

# Load Balancing

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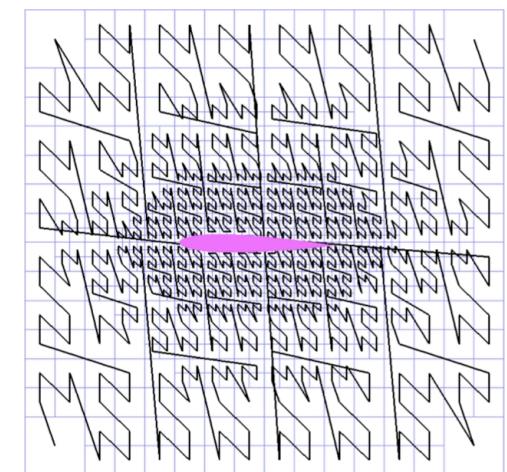
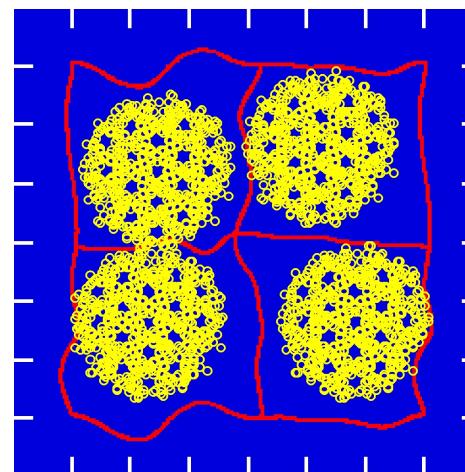
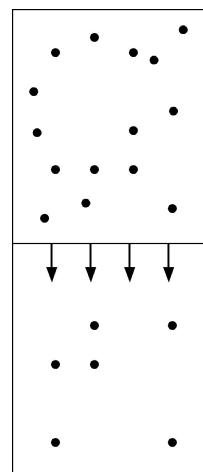
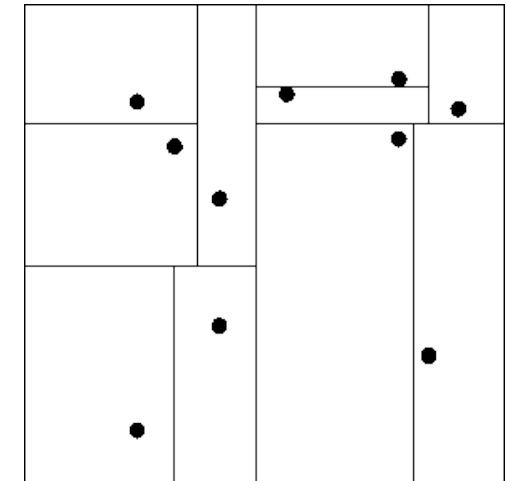
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# Load Balancing

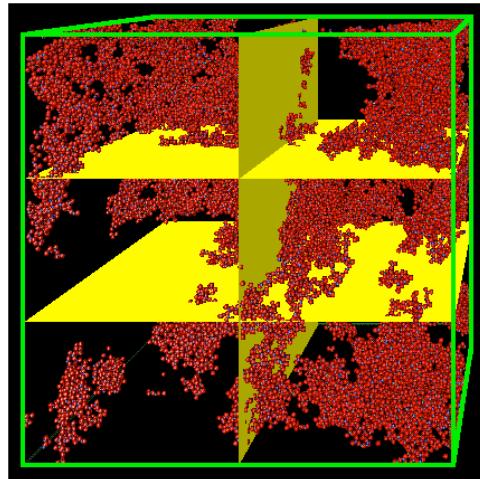
- Goal: Keep all processors equally busy while minimizing inter-processor communication for irregular parallel computations
- Issues:
  - Spatial data vs. generic graph
  - Static vs. adaptive
  - Incremental vs. non-incremental
- Load-balancing schemes:
  - Recursive bisection
  - Spectral method
  - Spacefilling curve
  - Curved space
  - Load diffusion



