



Scaling Agent-based Simulation of Contagion Diffusion over Dynamic Networks on Petascale Machines

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Contagion Diffusion

- The problem we are trying to solve
 - Contagion propagation across large interaction networks
 - ~ 300 million nodes, $\sim 1.5/70$ billion edges
- Examples
 - Infectious Disease
 - Norms and Fads (e.g., Smoking, Obesity)
 - Digital viruses (e.g., computer viruses, cell phone worms)
 - Human immune system modeling



EpiSimdemics

- EpiSimdemics is an individual-based modeling environment
 - Each individual is represented based on synthetic population of US
 - Each interaction between two co-located individuals is represented
- Uses a people-location bipartite graph as the underlying network.
- Planned: Add people-people graph for direct interactions
- Features
 - Time dependent and location dependent interactions
 - A scripting language to specify complex interventions
 - PTTS representation of disease and behavior



Example Person-Person Graph

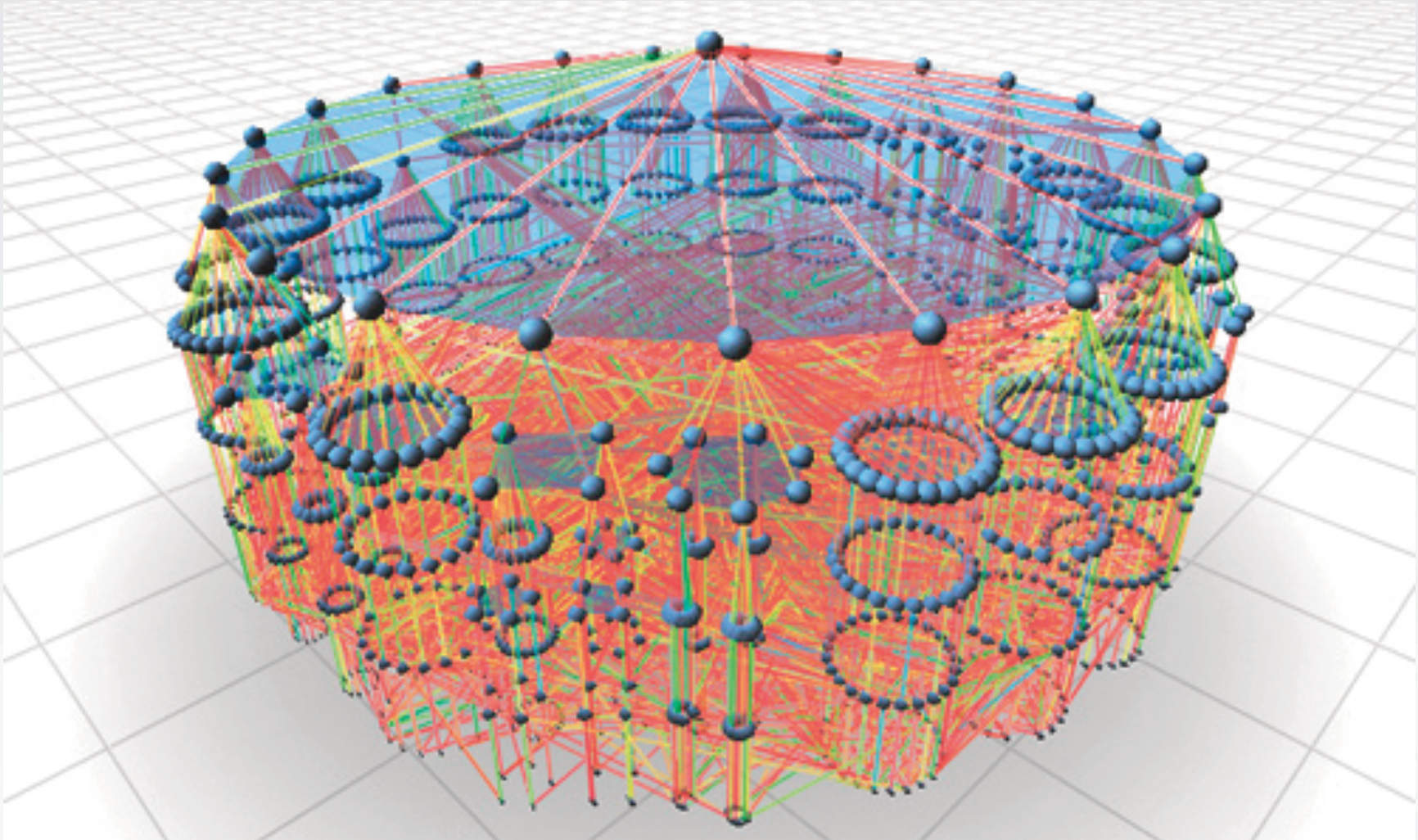


Image courtesy SDSC

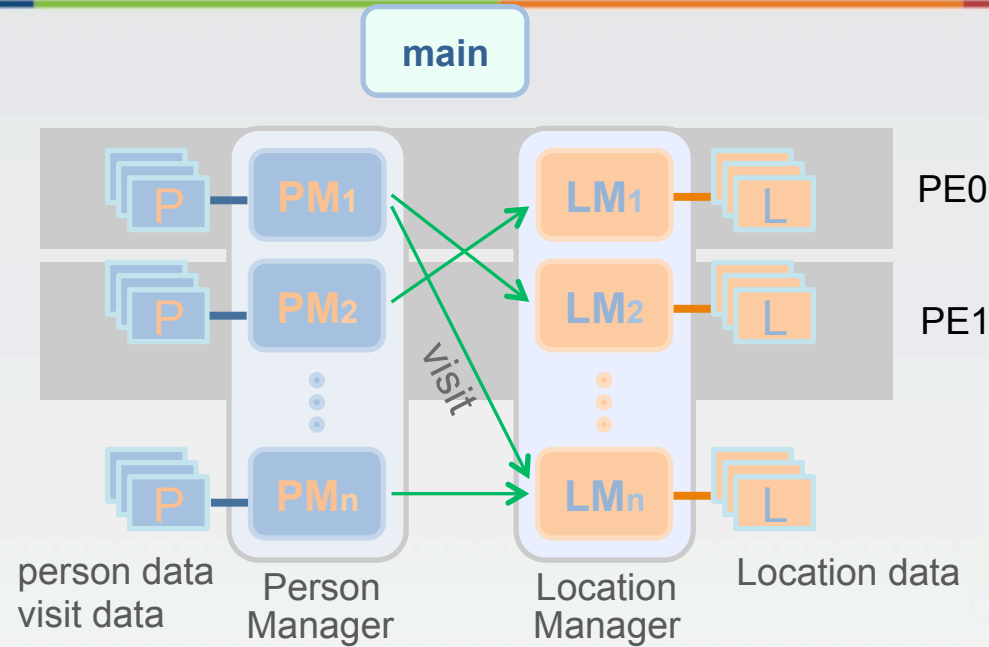


EpiSimdemics Algorithm

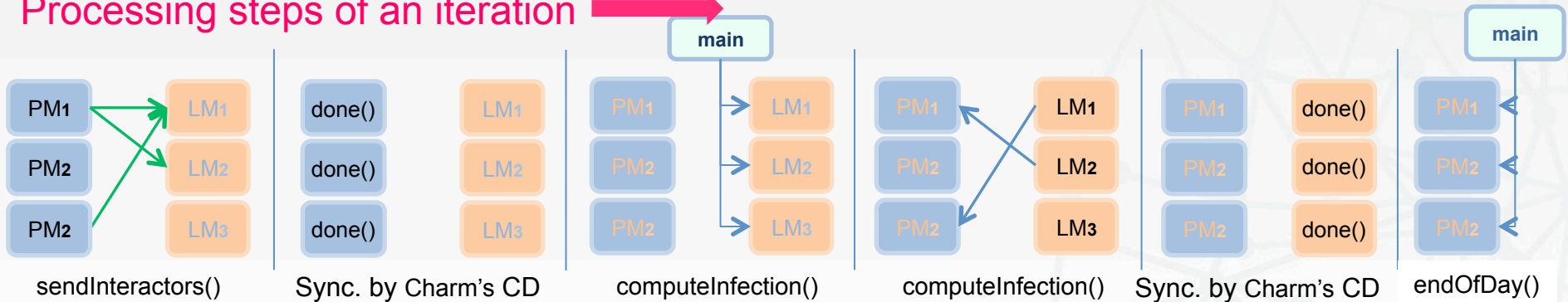
- For each timestep (e.g., a day)
 - In parallel, each person
 - Determines where they will go
 - Send a message to each location they will visit
 - In parallel, each location
 - Converts each message into an event pair
 - Calculates probability of infection between each co-located pair of infectious, susceptible people
 - Sends message to each newly infected person
 - In parallel, each infected person updates state
 - Global simulation state is updated



Charm Implementation

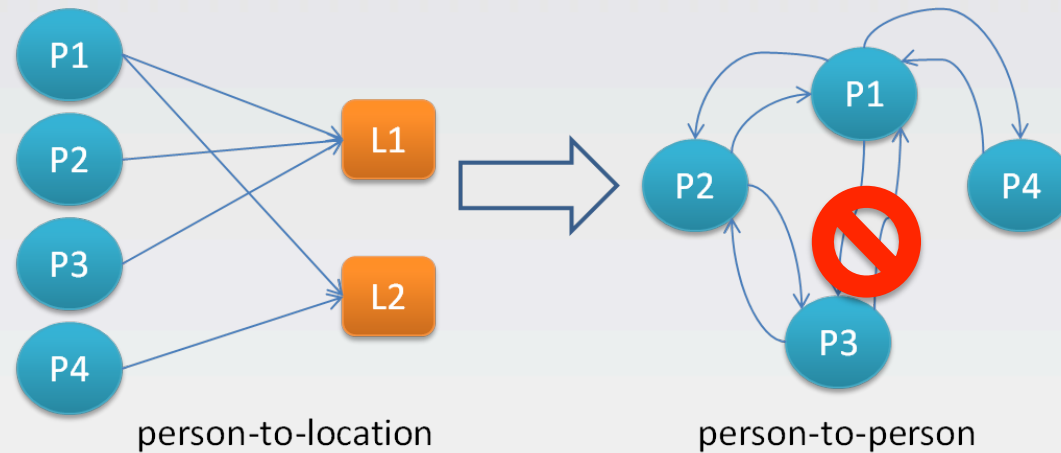


Processing steps of an iteration





Data organization



- P-L graph explicit, defines communication
- P-P graph implicit, defines computation, 50x more edges
- Both graphs evolve over time
- US Population
 - 270 million people, 70 million locations
 - 1.5 billion edges P-L graph
 - ~75 billion edges P-P graph (potential interactions/step)



