Speculative High-Performance Simulation

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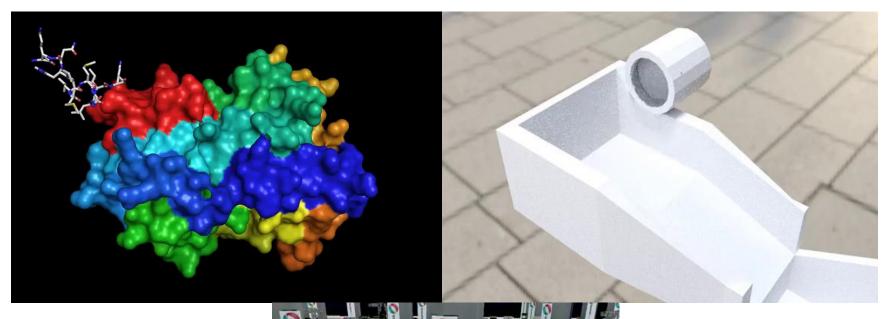


Simulation

- From latin *simulare* (to mimic or to fake)
- It is the imitation of a real-world process' or system's operation over time
- It allows to collect results long before a system is actually built (what-if analysis)
- It can be used to drive physical systems (symbiotic simulation)
- Widely used: medicine, biology, physics, economics, sociology, ...



Some Examples





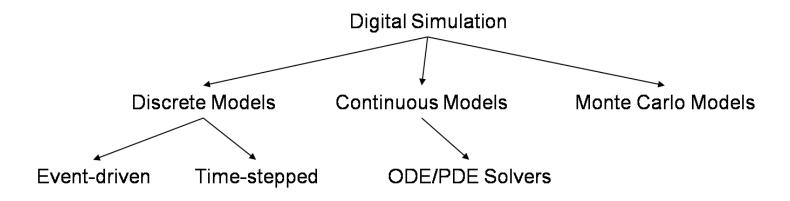




Main Categories of Simulation

- Continuous Simulation
- Monte Carlo Simulation
- Discrete-Event Simulation

Simulation Taxonomy







Wall-Clock Time vs Logical Time

- Two different notions of time are present in a simulation
- **Wall-Clock Time**: the *elapsed time* required to carry on a digital simulation (the shorter, the higher is the performance)
- Logical Time: the actual simulated time
 - Also referred to as simulation time





Continuous Simulation

- It is typically employed for modeling physical phenomena
 - Usually relies on a set of equations to be solved periodically
- Commonly physical phenomena are expressed via differential equations
- A continuous simulation involves repeatedly solving equations to update the *state* of the modeled phenomenon





An Example: Diffusion Equation

 Let's consider the Bidimensional Diffusion Equation Case:

$$\frac{\partial u}{\partial t} = \alpha \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

or, more compactly:

$$u_t = \alpha(u_{xx} + u_{yy})$$





An Example: Diffusion Equation

- We approximate u(x, y, t) by a discrete function $u_{i,j}^{(m)}$
 - $-x = i\Delta x$
 - $-y = i\Delta y$
 - $-t=i\Delta t$
- This approximation is not enough for simulation: we must be able to compute a *future* state starting from the *current one*
- We use finite difference to transform it into a recurrence relation





Finite Difference

- A finite difference is a mathematical expression of the form f(x+b) f(x+a)
 - Forward difference: $\Delta_h[f](x) = f(x+h) f(x)$
 - Backward difference: $\nabla_h[f](x) = f(x) f(x h)$
 - Central difference: $\delta_h[f](x) = f(x + \frac{1}{2}h) f(x \frac{1}{2}h)$
- Using finite difference, the *finite-difference method* can be applied to solve differential equations
- Finite differences are used to *approximate derivatives*: it is a discretization method



An Example: Diffusion Equation

 Applying finite (forward) difference approximations to the derivatives we obtain:

$$\frac{u_{i,j}^{(m+1)} - u_{i,j}^{(m)}}{\Delta t} = \alpha \left[\left(\frac{u_{i+1,j}^{(m)} - 2u_{i,j}^{(m)} + u_{i-1,j}^{(m)}}{(\Delta x)^2} \right) + \left(\frac{u_{i,j+1}^{(m)} - 2u_{i,j}^{(m)} + u_{1,j-1}^{(m)}}{(\Delta y)^2} \right) \right]$$

To simulate, we transform it into:

$$u_{i,j}^{(m+1)} = u_{i,j}^{(m)} + \alpha \Delta t \left[\left(\frac{u_{i+1,j}^{(m)} - 2u_{i,j}^{(m)} + u_{i-1,j}^{(m)}}{(\Delta x)^2} \right) + \left(\frac{u_{i,j+1}^{(m)} - 2u_{i,j}^{(m)} + u_{1,j-1}^{(m)}}{(\Delta y)^2} \right) \right]$$

• This gives us an expression of $u_{i,j}^{(m+1)}$



Stability of the Simulation

- This is an *approximation* of a continuous system
- Is the result correct *independently* of the selected time step?
- Stability reflects the sensitivity of Differential Equation solution to perturbations
- If the solutions are *stable*, they converge and perturbations are damped out
- When we step from an approximation to the next, we land on a different solution from what we started from





An Example: Diffusion Equation

• In case of 2D Heat Simulation, we rewrite u_t as:

$$u_{j,k}^{(m)} = u^{(m)} e^{i(\beta j \Delta x + \gamma k \Delta y)}$$

The resulting amplification factor becomes:

$$\rho(\beta,\gamma) = 1 + 2\alpha \frac{\Delta t}{\Delta x^2} (\cos(\beta \Delta x) - 1) + 2\alpha \frac{\Delta t}{\Delta y^2} (\cos(\gamma \Delta y) - 1)$$

Neumann boundary conditions lead to:

$$-1 \le \rho(\beta, \gamma) \le 1$$





An Example: Diffusion Equation

- We know that $-2 \le \cos(\beta \Delta x) 1 \le 0$ and $-2 \le \cos(\gamma \Delta y) 1 \le 0$
- The right-hand inequality holds for all β and γ
- The left-hand inequality leads to:

$$2\alpha \frac{\Delta t}{\Delta x^2} + 2\alpha \frac{\Delta t}{\Delta x^2} \le 1$$

$$\Delta t \leq \frac{1}{2\alpha} \left(\frac{\Delta x^2 \Delta y^2}{\Delta x^2 + \Delta y^2} \right)$$





How is this useful programmatically?

- Simulation is an approximation of reality
- We want our approximation to resemble reality as much as possible
- Setting a simulation time step such that:

$$\Delta t > \frac{1}{2\alpha} \left(\frac{\Delta x^2 \Delta y^2}{\Delta x^2 + \Delta y^2} \right)$$

gives a simulation which is *incorrect*





Initial and Boundary Conditions

- $u_{i,j}^{(m+1)}$ is derived using $u_{i,j}^{(m)}$
- Then, we must give a numerical value to $u_{i,i}^{(0)}$
- Furthermore, we must specify boundary conditions to the Laplacian
 - We can arbitrarily set it to 0

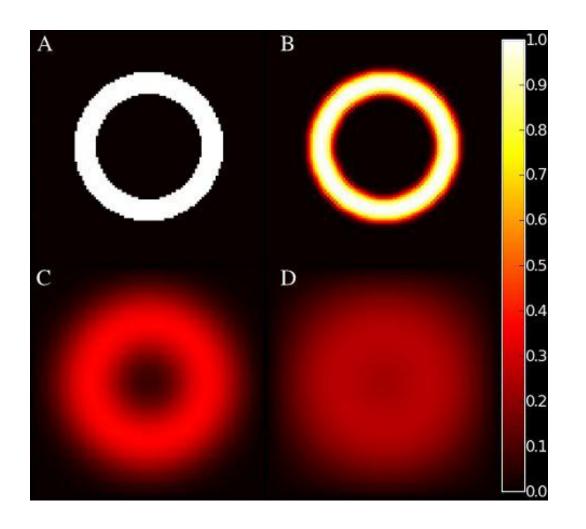
ring at (0.5, 0.5)



$$u_{i,j}^{(0)} = \left\{ egin{array}{ll} 1 & ext{if } 0.05 \leq (i\Delta x - 0.5)^2 + (j\Delta y - 0.5)^2 \leq 0.1 \\ 0 & ext{otherwise} \end{array}
ight.$$



Evolution of the System







Coding the Problem

- We repeatedly solve the differential equations
- We rely on a *loop* to do this:

```
for m in range(1, timesteps+1):
    recompute_u(u, ui)
```

 The code to update the state of the system looks like:

```
def recompute_u(u, ui):
    for i in range(1,nx-1):
        for j in range(1,ny-1):
            uxx = ( ui[i+1,j] - 2*ui[i,j] + ui[i-1, j] )/dx2
            uyy = ( ui[i,j+1] - 2*ui[i,j] + ui[i, j-1] )/dy2
            u[i,j] = ui[i,j]+dt*a*(uxx+uyy)
```



Coding the Problem: Initial Conditions

```
1 dx=0.01 # Interval size in x-direction.
  dy=0.01 # Interval size in y-direction.
 3
4 \text{ nx} = int(1/dx)
 5 \text{ ny} = \frac{\text{int}(1/\text{dy})}{1}
6
7 ui = sp.zeros([nx,ny])
8 u = sp.zeros([nx,ny])
9
  # Now, set the initial conditions (ui).
  for i in range(nx):
       for j in range(ny):
12
           if ((i*dx-0.5)**2+(j*dy-0.5)**2 <= 0.1)
13
               & ((i*dx-0.5)**2+(j*dy-0.5)**2>=.05)):
14
                   ui[i,j] = 1
15
```



EXAMPLE SESSION

Heat Diffusion Simulation in Python





What Lessons Have we Learnt?