# Data Locality in Parallelization

**Challenge:** Load balancing for irregular data structures

Irregular  
data-structures/  
processor-speed



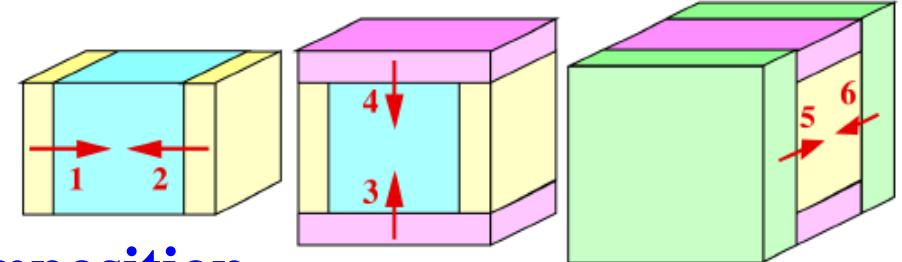
Map  
→



Parallel  
computer

**Optimization problem:**

- Minimize the load-imbalance cost
- Minimize the communication cost
- Topology-preserving spatial decomposition  
→ structured 6-step message passing minimizes latency



$$E = t_{\text{comp}} \left( \max_p |\{i \mid \mathbf{r}_i \in p\}| \right) + t_{\text{comm}} \left( \max_p |\{i \mid \|\mathbf{r}_i - \partial p\| < r_c\}| \right) \\ + t_{\text{latency}} \left( \max_p [N_{\text{message}}(p)] \right)$$

# Computational-Space Decomposition

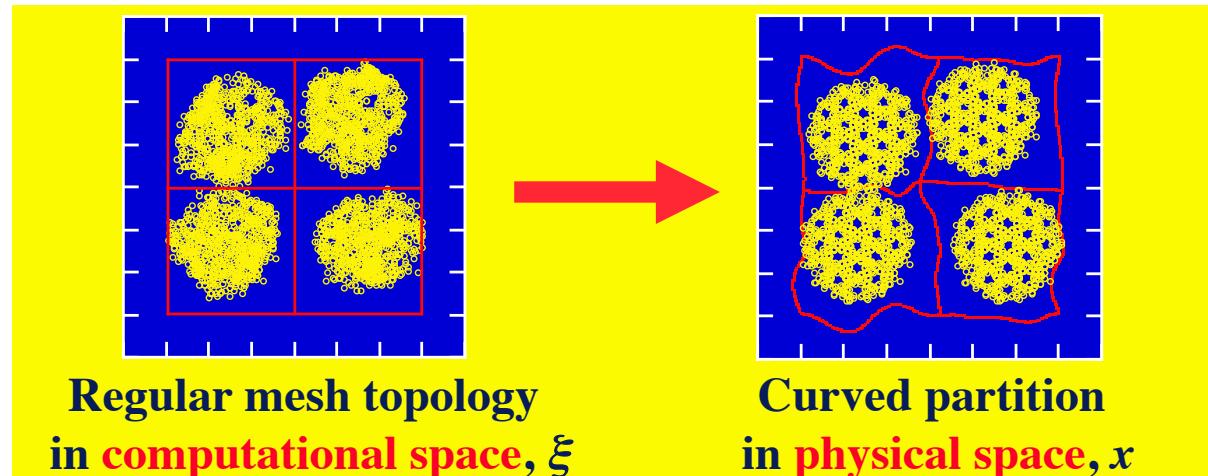
Topology-preserving “computational-space”  
decomposition in curved space

