CS 598sm

Probabilistic & Approximate Computing

http://misailo.web.engr.Illinois.edu/courses/cs598

Nondeterministic Approximation in Parallel Computations

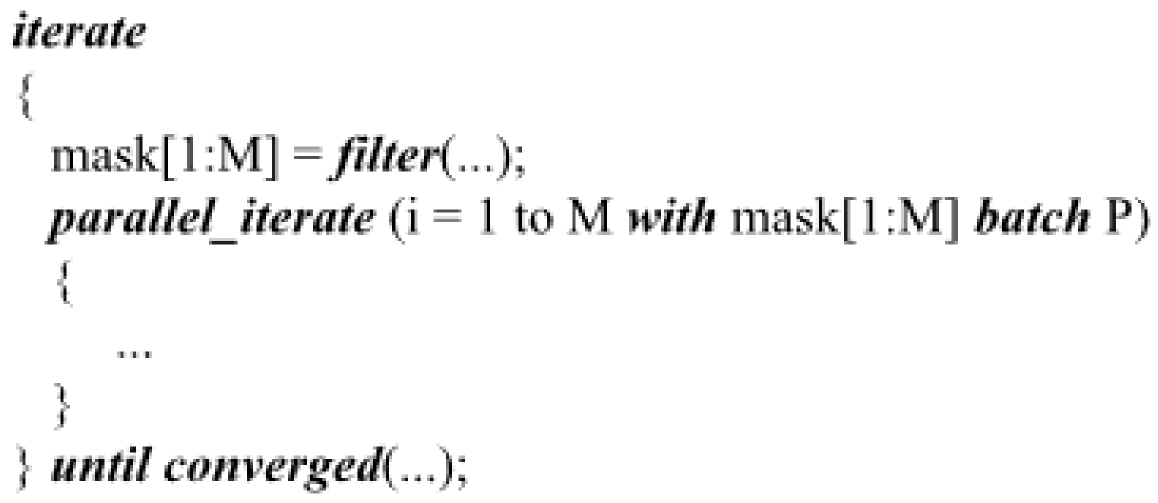
Removing synchronization and reading stale data

Various techniques over the years:

- Dropping tasks (Rinard 2006 ICS)
- Removing barriers (Rinard 2007 OOPSLA)
- Reading stale data (Thies et al. PLDI 2011)
- Removing locks
- Parallelizing with data races (Misailovic et al. 2012, 2013)
- Breaking data dependencies
- …

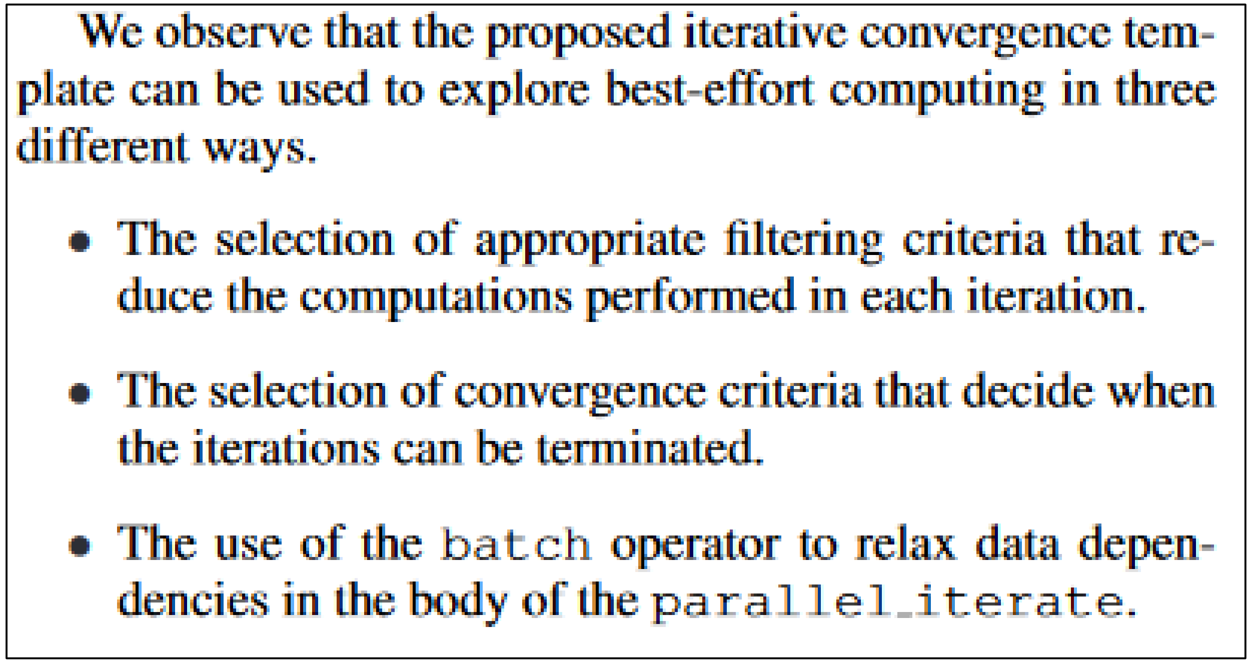
Best-Effort Parallel Execution Framework for Recognition and Mining Applications (IPDPS 2009)

Some Early Insights



```
iterate
{
  mask[1:M] = filter(...);
  parallel_iterate (i = 1 to M with mask[1:M] batch P)
  {
      ...
  }
} until converged(...);
```

Figure 4. Pseudocode of the best-effort iterative-convergence template.



We observe that the proposed iterative convergence template can be used to explore best-effort computing in three different ways.

- The selection of appropriate filtering criteria that reduce the computations performed in each iteration.
- The selection of convergence criteria that decide when the iterations can be terminated.
- The use of the `batch` operator to relax data dependencies in the body of the `parallel_iterate`.

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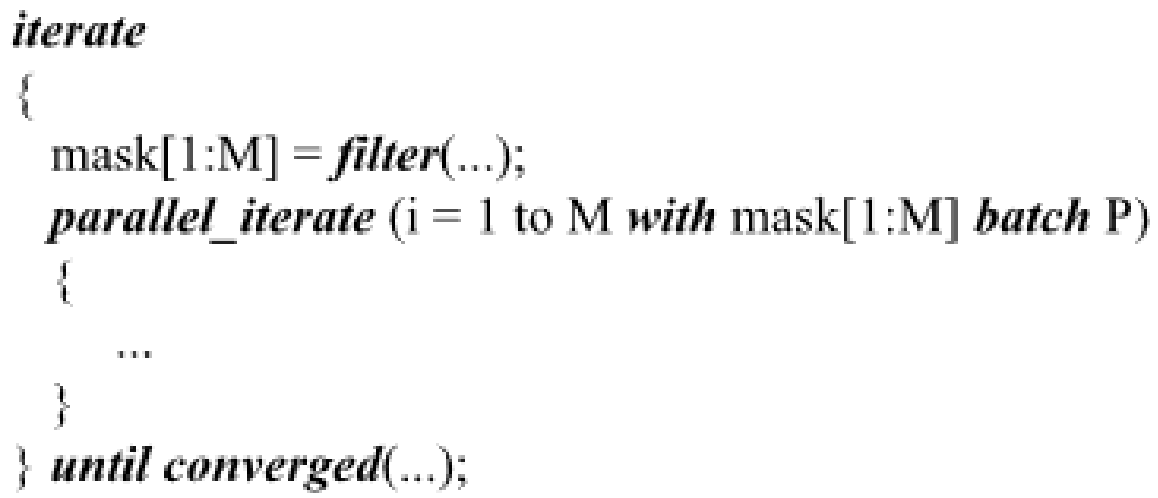

```
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{
  mask[1:M] = filter(...);
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  {
      ...
  }
} until converged(...);
```

Figure 4. Pseudocode of the best-effort iterative-convergence template.

Convergence-based pruning: Use converging data structures to speculatively identify computations that have minimal impact on results and eliminate them

Staged Computation: consider fewer points in early stages; gradually use more points in later stages to improve accuracy

Early Termination: Aggregate statistics to estimate accuracy and terminate before full convergence.

Sampling: Select a random subset of input data and use it to compute the results.

Dependency Relaxation: Ignore potentially redundant dependencies across iterations. Leads to more degree of parallelism or coarser granularity

Data Dependence

A **data dependence** from statement **S1** to statement **S2** exists if

1. there is a ***feasible execution path*** from S1 to S2, and
2. an instance of S1 ***references the same memory location*** as an instance of S2 in some execution of the program, and
3. at ***least one of the references is a store***.

Kinds of Data Dependence

Direct Dependence

```
X =…
…= X + …
```

Anti-dependence

```
… = X
X  = …
```

Output Dependence

```
X  = …
X  = …
```

Dependence Graph

A **dependence graph** is a graph with:

- Each ***node represents a statement***, and
- Each ***directed edge*** from S1 to S2, if there is a **data dependence** between S1 and S2 (where the instance of S2 follows the instance of S1 in the relevant execution).
    - S1 is known as a ***source*** node
    - S2 is known as a ***sink*** node

Kinds of Data Dependence

		Dependence Graph Edges
Direct Dependence	S1: X =… S2: … = X + …	$S_1 \longrightarrow S_2$
Anti-dependence	S1: … = X S2: X = …	$S_1 \not\longrightarrow S_2$
Output Dependence	S1: X = … S2: X = …	$S_1 \mathrel{\circ\!\!\!\longrightarrow} S_2$

Dependence Graph for Loops

(***Repeat***) A **dependence graph** is a graph with:

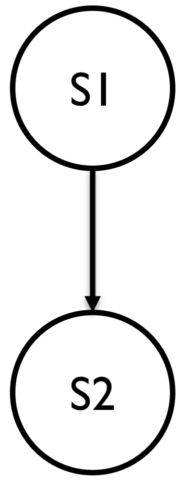
- one node per statement, and
- a directed edge from S1 to S2 if there is a data dependence between S1 and S2 (where the instance of S2 follows the instance of S1 in the relevant execution).

For loops: dependence graph is a ***summary of unrolled dependencies*** for different iterations

- Some (detailed) information may be lost

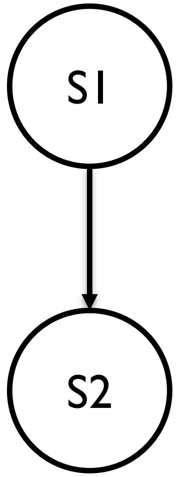
Dependence in Loops

```
        def X(), Y(), a(), i;
        do i = 1 to N
S1:         X(i) = a(i) + 2
S2:         Y(i) = X(i) + 1
        enddo
```


$$\begin{tikzcd} S1 \arrow[d] \\ S2 \end{tikzcd}$$

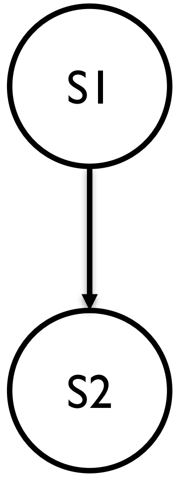
Dependence in Loops

```
        def X(), Y(), a(), i;
        do i = 1 to N
S1:         X(i+1) = a(i) + 2
S2:         Y(i) = X(i) + 1
        enddo
```


$$\begin{tikzcd} S1 \arrow[d] \\ S2 \end{tikzcd}$$

Dependence in Loops

```
        def X(), Y(), a(), i;
        do i = 2 to N
S1:         X(i) = a(i) + 2
S2:         Y(i) = X(i-1) + 1
        enddo
```



Dependence in Loops

```
        def X(), Y(), a(), i;
        do i = 1 to N
S1:         X(i) = a(i) + 2
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        enddo
```
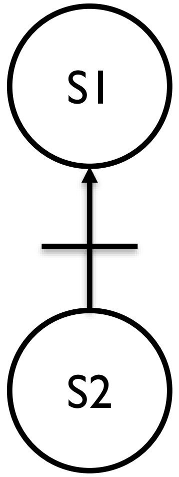
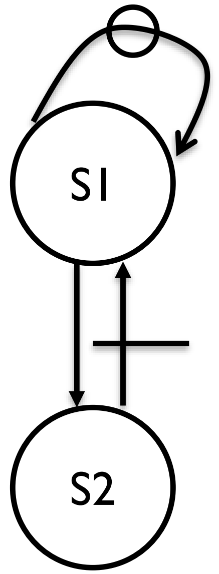



