Fault Tolerance (and a bit of Energy)

ICS632: Principles of High-Performance Computing

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Disclaimer

- These slides will provide a quick overview of many important questions faced by theoreticians and practitioners in HPC
- Most of this is still very much in the research and development stage
- It would take us way too long to explore all this content in depth
- We'll learn about some of the topics through research paper presentations

Towards exascale platforms

- The scale of parallel platforms has been steadily increasing for decades
 - number of cabinets, number of blades, number of processors, number of cores
- Several challenges arise (topics of entire conferences/workshops!)
 - Resilience to failures
 - Power consumption
 - Heat management
 - Network interconnects
- Some for people who build platforms, some for people who use platforms



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Outline

- 1 Why Fault Tolerance?
- 2 Checkpointing
- 3 A little theory
- 4 A little practice
- 5 Energy Consumption

Faults, Errors, and Failures

- A fault corresponds to an execution that does not go according to specification (hardware, software)
- A fault may cause an error, i.e., an incorrect system state
- An error may cause a failure, i.e., an unacceptable behavior (e.g., crash, wrong output)
- WARNING: terminology is all over the place in the literature
- Why do failures occur? Because redundancy is too costly
- General question: how to achieve reliability out of unreliable components?

All kinds of faults/failures

- Hardware faults:
 - Detected and corrected by hardware (ECC works)
 - Detected in hardware, but flagged as not corrected (e.g., double bit-flip)
 - Silent (bits are wrong, but you don't know!)
- Software faults:
 - Pure software faults (bugs)
 - Mis-handling of hardware faults
 - OS/firmware faults
 - Many of these are not silent, but not all
- Some failures can be handled by a "reboot", others by a "replace hardware"
 - In practice, "replacing" means "boot a spare"
 - So the two are very similar

How often do failures occur?

- Say you buy a component with Mean Time Between Failures (MTBF) T
- Now you put n components together in a platform
- The platform's MTBF is T/n
- When *n* is large, the MTBF will be low
- So we have a problem for (exa)scale
- Failure distributions are often assumed i.i.d. and exponential (memoryless) in the literature
- But in practice they are likely not i.i.d. and not memoryless (e.g., Weibull), which is much more difficult to work with for theoreticians

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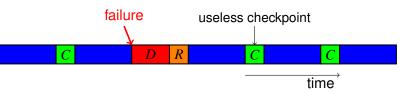
Checkpoint time, recovery time, down time

- Checkpoint time: C seconds
 - Depends on checkpoint size, storage medium
- Recovery time: R seconds
 - Depends on checkpoint size, storage medium
- Downtime: *D* seconds
 - After a failure, time for the logical host to start a recovery
 - Typically: constant time to bring a spare host on-line
- On a single processor:

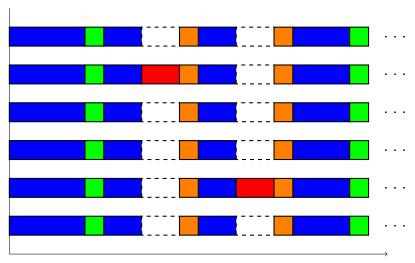


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Coordinated checkpointing on multiple processors



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"Theoretical" questions

- How often should one checkpoint?
 - Goal: minimize expected makespan
- Should checkpointing be periodic?
 - What everybody has done in practice
- Let's look at some development on one processor to get a sense of what theoreticians have done

Assuming Periodic checkpointing

- Many authors have proposed analytical expressions for the "optimal" checkpointing frequency, assuming that checkpointing must be periodic
 - or approximations thereof
- A famous such expression is given by J.W. Young
 - A First Order Approximation to the Optimal Checkpoint Interval, Communication of the ACM, 1974.
- Let's review how this bound is achieved, which will provide context for recent results

