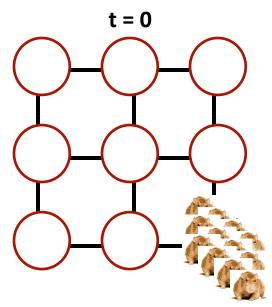
Assignment 3: GraphRats



Topics

- Application
- Implementation Issues
- Optimizing for Parallel Performance
- Useful Advice

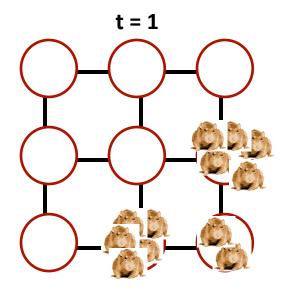
Basic Idea



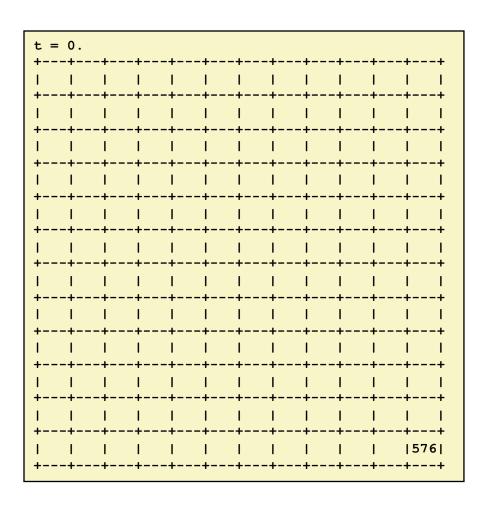
- Graph
 - K X K grid
- Initial State
 - Start with all R rats in corner

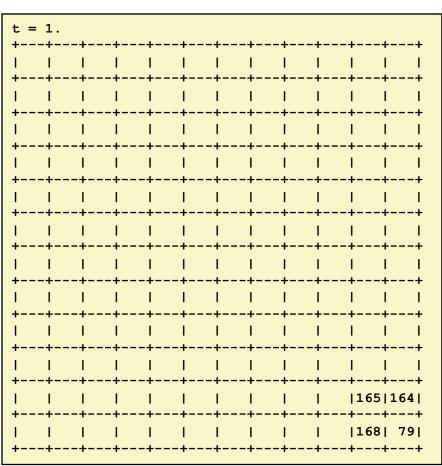
Transitions

- Each rat decides where to move next
 - Don't like crowds
 - But also don't like to be alone
- Weighted random choice

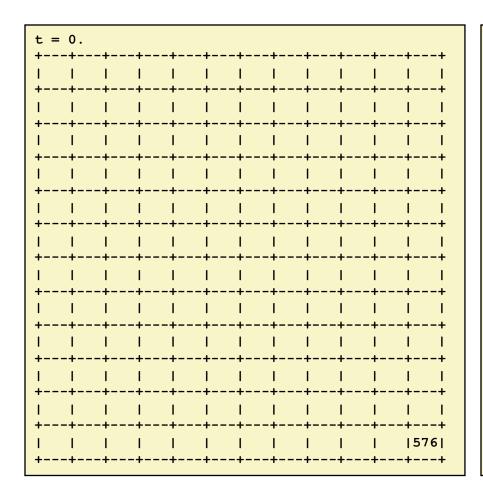


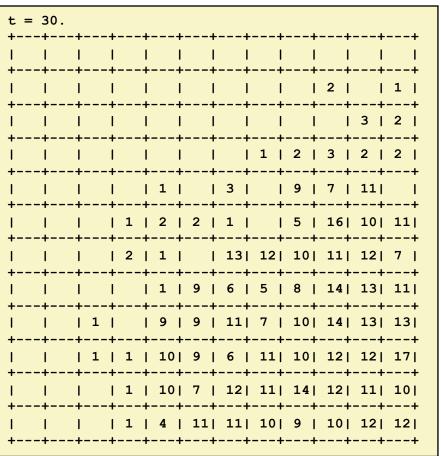
Node Count Representation (K = 12)