Curvilinear coordinate transformation

$$\xi = \mathbf{x} + \mathbf{u}(\mathbf{x})$$

Particle-processor mapping: regular 3D mesh topology

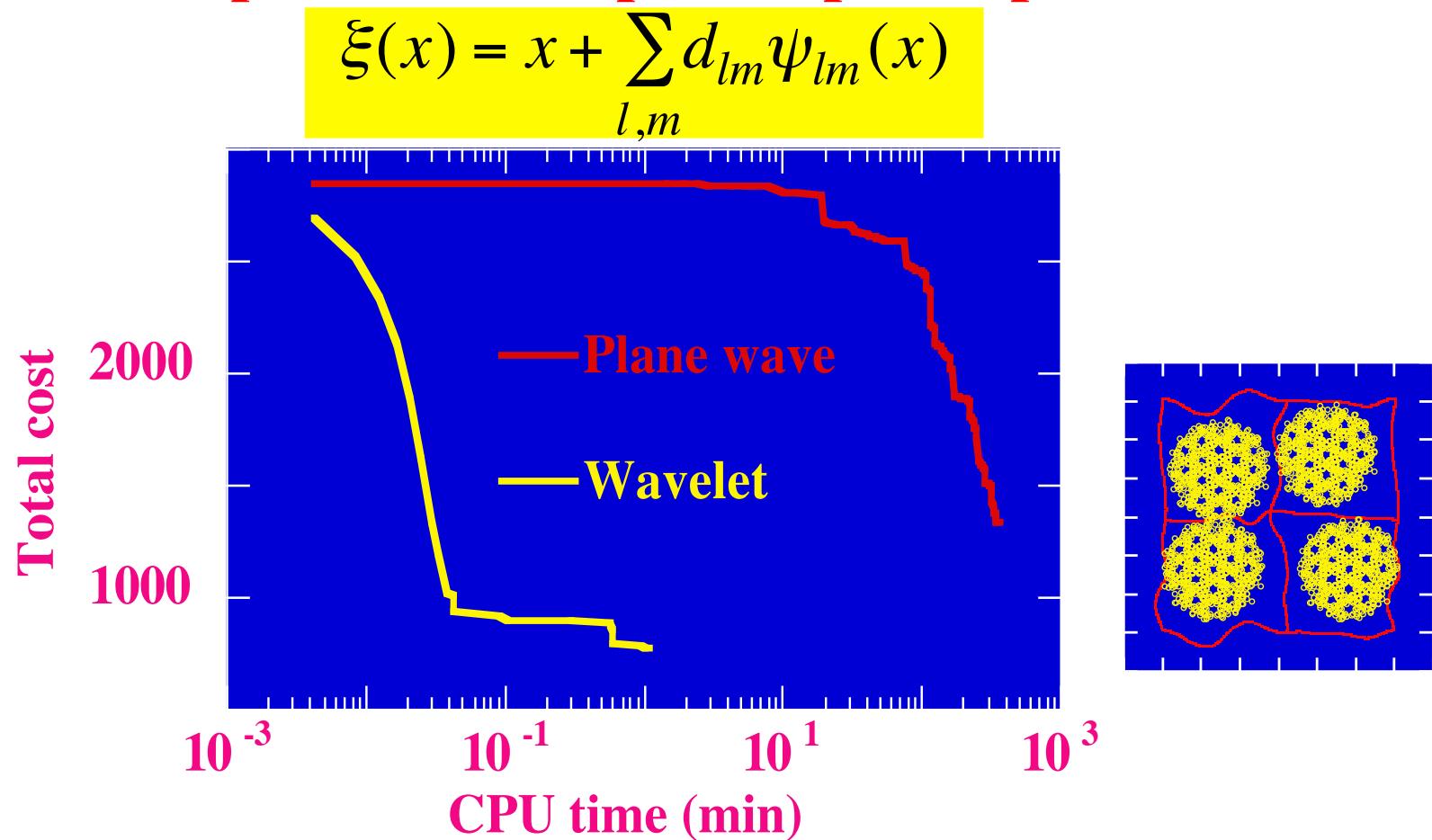
$$\begin{cases} p(\xi_i) = p_x(\xi_{ix})P_yP_z + p_y(\xi_{iy})P_z + p_z(\xi_{iz}) \\ p_\alpha(\xi_{i\alpha}) = \lfloor \xi_{i\alpha} P_\alpha / L_\alpha \rfloor \quad (\alpha = x, y, z) \end{cases}$$