- Before going distributed, we must be sure that the *sequential* implementation is efficient
- Stability conditions are not only a mathematician's concern!
- Continuous simulation is actually an approximation of the continuous behaviour of a system





Monte Carlo Simulation

- It is generally used to evaluate some property that is time independent
- It tries to explore densely the whole space of parameters of the phenomenon
 - Monte Carlo simulations sample probability distribution for each variable to produce hundreds or thousands of possible outcomes
- It is used to find (approximate) solutions of mathematical problems involving a high number of variables that cannot be easily solved analytically

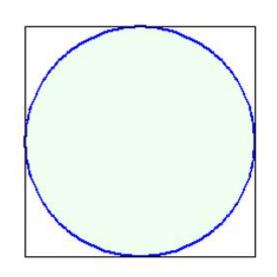




An Example: Computing π

- Let us consider a circle with *r*= 1
- The area of the circle is $\pi r^2 = \pi$
- The area of the sourrounding square is $(2r)^2 = 2^2 = 4$
- The ratio of the areas is:

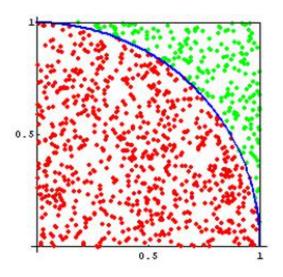
$$\rho = \frac{\pi r^2}{(2r)^2} = \frac{\pi}{4} = 0.7853981633974483$$





An Example: Computing π

- Randomly select points $\{(xi, yi)\}_{i=1}^n$ in the square
- Determine the ratio $\rho = \frac{m}{n}$
 - m is the number of points such that $x_i^2 + y_i^2 \le 1$
- Since $\rho = \frac{\pi}{4}$, then $\pi = \rho \cdot 4$







EXAMPLE SESSION

Monte Carlo PI Approximation





Event-Driven Programming

- Event-Driven Programming is a programming paradigm in which the flow of the program is determined by *events*
 - Sensors outputs
 - User actions
 - Messages from other programs or threads
- Based on a *main loop* divided into two phases:
 - Event selection/detection
 - Event handling
- Events resemble what interrupts do in hardware systems





Event Handlers

- An event handler is an asynchronous callback
- Each event represents a piece of application-level information, delivered from the underlying framework:
 - In a GUI events can be mouse movements, key pression, action selection, . . .
- Events are processed by an event dispatcher which manages associations between events and event handlers and notifies the correct handler
- Events can be queued for later processing if the involved handler is busy at the moment





Discrete Event Simulation (DES)

- A *discrete event* occurs at an instant in time and marks a change of state in the system
- DES represents the operation of a system as a chronological sequence of events
- If the simulation is run on top of a parallel/distributed system, it's named Parallel Discrete Event Simulation (PDES)





DES Building Blocks

Clock

- Independently of the measuring unit, the simulation must keep track of the current simulation time
- Being discrete, time hops to the next event's time

Event List

- At least the *pending event set* must be maintained by the simulation architecture
- Events can arrive at a higher rate than they can be processed
- Random Number Generators
- Statistics
- Ending Condition





DES Skeleton

```
1: procedure INIT
       End \leftarrow false
       initialize State, Clock
3:
       schedule INIT
5: end procedure
6:
7: procedure Simulation-Loop
       while End == false do
8:
           Clock \leftarrow next event's time
9:
10:
           process next event
           Update Statistics
11:
       end while
12:
13: end procedure
```



Implementation of a DES Kernel

- *General-purpose Simulation* is easy for DES
 - No notion of *model* in the main-loop pseudocode!
- Only prerequisites:
 - The model must implement actual handlers
 - The model requires APIs to inject new events in the system and pass entities' states from the kernel
- Multiple models can be run on the same kernel
 - Core reuse
 - Model-independent optimization of the kernel





Data Structures for Simulation: Priority Queue

- Is an abstract data type similar to a regular queue
- Elements have a priority associated with each of them
- An element with a high priority is served before
- Operations:
 - insert with priority: add an element to the queue with associated priority
 - pull highest priority element: remove the element from the queue that has the highest priority, and return it
- Highest priority can be either minimum or maximum value
- It can be used to implement the FEL
 - What about the ordering of simultaneous events?





Data Structures for Simulation: Calendar Queue

- A fast priority queue implementation (Brown, 1988)
- Composed of n buckets, each of width (or covering time) w
- Notion of *current time*
- Items with priority p >current time go into bucket:

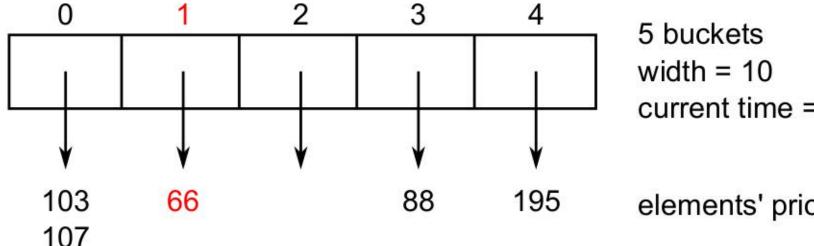
$$\left\lfloor \frac{p}{w} \right\rfloor \mod n$$

- n and w should be chosen so as to have few elements per bucket
 - Double or halve *n* and change *w* if the number of items grows or shrinks too much



Data Structures for Simulation: Calendar Queue

- Changing n involves no more that 3 moves of each event in the worst case
- w should be the average separation between events
- Calendar Queue has amortized O(1) operations cost



current time = 63

elements' priorities





API to Schedule Events and Set State

```
typedef struct _platform_event {
      double timestamp;
2
      unsigned int destination;
      unsigned int event_type;
4
      unsigned int size;
      void *payload;
  } platform_event;
8
  static calqueue *fel;
  static unsigned long long int processed_events = 0;
  static double simulation_time = 0;
  static unsigned int current_entity = UINT_MAX;
  static void **simulation_states;
14
15 unsigned int num_entities;
```



API to Schedule Events and Set State

```
16 extern void ScheduleNewEvent(unsigned int receiver, double
       timestamp, unsigned int event_type, void *event_content,
       unsigned int event_size) {
      platform_event *e;
17
18
      // Sanity checks
19
      if(timestamp < simulation_time) {</pre>
20
          fprintf(stderr, "Entity %d is trying to send events in the
21
              past. Current time: %f, scheduled time: %f\n",
              current_entity, simulation_time, timestamp);
          exit(EXIT_FAILURE);
22
      }
23
24
      // Populate the message data structure
25
      e = malloc(sizeof(platform_event));
26
      bzero(e, sizeof(platform_event));
27
```



API to Schedule Events and Set State

```
e->destination = receiver;
28
      e->timestamp = timestamp;
29
      e->event_type = event_type;
30
      e->size = event_size;
31
      e->payload = malloc(event_size);
32
      memcpy(e->payload, event_content, event_size);
33
34
      // Put the event in the Calendar Queue
35
      calqueue_put(fel, timestamp, e);
36
37 }
38
  extern void SetState(void *state) {
      simulation_states[current_entity] = state;
40
41 }
```



Initialization and Main Loop

```
int main(int argc, char **argv) {
      // Initialize data structures to handle entities
      num_entities = (int)strtol(argv[1], NULL, 10);
      printf("Initializing %d entities...\n", num_entities);
4
      simulation_states = malloc(sizeof(void *) * num_entities);
5
6
      // Allocate and initialize FEL
      fel = malloc(sizeof(calqueue));
8
      calqueue_init(fel);
9
10
      // Schedule INIT to entities
11
      for(i = 0; i < num_entities; i++) {</pre>
12
          current_entity = i;
13
          ProcessEvent(i, 0, INIT, NULL, 0, NULL);
14
      }
15
16
```





Initialization and Main Loop

```
// Main loop
17
      while(!calqueue_empty(fel)) {
18
          e = calqueue_get(fel);
19
20
          // Update current entity and simulation clock
21
          current_entity = e->destination;
22
          simulation_time = e->timestamp;
23
24
          ProcessEvent(current_entity, simulation_time, e->event_type,
25
               e->payload, e->size, simulation_states[current_entity])
26
          processed_events++;
27
28
```



29



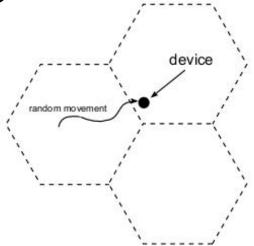
Initialization and Main Loop

```
if(e->payload != NULL)
31
              free(e->payload);
32
          free(e);
33
      }
34
35
      printf("Simulation complete after processing %llu events\n",
36
           processed_events);
37
      free(simulation_states);
38
      free(fel);
39
40 }
```



Personal Communication Service

- Networking System for mobile devices
- Interesting to study how different configurations behave
- Coverage area modeled as a set of adjacent hexagons
- Explicit modeling of channel allocation







EXAMPLE SESSION

Personal Communication Service





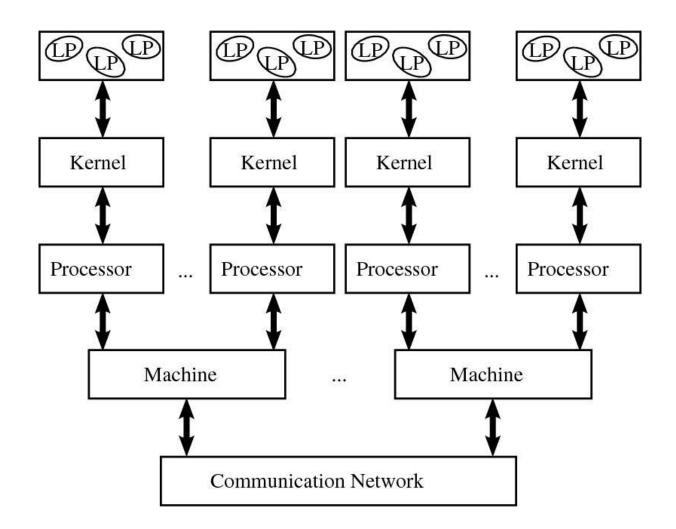
Parallel Discrete Event Simulation

- To increase the overall performance, DES models can be run on top of multiple computing nodes
 - Distributed and/or concurrent simulation
- The main goal is *transparency*
- Simulation models should not be modified



