Resilience Algorithms to Cope with Fail-Stop and Silent Errors

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HPC Days in Lyon 7 April, 2016 Joint work with

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Exascale platform

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

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

MTBF (individual node)			100 years
MTBF (platform of 10 ⁶ nodes)	30 secs	5 mins	50 mins

• Multiple failure sources: fail-stop error, silent data corruption, etc.

Need more reliable components! Need more scalable algorithms! Need more resilient techniques!

Fail-stop errors: e.g., resource crash, node failure

- Instantaneous error detection

Standard approach: periodic checkpointing, rollback and recovery



Well-known first-order approximation formula to compute optimal checkpointing interval [*Young 1973, Daly 2006*]:

$$W^* = \sqrt{2\mu C}$$

 μ : Platform MTBF

C: Checkpointing time

Silent errors (or silent data corruptions): e.g., soft faults in L1 cache, ALU, double bit flip, due to cosmic radiation, packaging pollution, etc.

- Arbitrary detection latency

Same approach?



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Keep multiple checkpoints?

Which checkpoint to recover from?

Need an active method to detect silent errors!



Promising approach: coupling checkpointing with verification



- Before each checkpoint, run some verification mechanism or error detection test
- Silent error, if any, is detected by verification
- Need to maintain only one checkpoint, which is always valid $\textcircled{\sc c}$



Methods for Detecting Silent Errors

General-purpose approaches

• Replication [*Fiala et al. 2012*] or triple modular redundancy and voting [*Lyons and Vanderkulk 1962*]

Application-specific approaches

- Algorithm-based fault tolerance (ABFT): checksums in dense matrices Limited to one error detection and/or correction in practice [*Huang and Abraham 1984*]
- Partial differential equations (PDE): use lower-order scheme as verification mechanism [*Benson, Schmit and Schreiber 2014*]
- Generalized minimal residual method (GMRES): inner-outer iterations [*Hoemmen and Heroux 2011*]
- Preconditioned conjugate gradients (PCG): orthogonalization check every *k* iterations, re-orthogonalization if problem detected [*Sao and Vuduc* 2013, *Chen 2013*]

Data-analytics approaches

- Dynamic monitoring of HPC datasets based on physical laws (e.g., temperature limit, speed limit) and space or temporal proximity [*Bautista-Gomez and Cappello 2014*]
- Time-series prediction, spatial multivariate interpolation [Di et al. 2014]

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General-purpose approaches



- Models
- Analysis of several patterns

2 Coping with Fail-stop and Silent Errors

3 Conclusion and Future Work

Coping with Silent Errors Models

• Analysis of several patterns

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3 Conclusion and Future Work

Failure arrivals follow exponential law $Exp(\lambda)$, where $\lambda = 1/\mu$.

- $P(\lambda, w) = 1 - e^{\lambda w}$ (memoryless)

Design a periodic computing pattern that minimizes the expected execution time (or makespan) of the application.



A pattern has the following characteristics:

- End with a verified checkpoint (avoid saving corrupted checkpoints)
- May contain intermediate verifications (for better performance)

Models

Execution overhead

Suppose an application is divided into periodic patterns of work W. If the expected execution time of a pattern is $\mathbb{E}(W)$, then

$$egin{array}{rcl} Makespan &pprox & rac{Total_work}{W} \cdot \mathbb{E}(W) \ &= & (1 + \mathbb{H}) \cdot Total_work \end{array}$$

where

$$\mathbb{H} = \frac{\mathbb{E}(W)}{W} - 1$$

denote the execution overhead of the pattern.

E.x. if W = 100, $\mathbb{E}(W) = 125$, then $\mathbb{H} = 25\%$.

Proposition

For large applications, minimizing expected makespan is equivalent to minimizing the execution overhead of a pattern.