A. Nakano & T. J. Campbell, *Parallel Comput.* **23**, 1461 ('97)

# Wavelet-based Adaptive Load Balancing

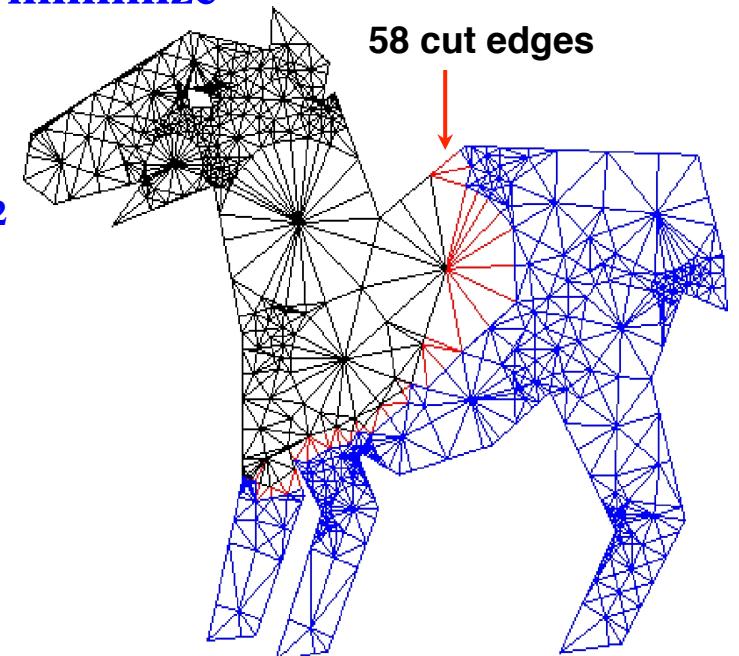
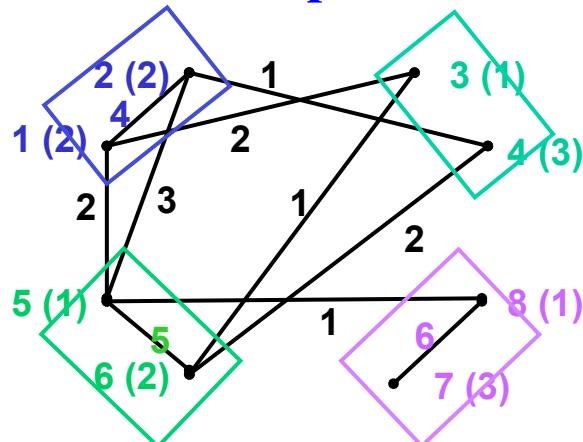
- Simulated annealing to minimize the load-imbalance & communication costs,  $E[\xi(x)]$
- Wavelet representation speeds up the optimization



A. Nakano, *Concurrency: Practice and Experience* 11, 343 ('99)

# Load Balancing as Graph Partitioning

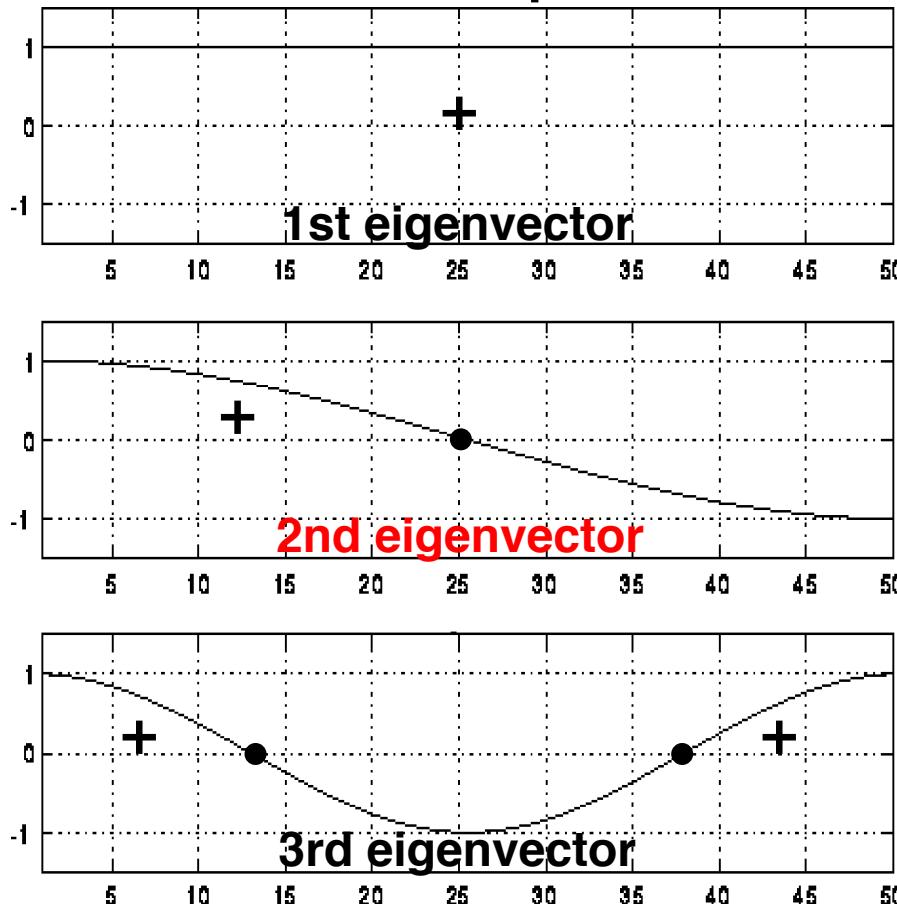
- Need: Decompose tasks without spatial indices
- Graph partitioning: Given a graph  $G = (N, E, W_N, W_E)$ 
  - $N$ : node set =  $\{j \mid \text{tasks}\}$
  - $W_N$ : node weights =  $\{w_N(j) : \text{task costs}\}$
  - $E$ : edge set =  $\{(j,k) \mid \text{messages from } j \text{ to } k\}$
  - $W_E$ : edge weights =  $\{w_E(j,k) : \text{message sizes}\}$
- choose a partition  $N = N_1 \cup N_2 \cup \dots \cup N_P$  to minimize
  - $\max_p \{\sum_{j \in N_p} w_N(j)\}$
  - $\max_{(p,q)} \{\sum_{j \in N_p, k \in N_q} w_E(j,k)\}$
- Graph bisection: Special case of  $N = N_1 \cup N_2$
- Choosing optimal partitioning is known to be NP-complete → need heuristics