Simulation Example



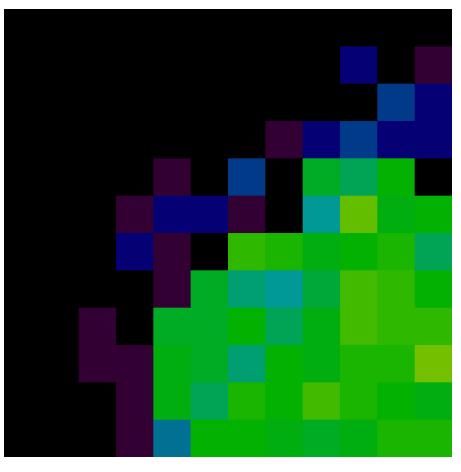


Visualizations

Text ("a" for ASCII)

t = 30.7 | 12 | 11 | 14 | 12 | 11 | 10 | | 1 | 4 | 11 | 11 | 10 | 9 | 10 | 12 | 12 |

Heat Map ("h")



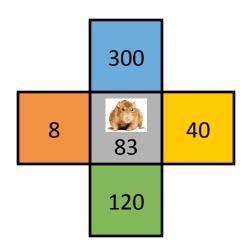
Running it yourself

```
linux> cd some directory
linux> git clone https//github.com/cmu15418/asst3-s19.git
linux> cd asst3-s19/code
Linux> make demoX
    X from 1 to 10
```

Demos

- 1: Text visualization, synchronous updates
- 2: Heap-map, synchronous updates

Determining Rat Moves



- Count number of rats at current and adjacent locations
 - Adjacency structure represented as graph
- Compute reward value for each location
 - Based on load factor l = count/average count
 - Ideal load factor (ILF) (varying)
 - α Fitting parameter (= 0.4)

Reward(
$$l$$
) = $\frac{1}{1 + (\log_2 [1 + \alpha(l - l^*)])^2}$

Reward Function

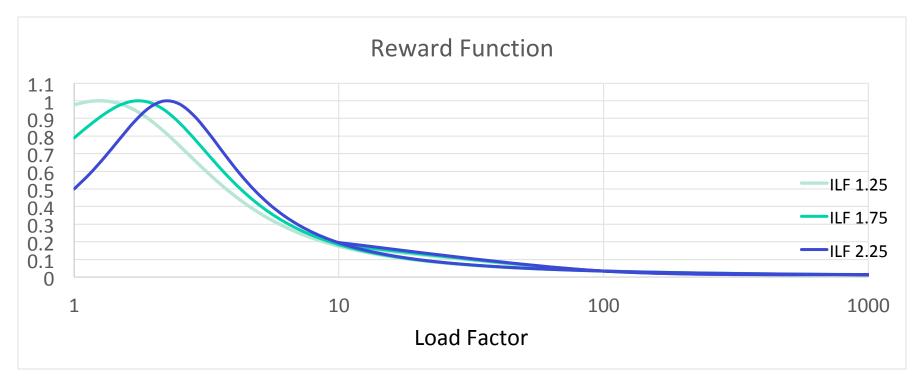
Reward(
$$l$$
) = $\frac{1}{1 + (\log_2 [1 + \alpha(l - l^*)])^2}$



- Maximized at ILF
 - Just above average population
 - Drops for smaller loads (too few) and larger loads (too crowded)

Reward Function (cont.)

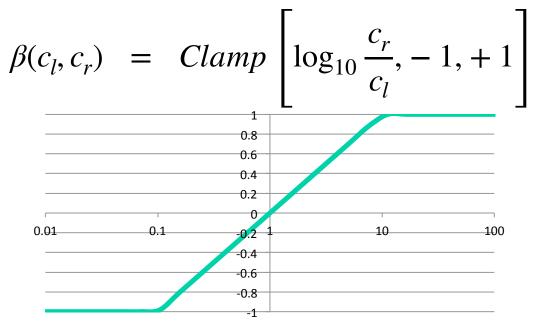
Reward(
$$l$$
) = $\frac{1}{1 + (\log_2 [1 + \alpha(l - l^*)])^2}$



- Falls off gradually
 - Reward(1000) = 0.0132

Computing Ideal Load Factor (ILF)

- Suppose node has count c_i and neighbor has count c_r
- Compute imbalance as



Computing Ideal Load Factor (cont.)