Complex, Layered Interventions

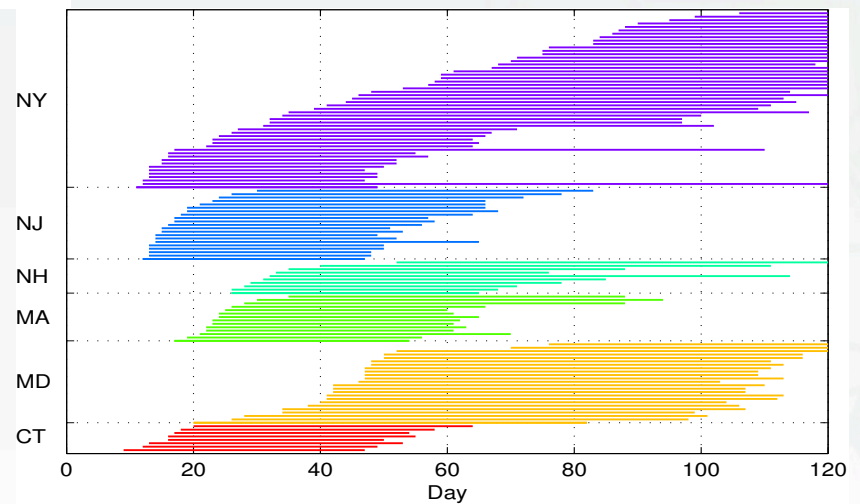
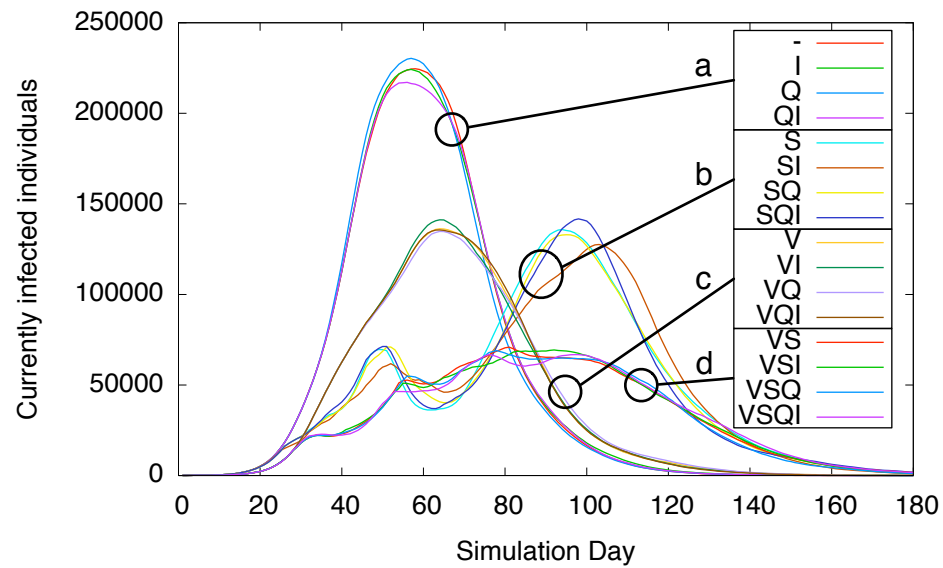
Intervention	Population	Compliance	When
Vaccination	Adult Children Crit Workers	25% 60% 100%	Day 0
School	Closure Reopen	60%	1.0% Children diagnosed (by county)
Quarantine	Crit Workers	100%	1.0% adults diagnosed
Self Isolate	All	20%	2.5% adults diagnosed

```
# stay home when symptomatic.  
intervention symptomatic  
set num_symptomatic++  
apply diagnose with prob=0.60  
schedule stayhome 3  
  
trigger disease.symptom >= 2  
apply symptomatic
```

```
# vaccinate 25% of adults  
intervention vaccinate_adult  
treat vaccine  
set num_vac_adult++  
  
trigger person.age > 18  
apply vaccinate_adult with prob=0.25
```