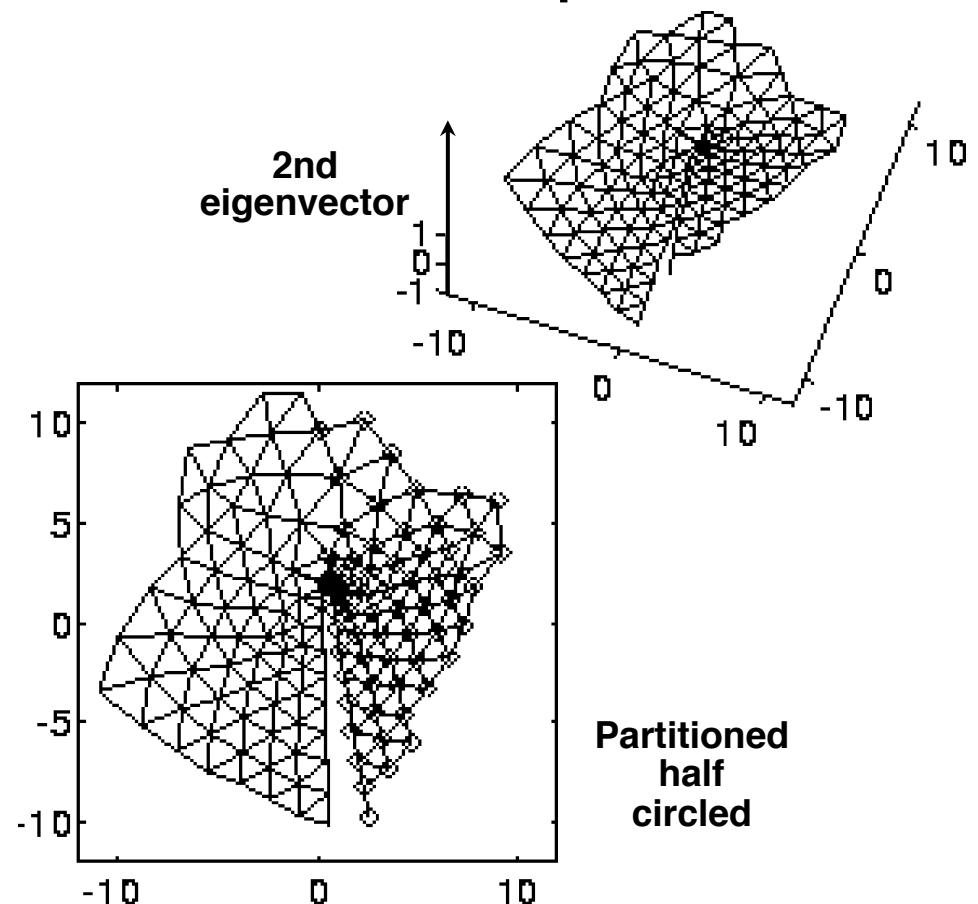
# Spectral Bisection: Motivation

1. Graph as point masses connected via harmonic springs
2. The node of the eigenvector of the Hessian matrix,  $\partial^2 V / \partial x^2$ , corresponding to the 2nd smallest eigenvalue separates the graph into 2

1D example



2D example



# Spectral Bisection

Laplacian matrix:

$L(G)$  of a graph  $G(N,E)$  is an  $|N|$  by  $|N|$  symmetric matrix:

- $L(G)(i,i) = \text{degree of node } i$  (number of incident edges)
- $L(G)(i,j) = -1$  if  $i \neq j$  and there is an edge  $(i,j)$
- $L(G)(i,j) = 0$  otherwise

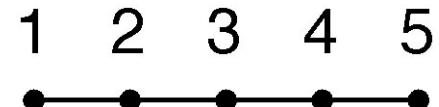
Theorems:

1. The eigenvalues of  $L(G)$  are nonnegative:  
 $\lambda_1 = 0 \leq \lambda_2 \leq \dots \leq \lambda_N$ )
2.  $\lambda_2(L(G)) \neq 0$  if and only if  $G$  is connected

Spectral bisection algorithm:

1. Compute eigenvector  $v_2$  corresponding to  $\lambda_2(L(G))$
2. For each node  $i$  of  $G$ 
  - a. if  $v_2(i) < 0$ , put node  $i$  in partition  $N-$
  - b. else put node  $i$  in partition  $N+$

Example



1    2    3    4    5

$$\begin{bmatrix} 1 & -1 \\ -1 & 2 & -1 \\ & -1 & 2 & -1 \\ & & -1 & 2 & -1 \\ 5 & & & -1 & 1 \end{bmatrix}$$

# $O(N)$ $\lambda_2$ Computation

## Lanczos algorithm:

- Given an  $N \times N$  symmetric matrix  $A$  (e.g.,  $L(G)$ ), compute a  $K \times K$  “approximation”  $T$  by performing  $K$  matrix-vector products, where  $K \ll N$
- Approximate  $A$ ’s eigenvalues & eigenvectors using  $T$ ’s

Choose an arbitrary starting vector  $r$

$b(0) = ||r||$

$j=0$

repeat

$j=j+1$

$q(j) = r/b(j-1)$

$r = A * q(j)$

$r = r - b(j-1) * v(j-1)$

$a(j) = v(j)^T * r$

$r = r - a(j) * v(j)$

$b(j) = ||r||$

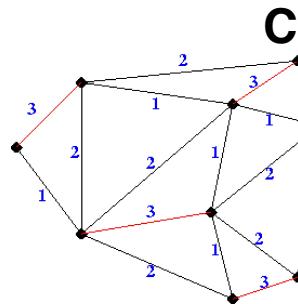
until convergence

$$T = \begin{bmatrix} a_1 & b_1 & & & \\ b_1 & a_2 & b_2 & & \\ \ddots & \ddots & \ddots & \ddots & \\ & b_{K-2} & a_{K-1} & b_{K-1} & \\ & & b_{K-1} & a_K & \end{bmatrix}$$

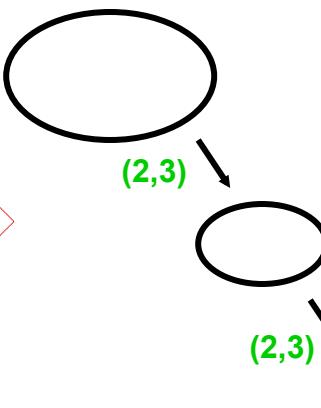
# Multilevel Partitioning

Recursively apply:

