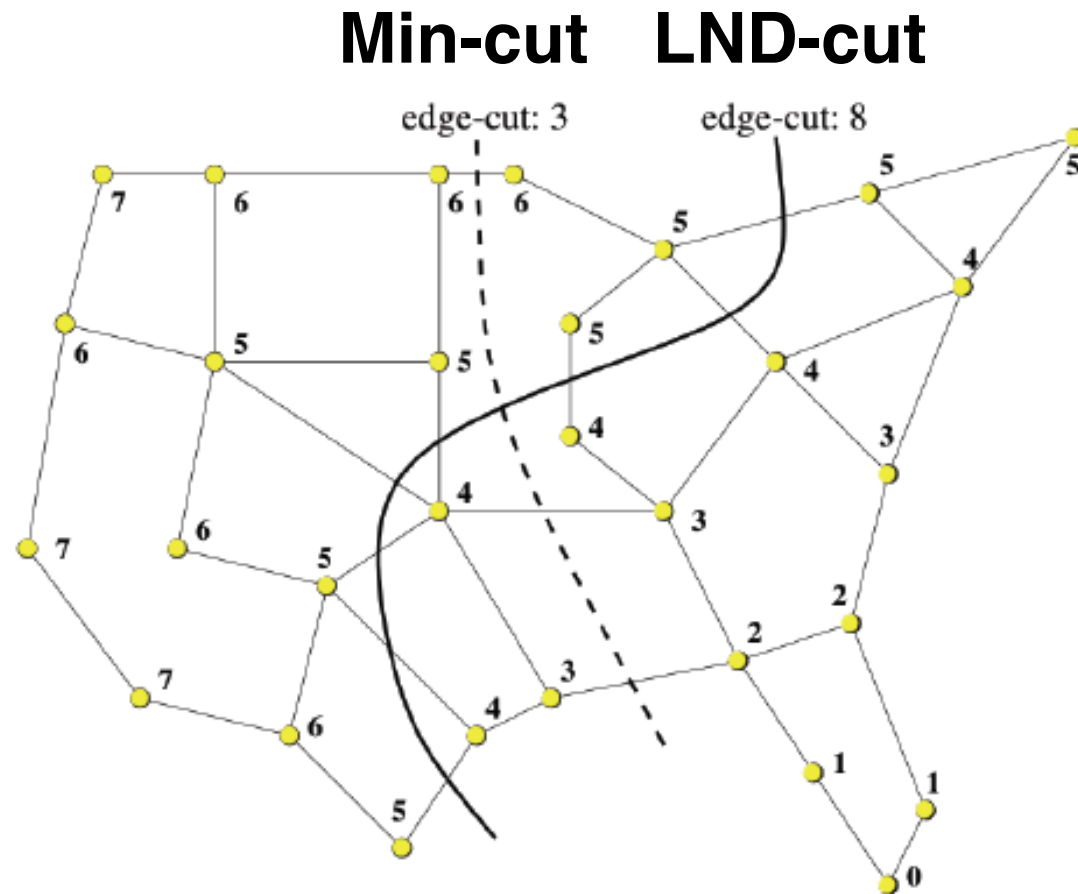
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Lecture 12: Load balancing and partitioning.
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Combinatorial Partitioning Techniques

- **Geometrical techniques** group vertices that are spatially close, whether they are connected or not
- **Combinatorial partitioning techniques** use adjacency information to group together vertices that are highly connected
- **Properties**
 - smaller edge cuts
 - reasonably fast
 - harder to parallelize

Levelized Nested Dissection (LND)

- Select initial vertex v_0 , preferably a peripheral vertex
- For each vertex, compute the distance to v_0 using a breadth first search starting from v_0
- When half of the vertices have been assigned, split the graph into two parts: assigned and unassigned
- Can repeat with different vertices as v_0 to improve edge cut