For node u with population p(u)

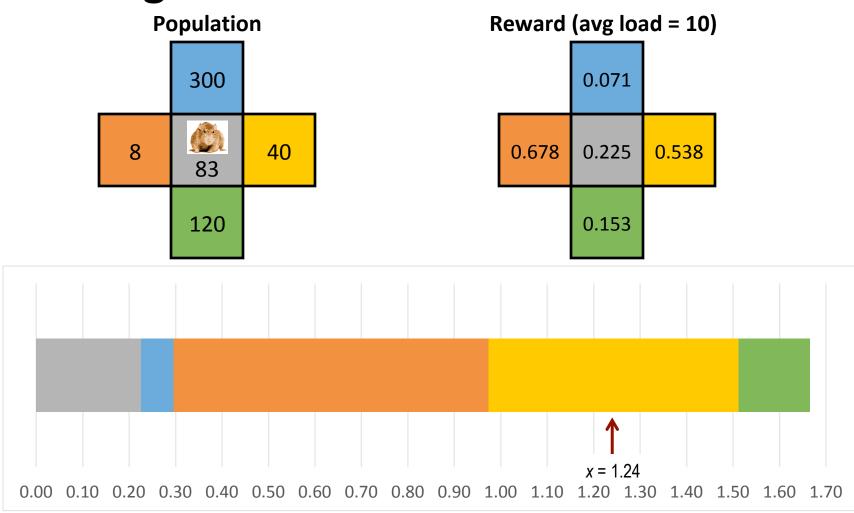
$$\hat{\beta}(u) = Avg_{(u,v)\in E} \left[\beta(p(u), p(v))\right]$$

Define ILF as

$$l^*(u) = 1.75 + 0.5 \cdot \hat{\beta}(u)$$

- Minimum 1.25
 - When adjacent nodes much less crowded
- Maximum 2.25
 - When adjacent nodes much more crowded
- Changes as rats move around

Selecting Next Move



- Choose random number between 0 and sum of rewards
- Move according to interval hit

Update Models

Synchronous

- Demo 2
- Compute next positions for all rats, and then move them
- Causes oscillations/instabilities

Rat-order

- Demo 3
- For each rat, compute its next position and then move it
- Smooth transitions, but costly

Batch

- Demo 4
- For each batch of B rats, compute next moves and then move them
- \blacksquare B = 0.02 * R
- Smooth enough, with better performance possibilities

What We Provide

- Python version of simulator
 - Demo 4
 - Very slow
- C version of simulator
 - Fast sequential implementation
 - Demo 5: 36X36 grid, 1,290 rats
 - Demo 6: 180X180 grid, 1,036,800 rats
 - That's what we'll be using for benchmarks!
- Generate visualizations by piping C simulator output into Python simulator
 - Operating in visualization mode
 - See Makefile for examples

Correctness

Simulator is Deterministic

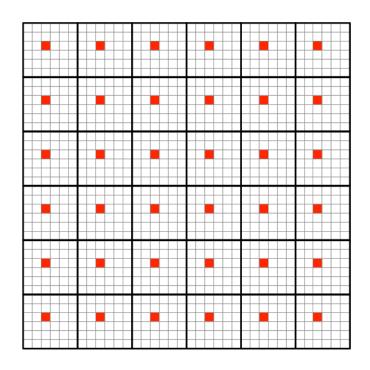
- Global random seed
- Random seeds for each rat
- Process rats in fixed order

You Must Preserve Exact Same Behavior

- Python simulator generates same result as C simulator
- Use regress.py to check
 - Only checks small cases
 - Useful sanity check
- Benchmark program compares your results to reference solution
 - Handles full-sized graphs

Graphs: Tiled (Demos 1-6)

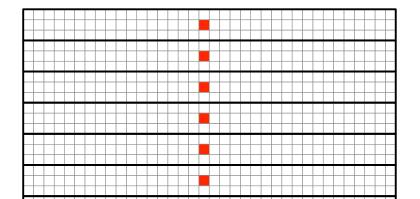
Rats spread quickly within region More slowly across regions Hub nodes tend to have high counts



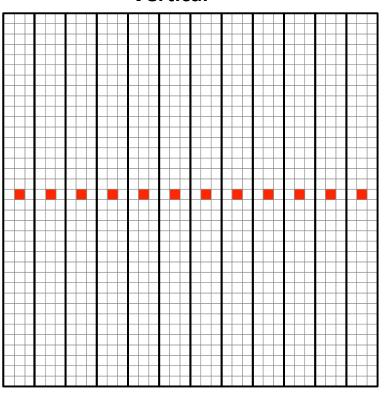
- Base grid
 - K X K nodes, each with nearest neighbor connectivity
- Hub (red) nodes connect to all other nodes in region
- For K = 180
 - Most nodes have degree ≤ 5
 - Hubs have degree 899