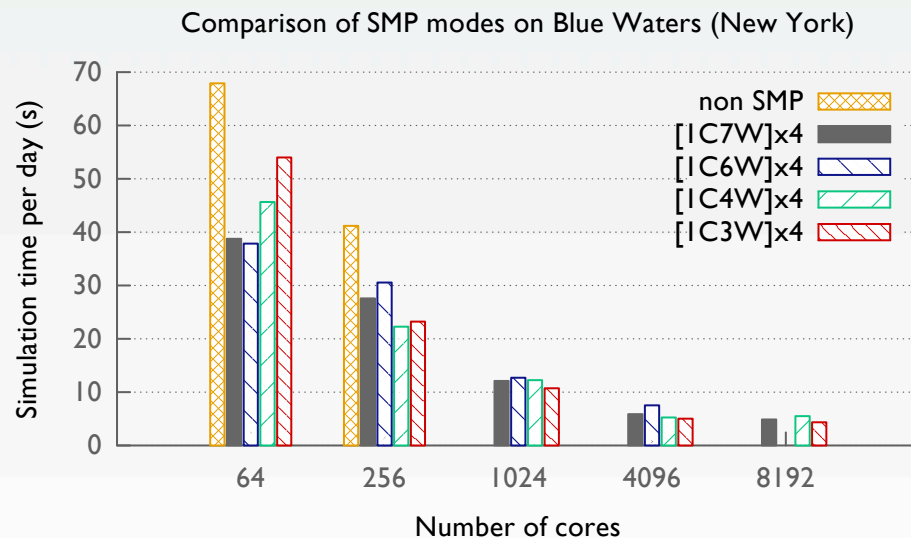

Effects of Interventions





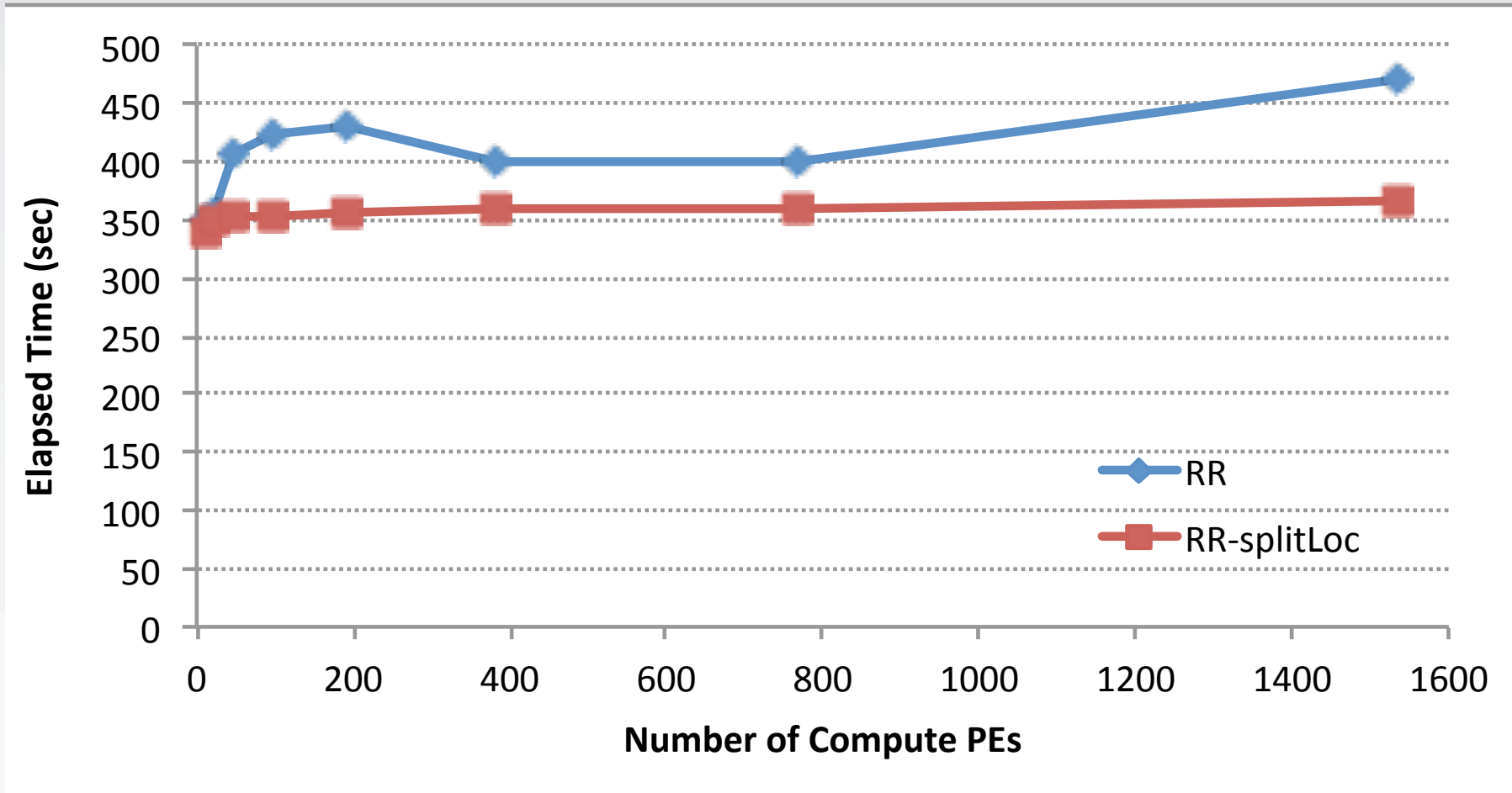
BlueWaters Setup

- Charm++ SMP mode
- Gemini network layer
- 4 processes/node
- 3 compute 1 comm threads per process
- Application based message coalescence





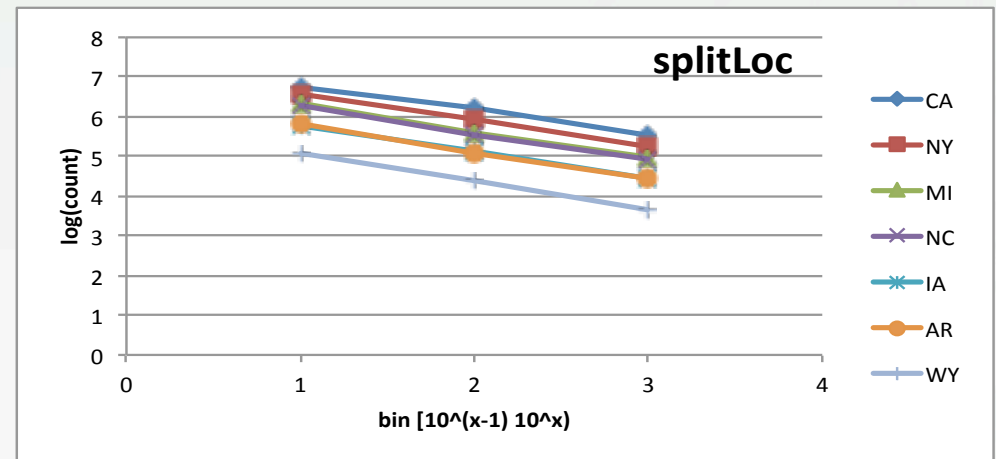
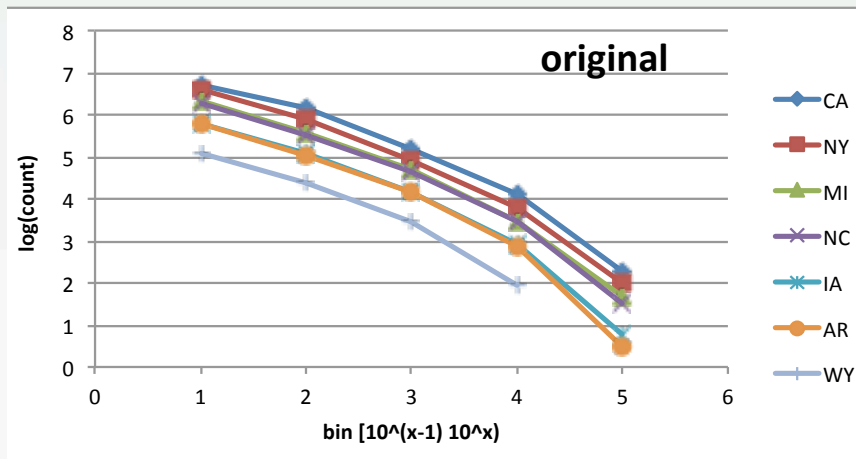
Weak Scaling





