Dynamic load-balancing on multi-FPGA systems
a case study

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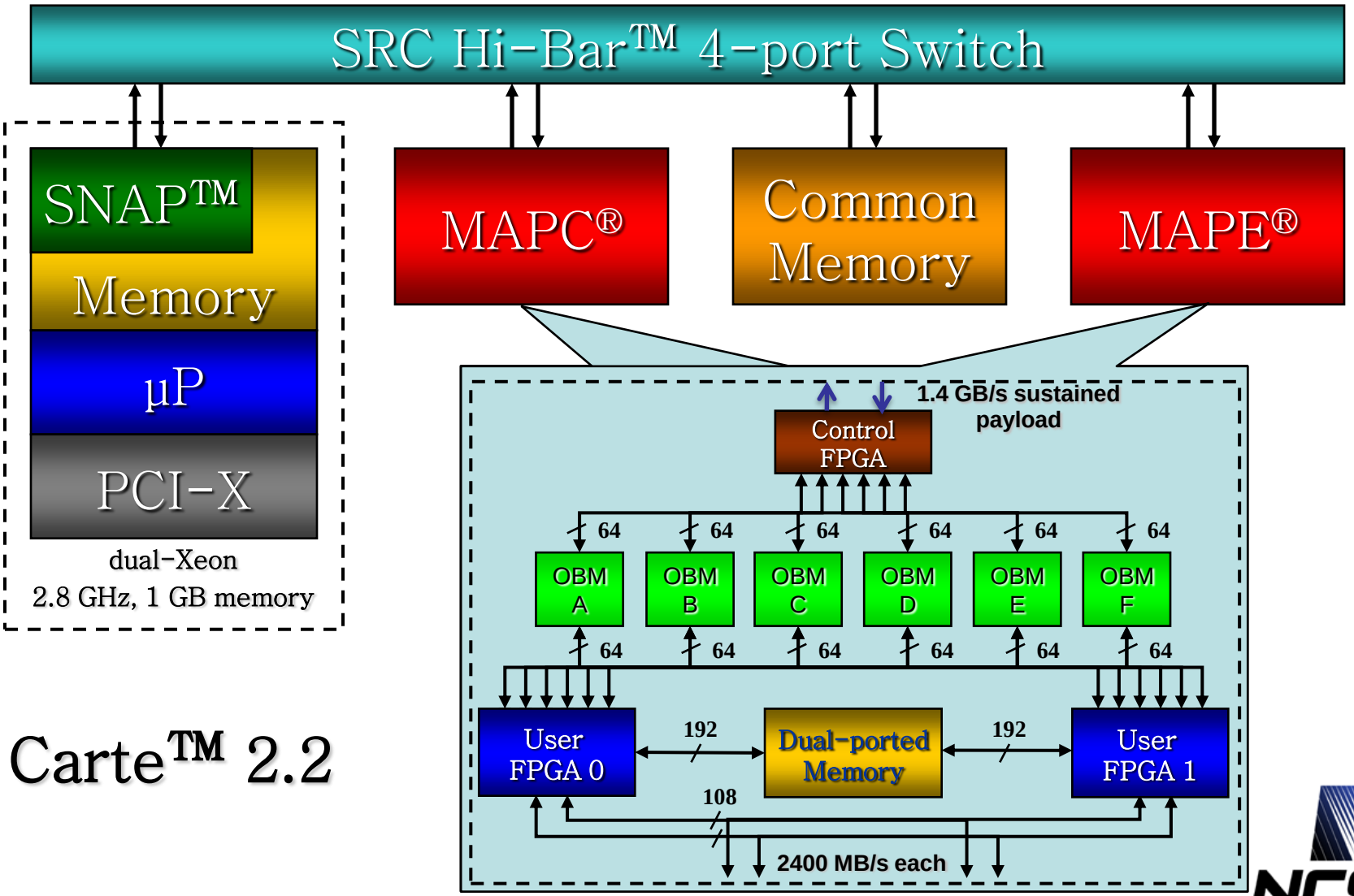
SRC-6 Reconfigurable Computer