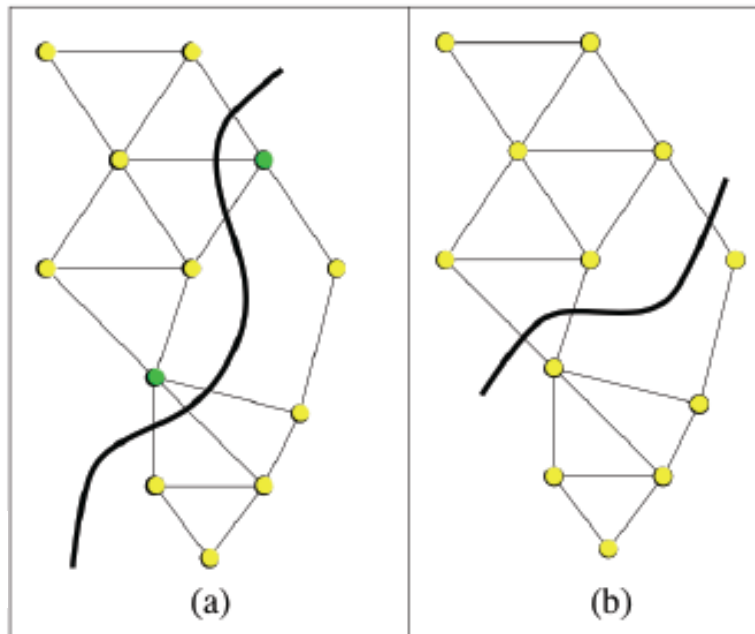


Kernighan-Lin (KL) Partition Refinement

- **Given:** partition of vertices into two disjoint sets A and B
- **Idea:** find $X \subseteq A$ and $Y \subseteq B$ such that swapping X to B and Y to A yields the greatest reduction in edge cut
- Finding optimal X and Y is intractable
- Kernighan-Lin performs multiple passes over V
- Each pass swaps two vertices, one from A and one from B

Before KL pass

Edge cut 6



Edge cut 3

After KL pass

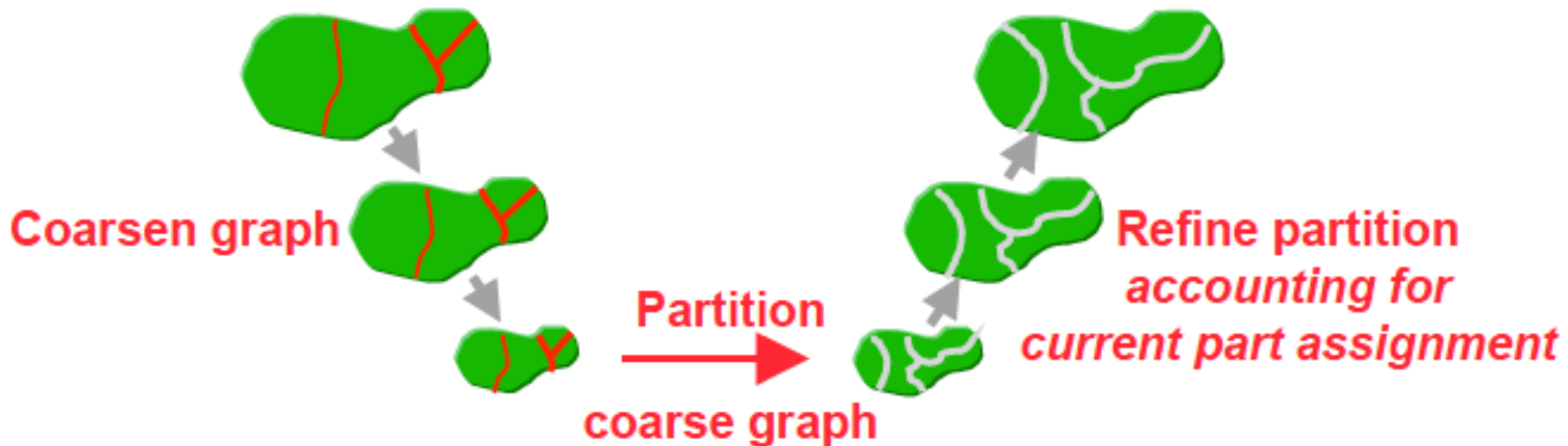
Figure Credit: K. Schloegel, et al.
Graph Partitioning for High
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In CRPC Parallel Computing
Handbook. Morgan Kauffman, 2000.

