Which verification for soft error detection?

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Computing at Exascale

Exascale platform:

- 10^5 or 10^6 nodes, each equipped with 10^2 or 10^3 cores
- Shorter Mean Time Between Failures (MTBF) μ

Theorem: $\mu_p = \dfrac{\mu_{\text{ind}}}{p}$ for arbitrary distributions

MTBF (individual node)	1 year	10 years	120 years
MTBF (platform of 10^6 nodes)	30 sec	5 mn	1 h

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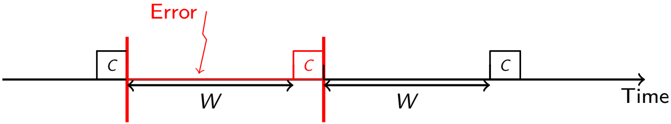
Need more reliable components!!

Need more resilient techniques!!!

General-purpose approach

Periodic checkpoint, rollback and recovery:



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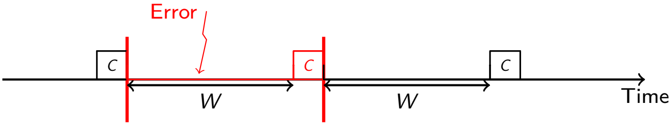

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- Silent errors (aka silent data corruptions): e.g., soft faults in L1 cache, ALU, double bit flip

Silent error is detected only when corrupted data is activated, which could happen long after its occurrence

Detection latency is problematic ⇒ risk of saving corrupted checkpoint!

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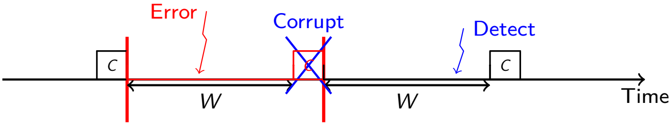

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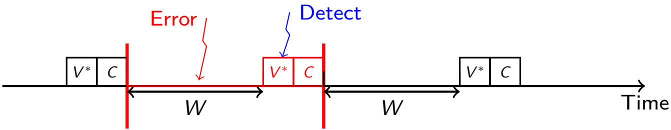
Coping with silent errors

Couple checkpointing with verification:



- Before each checkpoint, run some verification mechanism (checksum, ECC, coherence tests, TMR, etc)
- Silent error is detected by verification ⇒ checkpoint always valid ☺

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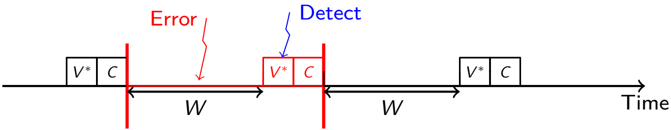

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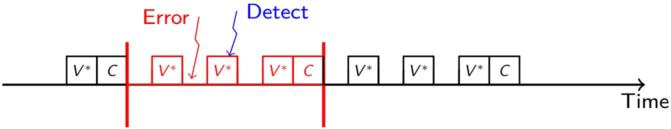
Optimal period (Young/Daly):

	Fail-stop (classical)	Silent errors
Pattern	$T = W + C$	$T = W + V^* + C$
Optimal	$W^* = \sqrt{2C\mu}$	$W^* = \sqrt{(C + V^*)\mu}$

One step further

Perform several verifications before each checkpoint:



- Pro: silent error is detected earlier in the pattern ☺
- Con: additional overhead in error-free executions ☹

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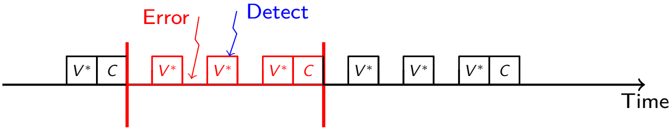

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How many intermediate verifications to use and the positions?

Partial verification

Guaranteed/perfect verifications (V^*) can be very expensive!

Partial verifications (V) are available for many HPC applications!

- Lower accuracy: recall $r = \frac{\#\text{detected errors}}{\#\text{total errors}} < 1$ ☹
- Much lower cost, i.e., $V < V^*$ ☺

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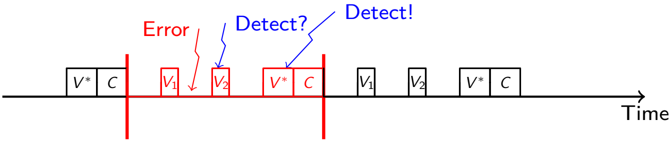

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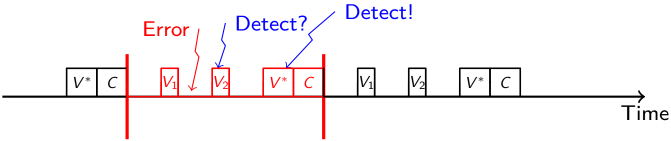


Which verification(s) to use? How many? Positions?