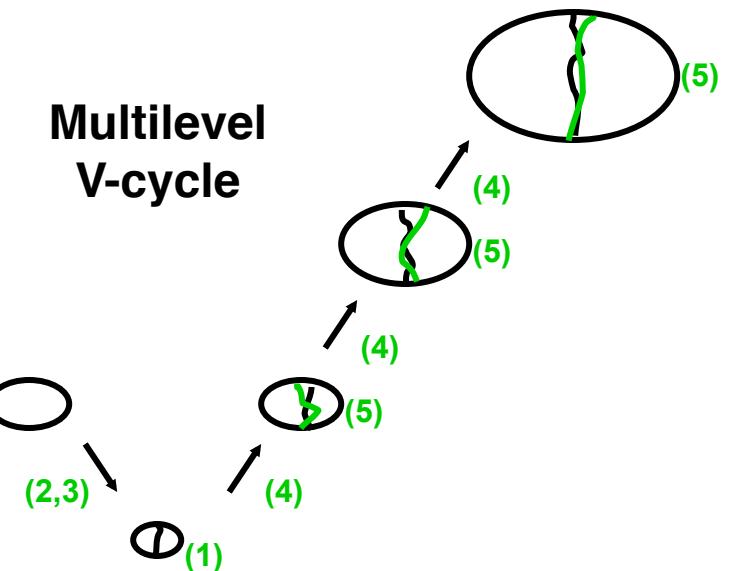
1. Replace  $G(N,E)$  by a coarse approximation  $G_c(N_c,E_c)$ , & partition  $G_c$
2. Use partition of  $G_c$  to obtain a rough partitioning of  $G$ , then uncoarsen & iteratively improve it



Coarsening



Multilevel  
V-cycle



```
(N+,N-) = Multilevel_Partition(N,E)
// returns N+ and N- where N = N+ ∪ N-
if |N| is small
  1 Partition G = (N,E) directly to get N = N+ ∪ N-
    Return (N+,N-)
  else
    2 Coarsen G to get an approximation G_c = (N_c,E_c)
    3 (N_c+,N_c-) = Multilevel_Partition(N_c,E_c)
    4 Expand (N_c+,N_c-) to a partition (N+,N-) of N
    5 Improve the partition (N+,N-)
    Return (N+,N-)
  endif
```

# An Extra Lesson

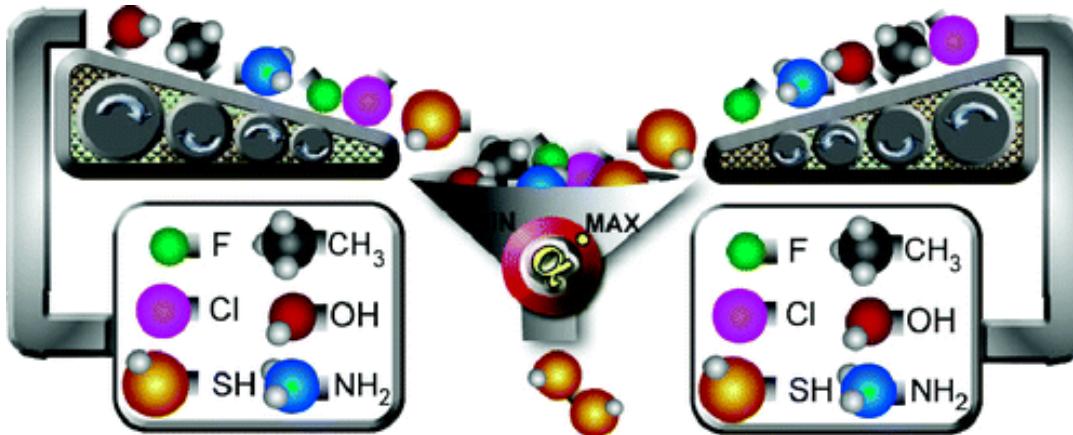
Continuous optimization is easier than discrete combinatorial optimization

- cf.* • Linear combination of atomic potentials (LCAP)

M. Wang *et al.*, *J. Amer. Chem. Soc.* **128**, 3228 ('06)

- Gradient-directed Monte Carlo (DGMC)

X. Hu, *J. Chem. Phys.* **129**, 064102 ('08)



$$\text{LCAP: } v(\vec{r}) = \sum_{\vec{R}, A} b_A^{\vec{R}} v_A^{\vec{R}}(\vec{r})$$