Multi-level Schemes

Strategy

- recursively coarsen graph in downward pass
- partition the coarsest graph
- refine the partition when unwinding each level of the recursion

If the graph is already partitioned, take that into account



Multi-level Schemes

- **Coarsening collapses pairs of vertices**
- **Different coarsening strategies**
 - pick random pairs
 - pick heavy edge pairs
- **Partition coarsest (smallest) graph using recursive bisection**
- **Use refinement, e.g. Kernighan-Lin on uncoarsened graph**

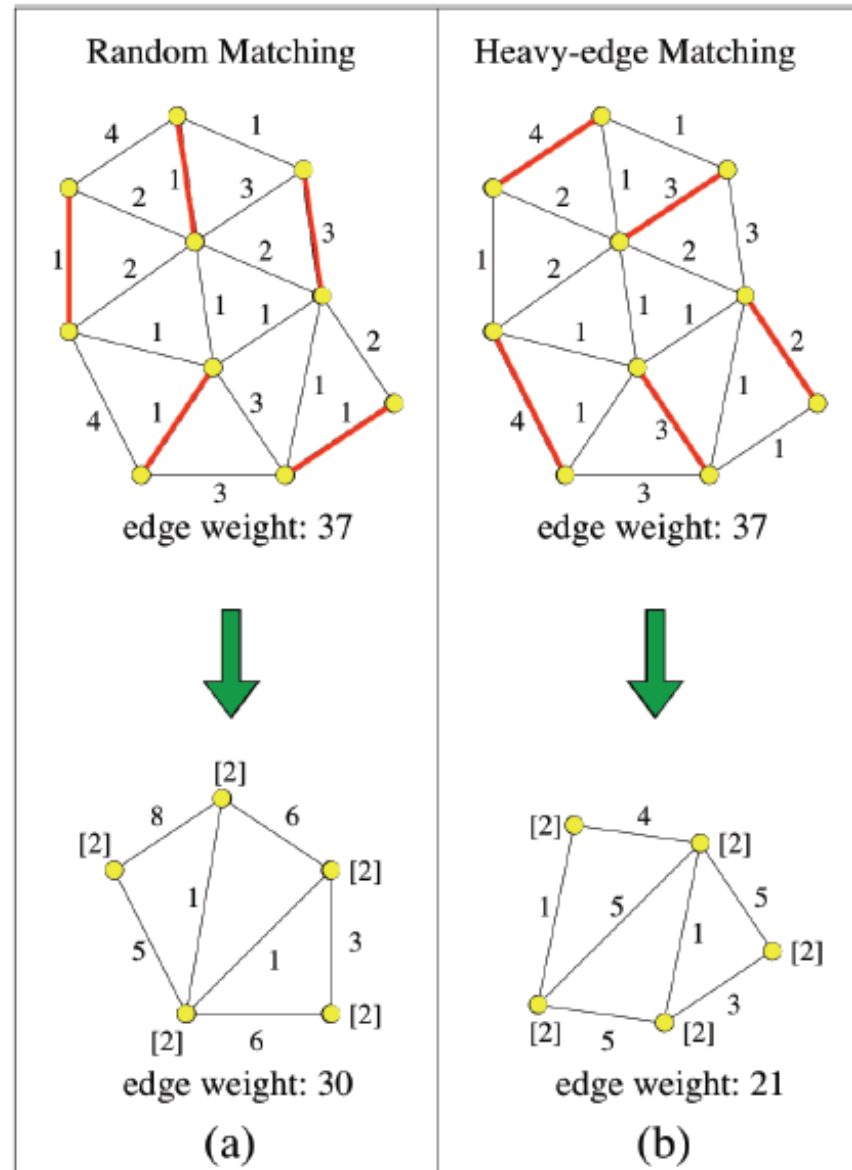
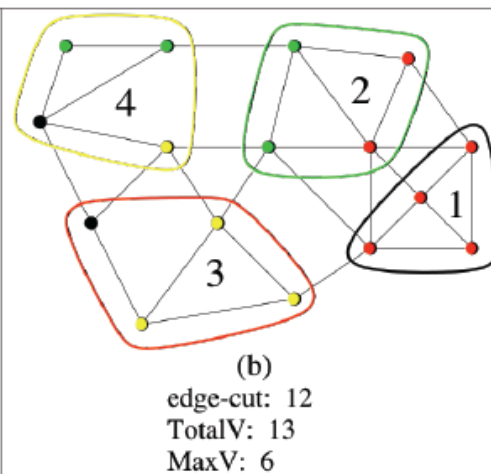
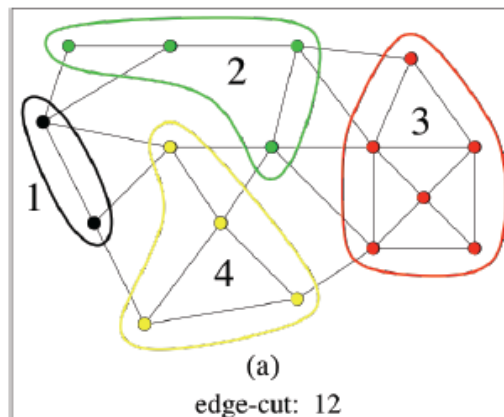