Young's approach

- Let T be the time between checkpoints
- Let T_w be the compute time wasted due to a failure
- Let us consider an interval T_i in between two failures



$$T_i = n \times (T+C) + T_w$$

Young's assumptions

- Objective: minimize $\mathbb{E}[T_w]$, where $T_w = T_i n(T + C)$
- Four questionable assumptions:
 - Assumption #1: failure arrival times follow an Exponential distribution of mean $1/\lambda$
 - Assumption #2: failures do not occur during checkpointing
 - Assumption #3: failures do not occur during recovery
 - Assumption #4: failures do not occur during downtime (i.e., on another processor)

Obtaining the approximation

- If T_i is in between n(T+C) and (n+1)(T+C), then $T_w = T_i nT$
 - subtract from the whole time the "useful" compute time
- Therefore:

$$\mathbb{E}[T_w] = \sum_{n=0}^{\infty} \int_{n(T+C)}^{(n+1)(T+C)} (t - nT) \lambda e^{\lambda t} dt$$

$$\Rightarrow \quad \cdots \quad \Rightarrow \quad \mathbb{E}[T_w] = 1/\lambda + T/(1 - e^{\lambda(T+C)})$$

$$\Rightarrow \quad \frac{d\mathbb{E}[T_w]}{dT} = \frac{1 - e^{\lambda(T+C)} + Te^{\lambda(T+C)}}{(1 - e^{\lambda(T+C)})^2}$$

Obtaining the approximation

- To find the optimal T we solve: $e^{\lambda T}e^{\lambda C}(1-\lambda T)-1=0$
- λT is small (because $1/\lambda$ is large)
- Using the approx $e^{\lambda T} = 1 + \lambda T + \lambda T^2/2$ and neglecting terms of degree 3, we obtain $\frac{1}{2}(\lambda T)^2 = 1 e^{-\lambda C}$
- λC is even smaller (because C is small), and we use the approx $e^{-\lambda C} = 1 \lambda C$
- We obtain Young's approximation:

$$T_{opt} \sim \sqrt{2C/\lambda}$$

■ Example: MTBF = 48 hours, C = 1 minute, then checkpoint every $T_{opt} = 75.9$ minutes

Going further

- With recovery time, Young's approximation becomes $T_{opt} \sim \sqrt{2C(R+1/\lambda)}$
 - J.T. Daly, A higher order estimate of the optimum checkpoint interval for restart dumps, FGCS 2006,
- Daly goes further and proposes the following approximation:

$$T_{opt} = \sqrt{2C/\lambda} \left[1 + \sqrt{\frac{C\lambda}{18}} + \frac{C\lambda}{18} \right] - C, \quad \text{if} \quad C < 2/\lambda$$
 $T_{opt} = 1/\lambda, \quad \text{if} \quad C \ge 2/\lambda$

■ Example: MTBF = 48 hours, C = 1 minute, then checkpoint every $T_{opt} = 75.2$ minutes

Daly's bound

- Pretty close to Young's bound unless *C* is relatively large
- Daly doesn't ignore recovery (even though in the final formula R isn't there!)
- Daly estimates the fraction of wasted work once a failure occurs (T_w) much better
- Daly allows failures during recovery, but not during checkpointing

- The assumption that $C << 1/\lambda = MTBF$ is likely invalid at large scale
 - $\blacksquare MTBF_{platform} = MTBF_{proc} / \#procs$
- The assumption that *C* is so small that there are no failures during checkpointing is likely invalid at large scale
- The assumption that there cannot be a failure during a downtime (of another host) is likely invalid at large scale
 - "Cascading" failures
- Are we even sure that periodic is optimal???

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- We focus on C_{max} minimization, or rather $\mathbb{E}[C_{max}]$ minimization
 - After all, this is the real objective, not $\mathbb{E}[T_w]$
- Let us first study the case of a sequential job that starts at time t₀
 - Sounds simple, but in fact it's already quite complicated
- Let's not make any assumption on the distribution for now: starting at time t_0 , failures occur at time $t_n = t_0 + \sum_{m=1}^{n} X_m$, where the X_m 's are *i.i.d* random variable
- $P_{suc}(x|\tau)$: the probability that there is no failure for the next x seconds knowing that the last failure was τ seconds ago
 - Given by the probability distribution