Coping with Silent Errors Models

• Analysis of several patterns

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Base Pattern P_c (Revisiting Young/Daly)



Proposition

The optimal checkpointing interval W^* and optimal execution overhead \mathbb{H}^* of the base pattern P_c are

$$egin{aligned} \mathcal{W}^* &= \sqrt{rac{V^*+\mathcal{C}}{\lambda}} \ \mathbb{H}^* &= 2\sqrt{\lambda(V^*+\mathcal{C})} + O(\lambda) \end{aligned}$$

	Fail-stop errors	Silent errors
Pattern	W + C	$W + V^* + C$
Optimal W^*	$\sqrt{\frac{2C}{\lambda}}$	$\sqrt{rac{V^*+C}{\lambda}}$
Optimal \mathbb{H}^*	$\sqrt{2\lambda C}$	$2\sqrt{\lambda(V^*+C)}$

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- ullet Silent errors detected earlier in the pattern igodot
- Additional overhead in fault-free execution 🙂

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When is it better to use intermediate verifications? What is the optimal checkpointing period? How many verifications to use? What are their positions?





Proposition

The optimal P_{v^*c} pattern has checkpointing interval W^* and contains n^* equi-spaced verifications:

$$n^{*} = \sqrt{\frac{C}{V^{*}}} \iff \text{necessary condition: } C > V^{*}$$

$$W^{*} = \sqrt{\frac{n^{*}V^{*} + C}{\frac{1}{2}(1 + \frac{1}{n^{*}})\lambda}} = \sqrt{\frac{2C}{\lambda}} > \sqrt{\frac{V^{*} + C}{\lambda}} \iff \text{base pattern}$$

$$\mathbb{H}^{*} = \sqrt{2\lambda V^{*}} + \sqrt{2\lambda C} + O(\lambda)$$

$$< 2\sqrt{\lambda(V^{*} + C)} + O(\lambda) \iff \text{base pattern}$$



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Practical no. of verifications must be an integer: $\max(1, \lfloor n^* \rfloor)$ or $\lceil n^* \rceil$

Observations

Observation 1

The expected time to execute a pattern of length W is

$$\mathbb{E}(W) = \underbrace{W + o_{\text{ff}}}_{\text{error-free time}} + \underbrace{\lambda W}_{\text{expected \#errors}} \cdot \underbrace{\left(f_{\text{re}} \cdot W + O(V^*) + R\right)}_{\text{expected re-execution time}} + O(\lambda)$$

- $o_{\rm ff}$: overhead in a fault-free execution, i.e., \sum resilience ops.
- f_{re}: fraction of re-executed work in case of faults.

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Asymptotically, minimizing $\mathbb H$ is equivalent to minimizing $\mathit{f}_{\rm re}\mathit{o}_{\rm ff}$

Example 1: Base pattern P_c

$$\mathbb{E}(W) = W + \underbrace{V^* + C}_{Off} + \lambda W(\underbrace{1}_{f_{re}} \cdot W + V^* + R) + O(\lambda)$$
$$W^* = \sqrt{\frac{V^* + C}{\lambda}} \text{ and } \mathbb{H}^* \approx 2\sqrt{\lambda(V^* + C)}$$

Example 2: Pattern P_{v^*c}

$$\mathbb{E}(W) = W + \underbrace{nV^* + C}_{o_{\mathrm{ff}}} + \lambda W \Big(\underbrace{\frac{1}{2} \Big(1 + \frac{1}{n}\Big)}_{f_{\mathrm{re}}} \cdot W + \frac{n+1}{2} V^* + R \Big) + O(\lambda)$$

$$W^* = \sqrt{\frac{nV^* + C}{\frac{1}{2}\left(1 + \frac{1}{n}\right)\lambda}} \text{ and } \mathbb{H}^* \approx 2\sqrt{\lambda \frac{1}{2}(nV^* + C)\left(1 + \frac{1}{n}\right)}$$

Guaranteed/perfect verifications can be very expensive

For HPC applications, many silent error detectors are partial

- Lower cost \bigcirc
- Lower accuracy 🙁

 $\cot V \ll \cot V^*$ of guaranteed verification

Pattern P_{vc} with Partial Verifications

Can we do better by using partial verifications in a pattern?