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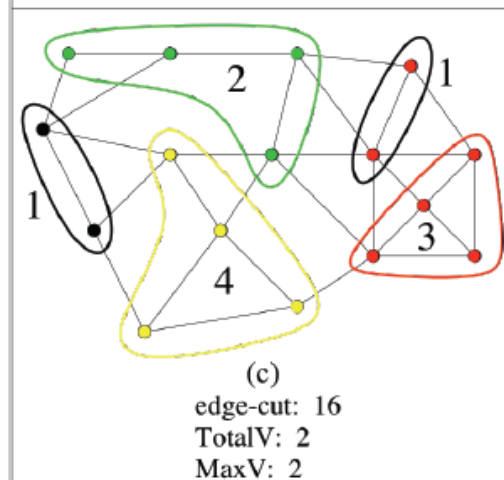
Repartitioning Methods

- Partition from scratch
- Incremental repartition methods
 - cut and paste
 - diffusion-based methods

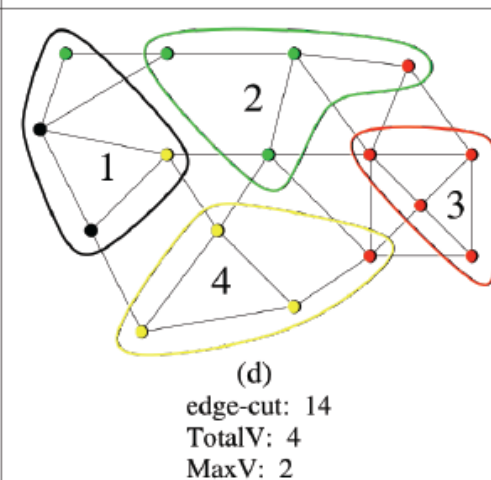
**Imbalanced partitioning
(vertex weights=1)**