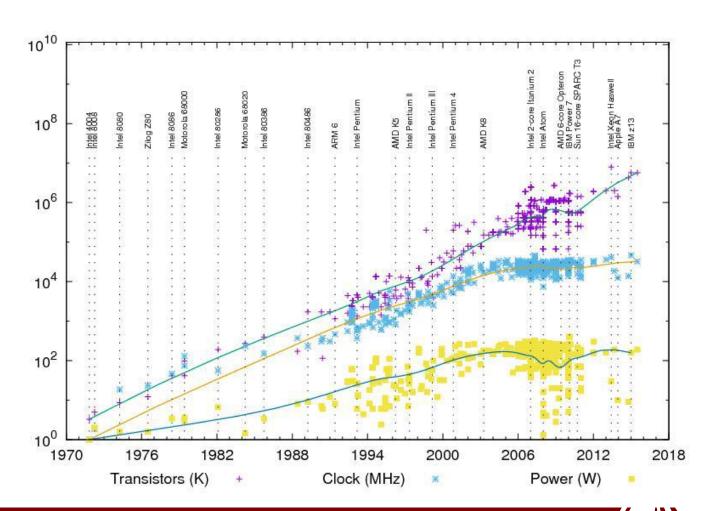


Traditional PDES execution support



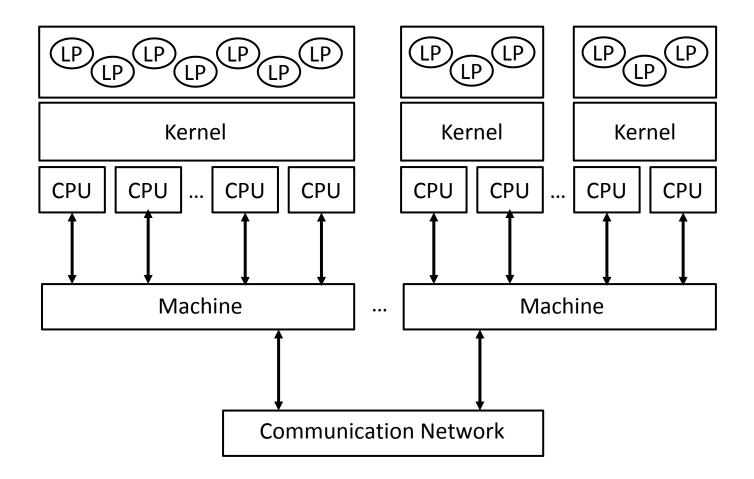


Why are multicores important?





Revisited PDES Architecture



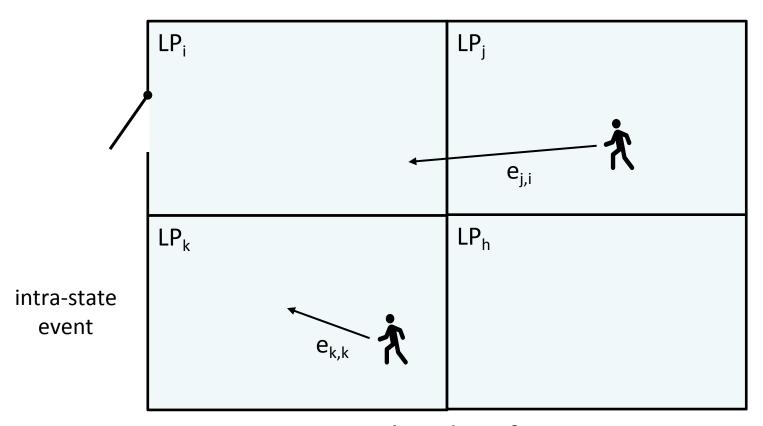




- Consider a simulation program composed of several *logical processes* exchanging timestamped messages
- Consider the *sequential execution*: this ensures that events are processed in timestamp order
- Consider the parallel execution: the greatest opportunity arises from processing events from different LPs concurrently
- Is *correctness* always ensured?



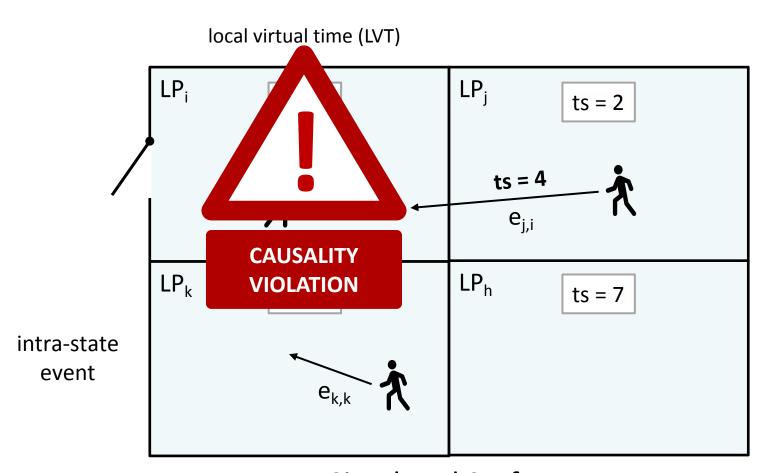




inter-state event

Simulated Surface

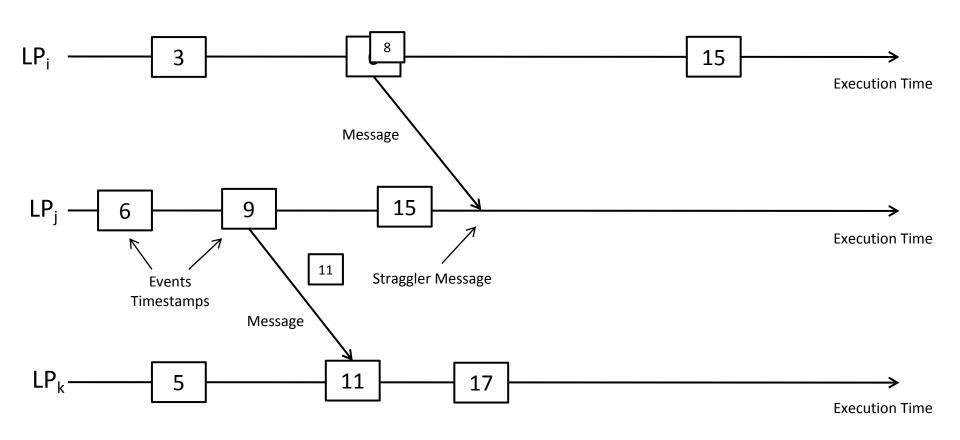




inter-state event

Simulated Surface









Conservative Synchronization

- Consider the LP with the *smallest* clock value at some instant *T* in the simulation's execution
- This LP could generate events relevant to every other LP in the simulation with a timestamp T
- No LP can process any event with timestamp larger than T





Conservative Synchronization

- If each LP has a *lookahead* of *L*, then any new message sent by al LP must have a timestamp of at least *T* + *L*
- Any event in the interval [T, T + L] can be safely processed
- *L* is intimately related to details of the simulation model

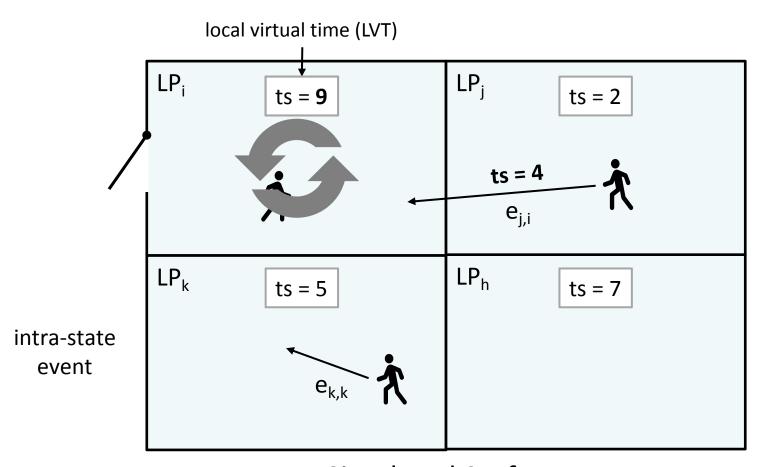


Optimistic Synchronization: Time Warp

- There are no state variables that are shared between LPs
- Communications are assumed to be reliable
- LPs need not to send messages in timestamp order
- Local Control Mechanism
 - Events not yet processed are stored in an input queue
 - Events already processed are not discarded
- Global Control Mechanism
 - Event processing can be undone
 - A-posteriori detection of causality violation





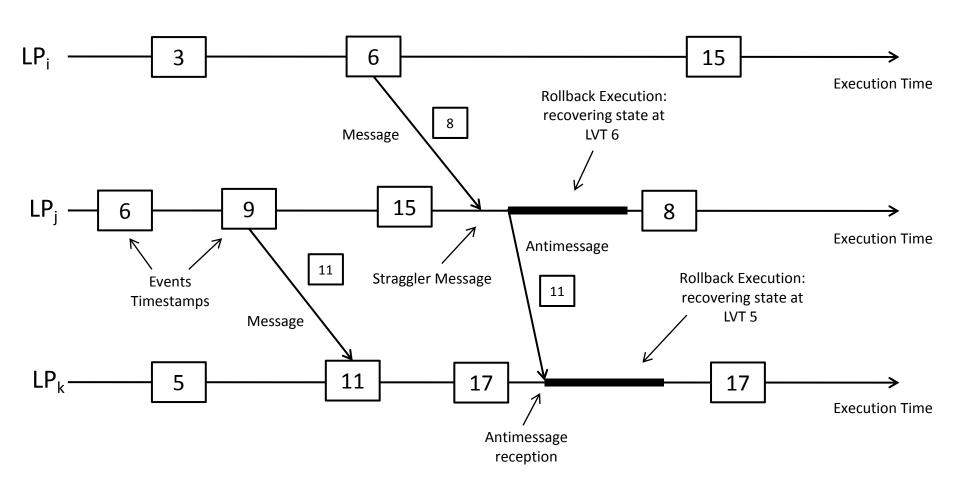


inter-state event

Simulated Surface



Time Warp: State Recoverability







Rollback Operation

- The rollback operation is fundamental to ensure a correct speculative simulation
- Its *time critical*: it is often executed on the *critical path* of the simulation engine
- 30+ years of research have tried to find optimized ways to increase its performance



- The traditional way to support a rollback is to rely on state saving and restore
- A state queue is introduced into the engine
- Upon a rollback operations, the "closest" log is picked from the queue and restored

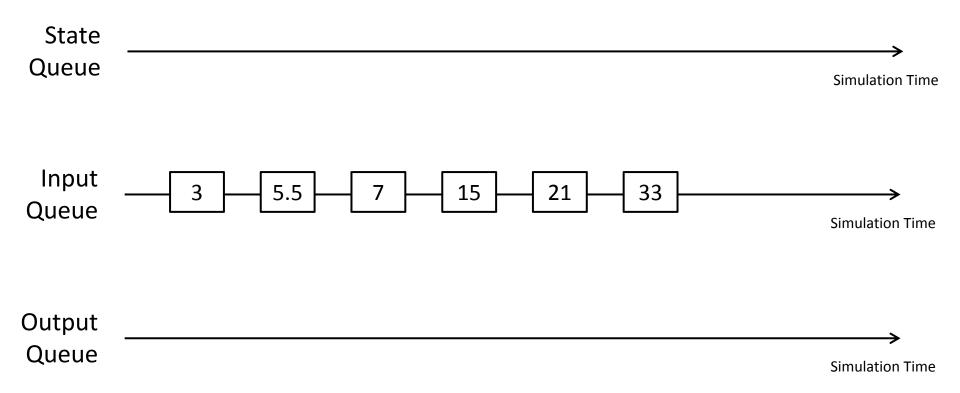
- What are the *technological* problems to solve?
- What are the *methodological* problems to solve?