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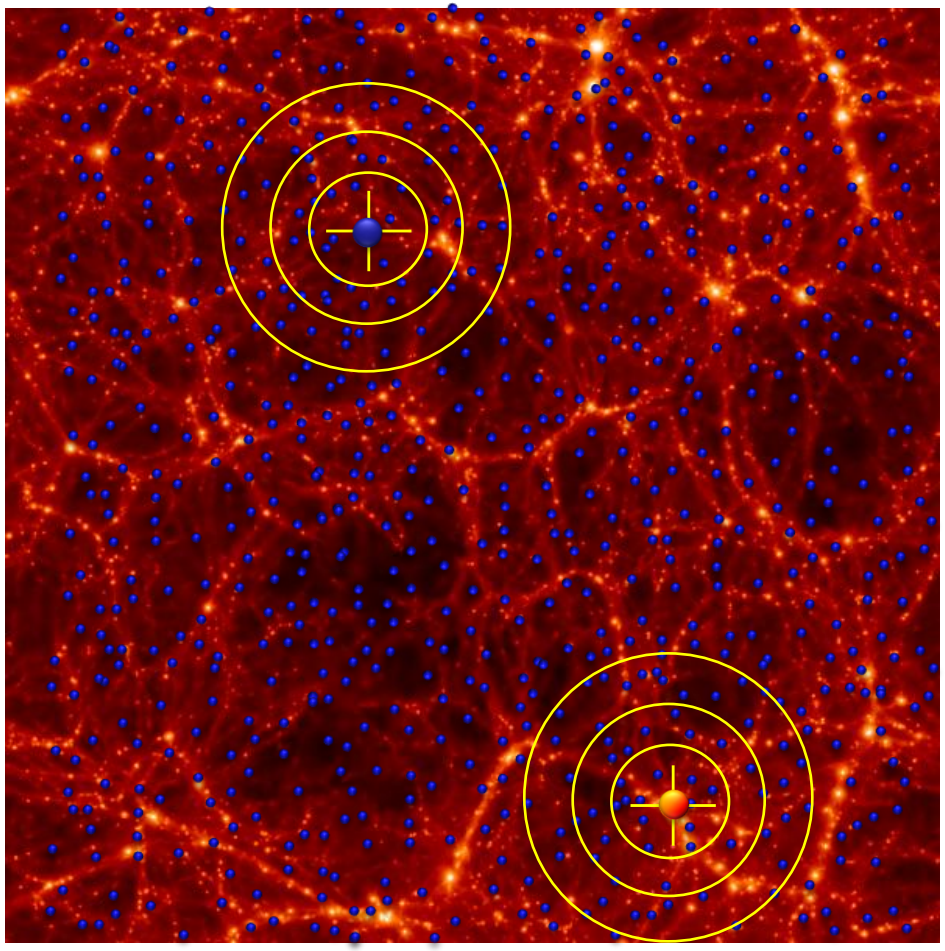
Angular Correlation Function



- **TPACF, denoted as $\omega(\theta)$, is the frequency distribution of angular separations θ between celestial objects in the interval $(\theta, \theta + \delta\theta)$**
  - θ is the angular distance between two points
- **Blue points (random data) are, on average, randomly distributed, red points (observed data) are clustered**
  - Blue points: $\omega(\theta)=0$
  - Red points: $\omega(\theta)>0$
- **Can vary as a function of angular distance, θ (yellow circles)**
  - Blue: $\omega(\theta)=0$ on all scales
  - Red: $\omega(\theta)$ is larger on smaller scales

Image source: http://astro.berkeley.edu/~mwhite/

The Method

- **The angular correlation function is calculated using the estimator derived by Landy & Szalay (1993):**

$$\omega(\theta) = \frac{\frac{1}{n_D^2} \cdot DD(\theta) - \frac{2}{n_D n_R} \sum DR_i(\theta)}{\frac{1}{n_R^2} \sum RR_i(\theta)} + 1$$