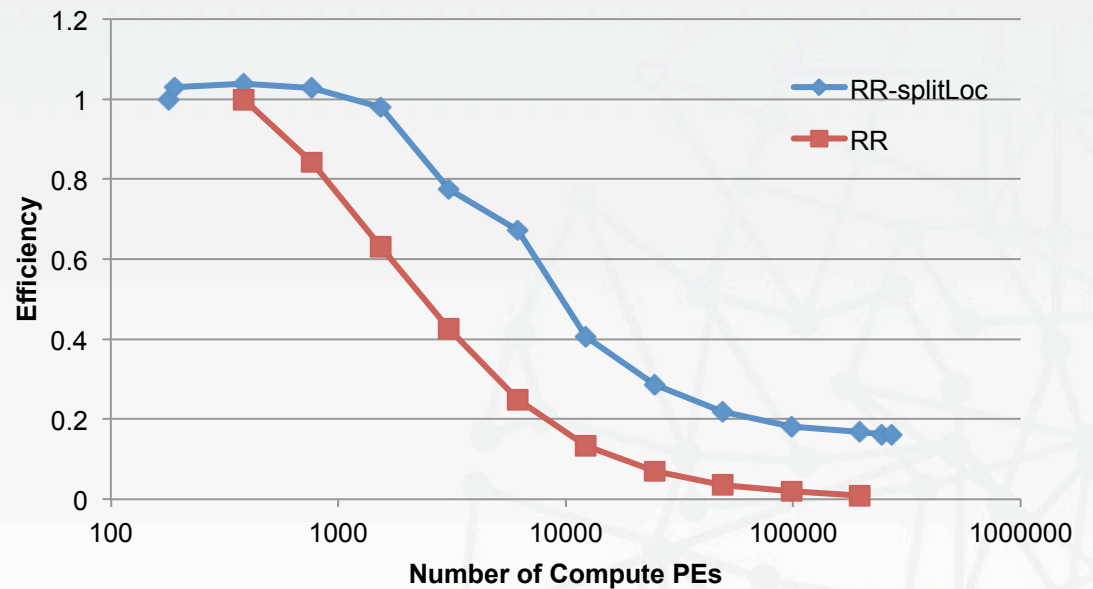
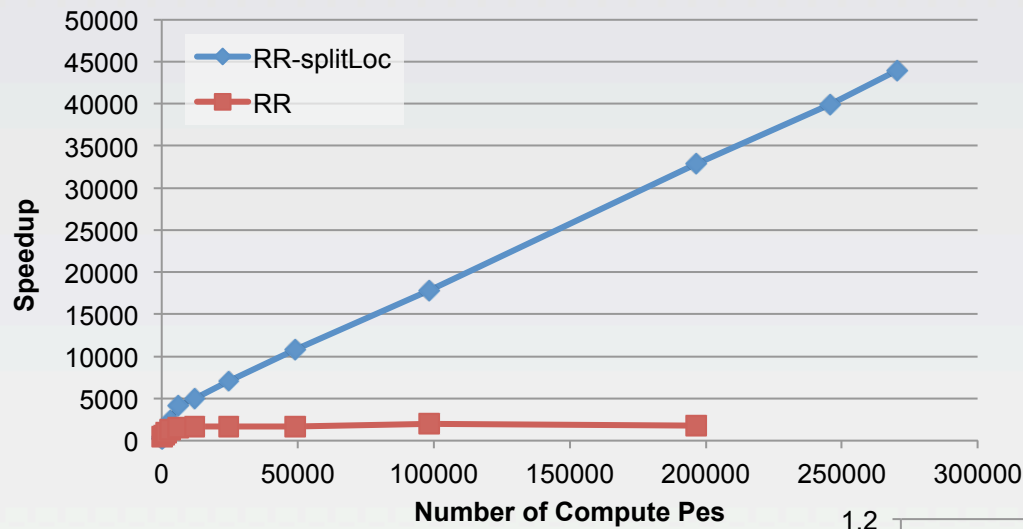
Location Granularity

- Location load depends on number of visits
- Location size follows power law
- Not apparent until running at scale





Scaling for US Population





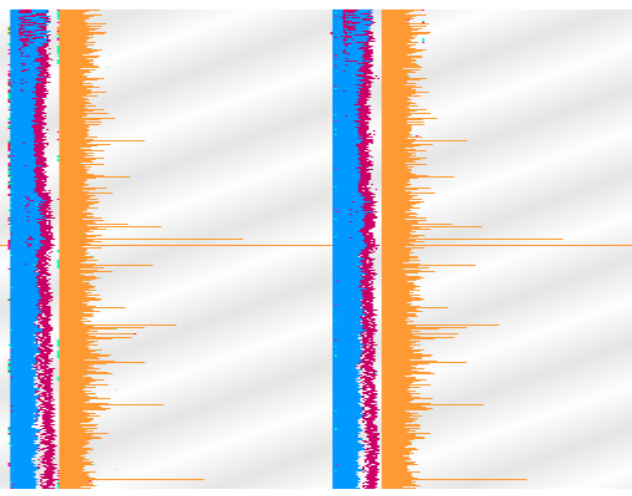
Static Partitioning

- Round Robin
 - Random distribution
 - Low overhead
 - Works well for small geographic areas (metro area)
- Graph Partitioner
 - Metis based partitioning
 - Multi-constraint (two phases separated by sync)
 - Higher Overhead
 - Helps as geographic area increases (state, national)