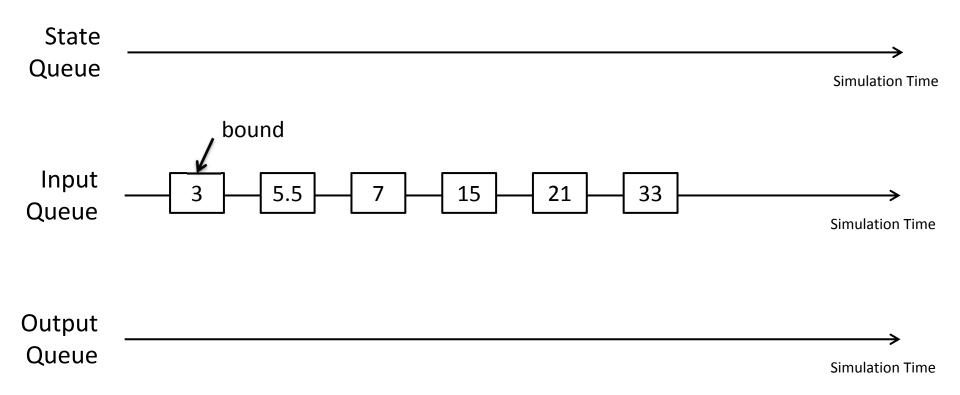






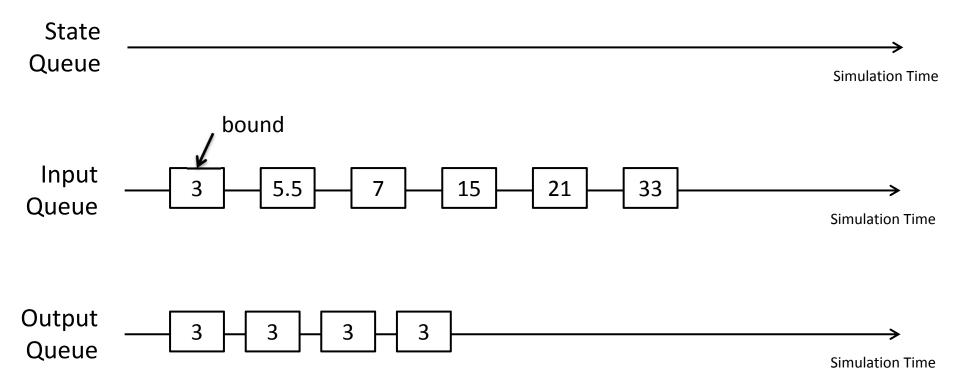






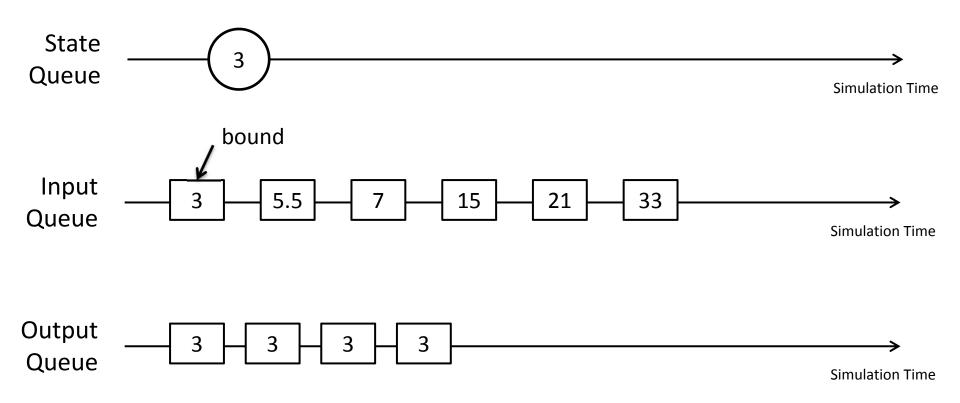






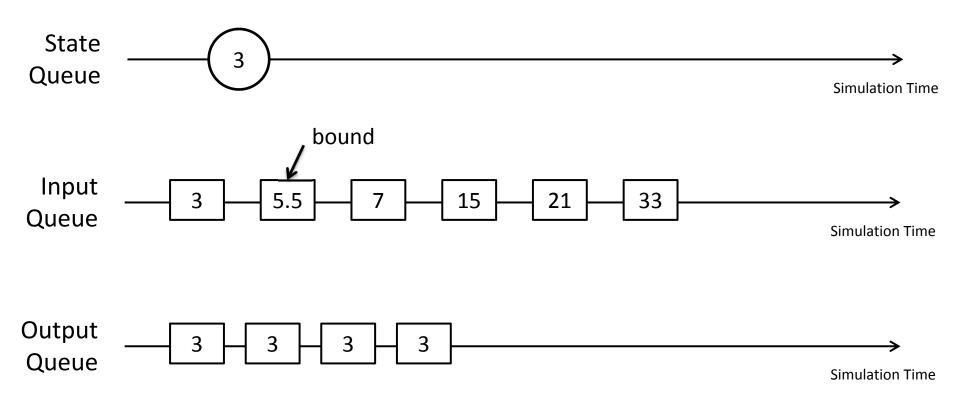






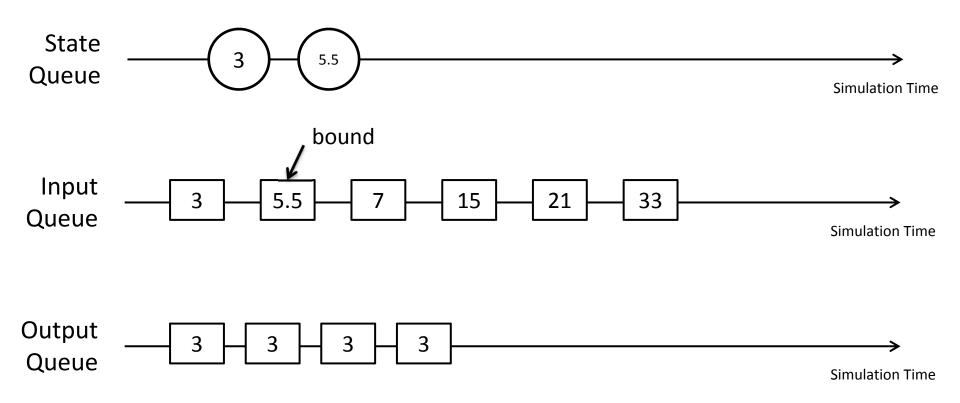






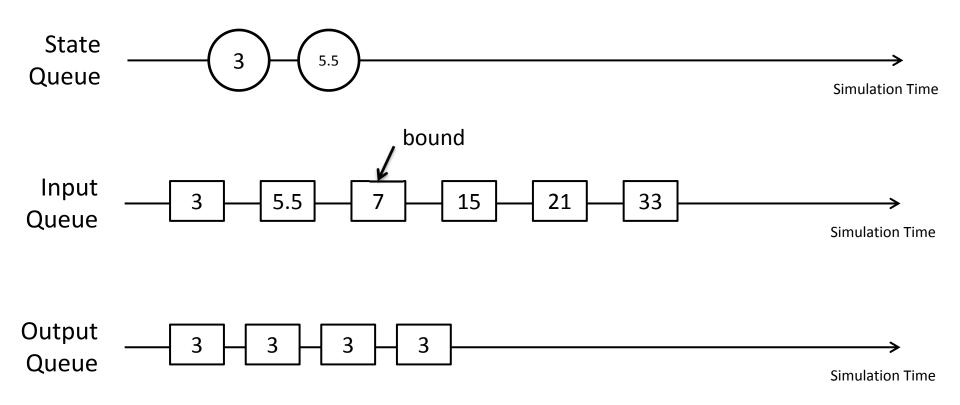




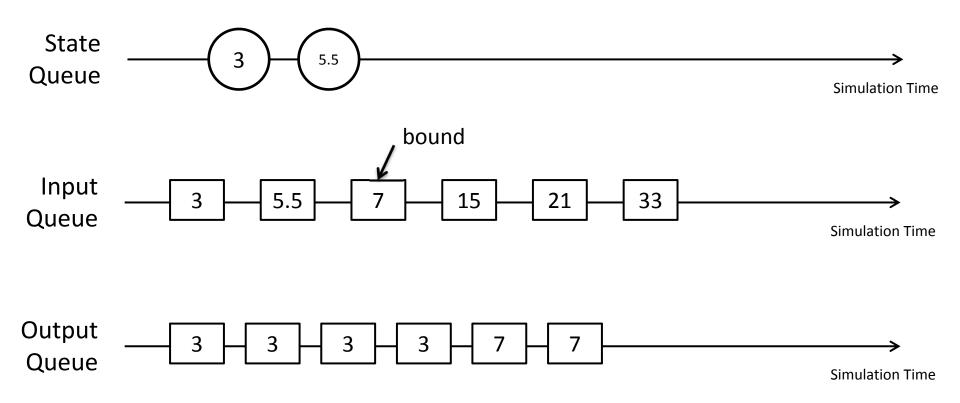






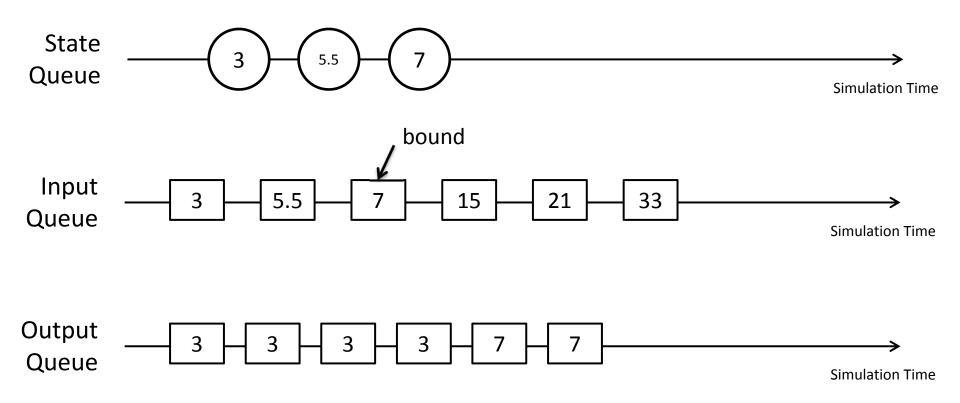










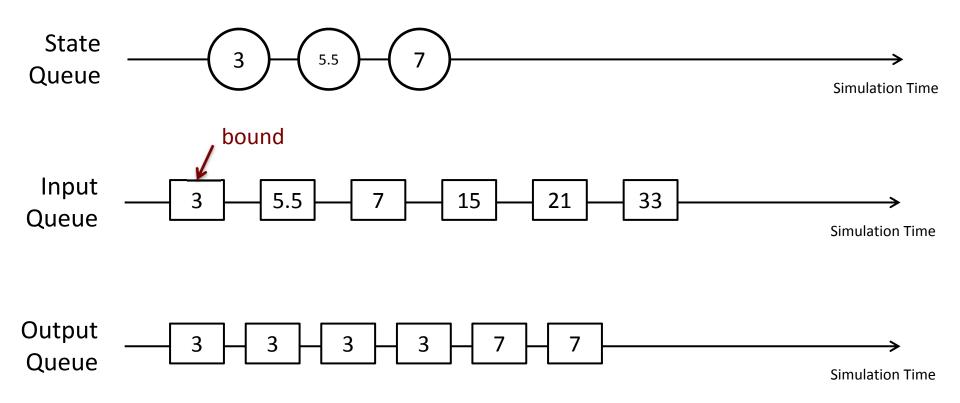






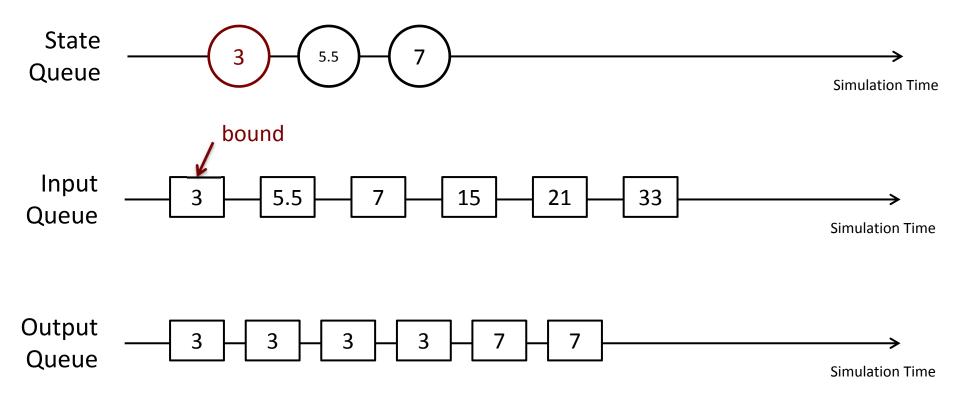






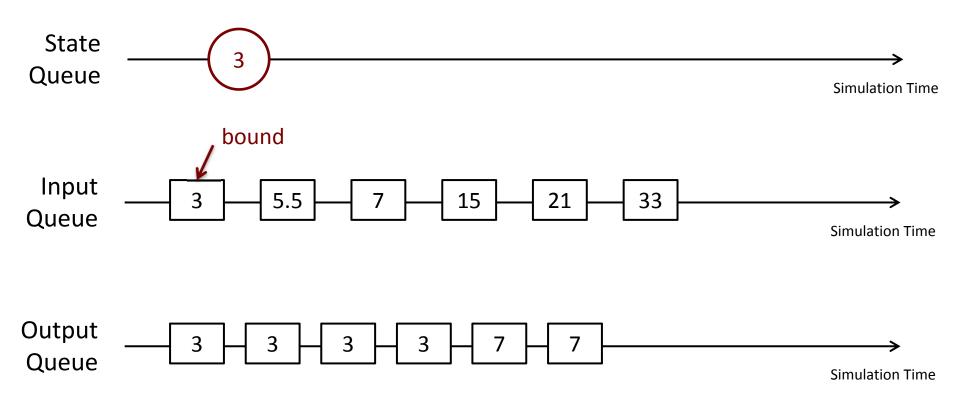






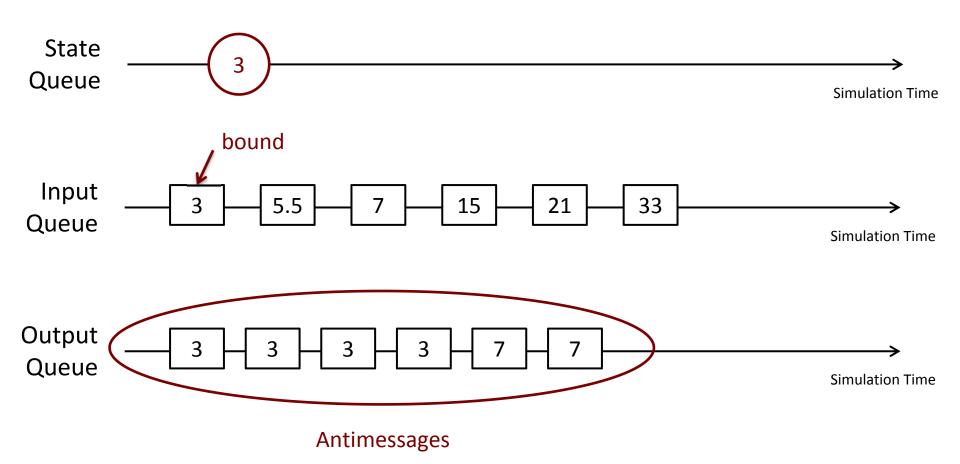




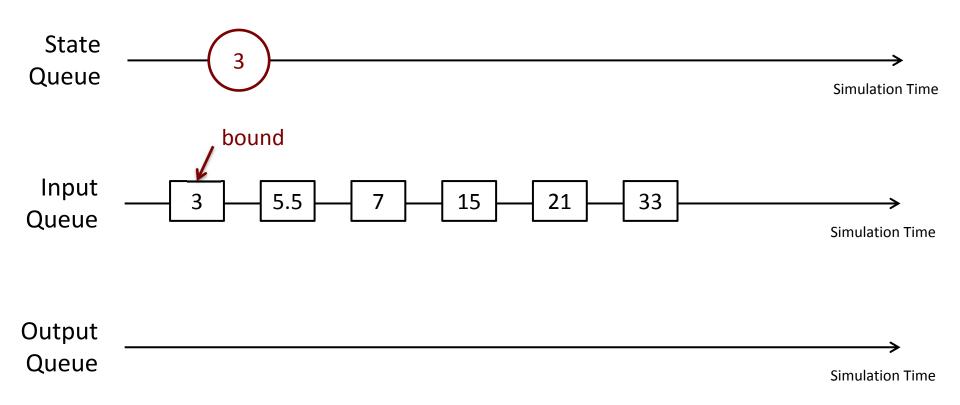






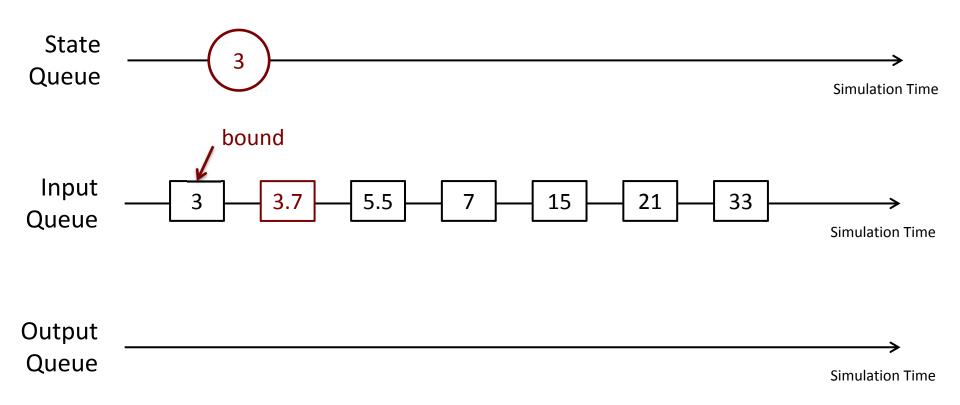






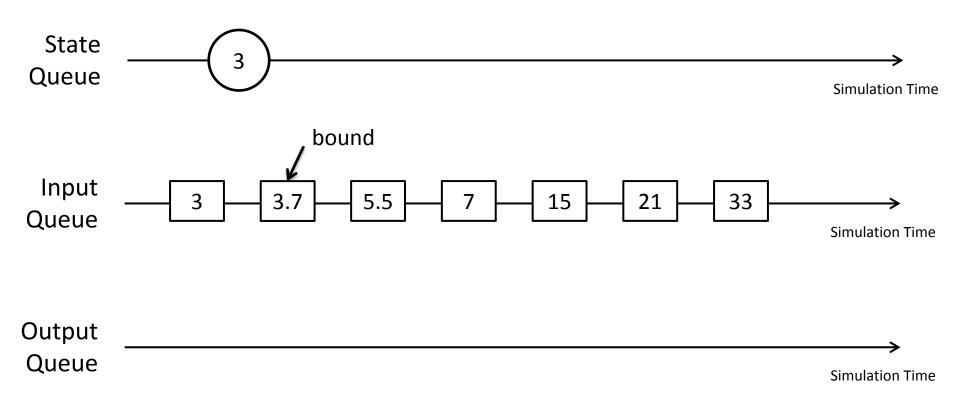


State Saving and Restore





State Saving and Restore





State Saving Efficiency

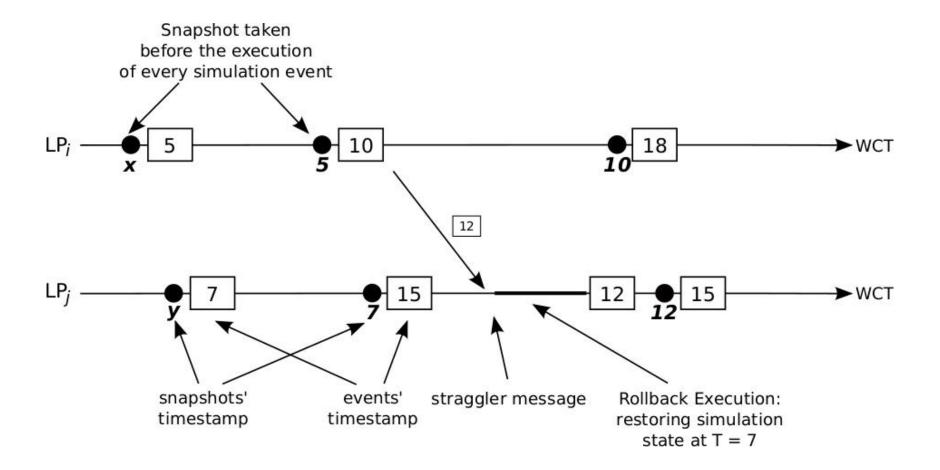
- How large is the simulation state?
- How often do we execute a rollback? (*rollback frequency*)
- How many events do we have to undo on average?

Can we do something better?



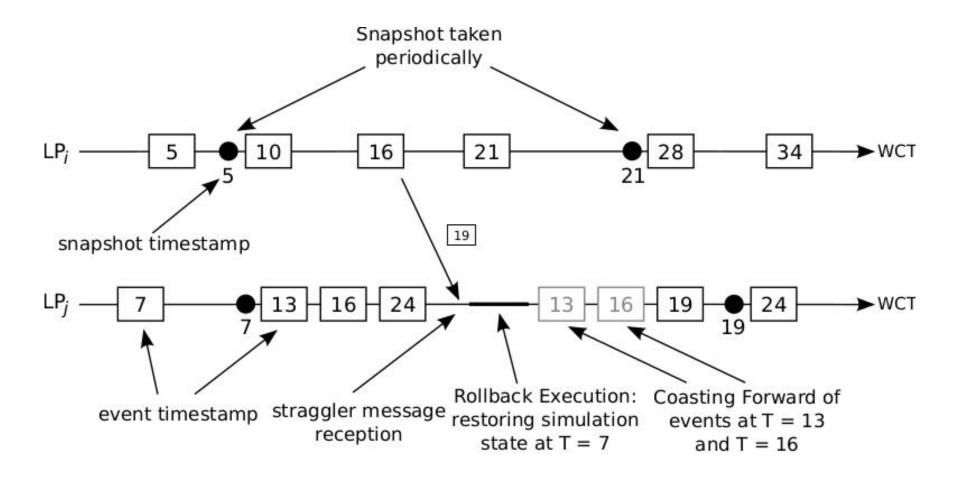


Copy State Saving





Sparse State Saving (SSS)







Coasting Forward

- Re-execution of already-processed events
- These events have been artificially undone!
- Antimessages have <u>not</u> been sent

- These events must be reprocessed in *silent* execution
 - Otherwise, we duplicate messages in the system!



When to take a checkpoint?

- Classical approach: periodic state saving
- Is this efficient?
 - Think in terms of memory footprint and wall-clock time requirements





When to take a checkpoint?

- Classical approach: periodic state saving
- Is this efficient?
 - Think in terms of memory footprint and wall-clock time requirements

- Model-based decision making
- This is the basis for *autonomic self-optimizing systems*
- Goal: find the best-suited value for χ



When to take a checkpoint?

$$\chi_{opt} = \left\lceil \sqrt{\frac{2\delta_s}{\delta_c} + \left(\frac{N}{k_r} + \gamma - 1\right)} \right\rceil$$

- δ_s : average time to take a snapshot
- δ_c : the average time to execute coasting forward
- *N*: total number of committed events
- k_r : number of executed rollbacks
- γ : average rollback length





Incremental State Saving (ISS)

- If the state is large and scarcely updated, ISS might provide a reduced memory footprint and a non-negligible performance increase!
- How to know what state portions have been modified?





Incremental State Saving (ISS)