Outline

Model and objective

Silent errors

- Poisson process: arrival rate $\lambda = 1/\mu$, where μ is platform MTBF
- Strike only computations; checkpointing, recovery, and verifications are protected

Resilience parameters

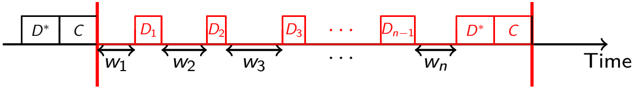
- Cost of checkpointing C, cost of recovery R
- k types of partial detectors and a perfect detector $\left(D^{(1)}, D^{(2)}, \ldots, D^{(k)}, D^{*}\right)$
  - $D^{(i)}$: cost $V^{(i)}$ and recall $r^{(i)} < 1$
  - D^{*}: cost V^{*} and recall $r^{*} = 1$

Design an optimal periodic computing pattern that minimizes execution time (or makespan) of the application

Pattern

Formally, a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$ is defined by

- W: pattern work length (or period)
- n: number of work segments, of lengths w_i (with $\sum_{i=1}^{n} w_i = W$)
- $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \dots, \alpha_n]$: work fraction of each segment ($\alpha_i = w_i / W$ and $\sum_{i=1}^{n} \alpha_i = 1$)
- $\mathbf{D} = [D_1, D_2, \dots, D_{n-1}, D^*]$: detectors used at the end of each segment ($D_i = D^{(j)}$ for some type j)



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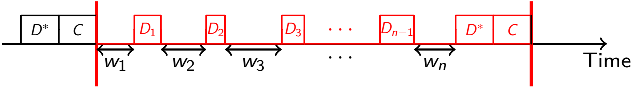

- Last detector is perfect to avoid saving corrupted checkpoints

- The same detector type $D^{(j)}$ could be used at the end of several segments

Outline

Summary of results

In a nutshell:

- Given a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$,
  - We show how to compute the expected execution time
  - We are able to characterize its optimal length
  - We can compute the optimal positions of the partial verifications

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In a nutshell:

- Given a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$,
  - We show how to compute the expected execution time
  - We are able to characterize its optimal length
  - We can compute the optimal positions of the partial verifications
- However, we prove that finding the optimal pattern is NP-hard
- We design an FPTAS (Fully Polynomial-Time Approximation Scheme) that gives a makespan within $(1 + \epsilon)$ times the optimal with running time polynomial in the input size and $1/\epsilon$
- We show a simple greedy algorithm that works well in practice

Summary of results

Algorithm to determine a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$:

- Use FPTAS or Greedy (or even brute force for small instances) to find (optimal) number n of segments and set $\mathbf{D}$ of used detectors
- Arrange the $n-1$ partial detectors in any order
- Compute $W^* = \sqrt{\frac{o_{\text{ff}}}{\lambda f_{\text{re}}}}$ and $\alpha_i^* = \frac{1}{U_n} \cdot \frac{1-g_{i-1}g_i}{(1+g_{i-1})(1+g_i)}$ for $1 \le i \le n$,

$$\text{where } o_{\text{ff}} = \sum_{i=1}^{n-1} V_i + V^* + C \text{ and } f_{\text{re}} = \frac{1}{2}\left(1 + \frac{1}{U_n}\right)$$

$$\text{with } g_i = 1 - r_i \text{ and } U_n = 1 + \sum_{i=1}^{n-1} \frac{1-g_i}{1+g_i}$$

Expected execution time of a pattern

Proposition

The expected time to execute a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$ *is*

$$\mathbb{E}(W) = W + \sum_{i=1}^{n-1} V_i + V^* + C + \lambda W(R + W\boldsymbol{\alpha}^T A\boldsymbol{\alpha} + \mathbf{d}^T\boldsymbol{\alpha}) + o(\lambda),$$

where A *is a symmetric matrix defined by* $A_{ij} = \frac{1}{2}\left(1 + \prod_{k=i}^{j-1} g_k\right)$ *for* $i \leq j$ *and* $\mathbf{d}$ *is a vector defined by* $\mathbf{d}_i = \sum_{j=i}^{n}\left(\prod_{k=i}^{j-1} g_k\right) V_i$ *for* $1 \leq i \leq n$.