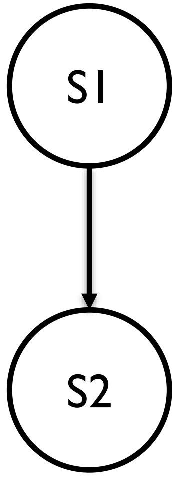
Dependence in Loops

```
          def X(), Y(), a(), i, t;
          do i = 1 to N
S1:          t = a(i) + 2
S2:          Y(i) = t + 1
          enddo
```



Dependence in Loops

```
        def X(), Y(), a(), i, t();
        do i = 1 to N
S1:        t(i) = a(i) + 2
S2:        Y(i) = t(i) + 1
        enddo
```


$$\begin{tikzcd} S1 \arrow[d] \\ S2 \end{tikzcd}$$

STOCHASTIC GRADIENT DESCENT (SGD)

Slides based on Linyi Li's Talk in CS 598 Last Year

MACHINE LEARNING AS OPTIMIZATION PROBLEM

$$\text{minimize}_\theta \; L(\theta) = \mathbb{E}_{x\sim D}\ell(x, f(x,\theta))$$

- $\theta \in \mathbb{R}^P$: model parameter
- D : data distribution
- $x \in \mathbb{R}^n$: data sample
- $f(\cdot,\cdot)$: the model output given input and parameters
- $\ell(\cdot,\cdot)$: loss function;

  it's smaller, closer $f(x,\theta)$ it gets to the ground truth

FINITE DATASET

- Usually, the dataset is finite.
- Suppose there are N data samples, then it becomes

$$\text{minimize}_\theta \ L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(x_i, f(x_i, \theta))$$

EXAMPLE

MNIST Classification

- Each sample x_i is given a true label $y_i \in \{0, \cdots, 9\}$.
- Model outputs 10-dimension confidence vector in $[0,1]^{10}$ summing up to 1.
- The cross-entropy loss on the sample:

$$\ell(x_i, f(x_i, \theta)) = -\sum_{k=1}^{C} \mathbf{1}[k = y_i] \log(f(x_i, \theta))_k$$
$$= \log(1/f(x_i, \theta)_{y_i})$$

Smaller loss, **higher** confidence on the correct label, and **higher** accuracy.

SGD

$$\boxed{L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(x_i, f(x_i, \theta))}$$

- A common way to solve the problem, is by using SGD:
  - Take the gradient of L with respect to θ: $\nabla_\theta L(\theta) (\in \mathbb{R}^P)$
  - To minimize L, we move the θ along the **opposite** direction:

$$\theta \leftarrow \theta - \gamma \nabla_\theta L(\theta)$$

    - γ : step size, a constant, positive small number
  - Take sufficient such small steps, until $L(\theta)$ does not change much.

EXAMPLE

- In our MNIST task, $f(x_i, \theta)_{y_i}$ is model **confidence score** for correct label
- ***Loss function:*** $\ell(x_i, f(x_i, \theta)) = \log(1/f(x_i, \theta)_{y_i})$
- ***Gradient:*** $$\nabla_\theta \ell(x_i, f(x_i, \theta)) = -\frac{\nabla_\theta f(x_i, \theta)_{y_i}}{f(x_i, \theta)_{y_i}}$$
- ***Parameter update by SGD:*** $$\delta = \gamma \frac{\nabla_\theta f(x_i, \theta)_{y_i}}{f(x_i, \theta)_{y_i}}$$
- δ: model parameter change
- Direction: move towards larger confidence;
  - smaller confidence, sharper change.

LEADING TO HOGWILD! ALGORITHM

DECOMPOSE $\nabla_\theta L(\theta)$

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(x_i, f(x_i, \theta))$$

$$\nabla L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \ell(x_i, f(x_i, \theta))$$

- A serial algorithm:

```
while (!converged($\theta$))
  for (int i=0; i<N; ++i)
    $\theta$ = $\theta$ - 1/N * $\nabla_\theta \ell\big(x_i, f(x_i, \theta)\big)$
```

DECOMPOSE $\nabla_\theta L(\theta)$

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(x_i, f(x_i, \theta))$$

$$\nabla L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \ell(x_i, f(x_i, \theta))$$

- A serial algorithm:

```
while (!converged($\theta$))
  for (int i=0; i<N; ++i)
    $\theta^{(t)}$ = $\theta^{(t-1)}$ - 1/N * $\nabla_\theta \ell\left(x_i, f\left(x_i, \theta^{(t-1)}\right)\right)$
```

PARALLELISM?

- A serial algorithm

```
for (int i=0; i<N; ++i)
  for (int j=0; j<|$\theta$|; ++j)
    $\theta_j$ = $\theta_j^{old}$ - 1/N * $\nabla_{\theta_j}\ell\left(x_i, f\left(x_i, \theta^{old}\right)\right)$
```

- One way to Parallelize

```
#parallel across K threads:
for (int i=k*N/K; i < (k+1)* N/K; ++i)
  for (int j=0; j<|$\theta$|; ++j)
    $\theta_j$ = $\theta_j^{old}$ - 1/N * $\nabla_{\theta_j}\ell\left(x_i, f\left(x_i, \theta^{old}\right)\right)$
```

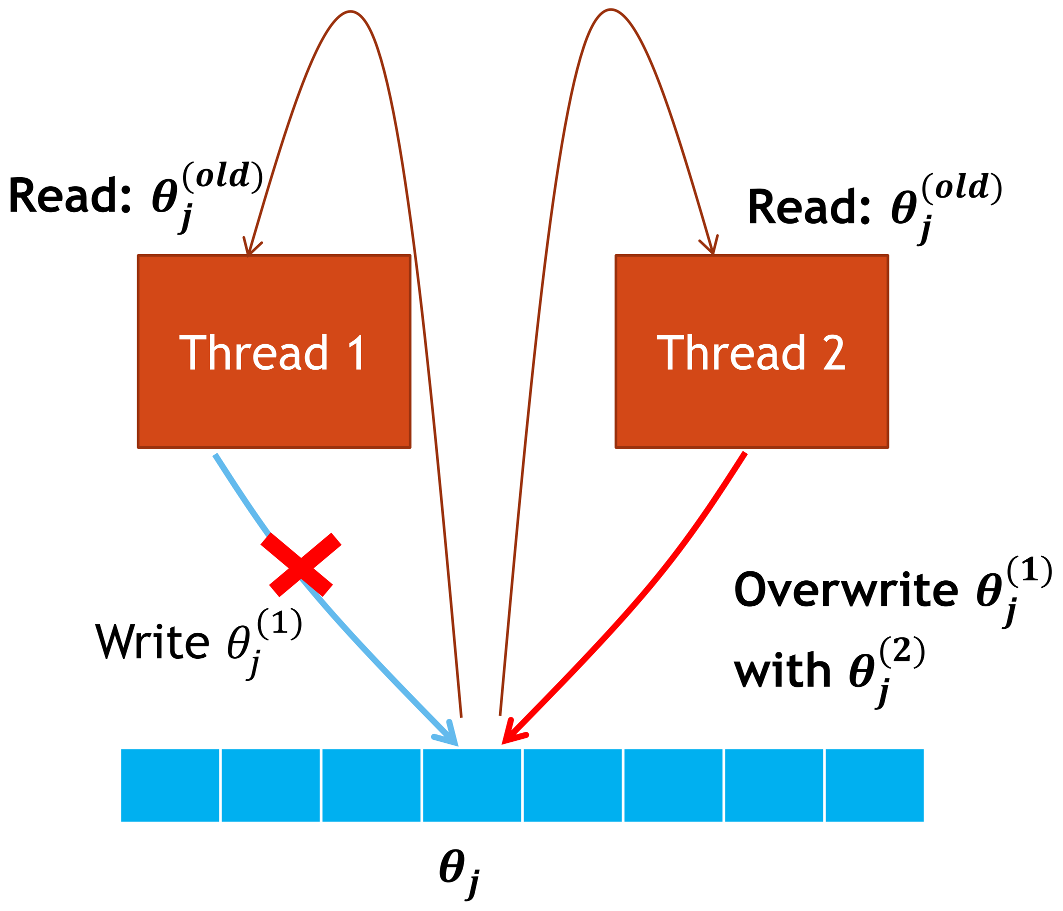
- Inner loop:

```
for (int j=0; j<|$\theta$|; ++j)
    $G(\theta_j^{old}) = \cdots$
    $\theta_j = \theta_j^{old} - G(\theta_j^{old})$
```

- With some transformation:

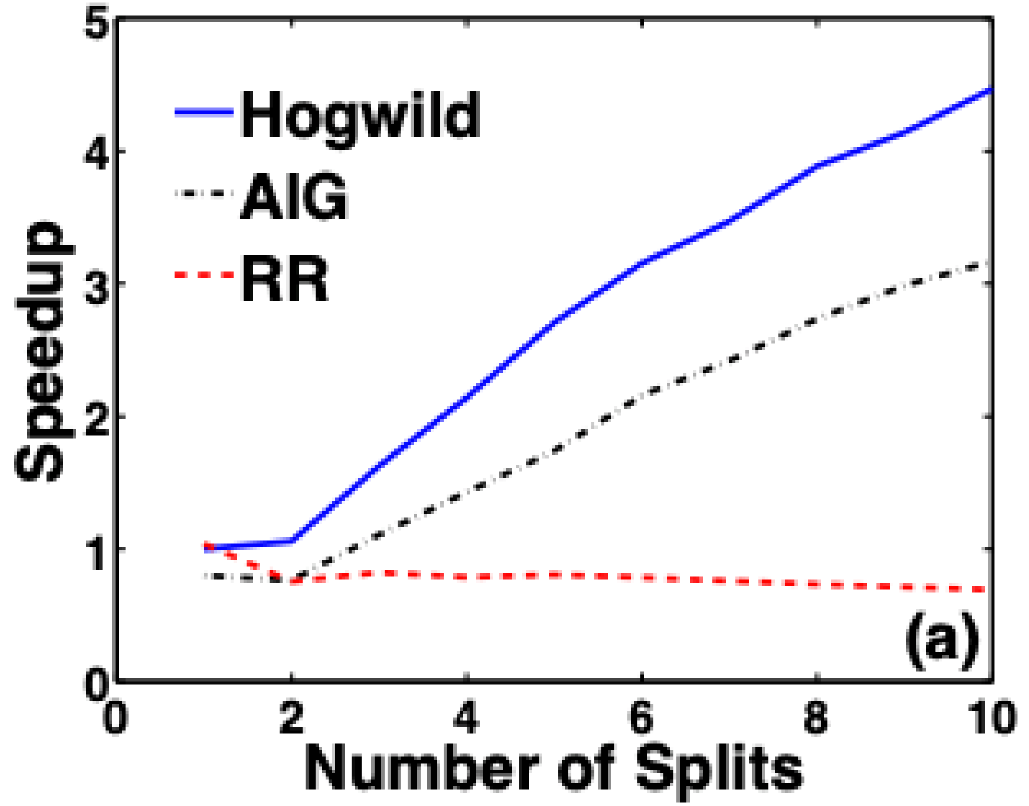
```
for (int j=0; j<|$\theta$|; ++j)
    $G(\theta_j^{old}) = \cdots$
    if $G(\theta_j^{old}) != 0$
        $\theta_j^{new} = \theta_j^{old} - G(\theta_j^{old})$
```

For each sample:
•Only small number of parameters updated;
•These parameters rarely overlap.



PARALLELISM?

- The version "RR" tries to improv on the locking cost by using a round-robin schedule of updates
- The version "AIG" does a fine locking of the elements of θ
- Most of the time, the change wil be for individual element of θ, b even fine-grained locking is expensive



KEY OBSERVATION: SPARSE SEPARABILITY

- The updates, even with the overwrite may give a good ‘delta’ direction
- Potential threat: it may not give ‘strong enough’ direction indication

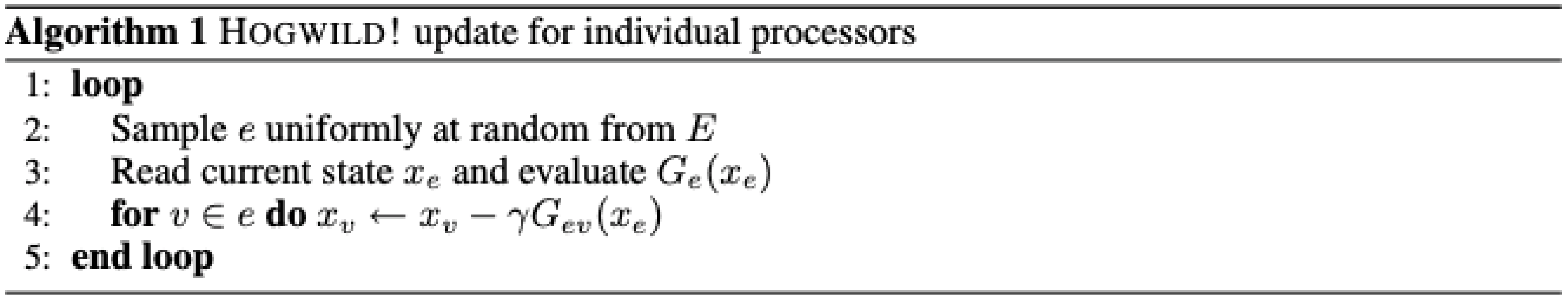
- For many real-world problems, the model:
  - Usually has **large number** of parameters.
  - Only uses **a small fraction** of parameters to predict each data sample.
  - Parameters used for predicting different samples **rarely overlap.**
  - Each parameter is **not often** used.