- If the state is large and scarcely updated, ISS might provide a reduced memory footprint and a non-negligible performance increase!
- How to know what state portions have been modified?
 - Explicit API notification (non-transparent!)
 - Operator Overloading
 - Static Binary Instrumentation
 - Compiler-assisted Binary Generation





Reverse Computation

- It can reduce state saving overhead
- Each event is associated (manually or automatically) with a reverse event
- A majority of the operations that modify state variables are constructive in nature
 - the undo operation for them requires no history
- Destructive operations (assignment, bit-wise operations, ...) can only be restored via traditional state saving



Reversible Operations

Туре	Description	Application Code			Bit Requirements		
		Original	Translated	Reverse	Self	Child	Total
TO	simple choice	if() s1	if() {s1; b=1;}	if(b==1){inv(s1);}	1	x1,	1+
		else s2	else {s2; b=0;}	else{inv(s2);}		x2	max(x1,x2)
T1	compound choice	if () s1;	if() {s1; b=1;}	if(b==1) {inv(s1);}	lg(n)	x1,	lg(n) +
	(n-way)	elseif() s2;	elseif() {s2; b=2;}	elseif(b==2) {inv(s2);}		x2,	max(x1xn)
		elseif() s3;	elseif() {s3; b=3;}	elseif(b==3) {inv(s3);}		,	
		else() sn;	else {sn; b=n;}	else {inv(sn);}		xn	
T2	fixed iterations (n)	for(n)s;	for(n) s;	for(n) inv(s);	0	X	n*x
T3	variable iterations	while() s;	b=0;	for(b) inv(s);	lg(n)	X	lg(n) +n*x
	(maximum n)		while() {s; b++;}				
T4	function call	foo();	foo();	inv(foo)();	0	X	x
T5	constructive	v@ = w;	v@ = w;	v = @w;	0	0	0
	assignment						
T6	k-byte destructive	v = w;	{b = v, v = w,}	v = b;	8k	0	8k
	assignment						
77	sequence	s1;	s1;	inv(sn);	0	x1+	x1++xn
		s2;	s2;	inv(s2);		+	
		sn;	sn;	inv(s1);		xn	
T8	Nesting of T0-T7	Recursively apply the above			Recursively apply the above		



Non-Reversible Operations: if/then/else

```
if(qlen > 0) {
    qlen--;
    sent++;
    qlen++;
}
```

 The reverse event must check an "old" state variables' value, which is not available when processing it!





Non-Reversible Operations: if/then/else

```
if(qlen > 0) {
    b = 1;
    qlen--;
    sent++;
}
if(b == 1) {
    sent--;
    qlen++;
}
```

- Forward events are modified by inserting "bit variables";
- The are additional state variables telling whether a particular branch was taken or not during the forward execution



Random Number Generators

- Fundamental support for stochastic simulation
- They must be <u>aware of the rollback operation!</u>
 - Failing to rollback a random sequence might lead to incorrect results (trajectory divergence)