- First-order approximation (as in Young/Daly's classic formula)
- Matrix A is essential to analysis. For instance, when $n = 4$ we have:

$$A = \frac{1}{2}\begin{bmatrix} 2 & 1+g_1 & 1+g_1g_2 & 1+g_1g_2g_3 \\ 1+g_1 & 2 & 1+g_2 & 1+g_2g_3 \\ 1+g_1g_2 & 1+g_2 & 2 & 1+g_3 \\ 1+g_1g_2g_3 & 1+g_2g_3 & 1+g_3 & 2 \end{bmatrix}$$

Minimizing makespan

For an application with total work W_{base}, the makespan is

$$\begin{aligned} W_{\text{final}} &\approx \frac{\mathbb{E}(W)}{W} \times W_{\text{base}} \\ &= W_{\text{base}} + H(W) \times W_{\text{base}}, \end{aligned}$$

where $H(W) = \frac{\mathbb{E}(W)}{W} - 1$ is the execution overhead

For instance, if $W_{\text{base}} = 100$, $W_{\text{final}} = 120$, we have $H(W) = 20\%$

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Minimizing makespan is equivalent to minimizing overhead!

$$H(W) = \frac{o_{\text{ff}}}{W} + \lambda f_{\text{re}} W + \lambda(R + \mathbf{d}^T \boldsymbol{\alpha}) + o(\lambda)$$

fault-free overhead: $o_{\text{ff}} = \sum_{i=1}^{n-1} V_i + V^* + C$

re-execution fraction: $f_{\text{re}} = \boldsymbol{\alpha}^T A \boldsymbol{\alpha}$

Optimal pattern length to minimize overhead

Proposition

The execution overhead of a pattern $\textsc{Pattern}(W, n, \alpha, \mathbf{D})$ *is minimized when its length is*

$$W^* = \sqrt{\frac{o_{ff}}{\lambda f_{re}}}.$$

The optimal overhead is

$$H(W^*) = 2\sqrt{\lambda o_{ff} f_{re}} + o(\sqrt{\lambda}).$$

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- When the platform MTBF $\mu = 1/\lambda$ is large, $o(\sqrt{\lambda})$ is negligible
- Minimizing overhead is reduced to minimizing the product $o_{\mathrm{ff}} f_{\mathrm{re}}$!
  - Tradeoff between fault-free overhead and fault-induced re-execution

Optimal positions of verifications to minimize f_{re}

Theorem

The re-execution fraction f_{re} of a pattern $\textsc{Pattern}(W, n, \boldsymbol{\alpha}, \mathbf{D})$ *is minimized when* $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$, *where*

$$\alpha_k^* = \frac{1}{U_n} \times \frac{1 - g_{k-1}g_k}{(1 + g_{k-1})(1 + g_k)} \quad \textit{for } 1 \leq k \leq n,$$

where $g_0 = g_n = 0$ *and* $U_n = 1 + \sum_{i=1}^{n-1} \frac{1-g_i}{1+g_i}$.

In this case, the optimal value of f_{re} *is*

$$f_{re}^* = \frac{1}{2}\left(1 + \frac{1}{U_n}\right).$$

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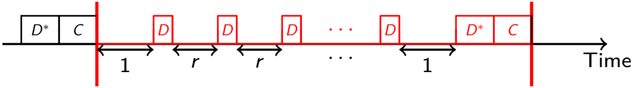
- Most technically involved result (lengthy proof of 3 pages!)
- Given a set of partial verifications, the minimal value of f_{re} does not depend upon their ordering within the pattern

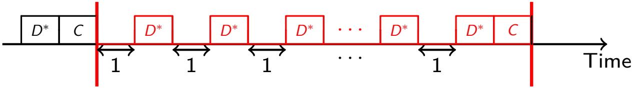
Two special cases

- When all verifications use the same partial detector (r), we get

$$\alpha_k^* = \begin{cases} \frac{1}{(n-2)r+2} & \text{for } k = 1 \text{ and } k = n \\ \frac{r}{(n-2)r+2} & \text{for } 2 \le k \le n-1 \end{cases}$$



- When all verifications use the perfect detector, we get equal-length segments, i.e., $\alpha_k^* = \frac{1}{n}$ for all $1 \le k \le n$



Optimal number and set of detectors

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Equivalent to the following optimization problem:

$$\text{Minimize} \qquad f_{\text{re}} o_{\text{ff}} = \frac{V^* + C}{2} \left(1 + \frac{1}{1 + \sum_{j=1}^{k} m_j a^{(j)}} \right) \left(1 + \sum_{j=1}^{k} m_j b^{(j)} \right)$$

$$\text{subject to} \qquad m_j \in \mathbb{N}_0 \quad \forall j = 1, 2, \ldots, k$$

accuracy: $a^{(j)} = \frac{1 - g^{(j)}}{1 + g^{(j)}}$ relative cost: $b^{(j)} = \frac{V^{(j)}}{V^* + C}$

accuracy-to-cost ratio: $\phi^{(j)} = \frac{a^{(j)}}{b^{(j)}}$

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NP-hard even when all detectors share the same accuracy-to-cost ratio (reduction from unbounded subset sum), but admits an FPTAS.