EXAMPLES

- Sparse SVM:
  - Data vector x_i's are sparse.
- Matrix Completion:
  - Learn large matrix $\boldsymbol{M}$ as the product of $\boldsymbol{AB}$, from few cells $\boldsymbol{M}_{ij}$'s.
- Graph Cuts
  - Partition graph nodes according to sparse similarity matrix.

RESULT ALGORITHM

- Update without lock is totally practical!
- Hogwild algorithm:



Algorithm 1 HOGWILD! update for individual processors

```
1: loop
2:     Sample $e$ uniformly at random from $E$
3:     Read current state $x_e$ and evaluate $G_e(x_e)$
4:     for $v \in e$ do $x_v \leftarrow x_v - \gamma G_{ev}(x_e)$
5: end loop
```

  - e is data sample $x_v = \theta$, $G_e(x_e)$ is gradient.
  - no lock on shared parameters x_e, totally asynchronous.

PERFORMANCE & EVALUATION

ASSUMPTIONS

We assume Lipschitz continuous differentiability of f with Lipschitz constant L:

$$\|\nabla f(x') - \nabla f(x)\| \leq L\|x' - x\|, \ \ \forall x', x \in X. \tag{8}$$

We also assume f is strongly convex with modulus c. By this we mean that

$$f(x') \geq f(x) + (x' - x)^T \nabla f(x) + \frac{c}{2}\|x' - x\|^2, \ \ \text{for all } x', x \in X. \tag{9}$$

When f is strongly convex, there exists a unique minimizer $x_\star$ and we denote $f_\star = f(x_\star)$. We additionally assume that there exists a constant M such that

$$\|G_e(x_e)\|_2 \leq M \ \ \text{almost surely for all } x \in X\,. \tag{10}$$

We assume throughout that $\gamma c < 1$. (Indeed, when $\gamma c > 1$, even the ordinary gradient descent algorithms will diverge.) Our main results are summarized by the following

THEORETICAL GUARANTEE

- Condition:
  - Convex function;
  - Gradient magnitude is bounded;
  - Number of workers is less than $n^{1/4}$, n is number of parameters;
  - Fine-tuned step size.

- After $k \geq \Theta\left(\frac{\log(1/\epsilon)}{\epsilon}\right)$ steps, $\mathbb{E}[f(x_k) - f_*] \leq \epsilon.$
- Serial SGD convergence rate: $\Theta(1/\epsilon)$.

❑ Hogwild can be further optimized to get the same rate.

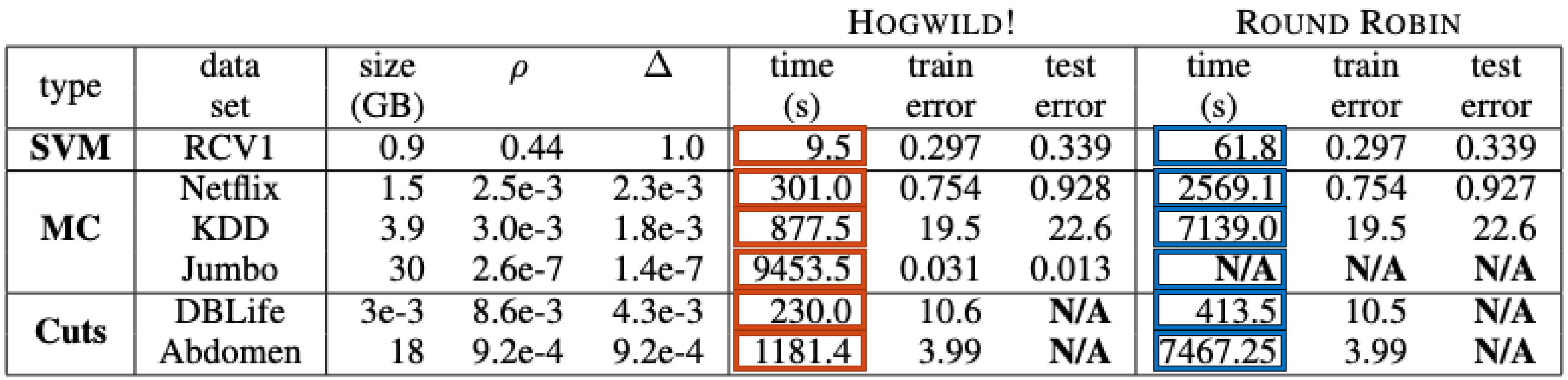
EXPERIMENTS

Baseline approaches:

- RR: processors are ordered; each update the decision variable in order
- AIG: only lock particular parameters when updating (θ_i's with gradients)
- Hogwild: no locking

Three applications:

- SVM (Sparse SVM), MC (Matrix Completion), Cuts (Graph Cuts)



					HOGWILD!			ROUND ROBIN		
type	data set	size (GB)	ρ	Δ	time (s)	train error	test error	time (s)	train error	test error
SVM	RCV1	0.9	0.44	1.0	9.5	0.297	0.339	61.8	0.297	0.339
MC	Netflix	1.5	2.5e-3	2.3e-3	301.0	0.754	0.928	2569.1	0.754	0.927
	KDD	3.9	3.0e-3	1.8e-3	877.5	19.5	22.6	7139.0	19.5	22.6
	Jumbo	30	2.6e-7	1.4e-7	9453.5	0.031	0.013	N/A	N/A	N/A
Cuts	DBLife	3e-3	8.6e-3	4.3e-3	230.0	10.6	N/A	413.5	10.5	N/A
	Abdomen	18	9.2e-4	9.2e-4	1181.4	3.99	N/A	7467.25	3.99	N/A

- Speed: Much faster than ordered locked update.
  - 9.5s vs 61.8s; 301.0s vs 2569.1s
- Accuracy: Almost the same training & test error.

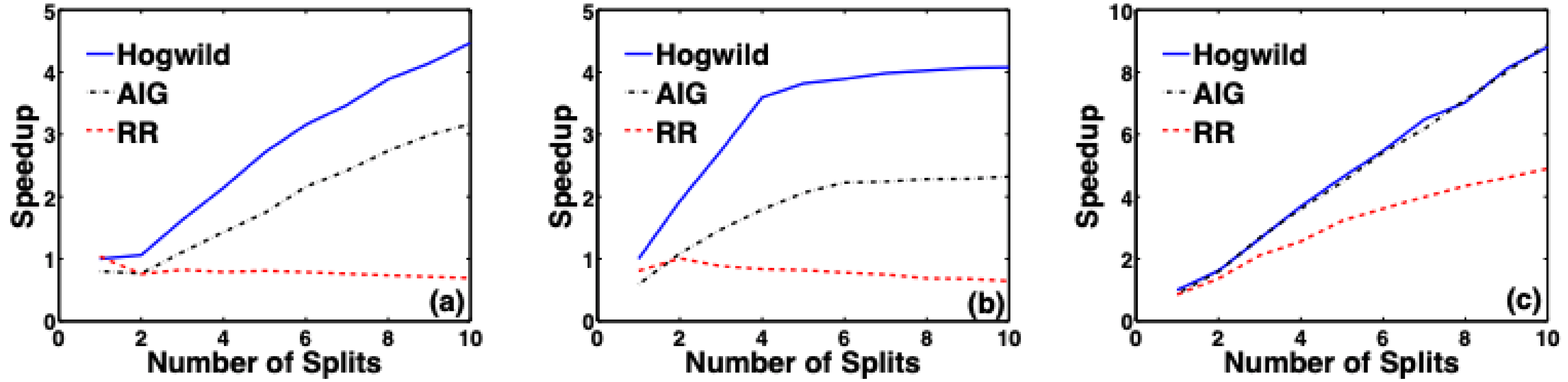
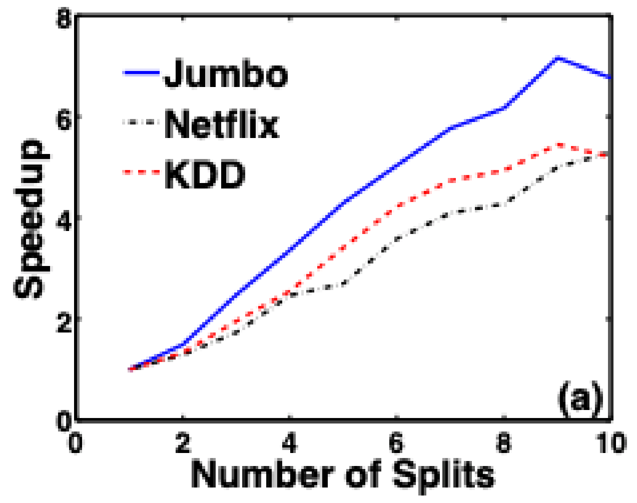


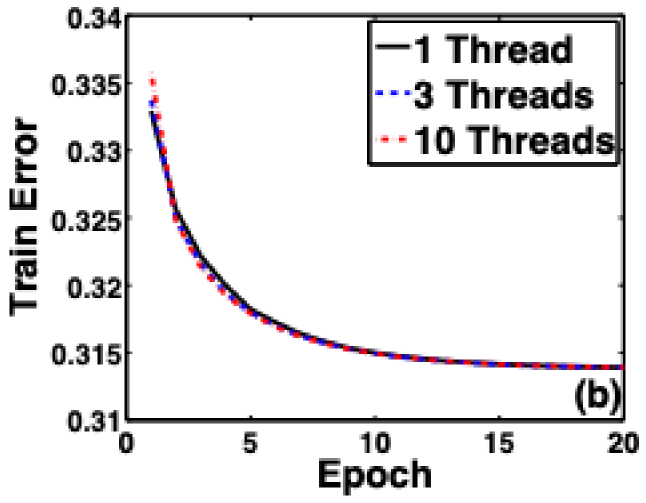
Figure 2: Total CPU time versus number of threads for (a) RCV1, (b) Abdomen, and (c) DBLife.

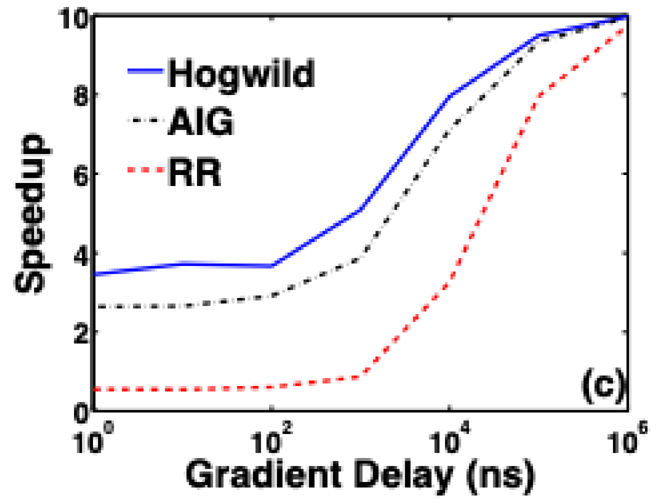
SPARSE SVM PROBLEM WITH 3 DATASETS

- Hogwild is much faster.
- Even only adding locks to all parameters, may significantly slow it down.

MATRIX COMPLETION PROBLEM







- Same trends for different datasets.
- Does not hurt accuracy.
- When gradient computation becomes slow, the gap shrinks.

GENERALIZATION & RECENT PROGRESS

HOW ABOUT NEURAL NETWORKS?