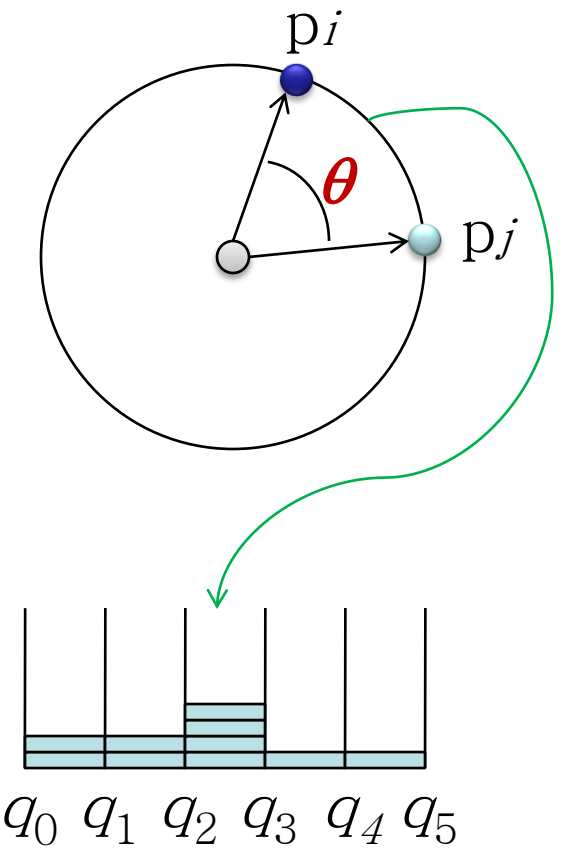
- **where *DD*(θ) and *RR*(θ) are the autocorrelation function of the data and random points, respectively, and *DR*(θ) is the cross-correlation between the data and random points.**

Serial Code Organization

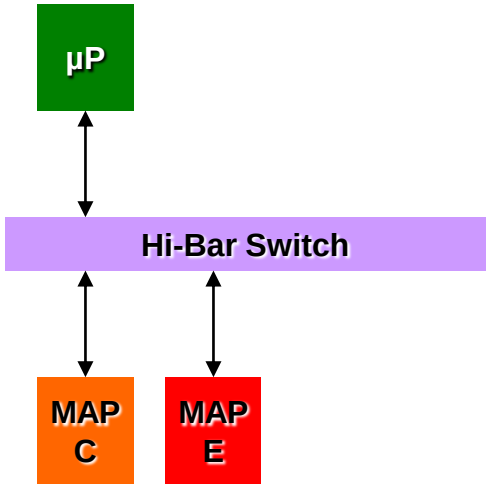
```
// pre-compute bin boundaries, binb

// compute DD
doCompute{CPU|MAP}(data, npd, data, npd, 1, DD, binb, nbins);

// loop through random data files
for (i = 0; i < random_count; i++)
{
    // compute RR
    doCompute{CPU|MAP}(random[i], npr[i], random[i], npr[i], 1, RRS, binb, nbins);

    // compute DR
    doCompute{CPU|MAP}(data, npd, random[i], npr[i], 0, DRS, binb, nbins);
}

// compute w
for (k = 0; k < nbins; k++)
{
    w[k] = (random_count * 2*DD[k] - DRS[k]) / RRS[k] + 1.0;
}
```