**Repartitioning
from scratch**



**Cut-and-paste
repartitioning**



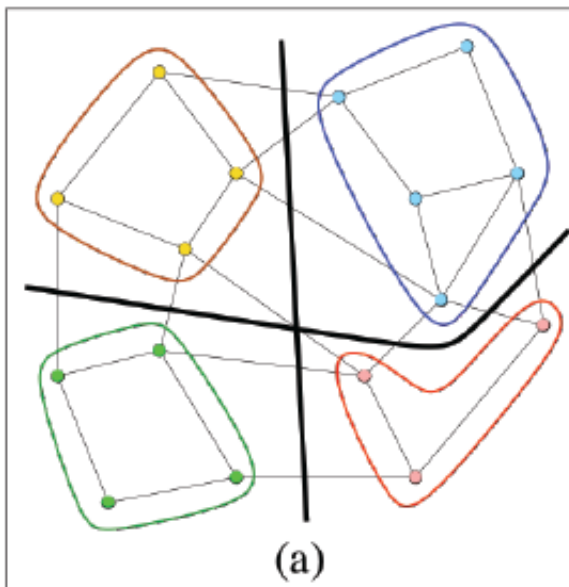
**Diffusive
repartitioning**

Figure credit: Robert Van Engelen. Graph Partitioning for High Performance Scientific Simulations. Slides. Spring 2009.

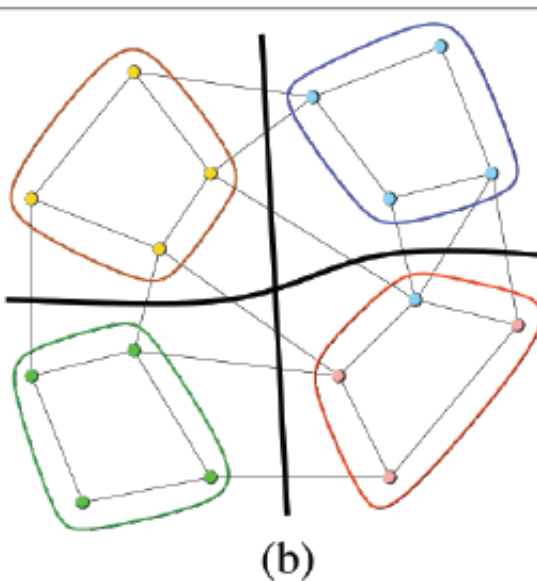
Comparing Repartitioning Methods

- Scratch-remap results in higher distribution costs compared to incremental methods that use local perturbations
- Incremental partitioning with cut-and-paste
 - moves fewest vertices between subdomains to restore balance
- Incremental diffusion-based methods