- A partial verification may raise false alarms (with prob. 1 p)
- A partial verification may miss errors (with prob. 1 r)
- Last verification guaranteed to avoid saving invalid checkpoints

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When is it better to use partial verifications? What is the optimal checkpointing period? How many partial verifications to use? What are their positions?

Proposition

The optimal pattern P_{vc} does not use any partial verification with constant precision p<1

In particular, the result holds if the precision satisfies $p=1-\Omega(\lambda^{1/2})$

- Intuitively, an imprecise verification becomes another error source with error probability 1 p
- With first-order approximation, probability of a silent error in the pattern is $1 e^{\lambda W} \approx \lambda W = \Theta(\lambda^{1/2})$

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Having a recall r < 1 is fine, because errors are rare and will eventually be detected by the final guaranteed verification

Tradeoff between recall and precision \Rightarrow maximize precision (e.g. p > 0.999 for $\lambda = 10^{-6}$)

We will assume p = 1 for subsequent analysis

Pattern P_{vc} with Partial Verifications



(1) Apply the $f_{re}o_{ff}$ analysis

Proposition

Suppose a pattern P_{vc} has *n* segments (n-1 partial verifications and one guaranteed verification), and the*i* $-th segment has <math>\alpha_i$ fraction of work. Then the pattern is characterized by

$$o_{ff} = (n-1)V + V^* + C$$

 $f_{re} = \alpha^T A \alpha$

where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \dots, \alpha_n]^T$ and A is a symmetric positive definite matrix defined by $A_{i,j} = \frac{1}{2} (1 + (1 - r)^{|i-j|})$ for $1 \le i, j \le n$
Pattern P_{vc} with Partial Verifications

(2) Determine α to minimize f_{re} (involved analysis)

Proposition

The re-execution fraction f_{re} of a pattern P_{vc} with n segments is minimized when $\alpha=\alpha^*$, where

$$\alpha_i^* = \begin{cases} \frac{1}{(n-2)r+2} & \text{for } i = 1, n \\ \frac{r}{(n-2)r+2} & \text{for } i = 2, 3, \dots, n-1 \end{cases}$$

and the optimal value of f_{re} is

$$f_{re}^* = \frac{1}{2} \left(1 + \frac{2-r}{(n-2)r+2} \right)$$



If all verifications are perfect (r = 1), we retrieve equal-length segments, i.e., $\alpha_i^* = \frac{1}{n}$ for all $1 \le i \le n$ and $f_{re}^* = \frac{1}{2} \left(1 + \frac{1}{n}\right)$

Pattern P_{vc} with Partial Verifications

(3) Minimize
$$f_{re}o_{ff} = \frac{1}{2} \left(1 + \frac{2-r}{(n-2)r+2} \right) \left((n-1)V + V^* + C \right)$$

• accuracy $a = \frac{r}{2-r}$ and relative cost $b = \frac{V}{V^*+C}$

• accuracy-to-cost ratio $\phi = \frac{a}{b}$

Proposition

The optimal P_{vc} pattern satisfies

$$n^{*} = 1 - \frac{1}{a} + \sqrt{\frac{1}{a}\left(\frac{1}{b} - \frac{1}{a}\right)} \quad \Leftarrow \text{ necessary condition: } \phi > 2$$
$$W^{*} = \sqrt{\frac{2(V^{*} + C)}{\lambda}\left(1 - \frac{1}{\phi}\right)} > \sqrt{\frac{2C}{\lambda}} \quad \Leftarrow \text{ Pattern } P_{v^{*}c}$$
$$\mathbb{H}^{*} = \sqrt{2\lambda(V^{*} + C)}\left(\sqrt{1 - \frac{1}{\phi}} + \sqrt{\frac{1}{\phi}}\right) + O(\lambda)$$
$$<\sqrt{2\lambda V^{*}} + \sqrt{2\lambda C} + O(\lambda) \quad \Leftarrow \text{ Pattern } P_{v^{*}c}$$