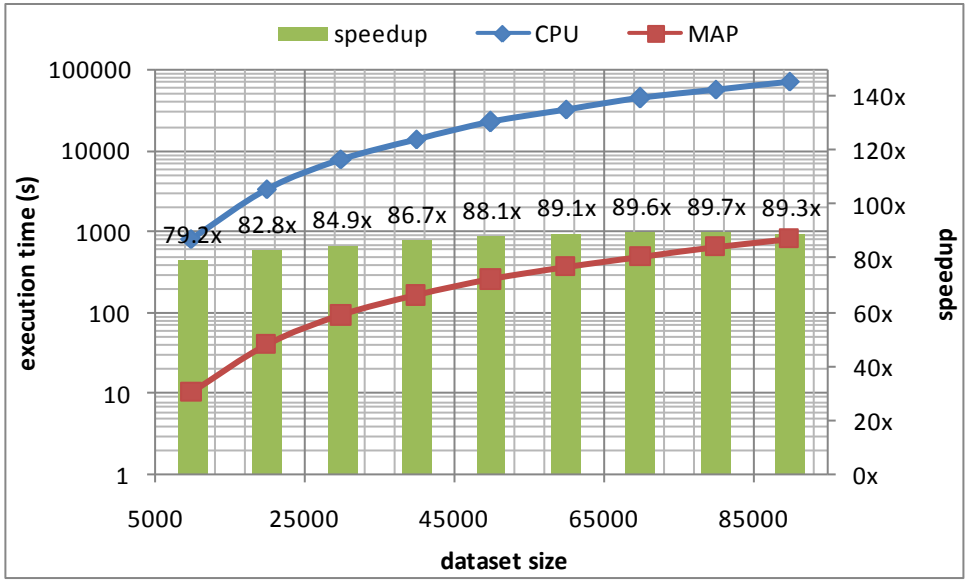
Reference C Kernel Implementation

```
for (i = 0; i < ((autoCorrelation) ? n1-1 : n1); i++)
{
   double xi = data1[i].x,  yi = data1[i].y,  zi = data1[i].z;

   for (j = ((autoCorrelation) ? i+1 : 0); j < n2; j++)
   {
      double dot = xi * data2[j].x + yi * data2[j].y + * data2[j].z;

      register int k, min = 0, max = nbins;
      if (dot >= binb[min]) data_bins[min] += 1;
      else if (dot < binb[max]) data_bins[max+1] += 1;
      // run binary search
      else  {
         while (max > min+1)
         {
            k = (min + max) / 2;
            if (dot >= binb[k])  max = k;
            else  min = k;
         };
         data_bins[max] += 1;
      }
   }
}
```

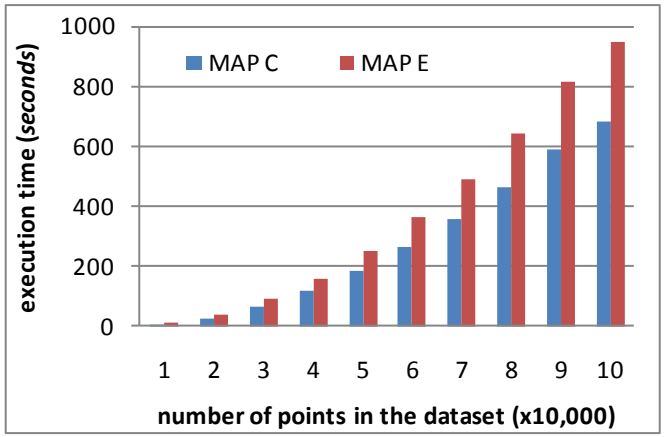


OpenMP Implementation





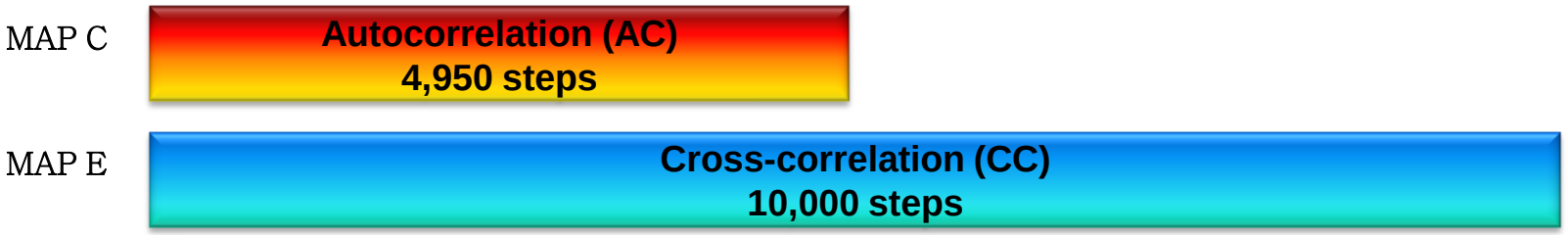

```
for (i = 0; i < random_count; i++)
{
        #pragma omp parallel sections
        #pragma omp section
        doComputeMAP1(…, mapC);

        #pragma omp section
        doComputeMAP2(…, mapE);
}
```