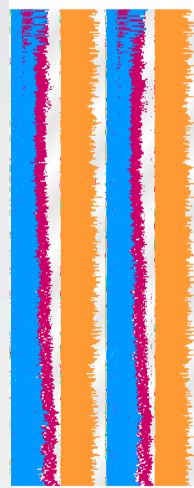


Static Partitioning - Results

RR 0.42 sec/step

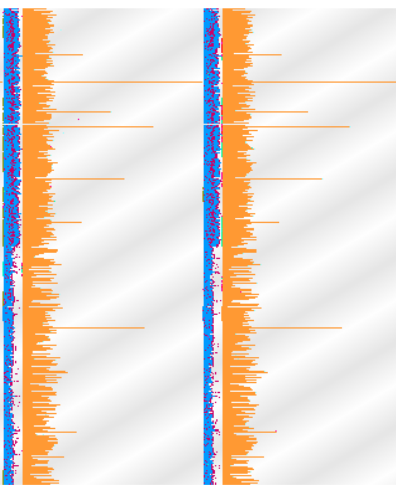


RR-splitLoc 0.12 sec/step

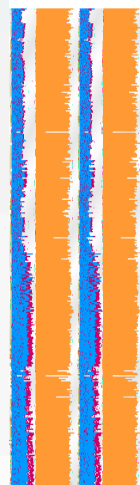


SendInteractor(). Person computation to generate visit messages
AddVisitMessage(). Location side message receive handling.
ComputeInfections(). Location computation of interaction among visitors