Greedy algorithm

Practically, a greedy algorithm:

- Employs only the detector with highest accuracy-to-cost ratio $\phi^{\text{max}} = \frac{a}{b}$

$$\text{Optimal number of detectors: } m^* = -\frac{1}{a} + \sqrt{\frac{1}{a}\left(\frac{1}{b} - \frac{1}{a}\right)}$$

$$\text{Optimal overhead: } H^* = \sqrt{\frac{2(C + V^*)}{\mu}}\left(\sqrt{\frac{1}{\phi^{\text{max}}}} + \sqrt{1 - \frac{1}{\phi^{\text{max}}}}\right)$$

- Rounds up the optimal rational solution $\lceil m^* \rceil$

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The greedy algorithm has an approximation ratio $\sqrt{3/2} < 1.23$

Outline

Simulation configuration

Exascale platform:

- 10^5 computing nodes with individual MTBF of 100 years
  $\Rightarrow$ platform MTBF $\mu \approx 8.7$ hours
- Checkpoint sizes of 300GB with throughput of 0.5GB/s
  $\Rightarrow$ $C = 600s$

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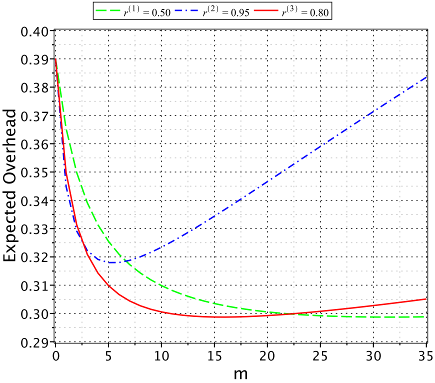
Realistic detectors (designed at ANL):

	cost	recall	ACR
Time series prediction $D^{(1)}$	$V^{(1)} = 3s$	$r^{(1)} = 0.5$	$\phi^{(1)} = 133$
Spatial interpolation $D^{(2)}$	$V^{(2)} = 30s$	$r^{(2)} = 0.95$	$\phi^{(2)} = 36$
Combination of the two $D^{(3)}$	$V^{(3)} = 6s$	$r^{(3)} = 0.8$	$\phi^{(3)} = 133$
Perfect detector D^*	$V^* = 600s$	$r^* = 1$	$\phi^* = 2$

Evaluation results

Using individual detector (greedy algorithm)



Best partial detectors offer ∼9% improvement in overhead.
Saving ∼55 minutes for every 10 hours of computation!

Evaluation results

Mixing two detectors: depending on application or dataset, a detector's recall may vary, but its cost stays the same

Realistic data again!
$r^{(1)} = [0.5, 0.9]$
$r^{(2)} = [0.75, 0.95]$
$r^{(3)} = [0.8, 0.99]$

$\phi^{(1)} = [133, 327]$
$\phi^{(2)} = [24, 36]$
$\phi^{(3)} = [133, 196]$

	m	overhead H	diff. from opt.
Scenario 1: $r^{(1)} = 0.51$, $r^{(3)} = 0.82$, $\phi^{(1)} \approx 137$, $\phi^{(3)} \approx 139$			
Optimal solution	(1, 15)	29.828%	0%
Greedy with $D^{(3)}$	(0, 16)	29.829%	0.001%
Scenario 2: $r^{(1)} = 0.58$, $r^{(3)} = 0.9$, $\phi^{(1)} \approx 163$, $\phi^{(3)} \approx 164$			
Optimal solution	(1, 14)	29.659%	0%
Greedy with $D^{(3)}$	(0, 15)	29.661%	0.002%
Scenario 3: $r^{(1)} = 0.64$, $r^{(3)} = 0.97$, $\phi^{(1)} \approx 188$, $\phi^{(3)} \approx 188$			
Optimal solution	(1, 13)	29.523%	0%
Greedy with $D^{(1)}$	(27, 0)	29.524%	0.001%
Greedy with $D^{(3)}$	(0, 14)	29.525%	0.002%

The greedy algorithm works very well in this practical scenario!

Outline

Conclusion

A first comprehensive analysis of computing patterns with partial verifications to detect silent errors

- Theoretically: assess the complexity of the problem and propose efficient approximation schemes
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Future directions

- Partial detectors with false positives/alarms

$$\text{precision } p = \frac{\#\text{true errors}}{\#\text{detected errors}} < 1$$

- Errors in checkpointing, recovery, and verifications
- Coexistence of fail-stop and silent errors

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Research report available at https://hal.inria.fr/hal-01164445v1