MAP C processor is idle 18% of the time

Simplified Performance Model

- **Analysis of a data/random file with 100 data points each**
  - Autocorrelation between the points in the random data file requires 100*(100-1)/2=4,950 steps
  - Cross-correlation between the observed data and random data requires 100*100=10,000 steps
  - MAP Series C processor is idle about 50% of the time!



Consider Data Partitioning…

Dataset A: 100 points

Dataset B: 100 points

Autocorrelation Jobs

- A1-A1 (ac)
- A1-A2 (cc)
- A1-A3 (cc)
- A2-A2 (ac)
- A2-A3 (cc)
- A3-A3 (ac)

Cross-correlation Jobs

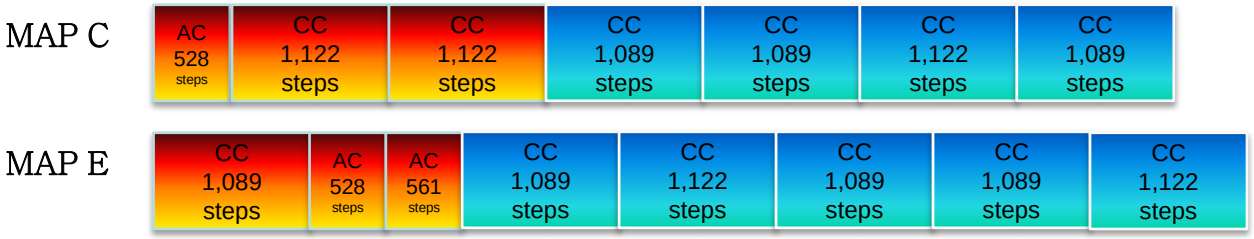
- A1-B1 (cc)
- A1-B2 (cc)
- A1-B3 (cc)
- A2-B1 (cc)
- A2-B2 (cc)
- A2-B3 (cc)
- A3-B1 (cc)
- A3-B2 (cc)
- A3-B3 (cc)