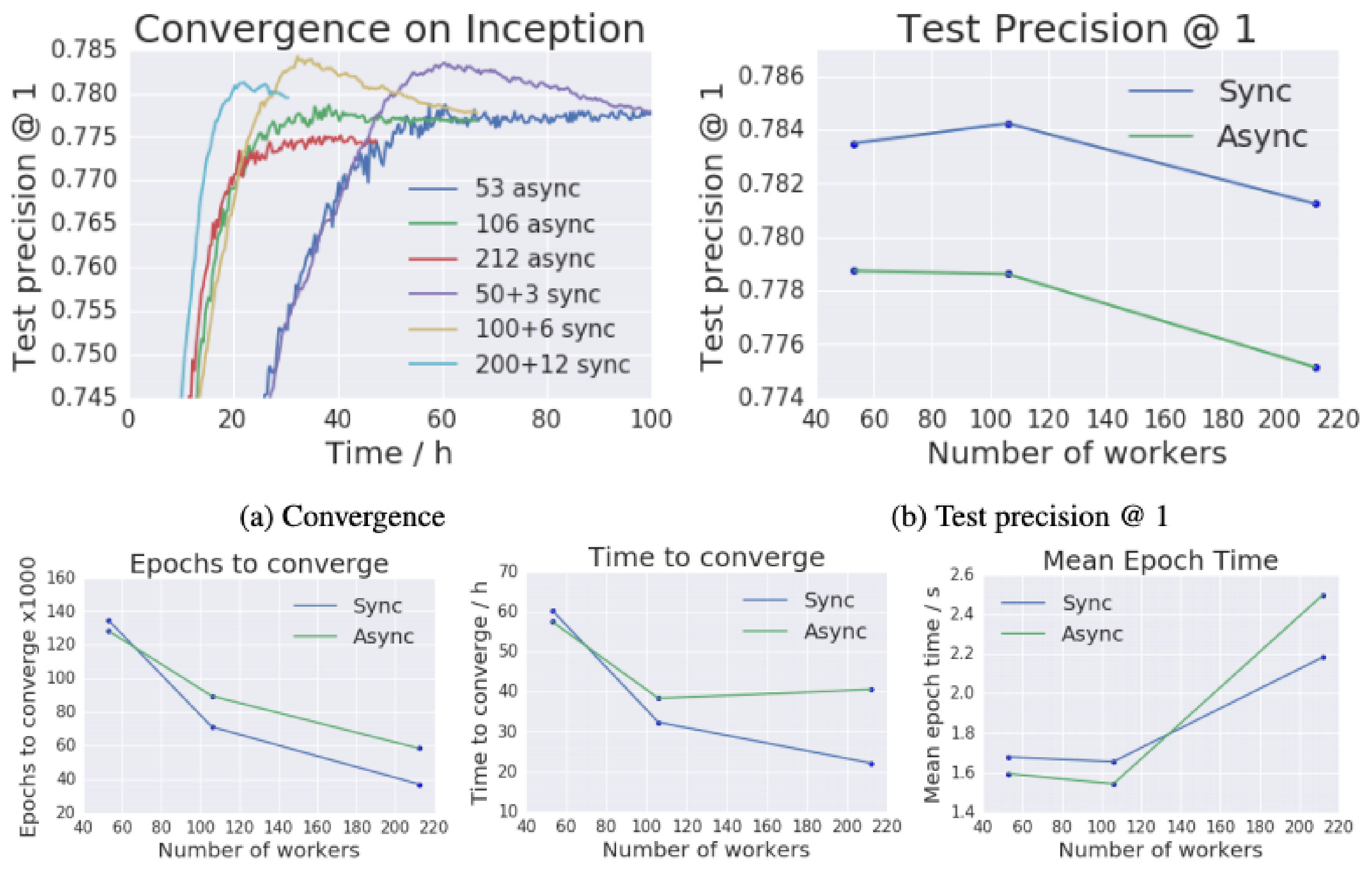
- The paper released in 2011, NN was not popular.
- SGD is also popular for NN training
- NN is non-convex, no theoretical guarantee.

- Can Hogwild **generalize** to NN?

IN TENSORFLOW

- Originally designed to use Hogwild (named asynchronous parameter updates).
- Also supports synchronous and synchronous with backups.
- See Tensorflow paper OSDI 2016

- In 2016, “Revisiting Distributed Synchronous SGD” (ICLR 2016 Workshop) experimented with comparing the strategies.



(a) Convergence (b) Test precision @ 1

(c) Epochs to converge (d) Time to converge (e) Mean epoch time

Figure 8: Convergence of Sync-Opt and Async-Opt on Inception model using varying number of machines. Sync-Opt with backup workers converge faster, with fewer epochs, to higher test accuracies.

- **Async**: similar to Hogwild
- **Sync**: lock and update; optimized

- In Hogwild, though each step may be faster, but more steps to converge.
- Slightly hurts accuracy, and takes more time to converge.

RECENT APPROACH

- Synchronous with **backup workers**:
  - n workers, but each step only requires $m < n$ workers' result to update.
  - Overcome stragglers.
  - SGD samples training data randomly;
    - each worker processes different batch;
    - **OK if ignored.**

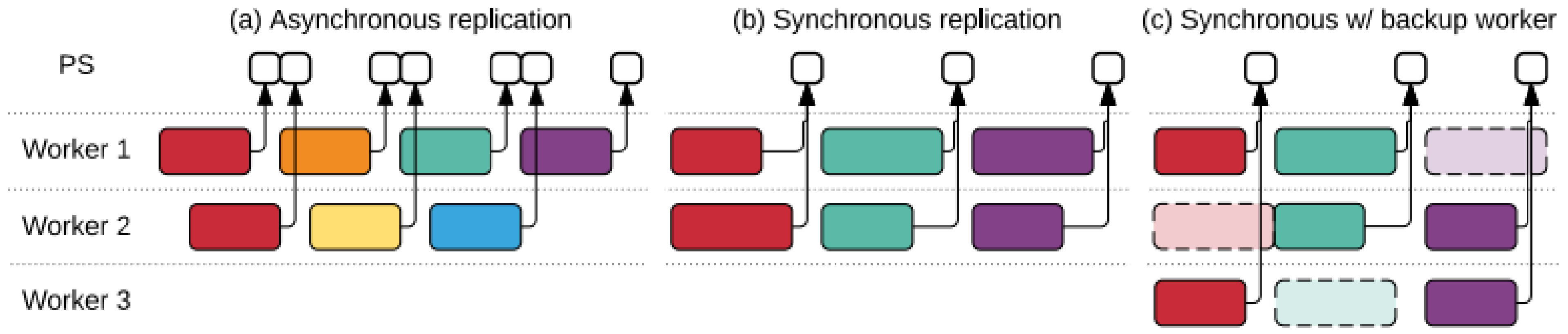
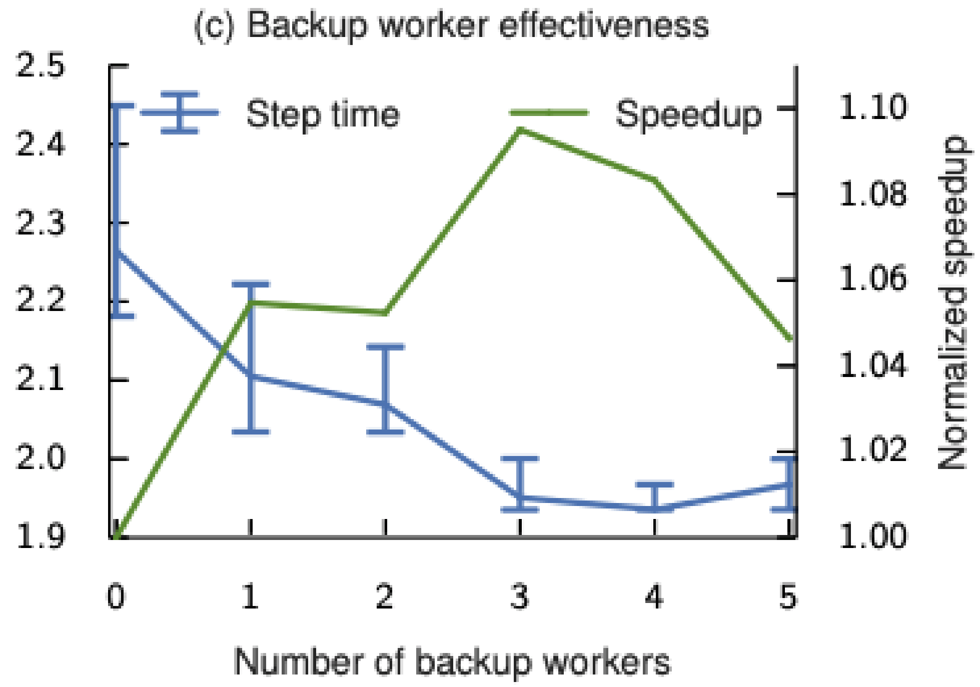

(a) Asynchronous replication
(b) Synchronous replication
(c) Synchronous w/ backup worker
PS
Worker 1
Worker 2
Worker 3

Figure 5: Three synchronization schemes for parallel SGD. Each color represents a different starting parameter value; a white square is a parameter update. In (c), a dashed rectangle represents a backup worker whose result is discarded.



- Backup workers accelerates synchronous up to roughly 10%.
- For large NN, gradient computing is the bottleneck
  - Hogwild is not fast that much.

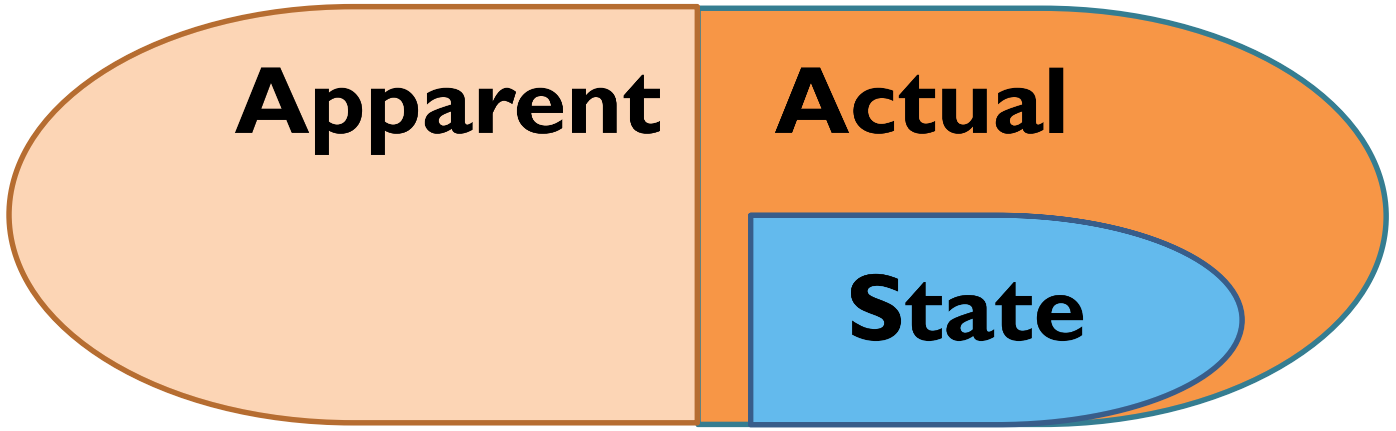
LET'S THINK NOW ABOUT GENERAL PROGRAMS

- Removing synchronization and reading stale data
- Various techniques over the years:
  - Dropping tasks (Rinard 2006 ICS)
  - Removing barriers (Rinard 2007 OOPSLA)
  - Reading stale data (Thies et al. PLDI 2011)
  - Removing locks
  - Parallelizing with data races (Misailovic et al. 2012, 2013)
  - Breaking data dependencies
  - …

Studying various iterative and non-iterative programs, typical speedup is around 20% to 30%

From Unconventional Parallelization of Nondeterministic Applications (ASPLOS'18)

Kinds of Dependencies



- **Actual:** exist in the program
- **State:** exist in the program and can be satisfied with extra code to match the original result, but faster than conventional
- **Apparent:** do not exist, but the compiler/developer cannot prove that they are unnecessary

Strict preservation of every actual dependencies may not necessary,

Preservation on any apparent dependency is not necessary

Dependencies in Non-deterministic Codes?