 - Think for example to the coasting forward operation

- Computers are precise and deterministic:
 - Where does randomness come from?



Random Number Generators

- Practical computer "random" generators are common in use
- They are usually referred to as *pseudo-random generators*
- What is the correct definition of randomness in this context?





Random Number Generators

"The deterministic program that produces a random sequence should be different from, and—in all measurable respects—statistically uncorrelated with, the computer program that uses its output"

- Two different RNGs must produce statistically the same results when coupled to an application
- The above definition might seem circular: comparing one generator to another!
- There is a certain list of statistical tests





Uniform Deviates

- They are random numbers lying in a specified range (usually [0,1])
- Other random distributions are drawn from a uniform deviate
 - An essential building block for other distributions
- Usually, there are system-supplied RNGs:

```
#include <stdlib.h>
#define RAND_MAX ...

void srand(unsigned seed);
int rand(void);
```





Problems with System-Supplied RNGs

• If you want a random float in [0.0, 1.0):

```
x = rand() / (RAND_MAX + 1.0);
```

- Be very (very!) suspicious of a system-supplied rand() that resembles the above-described one
- They belong to the category of linear congruential generators

$$I_{j+1} = a I_j + c \pmod{m}$$

• The recurrence will eventually repeat itself, with a period no greater than *m*





Problems with System-Supplied RNGs

- If m, a, and c are properly chosen, the period will be of maximal length (m)
 - all possible integers between 0 anbd m 1 will occur at some point
- In general, it may look a good idea
- Many ANSI-C implementations are flawed





An example RNG (from libc)

```
unsigned long next = 1;
2
3 int rand(void) {
      next = next * 1103515245 + 12345;
      return (unsigned int)(next / 65536) % 32768;
8 void srand(unsigned int seed) {
      next = seed;
10 }
```



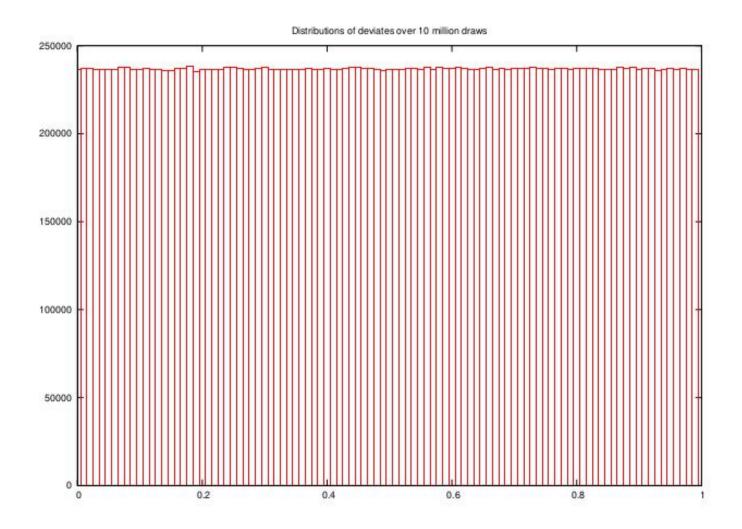
An example RNG (from libc)

```
This is where we can support the
  unsigned long next = 1;
                                    rollback operation: consider the seed
                                     as part of the simulation state!
  int rand(void) {
       next = next * 1103515245 + 12345;
       return (unsigned int)(next / 65536) % 32768;
8 void srand(unsigned int seed) {
       next = seed;
10 }
```