Pattern P_{vc} with Partial Verifications

Assessing the benefit of partial verifications on realistic platform

- 10⁵ computing nodes with individual MTBF of 100 years \Rightarrow platform MTBF $\mu = 31536s \approx 8.7$ hours
- Checkpoint size of 300GB with throughput of 0.5GB/s $\Rightarrow C = 600s = 10$ mins, and V^* in same order
- Partial verifications using lightweight detectors
 ⇒ V typically tens of seconds, and r ∈ [0.5, 0.95]

e.g.,
$$C = 600$$
, $V^* = 300$, $V = 30$ and $p = 1$, $r = 0.8$

	Pattern P_{vc}	Pattern P _{v*c}	Pattern P _c	
W*	$7335s \approx 2.04$ hours	7103s pprox 1.97 hours	$5328s \approx 1.48$ hours	
<i>n</i> *	6	2	1	
$lpha^*$	$\alpha_i = \begin{cases} 0.20, i = 1, 6\\ 0.15, i = 25 \end{cases}$	[0.5, 0.5]	[1]	
\mathbb{H}^*	28.6%	33.3%	33.8%	

Can we do better by using multiple types of partial verifications?

 $D^{(1)} = (V^{(1)}, r^{(1)}), D^{(2)} = (V^{(2)}, r^{(2)}), \dots, D^{(k)} = (V^{(k)}, r^{(k)})$



The *i*-th partial verification has type *j*, i.e., $V_i = V^{(j)}$ for some $1 \le j \le k$

Which verification is the optimal one to use? What is the optimal combination of partial verifications?

The optimal pattern P_{vc} uses the partial verification with the highest accuracy-to-cost ratio



- Result is based on optimal rational solution (*n*^{*})
- Overhead of rounded integer solution may no longer be optimal

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What is the optimal integer solution?

Finding the optimal P_{vc} pattern with k verification types is NP-complete, even when all verification types share the same accuracy-to-cost ratio, i.e., $\frac{a^{(j)}}{b^{(j)}} = \phi$ for all $1 \le j \le k$

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Approximation algorithms:

- FPTAS (Fully Polynomial-Time Approximation Scheme)
 - Overhead within $1 + \epsilon$ times the optimal with running time polynomial in the input size and $1/\epsilon$ for any $\epsilon > 0$.
 - The solution is independent of the ordering of the verifications
- Greedy algorithm
 - Compute the optimal solution using the one detector with the highest accuracy-to-cost ratio, and then round up the solution
 - This algorithm has approximation ratio $\sqrt{3/2} < 1.23$

Pattern with Multiple Partial Detectors

Performance evaluation on realistic platform

- 10⁵ computing nodes with individual MTBF of 100 years \Rightarrow platform MTBF $\mu \approx$ 8.7 hours
- Checkpoints size of 300GB with throughput of 0.5GB/s \Rightarrow C = 600s = 10 mins, and V* in same order
- Several realistic partial detectors based on data-analytics approach

	cost	recall	ACR
Time series prediction	$V^{(1)} = 3s$	$r^{(1)} = [0.5, 0.9]$	$\phi^{(1)} = [133, 327]$
Spatial interpolation	$V^{(2)} = 30s$	$r^{(2)} = [0.75, 0.95]$	$\phi^{(2)} = [24, 36]$
Combination of two	$V^{(3)} = 6s$	$r^{(3)} = [0.8, 0.99]$	$\phi^{(3)} = [133, 196]$
Perfect verification	$V^* = 600s$	$r^* = 1$	$\phi^* = 2$

A detector's recall may vary depending on the application or dataset

Pattern with Multiple Partial Detectors

Using one type of verification ($r^{(1)} = 0.5$, $r^{(2)} = 0.95$, $r^{(3)} = 0.8$)



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

Using multiple types of verifications

	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 $V^{(3)}$	(0, 16)	29.829%	0.001%			
Scenario 2: $r^{(1)} =$	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 $V^{(3)}$	(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 $V^{(1)}$	(27, 0)	29.524%	0.001%			
Greedy with $V^{(3)}$	(0, 14)	29.525%	0.002%			

The Greedy algorithm works very well in this practical setting!