- For the same input, nondeterministic programs produce different results in each run.
- Use the error margins of the ordinary execution to find less important dependencies
- Non-determinism masks broken (unsatisfied) dependencies
- Use inexpensive checks to make sure the speculative execution matches those expected from the original program

Opportunity for Accuracy (over 100 runs)

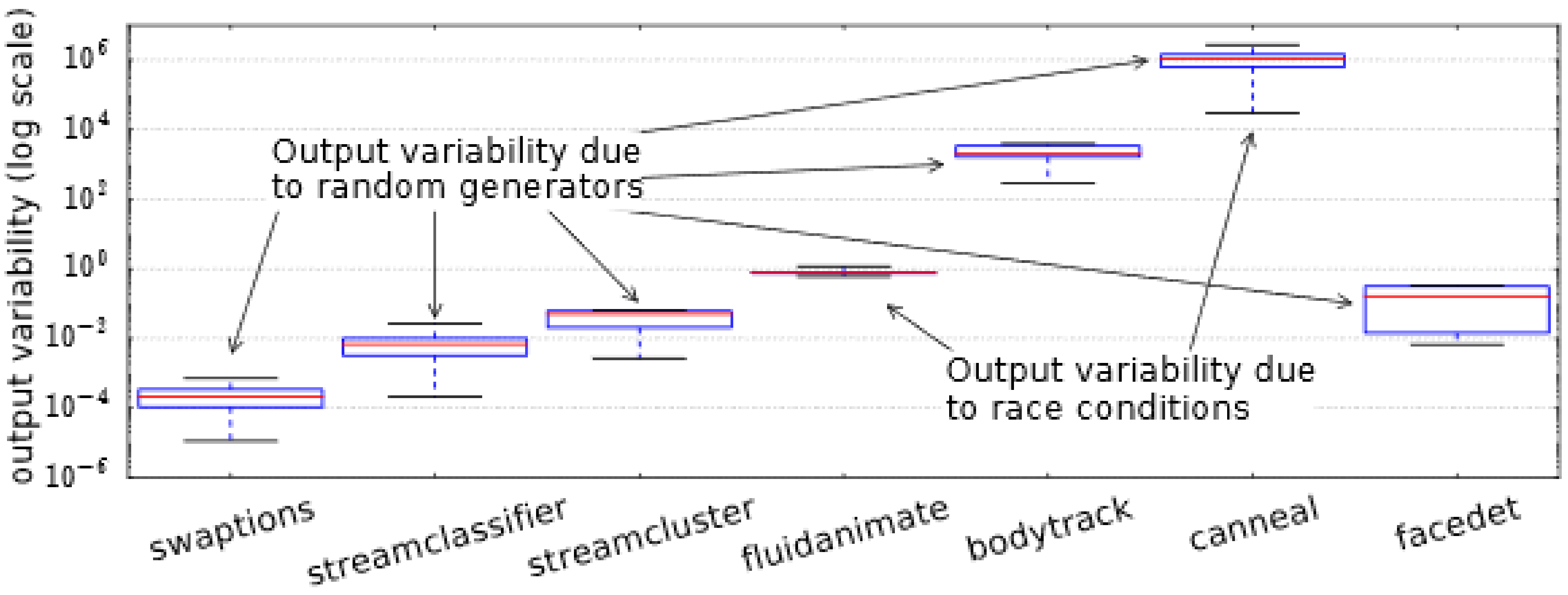
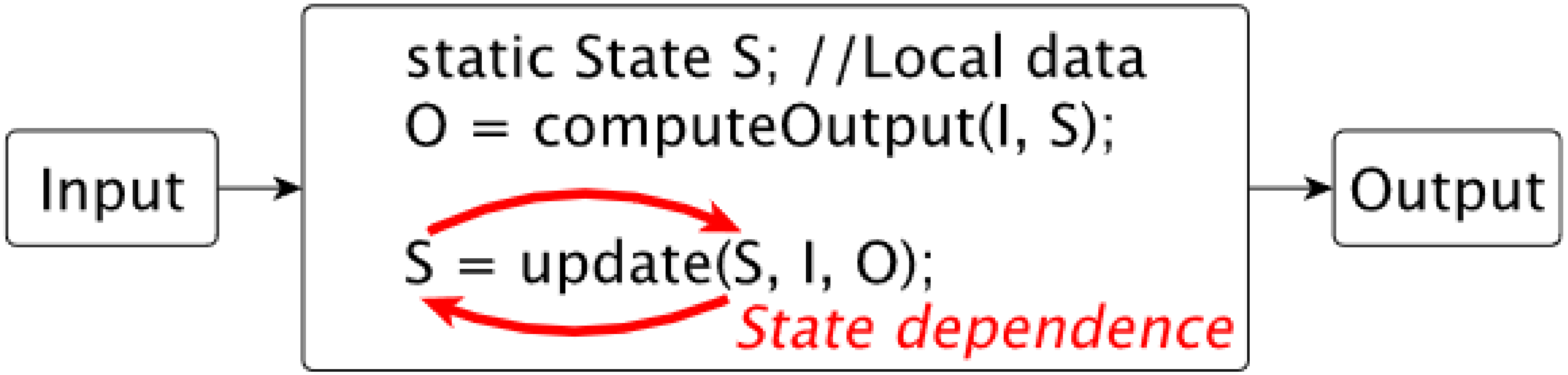


Figure 2. Output variability of nondeterministic PARSEC benchmarks. Several exhibit very high variability and are particularly amenable to STATS.

Opportunity State Dependency



```
static State S; //Local data
O = computeOutput(I, S);

S = update(S, I, O);
```

- Thread level parallelism is constrained by a sequential chain of dependences
- Opportunity: break this dependence to increase parallelism
- Fix: do 'speculation', if the result is too different, drop those updates and reexecute

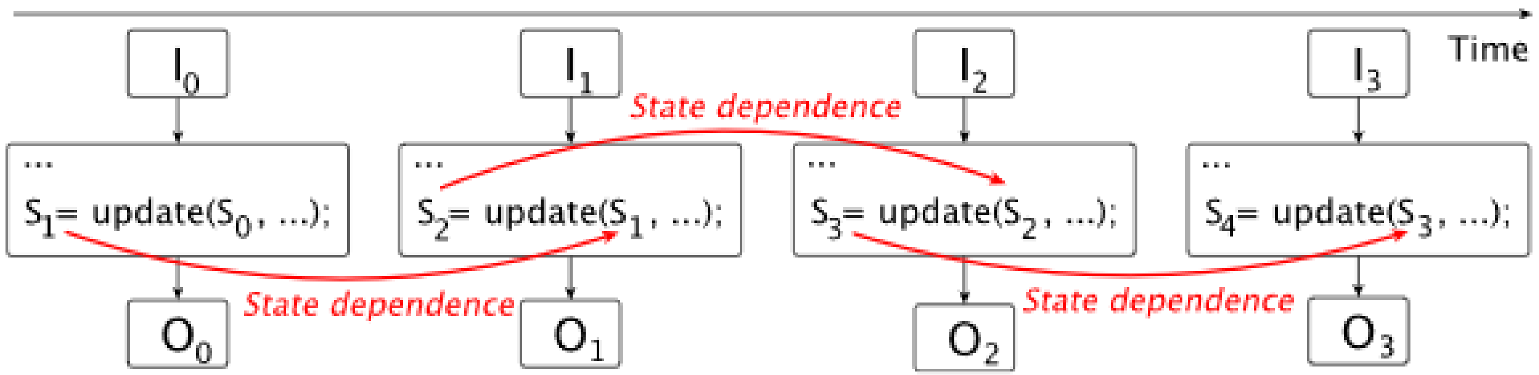
Approach

Break the dependency occasionally

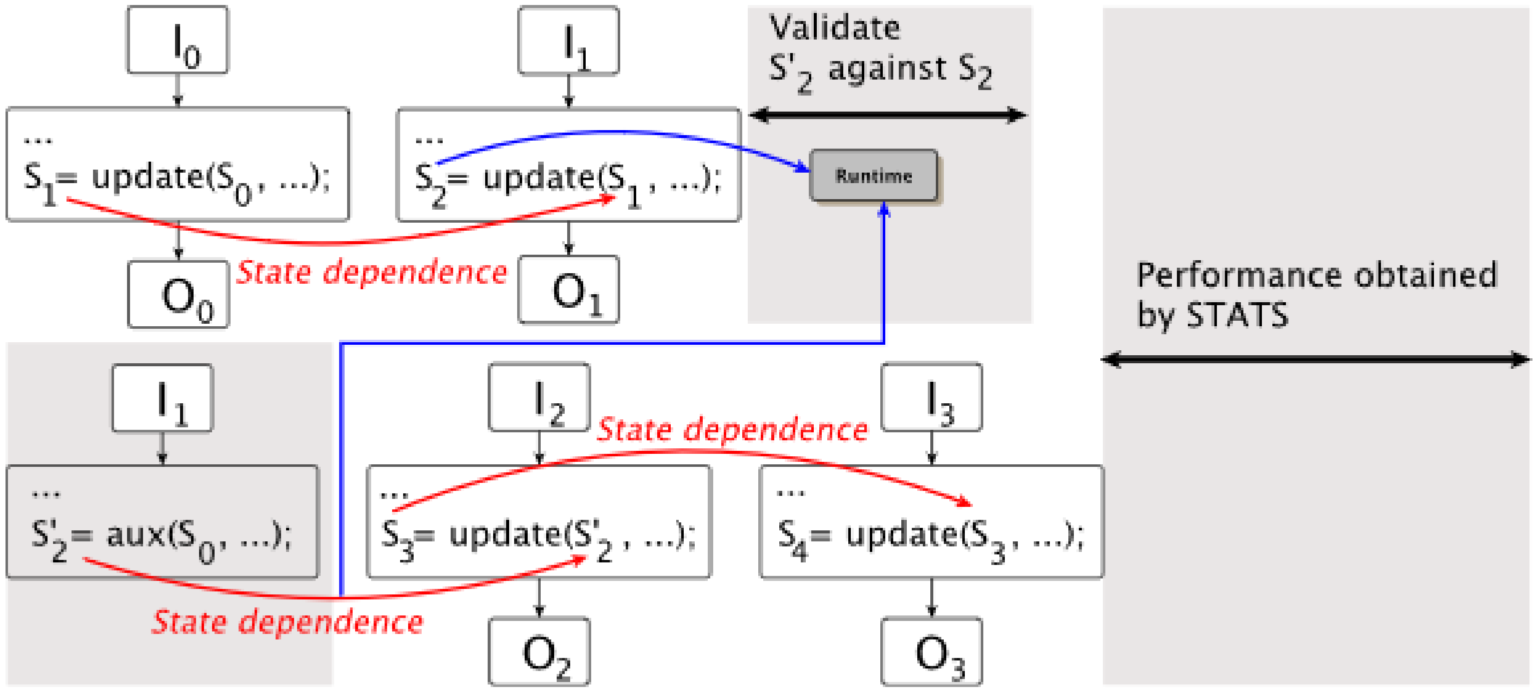
- Run inexpensive transfer function

Ensure that the impact is not large

- If small, continue,
- If large, reexecute (infrequently)


Time
I_0
I_1
I_2
I_3
... S_1= update(S_0, ...);
... S_2= update(S_1, ...);
... S_3= update(S_2, ...);
... S_4= update(S_3, ...);
State dependence
State dependence
State dependence
O_0
O_1
O_2
O_3

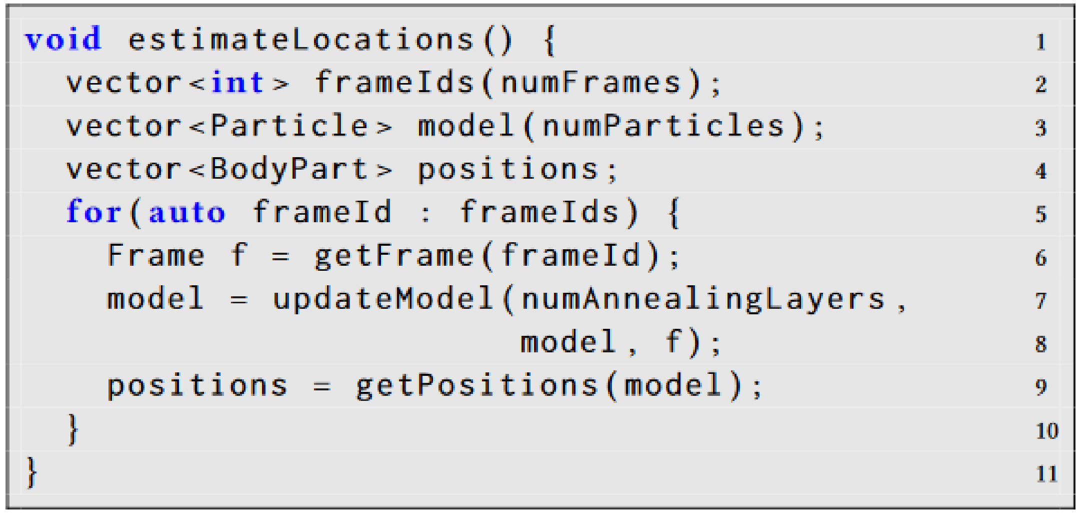
(a) Execution serialization due to a state dependence