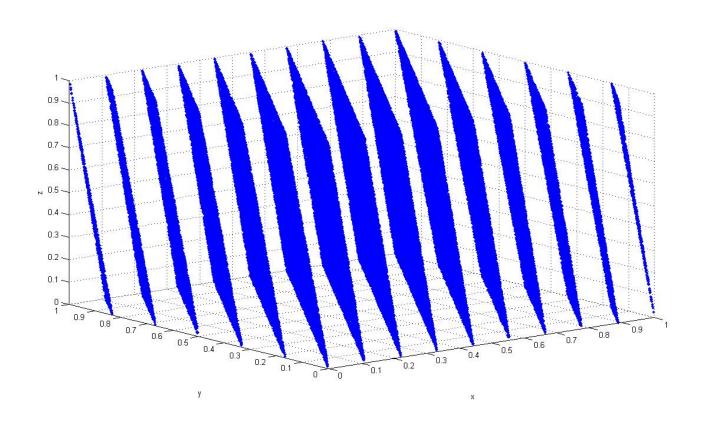
Problems with System-Supplied RNGs







Problems with System-Supplied RNGs



In an n-dimensional space, the points lie on at most $m^{1/n}$ hyperplanes!





Functions of Uniform Deviates

• The probability p(x)dx of generating a number between x and x+dx is:

$$p(x)dx = \begin{cases} dx & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

• p(x) is normalized:

$$\int_{-\infty}^{\infty} p(d)dx = 1$$

• If we take some function of x like y(x):

$$|p(y)dy| = |p(x)dx| \Rightarrow p(y) = p(x) \left| \frac{dx}{dy} \right|$$





Exponential Deviates

• Suppose that $y(x) \equiv -ln(x)$, and that p(x) is uniform:

$$p(y)dy = \left| \frac{dx}{dy} \right| dy = e^{-y} dy$$

- This is distributed exponentially
- Exponential distribution is fundamental in simulation
 - Poisson-random events, for example the radioactive decay of nuclei, or the more general interarrival time

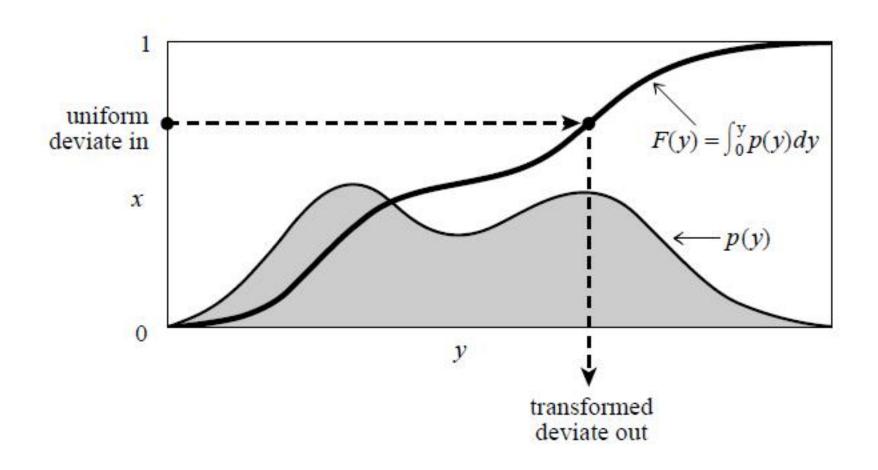


Exponential Deviates

```
#include <math.h>
  float expent(long *idum) {
      float dum;
      do {
6
          dum = rand(idum);
      } while (dum == 0.0);
9
      return -log(dum);
10
11 }
```



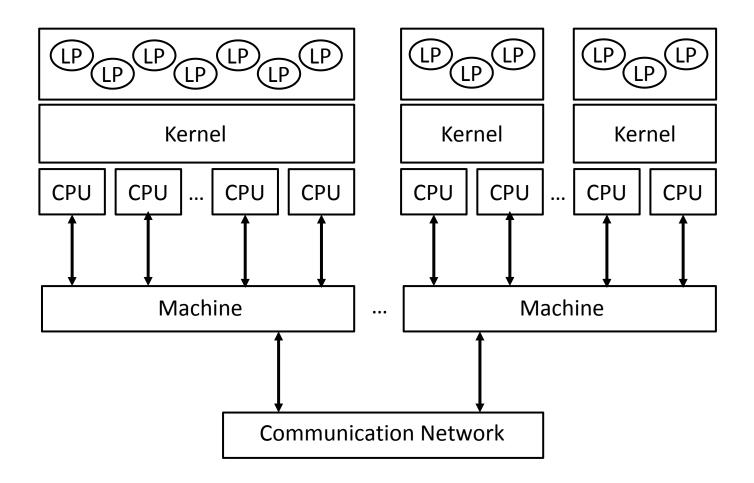
Deviate Transformation







Scheduling Events







Scheduling Events

- A single thread takes care of a certain number of LPs at any time
- We have to avoid *inter-LPs rollbacks*
- Lowest-Timestamp First:
 - Scan the input queue of all LPs
 - Check the bound of each LP
 - Pick the LP whose next event is closest in simulation time





- In a PDES system, memory usage is always increasing
 - We do not discard events
 - We take a lot of snapshots!

- We must find a way to implement a garbage collector
 - During the execution of an event at time T, we can schedule events at time $t \ge T$

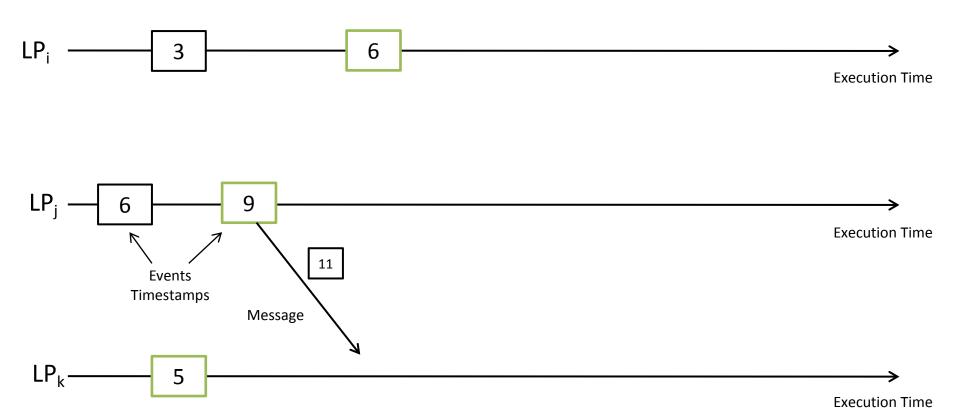




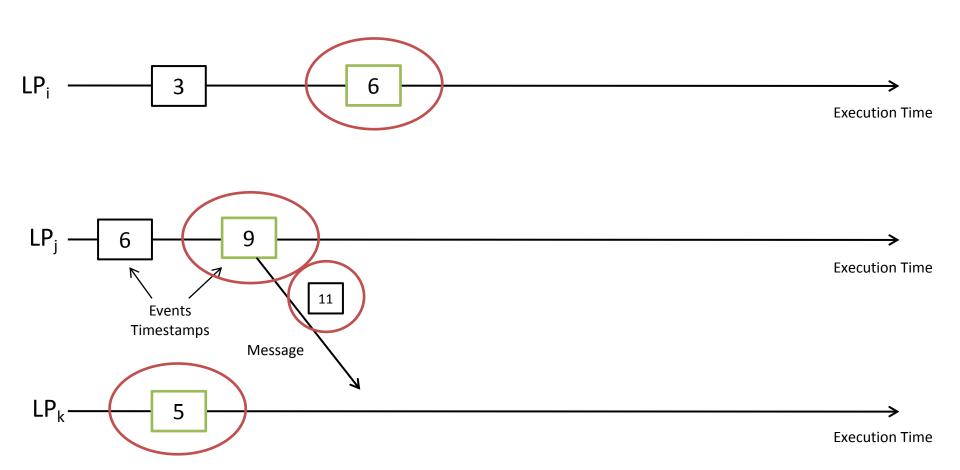
At a specific wall-clock time t, the GVT is defined as the minimum between:

- All virtual times in all virtual clocks at time t;
- The timestamps of all sent but not yet processed events at time t