Other graphs





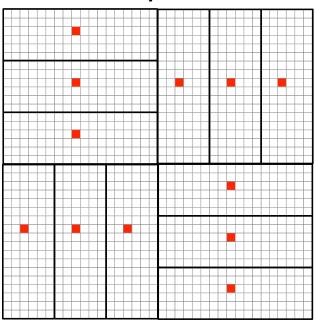
Vertical



- Larger regions
- k = 180: Max degree = 2,699

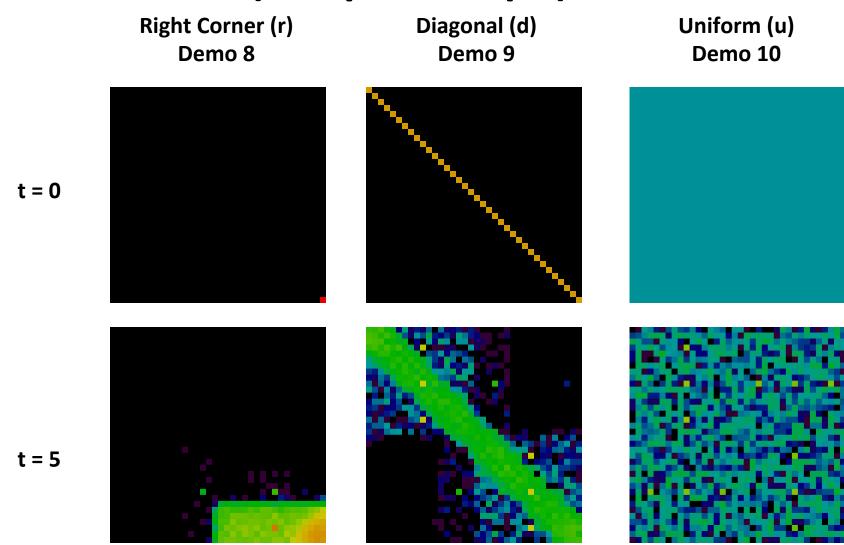
Other graphs





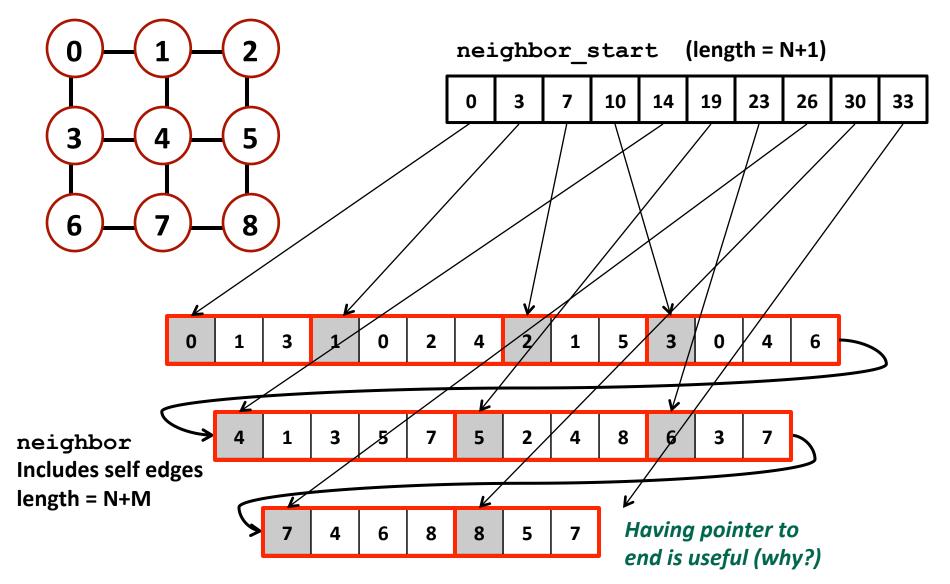
- Larger regions
- k = 180: Max degree = 2,699

Initial States (Parquet Graph)