I_0
I_1
Validate S'_2 against S_2
... S_1= update(S_0, ...);
... S_2= update(S_1, ...);
Runtime
State dependence
O_0
O_1
Performance obtained by STATS
I_1
I_2
I_3
State dependence
... S'_2= aux(S_0, ...);
... S_3= update(S'_2, ...);
... S_4= update(S_3, ...);
State dependence
O_2
O_3

(b) Additional TLP generated by auxiliary code

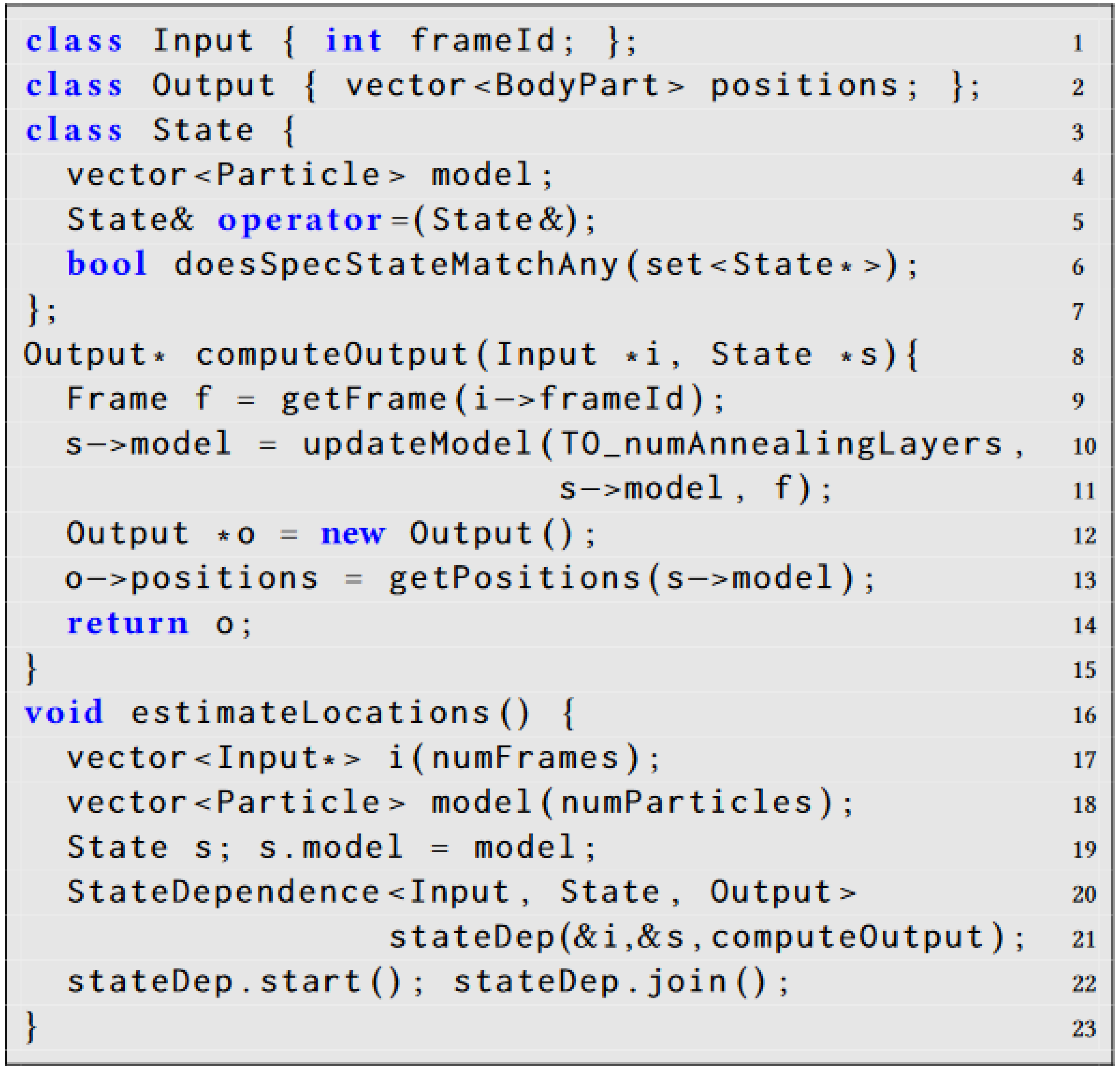
Code Modification

Bodytrack: Pose estimation program



```
void estimateLocations() {
  vector<int> frameIds(numFrames);
  vector<Particle> model(numParticles);
  vector<BodyPart> positions;
  for(auto frameId : frameIds) {
    Frame f = getFrame(frameId);
    model = updateModel(numAnnealingLayers,
                        model, f);
    positions = getPositions(model);
  }
}
```

Figure 7. Original code of bodytrack.



```
class Input { int frameId; };
class Output { vector<BodyPart> positions; };
class State {
  vector<Particle> model;
  State& operator=(State&);
  bool doesSpecStateMatchAny(set<State*>);
};
Output* computeOutput(Input *i, State *s){
  Frame f = getFrame(i->frameId);
  s->model = updateModel(TO_numAnnealingLayers,
                         s->model, f);
  Output *o = new Output();
  o->positions = getPositions(s->model);
  return o;
}
void estimateLocations() {
  vector<Input*> i(numFrames);
  vector<Particle> model(numParticles);
  State s; s.model = model;
  StateDependence<Input, State, Output>
               stateDep(&i,&s,computeOutput);
  stateDep.start(); stateDep.join();
}
```

Figure 8. Use of SDI in bodytrack.

Extracting Parallelism: Speedup

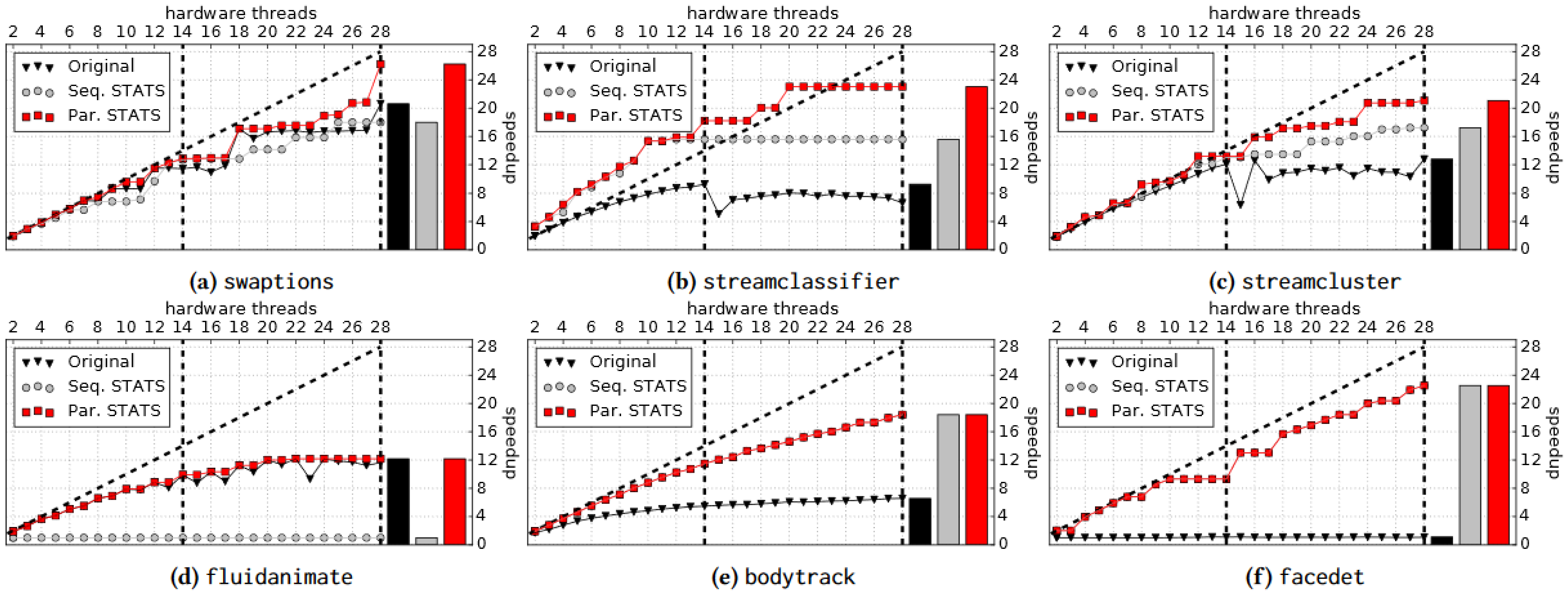


Figure 12. For most benchmarks, STATS generates a significant amount of extra parallelism that saturates the hardware resources of our platform. "Original" is the out-of-the-box benchmark that has been parallelized by traditional means. "Seq. STATS" ("Par. STATS") is the binary generated by STATS starting from the sequential (multi-threaded) version of a benchmark. The bar graphs show maximum speedup.

Energy Consumption

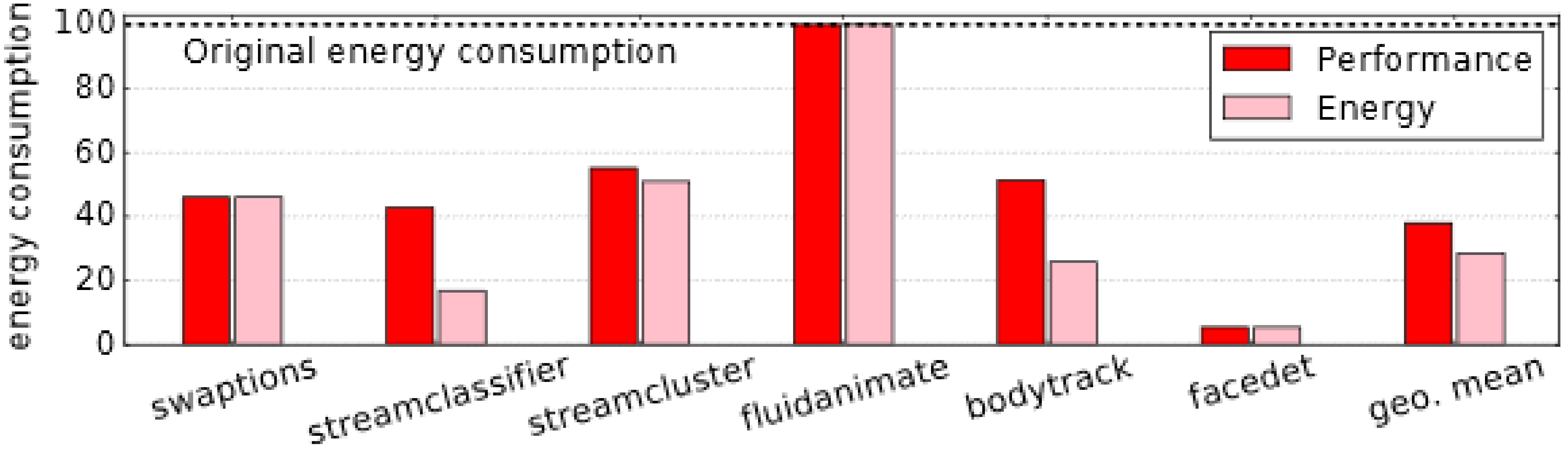


Figure 15. The binaries generated by STATS use considerably less energy compared to the original benchmarks.