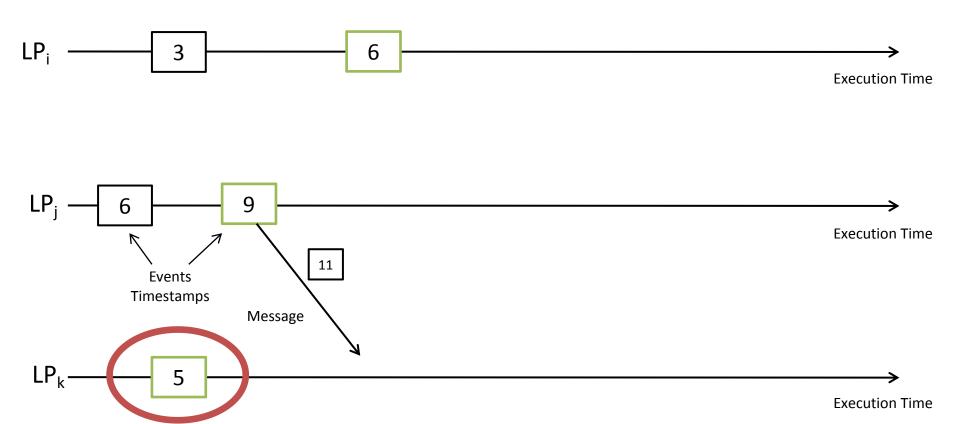








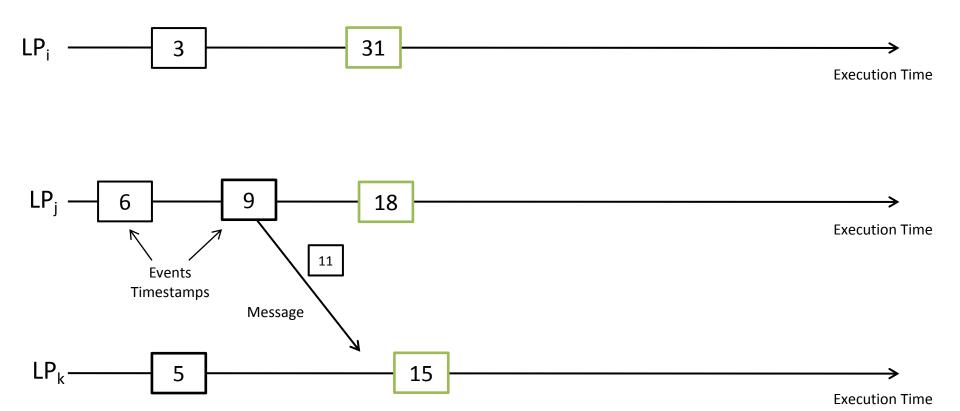








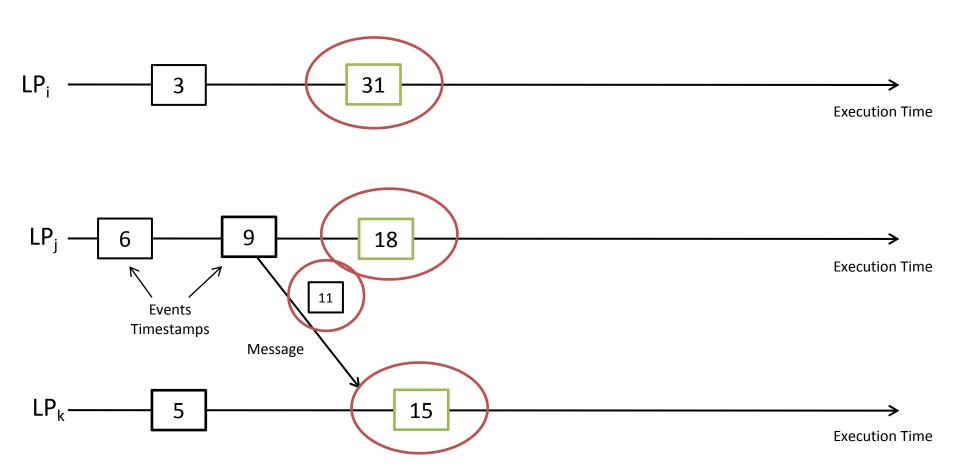
Global Virtual Time







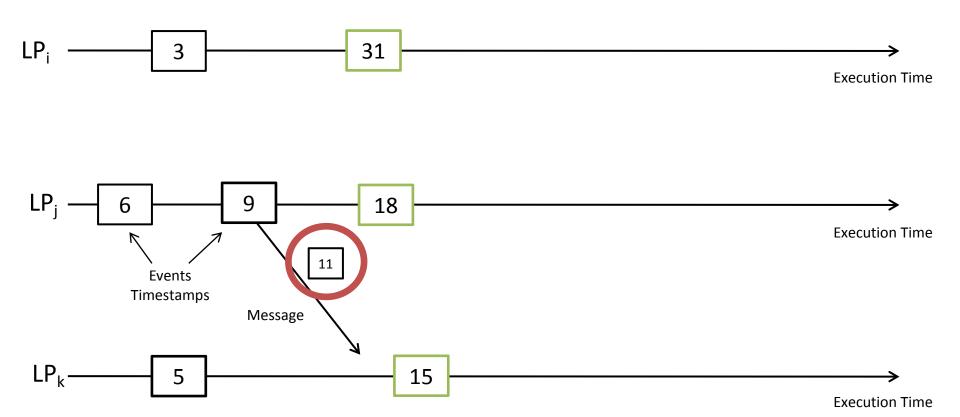
Global Virtual Time







Global Virtual Time





GVT Operations

- Once a correct GVT value is determined we can perform two actions:
 - Fossil Collection: the actual garbage collection of old memory buffers
 - Termination Detection

• GVT identifies the *commitment horizon* of the speculative execution





How Accurate is Speculative Simulation?

- Sequential Simulation is perfect for fine-grain inspection of predicates
 - It does not scale
 - Models are getting larger and larger everyday
- Parallel/Distributed simulation has great performance
- Fine-grain inspection is not viable
 - Process coordination is required
 - This hampers the achievable speedup





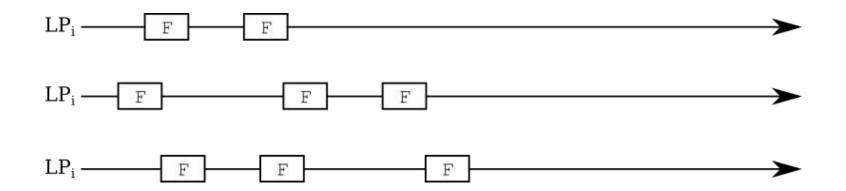
How Accurate is Speculative Simulation?

- Speculative Simulation inserts an additional delay
- The inspection of a global simulation state is delayed until a portion of the simulation trajectory becomes committed
- Inspection can be done after a GVT value has been computed





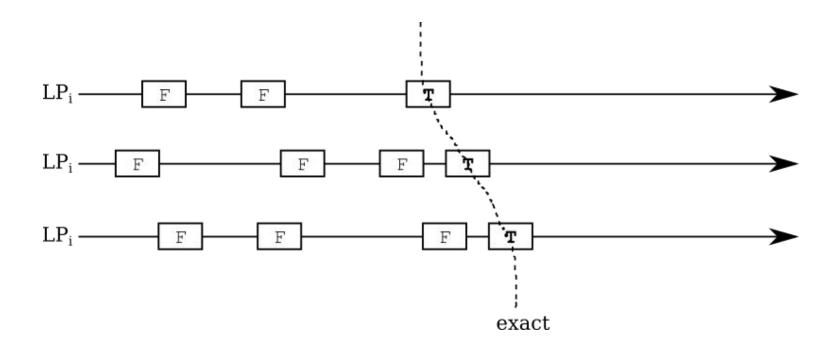
The Completion-Shift Problem







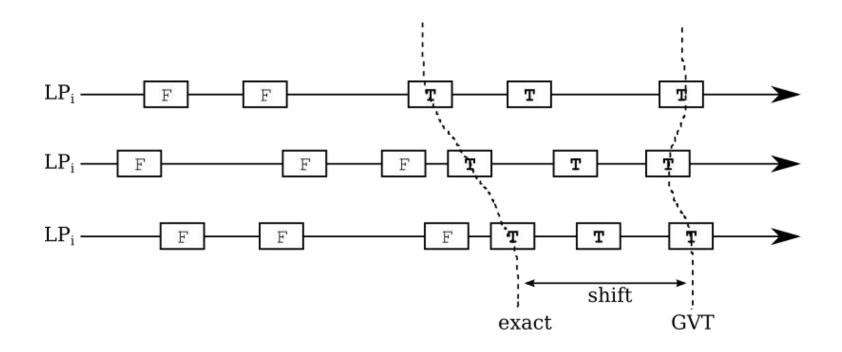
The Completion-Shift Problem







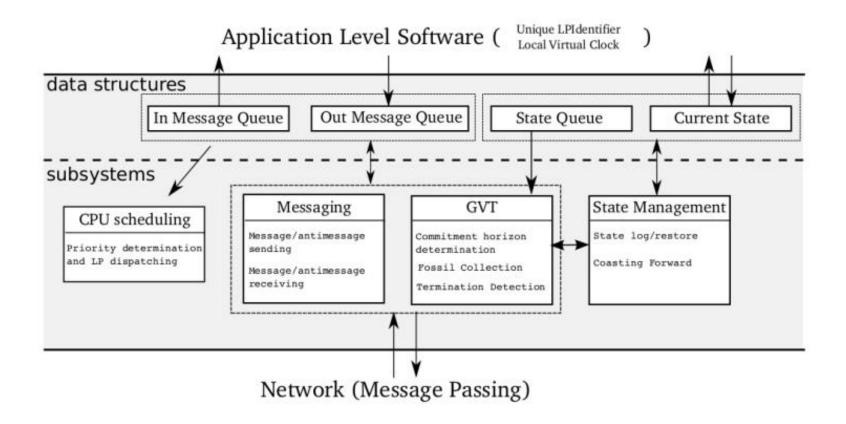
The Completion-Shift Problem







Time Warp Fundamentals





ROOT-Sim

 The ROme OpTimisti Simulator https://github.com/HPDCS/ROOT-Sim



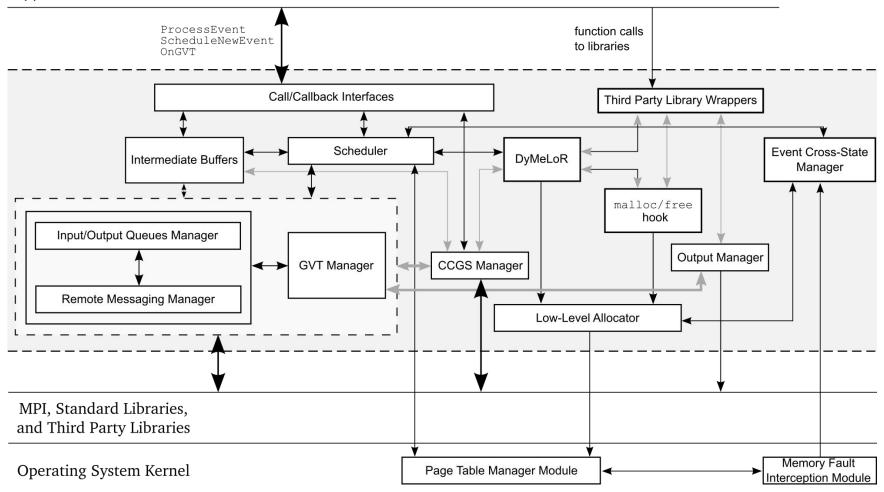
- A general-purpose speculative simulation kernel based on both state saving and reversibility
- Targets complete transparency towards the model developer
- It can transparently deploy and run legacy models





ROOT-Sim Internals

Application Level Software





EXAMPLE SESSION

PCS on ROOT-Sim