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- Let w denote an amount of work that remains to be done
 - i.e., a number of seconds of computation
- Let $T(w|\tau)$ be the time needed to complete w units of work given that the last failure was τ seconds ago
 - Accounting for failures
- Our objective: minimize $\mathbb{E}[T(W_{total}|\tau)]$
 - \blacksquare W_{total} : the total amount of work to be done
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Checkpointing strategy

- A checkpointing strategy is a decision procedure as follows
- Given w and τ , how much work w_1 should we attempt?
 - The attempted amount of work is called a "chunk"
- Attempt: repeatedly try the chunk until success
 - Success: $w_1 + C$ seconds without failure (note the +C)
- Then, we ask the question again for $w w_1$ work and an updated τ , until remains 0 units of work
- The checkpointing strategy chooses a sequence of chunk sizes and the number of chunks

Recursion for $T(w|\tau)$

- $T(0|\tau) = 0$ (no work is done in 0 seconds)
- $T(w|\tau) = w_1 + C + T(w w_1|\tau + w_1 + C)$, if there is no failure in the next $w_1 + C$ seconds
 - Everything went well, we now have $w w_1$ work to do, and the last failure is now $w_1 + C$ seconds further in the past
- $T(w|\tau) = T_{wasted}(w_1 + C|\tau) + T(w|R)$, otherwise
 - We've wasted a bunch of time, we still have w work to do, and the last failure happened (ended) right before the last successful recovery
 - $T_{wasted}(w_1 + C|\tau)$: computation up to a failure + downtime + a recovery during which there can be failures
- We can weigh each case in the recursion by its probability

..

Computing $\mathbb{E}[T]$

- Probability that there is no failure in the next $w_1 + C$ second: $P_{suc}(w_1 + C|\tau)$
- Therefore:

$$\begin{split} \mathbb{E}[T(W_{total}|\tau)] &= \\ P_{suc}(w_1 + C|\tau) \times (w_1 + C + \mathbb{E}[T(W_{total} - w_1|\tau + w_1 + C)]) + \\ (1 - P_{suc}(w_1 + C|\tau)) \times (\mathbb{E}[T_{wasted}(w_1 + C|\tau)] + E(T(W_{total}|R)) \end{split}$$

 \blacksquare Remains to compute T_{wasted}

Computing $\mathbb{E}[T]$

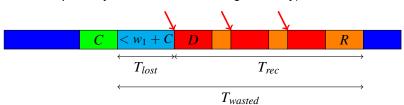
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Computing T_{wasted} , sort of

- $T_{wasted}(w_1 + C|\tau) = T_{lost}(w_1 + C|\tau) + T_{rec}$
 - $T_{lost}(x|\tau)$: amount of time before a failure knowing that a failure occurs in the next x seconds and that the last failure was τ seconds ago
 - T_{rec} : time spent to do the recovery (D + R in the best case, possibly more if failures during recovery)



Computing T_{rec}

■ We can compute T_{rec} as a function of T_{lost} :

$$T_{rec} = \left\{ \begin{array}{l} D+R \quad \text{with probability } P_{suc}(R|0), \\ D+T_{lost}(R|0)+T_{rec} \\ \quad \text{with probability } 1-P_{suc}(R,0). \end{array} \right.$$

- If there is no failure for R seconds right after the downtime (probability $P_{suc}(R|0)$), then the recovery takes time D+R
- If there is a failure (probability $1 P_{suc}(R, 0)$), then we spend D seconds of downtime, waste $T_{lost}(R|0)$ seconds trying a recovery that would have lasted R seconds if successful, and then we still have to recover anyway, which requires T_{rec} seconds

Computing T_{rec}

Weighing both cases by their probabilities we have

$$\mathbb{E}[T_{rec}] = P_{suc}(R|0) \times (D+R) +$$

$$(1 - P_{suc}(R|0)) \times (D + \mathbb{E}[T_{lost}(R|0)] + \mathbb{E}[T_{rec}])$$

which gives us:

$$\mathbb{E}[T_{rec}] = D + R + \frac{1 - P_{suc}(R|0)}{P_{suc}(R|0)} (D + \mathbb{E}(T_{lost}(R|0)))$$

$$\mathbb{E}[T_{wasted}(w_1 + C|\tau)] = \\ \mathbb{E}[T_{lost}(w_1 + C|\tau)] + D + R + \frac{1 - P_{suc}(R|0)}{P_{suc}(R|0)}(D + \mathbb{E}(T_{lost}(R|0)))$$