GP 0.37 sec/step



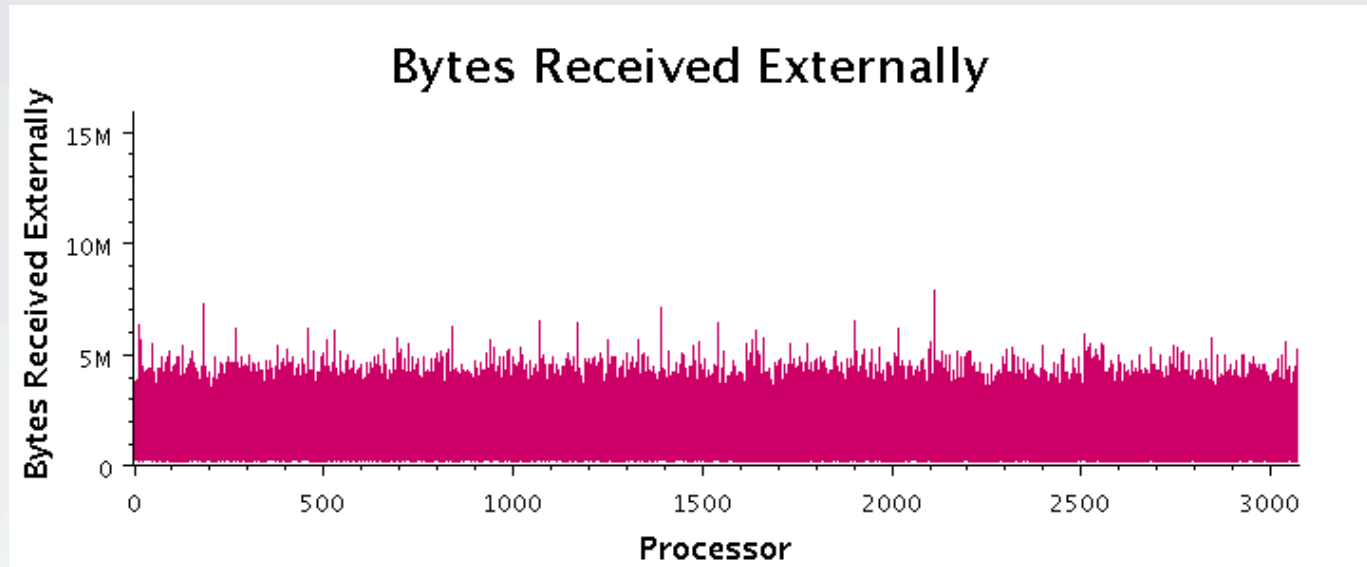
GP-splitLoc 0.09 sec/step



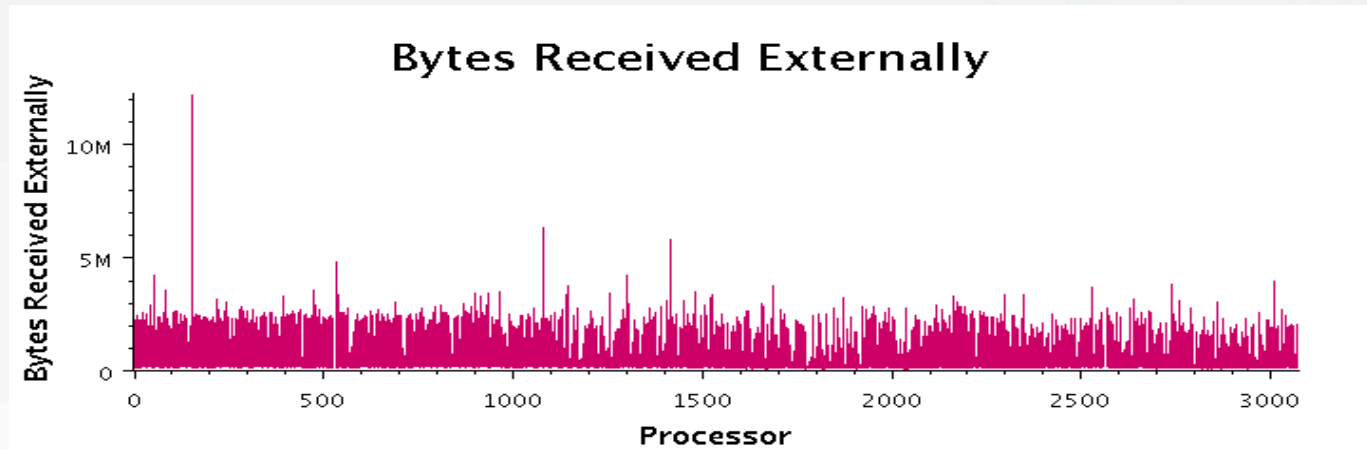


Message Volume

Round Robin



Graph Partitioner



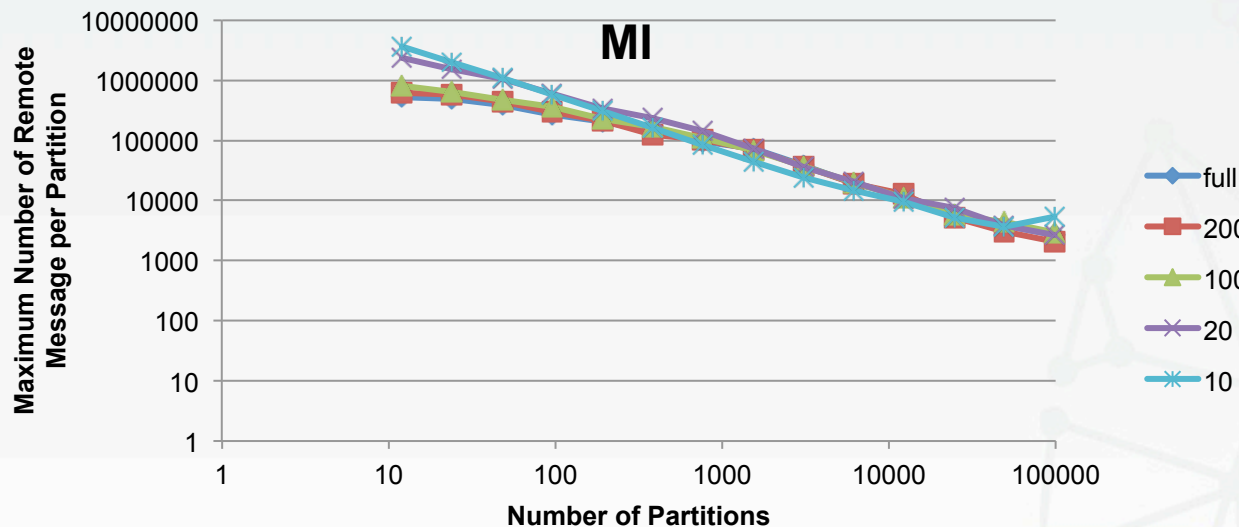
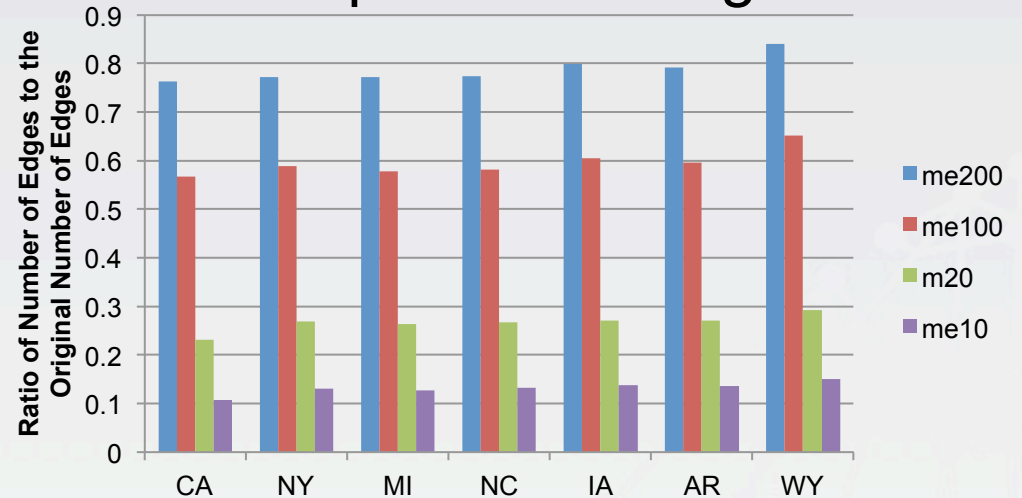