Accuracy Impact: Can run more

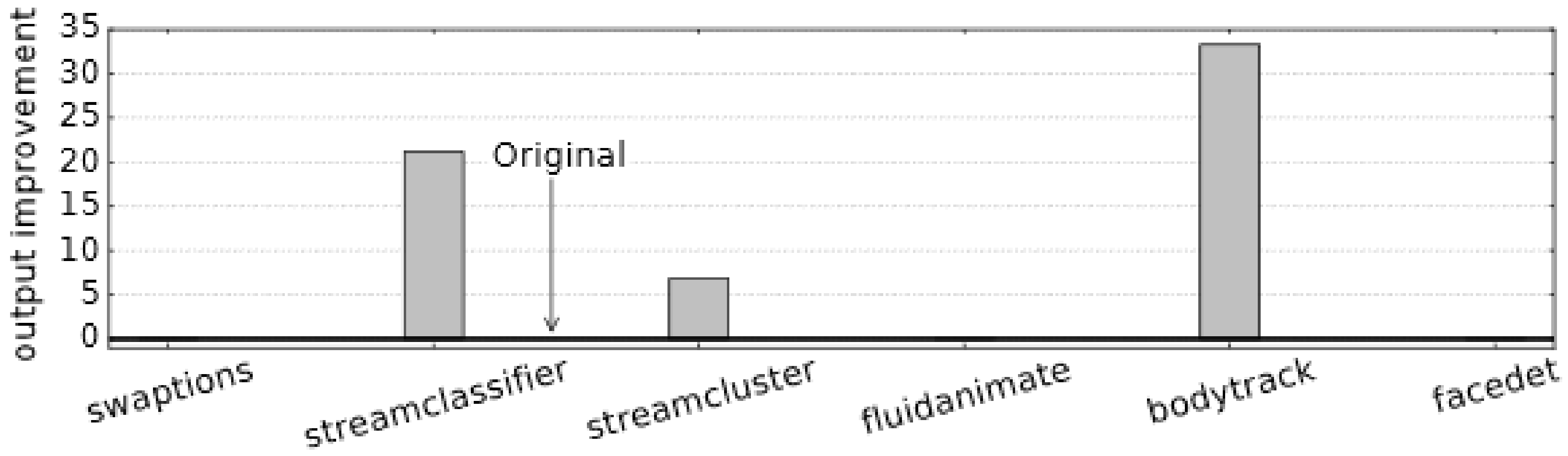


Figure 16. STATS can increase the original output quality by spending the saved time to iterate more over the same dataset.

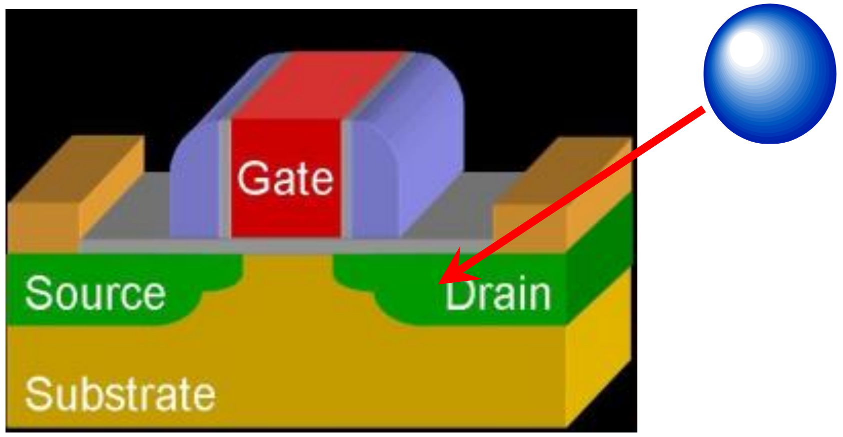
Where is it good to use: *Applications that analyze a long stream of data (e.g., bodytrack, facedet, streamcluster) where the information about inputs that is automatically computed (e.g., 3Dlocation of bodies, 2D location of faces, centroids of multi-dimensional points) has the* **"short memory"** *dependence property.*

Soft Errors: Nondeterminism from Hardware

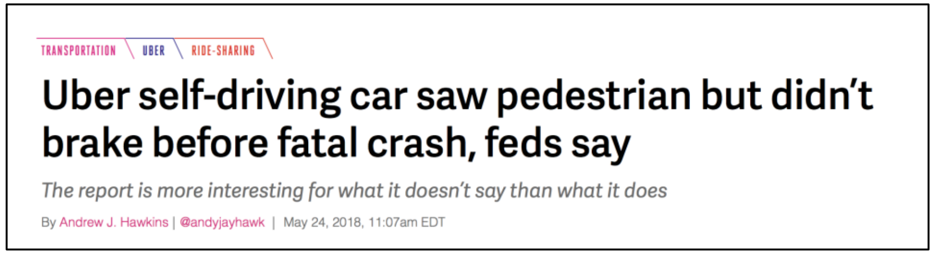
As technology scales, hardware reliability is more important

Hardware more susceptible to transient (soft) errors

Many applications require very high reliability guarantees



Soft Error



TRANSPORTATION \ UBER \ RIDE-SHARING

Uber self-driving car saw pedestrian but didn't brake before fatal crash, feds say

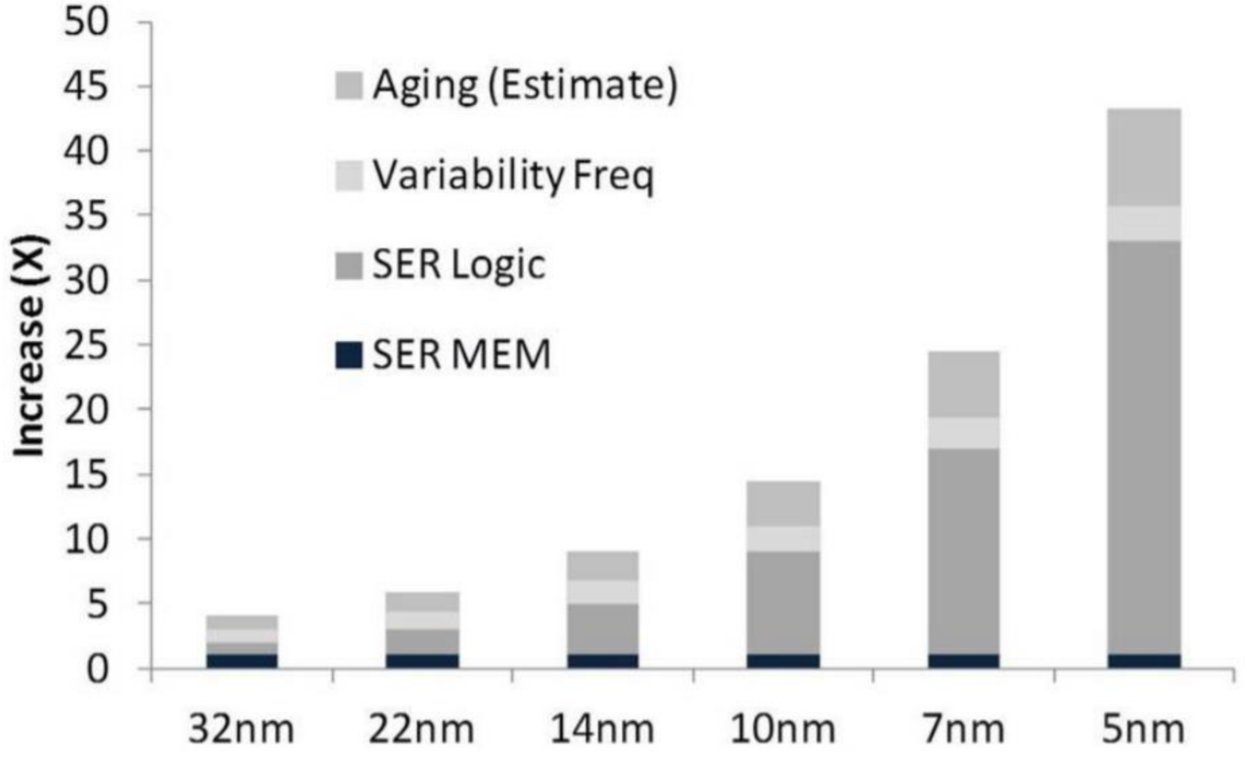
The report is more interesting for what it doesn't say than what it does

By Andrew J. Hawkins | @andyjayhawk | May 24, 2018, 11:07am EDT

"Volkswagen reported ~20% disengagements due to software hang/crashes", WAYMO, CA DMV 2016 Dataset, DSN 2018

Slide by Abdulrahman Mahmoud

Unreliable Hardware

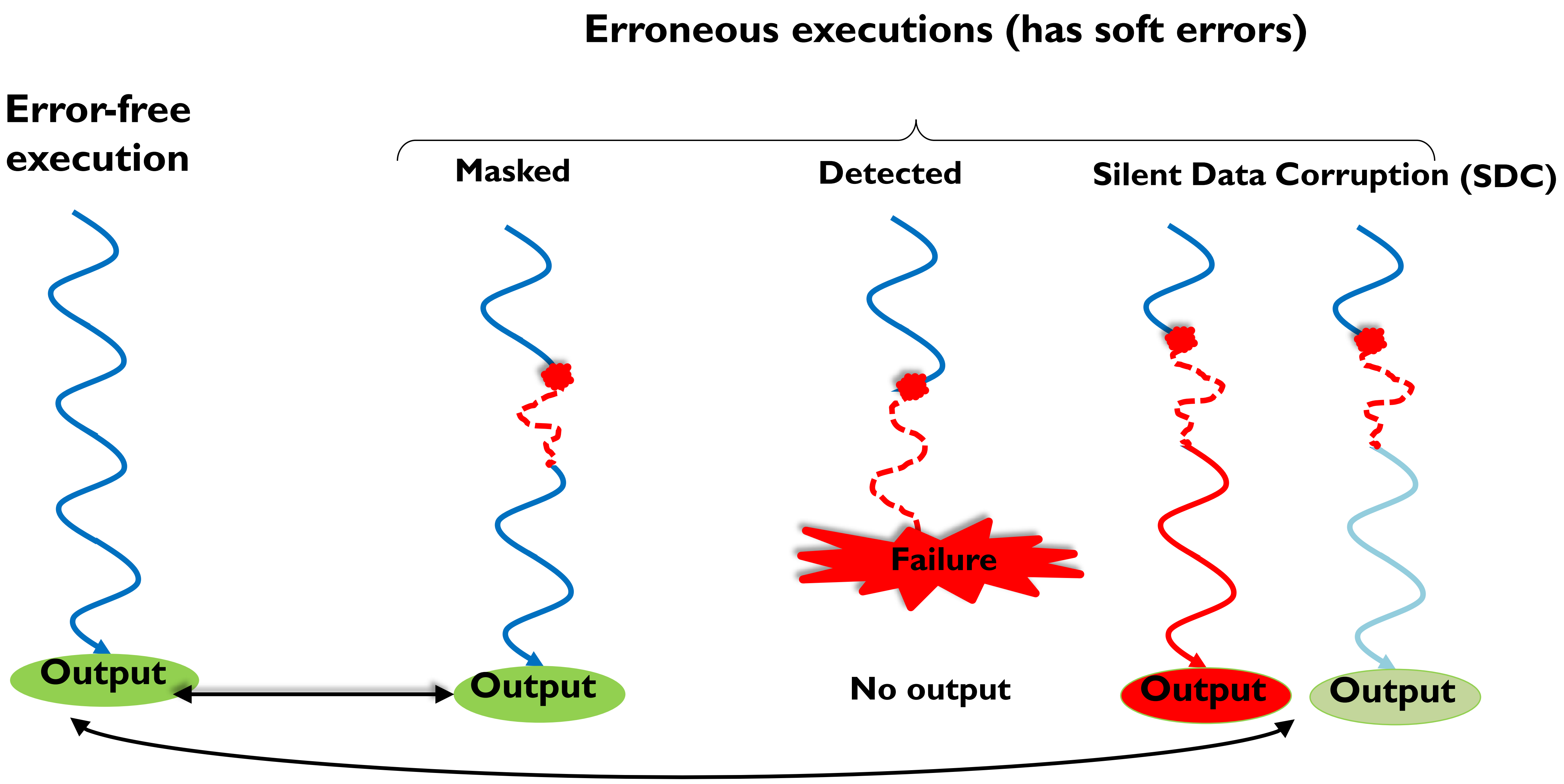


Process size vs. error rate

Architects make great efforts to minimize errors

Some errors slip through the cracks – silently corrupt computation results

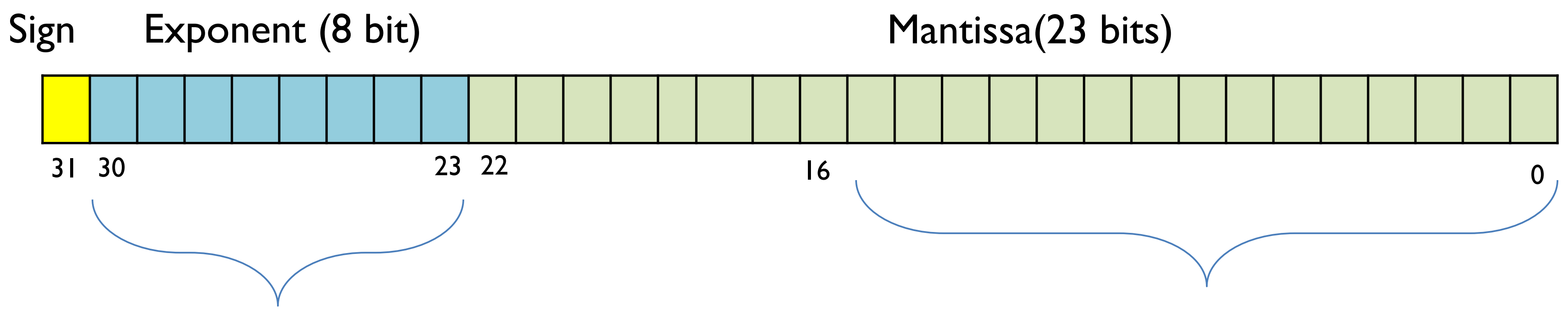
Image from "Inter-Agency Workshop on HPC Resilience at Extreme Scale", DoD, '12



Graphic by Abdulrahman Mahmoud

How do We See at Software Level?