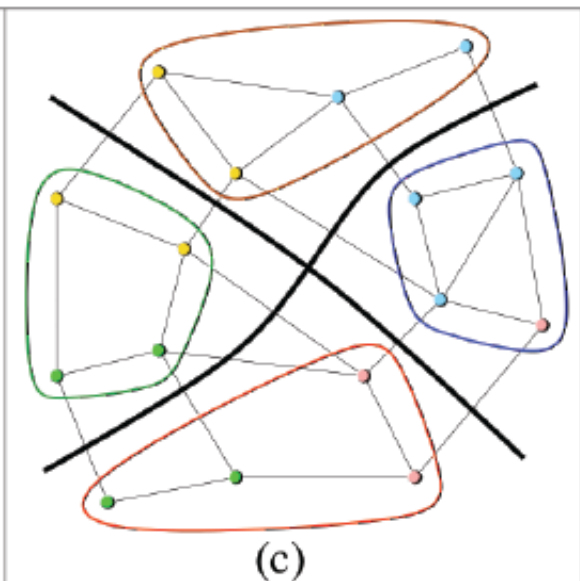
Imbalanced
partitioning



Incremental
partitioning

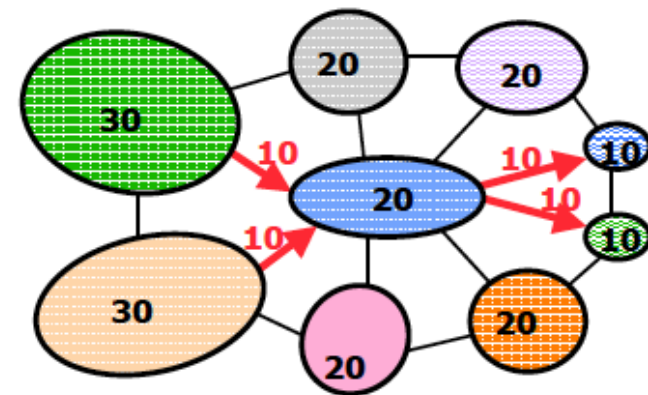
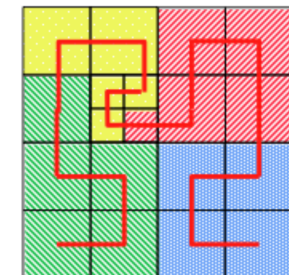
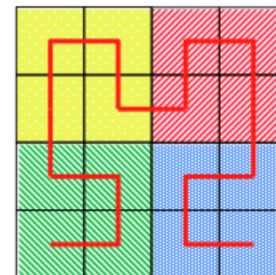
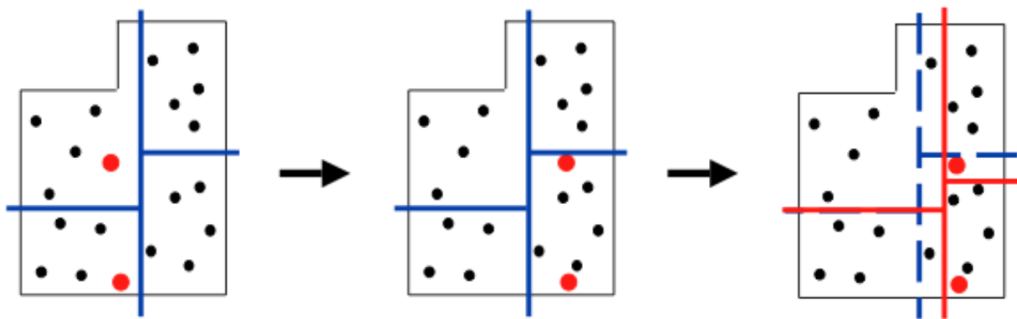


Scratch-remap
partitioning



Diffusion-based Methods

- Address two questions
 - how much work should be transferred
 - which tasks should be transferred
- Attempt to minimize the difference between original and final repartitioning by making incremental changes
- Global diffusion schemes consider entire graph
 - recursive bisection diffusion partitioners
 - adaptive space-filling curve partitioners