Coping with Silent Errors

- Models
- Analysis of several patterns

2 Coping with Fail-stop and Silent Errors



Coping with Fail-stop and Silent Errors

Fail-stop errors and silent errors coexist in large-scale platforms A resilience pattern needs to cope with both error sources simultaneously

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Two-level checkpointing and verification framework

- Fail-stop errors (λ_f) are handled by disk checkpoints (C_D)
- Silent errors (λ_s) are handled by in-memory checkpoints (C_M) and verifications (guaranteed V* or partial V)



Framework enforcing two properties:

- A guaranteed verification before each memory checkpoint ⇒ Checkpoints always valid
- A memory checkpoint before each disk checkpoint
 ⇒ Always recover from latest checkpoints

Two-level Base Pattern P_D (Revisiting Young/Daly Again)



Proposition

The optimal checkpointing interval W^* and optimal execution overhead H^* of the two-level base pattern P_D are

$$W^* = \sqrt{rac{V^* + C_M + C_D}{\lambda_s + rac{\lambda_f}{2}}}$$
 $\mathbb{H}^* = 2\sqrt{\left(\lambda_s + rac{\lambda_f}{2}
ight)(V^* + C_M + C_D)} + O(\lambda)$

	Fail-stop errors	Silent errors	Both errors
Pattern	$W + C_D$	$W + V^* + C_M$	$W + V^* + C_M + C_D$
Optimal W^*	$\sqrt{\frac{2C_D}{\lambda_f}}$	$\sqrt{rac{V^*+C_M}{\lambda_s}}$	$\sqrt{rac{V^*+C_M+C_D}{\lambda_s+rac{\lambda_f}{2}}}$
$Optimal\ \mathbb{H}^*$	$\sqrt{2\lambda_f C_D}$	$2\sqrt{\lambda_s(V^*+C_M)}$	$2\sqrt{\left(\lambda_s+\frac{\lambda_f}{2}\right)\left(V^*+C_M+C_D\right)}$

Various Two-level Patterns



Summary of Results

Parameters of various optimal patterns

- W*: optimal pattern length
- *n*^{*}: optimal #memory checkpoints between two disk checkpoints
- *m*^{*}: optimal #verifications between two memory checkpoints