MAP C

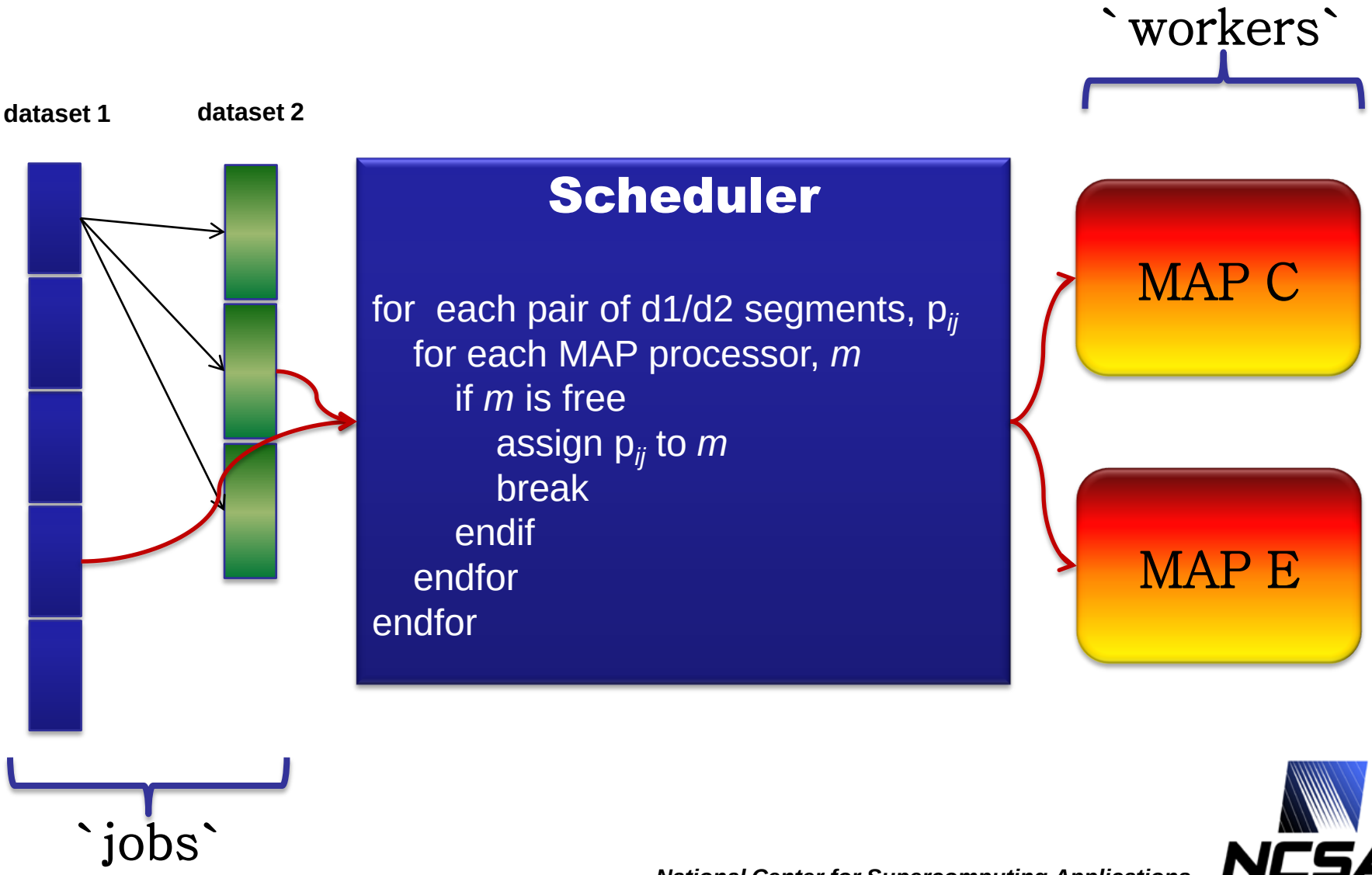
MAP E

Consider Data Partitioning…

- **Analysis of a data/random file with 100 data points each**
  - Each data file is divided into 3 equally sized segments
  - Autocorrelation is computed first, followed by the cross-correlation
  - Each MAP processor is invoked with the first available unprocessed pair of segments
  - MAP Series C processor is idle about 7% of the time!