Putting it all together, $\mathbb{E}[T(W_{total}, \tau)]$

$$\begin{split} \mathbb{E}[T(W_{total}|\tau)] &= \\ P_{suc}(w_1 + C|\tau) \times (w_1 + C + \mathbb{E}[T(W_{total} - w_1|\tau + w_1 + C)]) + \\ (1 - P_{suc}(w_1 + C|\tau)) \times (\mathbb{E}[T_{lost}(w_1 + C|\tau)] + D + R + \\ \frac{1 - P_{suc}(R|0)}{P_{suc}(R|0)}(D + \mathbb{E}[T_{lost}(R|0)])) + \mathbb{E}[T(W_{total}|R)]) \end{split}$$

Easy, right? ©

- Goal: find w_1 that minimizes the above expression
 - Note the recursion (yikes!)
- Remains to know how to compute $P_{suc}(x|y)$ and $\mathbb{E}[T_{lost}(x|y)]$
- And so we make assumptions about the failure distribution...

Exponential failures

■ With exponentially distributed inter-failure times $(P(X = t) = \lambda e^{-\lambda t})$ we obtain:

$$\mathbb{E}[T_{lost}(x|y)] = \int_0^\infty tP(X=t|t< x)dt = \frac{1}{\lambda} - \frac{x}{e^{\lambda x} - 1}$$
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- Both expressions above do not involve *y* because the Exponential distribution is memoryless
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Exponential failures

$$\mathbb{E}[T(W_{total})] = e^{-\lambda(w_1+C)}(w_1 + C + \mathbb{E}[T(W_{total} - w_1)]) + (1 - e^{-\lambda(w_1+C)})(\frac{1}{\lambda} - \frac{w_1+C}{e^{\lambda(w_1+C)} - 1} + D + R + \frac{1 - e^{-\lambda R}}{e^{-\lambda R}}(D + \frac{1}{\lambda} - \frac{R}{e^{\lambda R} - 1} + \mathbb{E}[T(W_{total})]))$$

- Assume that there are K chunks
- We can write an equation for $\mathbb{E}[T(W_{total})]$ as a function of $\mathbb{E}[T(W_{total} w_1)]$
- We can write an equation for $\mathbb{E}[T(W_{total} w_1)]$ as a function of $\mathbb{E}[T(W_{total} w_1 w_2)]$
- ..
- We can then solve the recursion!!
 - A LOT of (easy but very tedious) math

Solved recursion

■ We obtain a general form for $\mathbb{E}[T(W_{total})]$:

$$\mathbb{E}[T(W_{total})] = A \times \sum_{i=1}^{K} (e^{\lambda(w_i + C)} - 1)$$

- \bullet $e^{\lambda(w_i+C)}$ is a convex function of w_i
- Therefore, $\mathbb{E}[T(W_{total})]$ is minimized when all w_i 's are equal
- After decades of periodic checkpointing research, we finally know that it's optimal!! (for exponential failures)
- Important: we made NO approximations
- Checkpointing Strategies for Parallel Jobs, Bougeret, Casanova, Rabie, Robert, Vivien [Supercomputing 2011]

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Other theoretical results, and impact

- The same result holds for parallel jobs
 - But we cannot compute the optimal makespan
- If failures are non-memoryless, then periodic is no necessarily optimal
 - The optimal checkpointing strategy can be computed via complicated dynamic programming for Weibull failures
- Nice theory, but if you're a practitioner:
 - You are doing periodic anyway because it's easy
 - Empirical results show that periodic is really bad only in corner cases
 - You know that failures are not i.i.d. anyway, so he theory doesn't apply
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Checkpointing overhead