Pattern	W*	<i>n</i> *	<i>m</i> *	H*
P _D	$\sqrt{\frac{V^*+C_M+C_D}{\lambda_s+\frac{\lambda_f}{2}}}$	-	-	$2\sqrt{\left(\lambda_s+\frac{\lambda_f}{2}\right)\left(V^*+C_M+C_D\right)}$
\mathbf{P}_{DV^*}	$\sqrt{\frac{\frac{m^*V^*+C_M+C_D}{\frac{1}{2}\left(1+\frac{1}{m^*}\right)\lambda_s+\frac{\lambda_f}{2}}}$	-	$\sqrt{rac{\lambda_s}{\lambda_s+\lambda_f}}\cdotrac{C_M+C_D}{V^*}$	$\sqrt{2(\lambda_s + \lambda_f)C_M + C_D} + \sqrt{2\lambda_sV^*}$
P_{DV}	$\sqrt{\frac{(m^*-1)V + V^* + C_M + C_D}{\frac{1}{2}(1 + \frac{2V}{(m^*-2)r+2})\lambda_5 + \frac{\lambda_f}{2}}}$	_	$2-rac{2}{r}+\sqrt{rac{\lambda_s}{\lambda_s+\lambda_f}}$	$\sqrt{2(\lambda_s + \lambda_f)\left(V^* - \frac{2-r}{r}V + C_M + C_D\right)}$
	$\sqrt{\frac{1}{2}\left(1+\frac{2-r}{(m^*-2)r+2}\right)\lambda_s+\frac{\lambda_t}{2}}$		$\times \sqrt{rac{2-r}{r}\left(rac{V^*+C_M+C_D}{V}-rac{2-r}{r} ight)}$	$+\sqrt{2\lambda_srac{2-r}{r}V}$
\mathbf{P}_{DM}	$\sqrt{\frac{n^*(V^*+C_M)+C_D}{\frac{\lambda_x}{n^*}+\frac{\lambda_f}{2}}}$	$\sqrt{\frac{2\lambda_s}{\lambda_f}} \cdot \frac{C_D}{V^* + C_M}$	_	$2\sqrt{\lambda_s(V^*+C_M)}+\sqrt{2\lambda_fC_D}$
\mathbf{P}_{DMV^*}	$\sqrt{\frac{n^{*}m^{*}V^{*} + n^{*}C_{M} + C_{D}}{\frac{1}{2}\left(1 + \frac{1}{m^{*}}\right)\frac{\lambda_{S}}{n^{*}} + \frac{\lambda_{f}}{2}}}$	$\sqrt{\frac{\lambda_s}{\lambda_f} \cdot \frac{C_D}{C_M}}$	$\sqrt{\frac{C_M}{V^*}}$	$\sqrt{2\lambda_f C_D} + \sqrt{2\lambda_s C_M} + \sqrt{2\lambda_s V^*}$
P_{DMV}	$\sqrt{\frac{n^*(m^*-1)V+n^*(V^*+C_M)+C_D}{\frac{1}{2}\left(1+\frac{2-r}{(m^*-2)r+2}\right)\frac{\lambda_S}{n^*}+\frac{\lambda_f}{2}}}$	$\sqrt{\frac{\lambda_s}{\lambda_s}}$	$2 - \frac{2}{r}$	$\sqrt{2\lambda_f C_D} + \sqrt{2\lambda_s \left(V^* - \frac{2-r}{r}V + C_M\right)}$
	$V = \frac{1}{2} \left(1 + \frac{2-r}{(m^*-2)r+2} \right) \frac{\lambda_s}{n^*} + \frac{\lambda_f}{2}$	$\sqrt{\frac{\lambda_s}{\lambda_f}} \cdot \frac{C_D}{V^* - \frac{2-r}{r}V + C_M}$	$+\sqrt{rac{2-r}{r}\left(rac{V^*+C_M}{V}-rac{2-r}{r} ight)}$	$+\sqrt{2\lambda_s \frac{2-r}{r}V}$

Performance Evaluation

• Parameters of four real platforms [Moody et al. 2010]

•
$$V^* = C_M$$
, $V = C_M/100$ and $r = 0.8$

platform	#nodes	λ_f	λ_s	CD	См
Hera	256	9.46e-7	3.38e-6	300 <i>s</i>	15.4 <i>s</i>
Atlas	512	5.19e-7	7.78e-6	439 <i>s</i>	9.1 <i>s</i>
Coastal	1024	4.02e-7	2.01e-6	1051 <i>s</i>	4.5 <i>s</i>
Coastal SSD	1024	4.02e-7	2.01e-6	2500 <i>s</i>	180.0 <i>s</i>



A linear chain of *n* task, and each task T_i is characterized by a work w_i Resilience operations (e.g., checkpoint, verification) possible only at the end of a task

$$(1) \rightarrow (2) \rightarrow (3) \rightarrow \cdots \rightarrow (n)$$

Which tasks to checkpoint (memory or disk) and which tasks to verify (guaranteed or partial) to minimize the expected makespan?

Optimal algorithm based on dynamic programming:

- Complexity $O(n^4)$ using only guaranteed verification
- Complexity $O(n^6)$ using also partial verification

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- Models
- Analysis of several patterns

2 Coping with Fail-stop and Silent Errors



Conclusion

Summary

- First comprehensive analysis of computing patterns to cope with silent errors
- Two-level checkpointing and verification framework to cope with fail-stop and silent errors
- Optimal dynamic programming algorithms for linear task graph
- Performance evaluation based on parameters from real platforms

Future Work

- Analysis of multi-level/hierarchical checkpointing patterns
- Coping with failures in computational workflows modeled as directed acyclic graphs (DAGs)

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