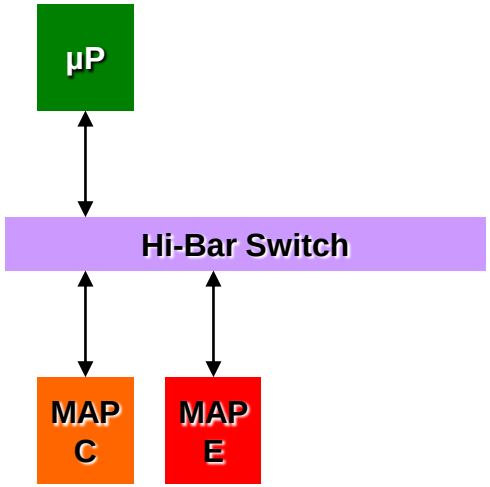
Job Scheduler



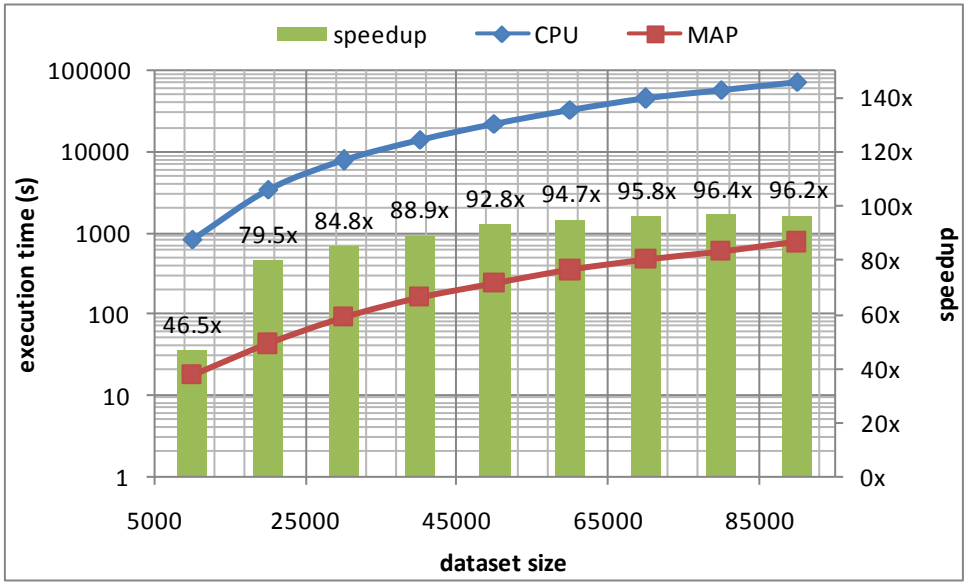
Job Scheduler Implementation

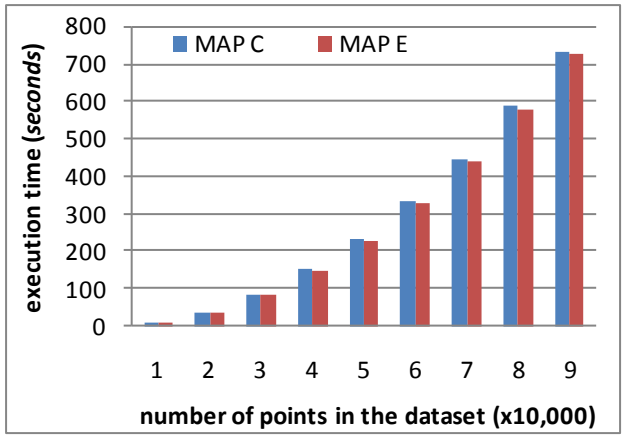
```
do {
      for (k = 0; k < K; k++) {                                   // loop thru all the jobs
         if (job[k].status == running) continue;                  // let it run
         if (job[k].status == done) continue;                     // nothing to do anymore
         if (job[k].status == finished) {                         // need to get results back
               pthread_join(job[k].thread, (void **)&mytd);       // join the thread
               for (i = 0; i < nbins+2; i++) res[i] += mytd->res[i];  // copy results
               job[k].status = done;                              // set status to done
               TOTAL++;                                           // count number of fully executed jobs
               continue;
         }
         for (t = NPROCS-1; t >= 0; t--)  {                       // is there a free MAP to run this job?
               if (thread_stat[t] == busy) continue;              // thread is busy
               if (self && i == j && t == 1) continue;            // not suitable thread for 'self'
               struct my_thread_data *mytd = (struct my_thread_data *)malloc(sizeof(struct my_thread_data));
               pthread_create(&(job[k].thread), NULL, my_map_proc, (void *)mytd);
               thread_stat[t] = busy;                             // lock it
               job[k].status = running;                           // set status to running
               break;                                             // no need to check the rest of the MAPs
         }
      }
      usleep(1000);
} while (TOTAL != K);
```

Load-balanced Implementation




```
for (i = 0; i < random_count; i++)
{
        JobScheduler(data, random);

        JobScheduler(random, random);
}
```





MAP E processor is idle lees than 1% of the time

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Conclusions

- **Pros**
  - A 9% performance improvement due to a better utilization of the idle resources
  - Near-identical load on each of the MAPs
  - Scalable solution that allows to mix compute subroutines with different performance characteristics
- **Cons**
  - Performance hit for the smaller datasets due to the overhead in calling the MAP processors
  - More complex execution flow and data management

Acknowledgements

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