- Assume you have some magical, fast way to determine the optimal checkpointing policy for realistic failures
- That's all well and good, but you cannot scale due to C being large!
 - Parallel efficiency drops as *p* increases (Amdahl's law)
- At large scale, your application will spend more time saving state than computing state!!!
- Crucial research problem: reduce checkpointing overhead
- Let's see what people have done/proposed

Reducing the checkpoint size

- Brute-force system-level checkpointing: save the whole address space
 - What Sean is trying to install on our Cray cluster for sequential jobs
- Problem: only a (small) fraction of the address space is needed for a recovery
 - Example: only the iteration number and 2 arrays
- More scalable application-level checkpointing: save only what data is necessary for recovery
- Drawback: you must modify application code to checkpoint
 - Note that automatic system-level checkpointing of MPI applications is tough anyway

Zero checkpoint size?

- In some (lucky?) cases, the algorithm in the application can provide clever ways to "reconstruct" a checkpoint without ever saving it!
- Algorithm Based Fault Tolerance (ABFT):
 - A technique by which the algorithm is modified, and made less efficient, to compute on encoded (with checksums) data, so that (otherwise silent) errors can be corrected
- Has been extended to deal with "fail-stop" errors
 - Maintain checksums
 - Use checksums to reconstruct lost data
- Mostly used for linear algebra applications
- Sort of like RAID 2 (parity bits, no duplication) in memory

Reducing the checkpointing time

- One big problem is that when a checkpoint occurs, all processes say "save my state" at the same time!
 - e.g., if you have a NAS, the bandwidth to it becomes a massive bottleneck
- Several solutions have been proposed:
 - Use a cluster with fast storage (SAN)
 - Save only to local disk
 - But then you can't recover from a fatal hardware failure
 - Save to a "buddy" (save my state on my neighbor's disk)
 - Go diskless: keep my checkpoint in my buddy's memory
 - But then it must fit

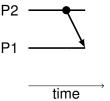
Go uncoordinated

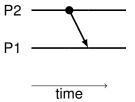
- In many cases the "we all save at the same time" is a showstopper
- Radical idea: allow uncoordinated checkpointing:
 - Processes can checkpoint their data whenever they want/choose
 - Should create a "smooth/low" load on the storage system
- Big challenge: how do we perform recovery?
- Let's see the canonical example

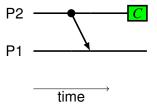
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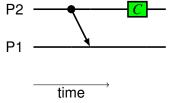
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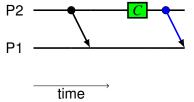
time

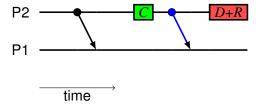


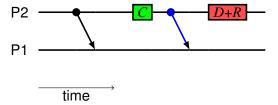


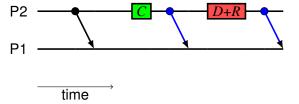


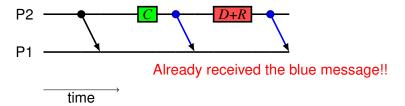












Message Logging

- To deal with the previous, and many more complex situations, we need to do some kind of message logging
- We keep track of messages sent/received, and ignore redundant copies
- How to do this efficiency and correctly is not easy
- Many "fault-tolerance MPI" implementations do this now as a matter of course
- An enormous theoretical/applied literature on this problem

Hierarchical Checkpointing: Do it all!

- The term "hierarchical" scheduling refers loosely to a solution that applies many (all?) of the previous techniques together
- And still, projections show that this won't be enough to achieve parallel efficiency on upcoming "exascale" machines
- So we need other techniques in addition to checkpoint-rollback-recovery...

Replication

- Run redundant processes to increase the MTBF!
 - Some MPI implementations can do this transparently!
- Good: we can checkpoint much less frequently
- Bad: we "waste" resources (and power!)
- It may seem surprising that we can gain anything by wasting resources
- But it all works out because using p/2 processors has higher parallel efficiency than using p processors
- Let's see an example...

Redundant processors can help!