`float x:`



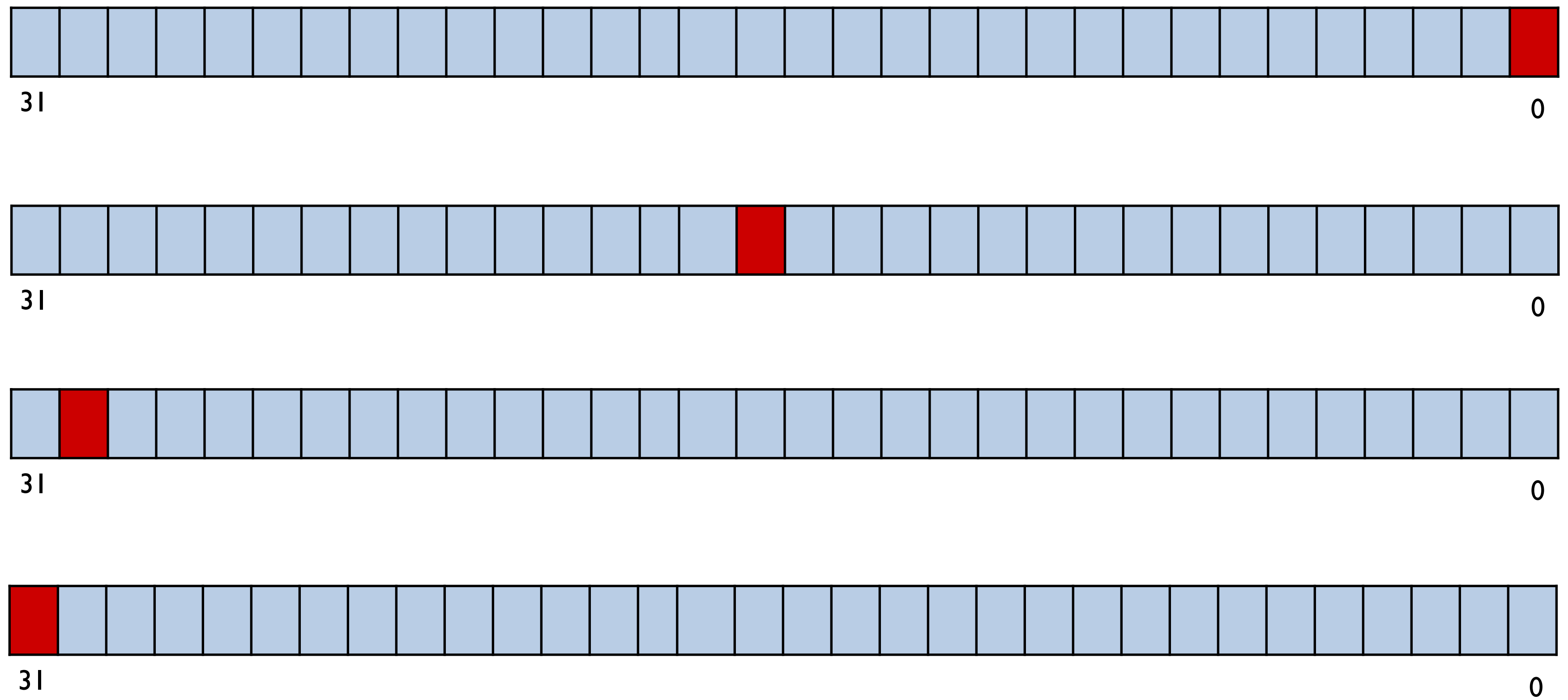
Often large impact

Often small impact

How do We See at Software Level?

Corrupted Bits

`int x:`



But also int* x… what happens then?

Challenges and Traditional Solutions

Detection:

- **Run twice, compare the results**
- **Instruction Replication**
- **Algorithm-based fault tolerance**

Recovery:

- **Checkpoint-restart**
- **Run three times, do majority voting**

Challenges and Approximate Solutions

Detection:

- **Run twice, compare the results**
- **Instruction Replication**
- **Algorithm-based fault tolerance**

Recovery:

- **Checkpoint-restart**
- **Run three times, do majority voting**

Run exact and approximate versions, ensure they don't differ by too much

Challenges and Approximate Solutions

Detection:

- Run twice, compare the results
- Instruction Replication
- Algorithm-based fault tolerance

Recovery:

- Checkpoint-restart
- Run three times, do majority voting

Replicate only some instructions

For the others, either rely on the property of the computation or develop inexpensive checkers

Challenges and Approximate Solutions

Detection:

- Run twice, compare the results
- Instruction Replication
- Algorithm-based fault tolerance

Recovery:

- Checkpoint-restart
- Run three times, do majority voting

Make the algorithmic techniques aware of the approximation

Challenges and Approximate Solutions

Detection:

- Run twice, compare the results
- Instruction Replication
- Algorithm-based fault tolerance

Recovery:

- Checkpoint-restart
- Run three times, do majority voting

Checkpoint only a small part of the state

Restart only when necessary

Challenges and Approximate Solutions

Detection:

- Run twice, compare the results
- Instruction Replication
- Algorithm-based fault tolerance

Recovery:

- Checkpoint-restart
- Run three times, do majority voting

If we need to re-execute, run only approximate algorithm

Try to do 'local repair' on the output

Lightweight Check and Recover

```
z = x*y
z’ = x*y
z==z’ ?
```

Code Re-Execution (SWIFT, DRIFT, Shoestring)

```
y = foo(x)
DNN(x,y) ?
```

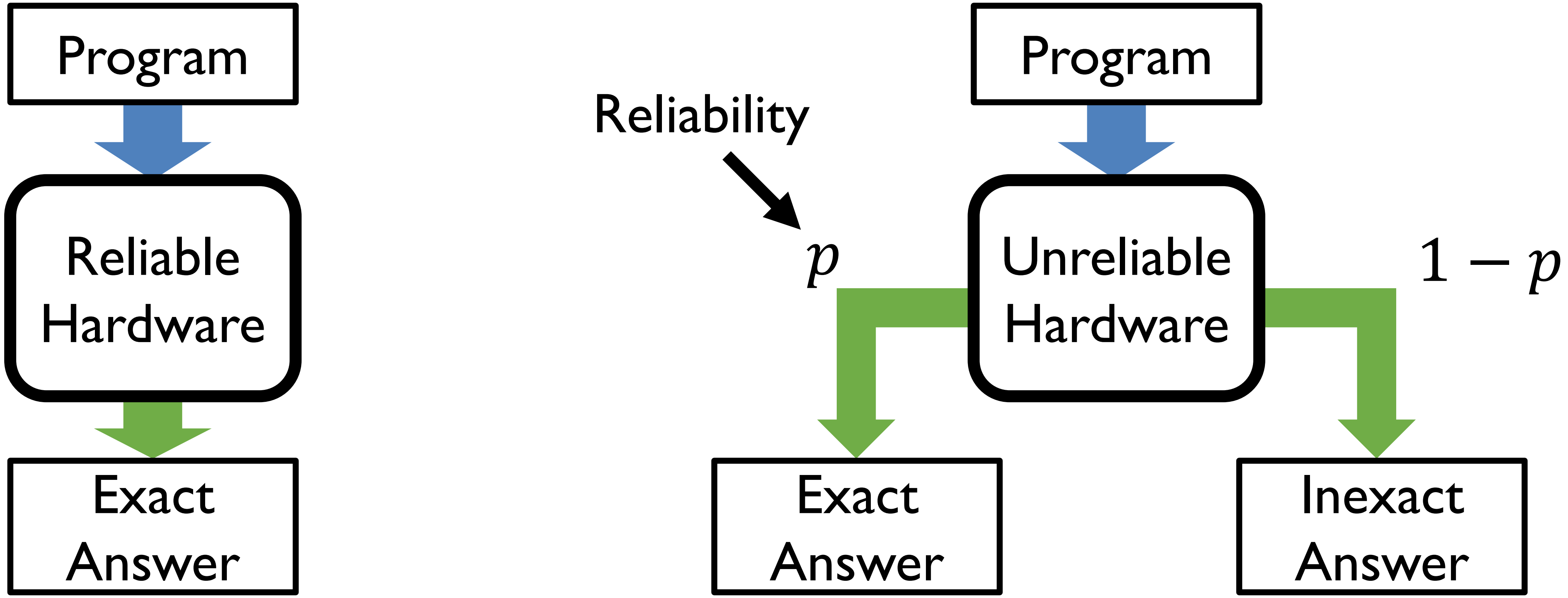
Anomaly Detection (Topaz, Rumba)

```
s = SAT(p)
verify(s,p) ?
```

Verification (for NP-Complete)

Slide by Keyur Joshi

Reliability



Reliability is the probability of obtaining the *exact* answer

The Try-Check-Recover Mechanism

Some research languages[1,2] expose *Try-Check-Recover mechanisms*:

```
try { solution = SATSolve(problem) }
```
Unreliable code

```
check { satisfies(problem, solution) }
```
Checks for errors

```
recover { solution = SATSolve(problem) }
```
Recovery code

[1]"Relax", M. de Kruijf, S. Nomura, and K. Sankaralingam, ISCA '10 [2]"Topaz", S. Achour and M. Rinard, OOPSLA '15

Slide by Keyur Joshi

Code Re-Execution – SWIFT[1]

```
// Instruction 1
try { z = x*y [p_try] rnd(); }
check { z == (x*y [p_try] rnd()) }
recover { z = x*y [p_rec] rnd(); }
// Instruction 2
try { w = x+y [p_try] rnd(); }
check { w == (x+y [p_try] rnd()) }
recover { w = x+y [p_rec] rnd(); }
```

[1] G.A. Reis, J. Chang, N. Vachharajani, R. Rangan, and D. August, CGO '05

Code Re-Execution – DRIFT[1]

```
// Instruction 1 and 2
try {
  z = x*y [p_try] rnd();
  w = x+y [p_try] rnd();
}
check {
  z == (x*y [p_try] rnd()) && w == (x+y [p_try] rnd())
}
recover {
  z = x*y [p_rec] rnd();
  w = x+y [p_rec] rnd();
}
```

[1] K. Mitropoulou, V. Porpodas, and M. Cintra, LCPC '13

Code Re-Execution – Shoestring[1]

```
// Instruction 1
try { z = x*y [p_try] rnd(); }
check { z == (x*y [p_try] rnd()) }
recover { z = x*y [p_rec] rnd(); }
// Instruction 2 not considered critical
w = x+y [p_try] rnd();
```

[1] S. Feng, S. Gupta, A. Ansari, and S. Mahlke, ASPLOS '10

Anomaly Detection – Topaz[1]

```
try {
   z = f(x,y) [p_try] rnd();
}
check {
   isUnusual(x,y,z)
}
recover {
   z = f(x,y) [p_rec] rnd();
}
```

[1] S. Achour and M. Rinard, OOPSLA '15

Hardware Error Flag[1,2]

```
try {
  z = x*y [p_try] rnd();
}
check {
  !(read_hw_err_flag())
}
recover {
  z = x*y [p_rec] rnd();
}
```

[1]"Relax", M. de Kruijf et al., ISCA '10 [2]"Replica", V. Fernando et al., ASPLOS '19