Graph Sparsification

Goal: Improve runtime of Graph Partitioning

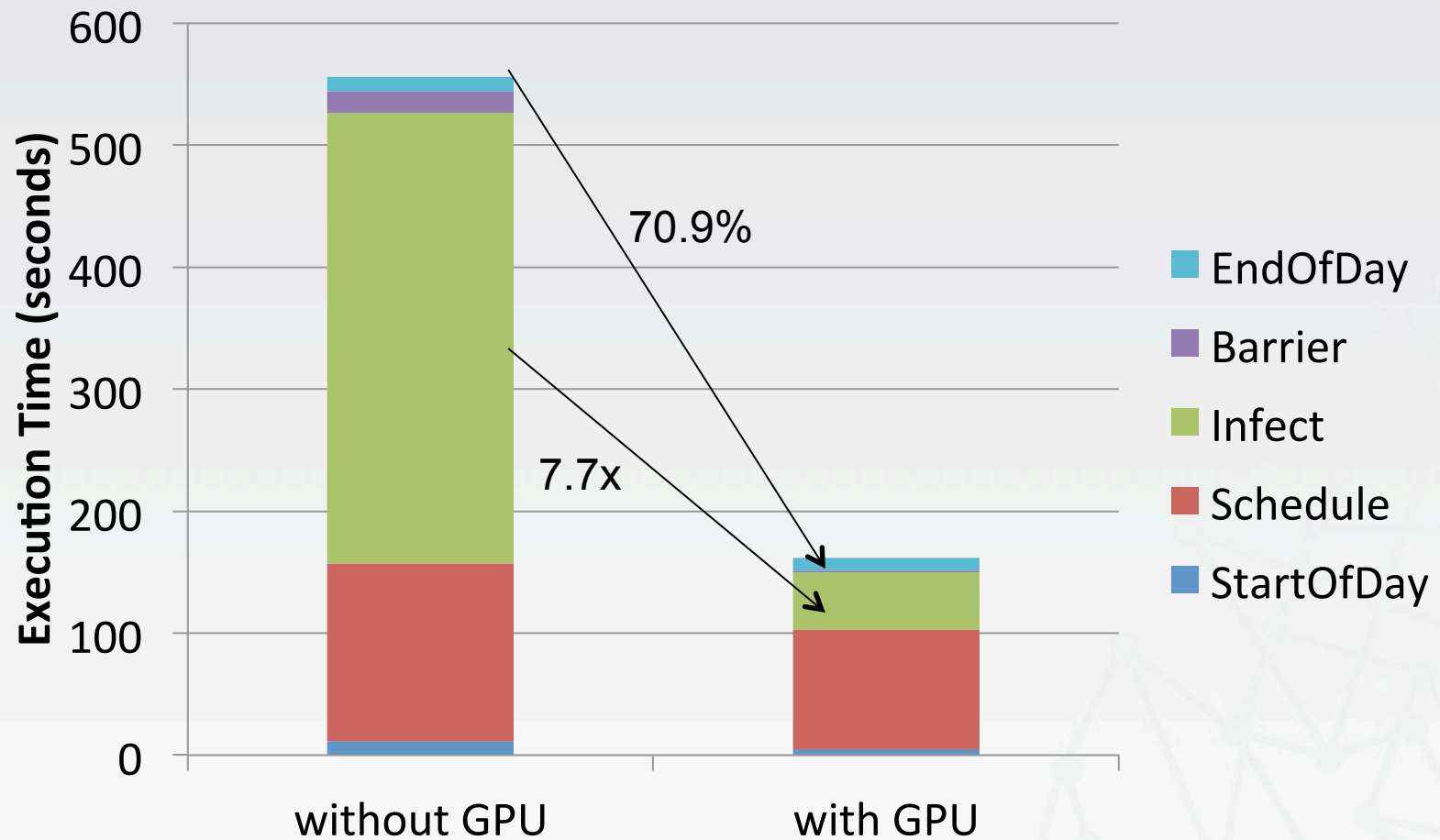
Procedure

- Randomly remove edges from high degree nodes
- Partition sparse graph
- Use full graph for execution





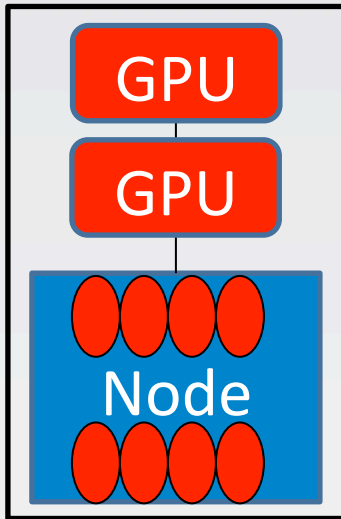
Impact of GPU Acceleration on Execution Profile



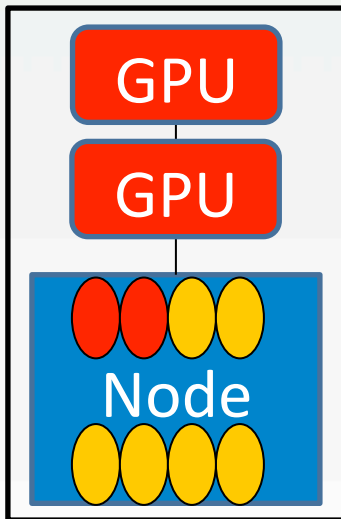
Assume 1CPU cores per GPU devices, in practice, CPU > GPU



GPU-CharmSimdemics Scenarios



- Scenario 1 – All chares from all CPU processes offload simultaneously to GPU
 - GPUs (Kepler) maintain tasks queue from different processes
 - Inefficient: CPUs will be idle waiting for GPU execution to complete



- Scenario 2 – Chares from only some select CPU processes offload to GPU
 - 1:1 ratio can be maintained between "GPU" processes and GPUs
 - But, "GPU" chares will finish sooner than "CPU" chares, i.e. load imbalance
 - Use LB methods of Charm++ to rebalance chares



Future Work

- Dynamic Load Balancing with semantic information
 - Prediction model based on past runs
 - Information from simulation state variables
 - Use dynamic interventions – more variable load
- Try Charm++ Meta Load Balancer
- Further improvements to initial partitioning
 - Minimize message imbalance as well as edge-cut
- Message reduction
- Sequential replicates to amortize data load time
- Scale to global population - 10 billion people



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