- lacktriangle Processors fail exponentially with MTBF $1/\lambda$
- We have an application that runs in time $\alpha + \beta/p$ on p processors when no failures occur
- We checkpoint every $X = \sqrt{2C/\lambda}$ (Young)
- Our makespan is: $\alpha + \beta/p + \frac{\alpha + \beta/p}{X} \times C$
- Now we replicate each process, thus running on p/2 "more reliable processors"
- The MTBF of a pair of processors is now $(3/2)(1/\lambda)$
 - Compute integrals to verify this...
- We checkpoint every $Y = \sqrt{2C(3/2)/\lambda} = \sqrt{3C/\lambda}$
- Our makespan is now: $\alpha + 2\beta/p + \frac{\alpha + 2\beta/p}{Y} \times C$

Redundant processors can help! (2)

- The math on the previous slide is really back-of-the-envelope (e.g., makespan values are for the failure-free case)
- Let's pick values : $\alpha = 1$, $\beta = 100$, C = 10, $\lambda = 0.001$
- For p = 1000
 - No replication: 1.125 time units
 - Replication: 1.222 time units (replication hurts)
- For p = 100000
 - No replication: 1.022 time units (horrendous efficiency)
 - Replication: 1.018 time units (replication helps)

Failure Prediction

- Another idea to use in conjunction with checkpointing is Failure Prediction
- Hardware sensors can provide a good sense of when a processor might fail in the future
 - Based on "precursor" events
- Simple idea: checkpoint proactively only when a failure seems likely in the short term
- Raises all types of interesting questions about false positive and false negative
- This is often called "failure avoidance"

What about silent errors?

- Dealing with silent errors has become a hot research topic
- Simple idea: perform (periodic?) checks on the data
- Trade-off:
 - Checking data infrequently leaves you open to a lot of waste
 - Checking data frequently has a lot of overhead
- Must be combined with checkpointing
- Typically we have various "checkers", some expensive and accurate, some cheap and less accurate
- Problem: deciding when and how to check for silent errors

Fault-Tolerance for parallel applications

- This was a whirlwind tour of fault-tolerance
- It is a huge area of research and development, that goes from pure theory to pure engineering
- Hardware developments shape the field constantly
- There is no current consensus on what will work for exascale, but there are many pathways
- Every month new papers are being published :)
- One recent workshop report: Addressing failures in exascale computing, Snir et al., IJHPCA 28(2), 129–173, 2014.

Outline

- 1 Why Fault Tolerance?
- 2 Checkpointing
- 3 A little theory
- 4 A little practice
- 5 Energy Consumption

Power is money

- Power budget is a key issue for large-scale platform
 - Hence building them next to powerplants
- Many engineering issues to reduce power consumption:
 - Microprocessor design
 - Novel cooling approaches
 - Green energies
 - **.**.
- But given a system with some power-management "knobs," what do you do for a given application?
 - e.g., is your fault tolerant solution too power-hungry?
 - e.g., does your idea to decrease makespan by 1% increase power consumption by 50%?

DVFS

- Common power-management techniques are Dynamic Voltage Scaling (DVS) and Dynamic Frequency Scaling
- Modern microprocessors allow voltage/frequency to be modified in software
- Without getting into details: you can slow down your computation and save on energy
 - e.g., Power consumption is a polynomial function of the frequency / voltage
- The question then becomes: by how much should I slow down my nodes to achieve energy and performance goals?
- Interestingly, if I take the voltage too low, then I can create silent errors (i.e., computation is wrong)

A slew of (interesting) problems

- Say you have a parallel application and you:
 - Can run on some number of processors in a platform with DVFS-enabled processors
 - Use process duplication or not
 - Use some complex hierarchical checkpointing
 - Want to detect silent errors and have a bunch of detectors of various cost and accuracy
- How to decide on all the above?
- Sample research questions:
 - Q: minimize makespan for a given energy budget
 - Q: minimize energy given a makespan bound
 - Q: mimimize chances of having a wrong result given a makespan bound and budget

A very active research area

- Questions pertaining to fault tolerance and to energy are being investigated extremely actively
- We only scratched the surface here
- But some of the papers you'll present this semester touch on concerns of fault tolerance and power...