Computing on Graphs

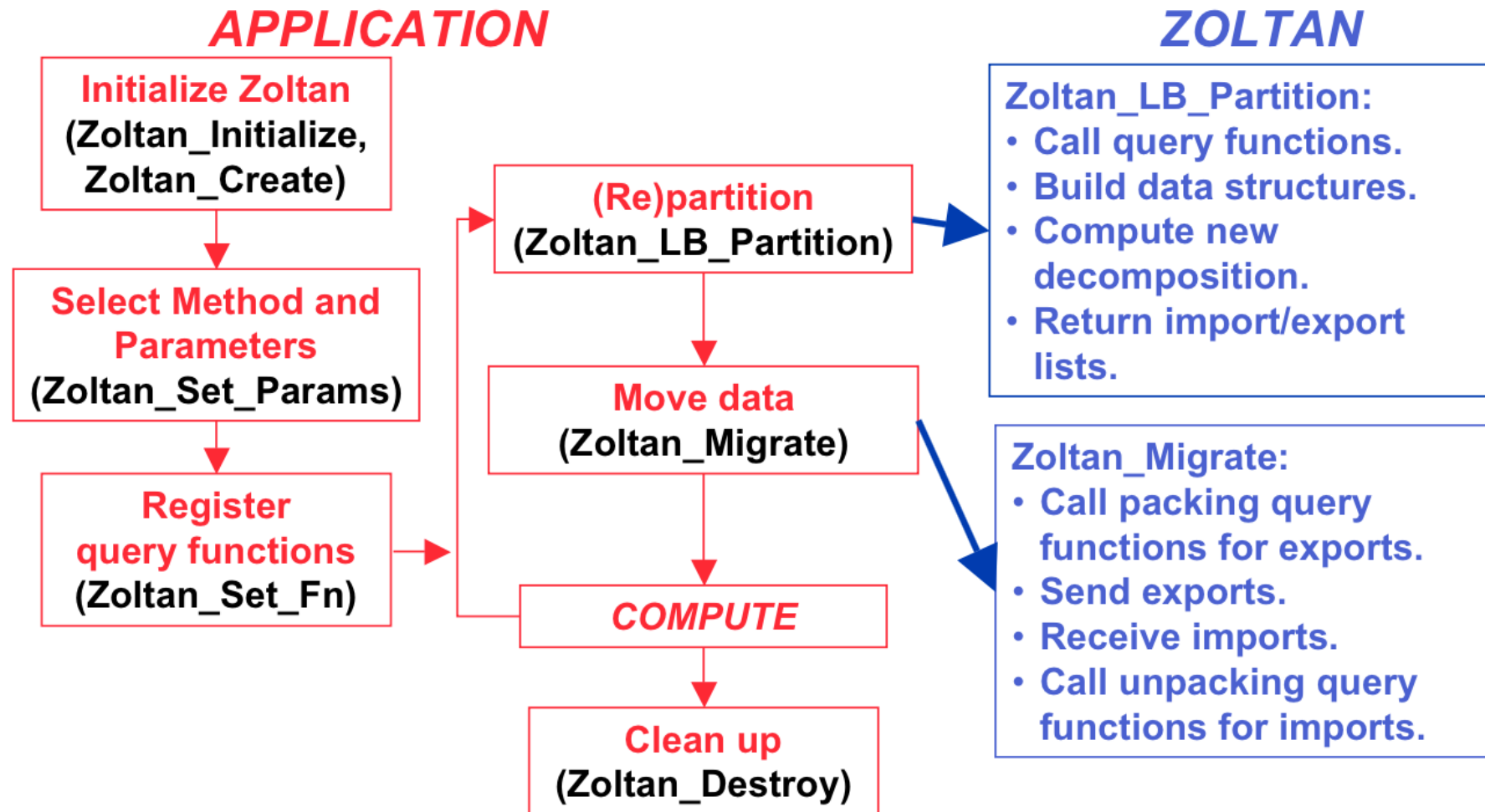
- **Precompute your communication schedule**
 - what has to be communicated to whom
- **Locally partition data into separate parts**
 - elements that can be computed with local information only
 - elements that require non-local elements to compute
- **Begin communicating your data to neighbors**
 - post non-blocking receives
 - issue non-blocking sends
- **Perform your local computation**
- **Wait for communication from neighbors**
- **Perform computation on non-local data**

Sandia's Zoltan Library

- **Dynamic load-balancing and parallel partitioning tools that distribute data over sets of processors**
- **Data migration tools for redistribution**
- **Parallel graph/matrix ordering algorithms**
- **Parallel graph coloring algorithms**
- **Distributed data directories that efficiently locate off-processor data**
- **An unstructured communication package that greatly simplifies interprocessor communication**
- **A dynamic memory debugging package for use on parallel systems**

[**http://www.cs.sandia.gov/zoltan/**](http://www.cs.sandia.gov/zoltan/)

Sandia's Zoltan Library



<http://www.cs.sandia.gov/zoltan/>

References

- Kirk Schloegel, George Karypis, and Vipin Kumar. Graph Partitioning for High Performance Scientific Simulations. CRPC Parallel Computing Handbook. Dongarra, Foster, Kennedy, Torczon, White, editors. Morgan Kauffman, 2000.
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