Graph Representation

N node, M edges



Sample Code

- From sim.c
- Compute reward value for node

```
/* Compute weight for node nid */
static inline double compute_weight(state_t *s, int nid)
{
   int count = s->rat_count[nid];
   double ilf = neighbor_ilf(s, nid);
   return mweight((double) count/s->load_factor, ilf);
}
```

- Simulation state stored in state t struct
- Reward function computed by mweight

Sample Code

- From sim.c
- Compute sum of reward values for node
- Store for later reuse

```
/* Compute sum of weights in region of nid */
static inline double compute sum weight(state t *s, int nid)
   qraph t *q = s->q;
   double sum = 0.0;
    int eid;
    int eid start = g->neighbor start[nid];
    int eid end = g->neighbor start[nid+1];
    for (eid = eid start; eid < eid end; eid++) {</pre>
        int nbrnid = g->neighbor[eid];
        double w = compute weight(s, nbrnid);
        s->node weight[nbrnid] = w;
        sum += w;
    return sum;
```

Sample Code

Compute next move for rat

```
static inline int next random move(state t *s, int r)
    int nid = s->rat position[r];
    random t *seedp = &s->rat seed[r];
   double tsum = compute sum weight(s, nid);
   graph_t *g = s->g;
double val = next_random_float(seedp, tsum);
   double psum = 0.0;
    int eid;
    int eid_start = g->neighbor_start[nid];
    int eid end = q->neighbor start[nid+1];
    for (eid = eid start; eid < eid end; eid++) {</pre>
        psum += s->node weight[neighbor[eid]];
        if (val < psum) {</pre>
            return g->neighbor[eid];
```

Sequential Efficiency Considerations

- Consider move computation for rat at node with degree D
 - How many (on average) iterations of loop in next random move?
 - Is there a better way?
- Provided code uses many optimizations
 - Precompute weights at start of batch
 - Fast search

Finding Parallelism

Sequential constraints

- Must complete time steps sequentially
- Must complete each batch before starting next
 - ILF values and weights then need to be recomputed

Sources of parallelism

- Over nodes
 - Computing ILFs and reward functions
- Over rats (within a batch)
 - Computing next moves
 - Updating node counts

Performance Measurements

Nanoseconds per move (NPM)

- R rats running for S steps
- Requires time T
- NPM = $10^9 * T / (R * S)$
- Reference solution:
 - 665 NPM for 1 thread
 - 84 NPM for 12 threads
 - 7.9 X speedup

Performance Targets

Benchmarks

- 6 combinations of graph/initial state
- Each counts 15 points

Target performance

- T = measured time
- T_r = time for reference solution
- $T_r / T = How well you reach reference solution performance$
 - Full credit when > 0.9
 - Partial when ≥ 0.5

Machines

Latedays cluster

- 16 worker nodes + 1 head node
- Each is 12-core Xeon processor (dual socket with 6 cores each)
- You submit jobs to batch queue
- Assigned single processor for entire run
- Python script provided

Code Development

- OK to do code development and testing on other machines
- But, they have different performance characteristics
- Make sure to use 6 or 12 threads to ensure correct partitioning of nodes across processors

Instrumenting Your Code

- How do you know how much time each activity takes?
 - Create simple library using cycletimer code
 - Bracket steps in your code with library calls
 - Use macros so that you can disable code for maximum performance

```
START_ACTIVITY(ACTIVITY_NEXT);
#pragma omp parallel for schedule(static)
for (ri = 0; ri < local_count; ri++) {
    int rid = ri + local_start;
    s->rat_position[rid] = fast_next_random_move(s, rid);
}
FINISH_ACTIVITY(ACTIVITY_NEXT);
```

Evaluating Your Instrumented Code

1 thread

```
194 ms
              1.0 %
                        startup
             11.1 %
2077 ms
                        compute weights
             21.6 %
4029 ms
                        compute sums
             62.8 %
11733 ms
                        find moves
             3.5 %
  651 ms
                        set ops
    3 ms
              0.0 %
                        unknown
```

12 threads

```
192 ms
             3.2 %
                       startup
 426 ms
            7.0 %
                       compute weights
            15.5 %
 940 ms
                       compute sums
            52.3 %
                       find moves
3168 ms
            21.9 %
1325 ms
                       set ops
   2 ms
             0.0 %
                       unknown
```

- Can see which activities account for most time
- Can see which activities limit parallel speedup

Some Logos



GraphChi: Going small with GraphLab



