Scaling Resiliency and Analysis Via Machine Learning

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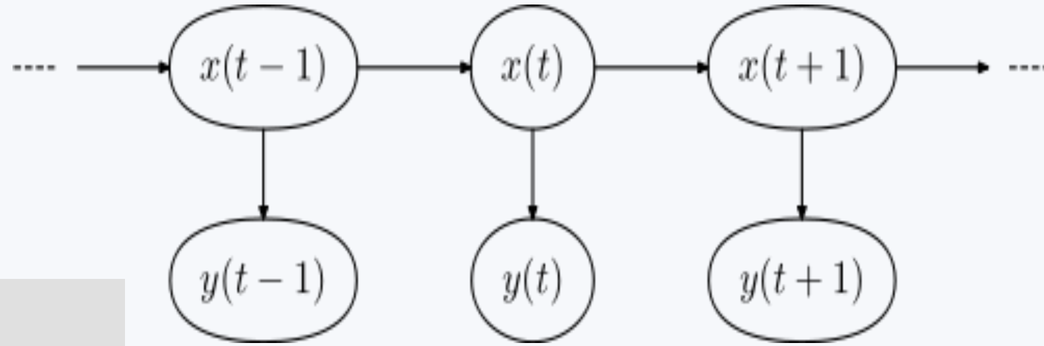
What if a Resilience and Checkpointing Solution Provided

- Improved Resilience via more frequent relevant checkpoints, while
- Reducing the amount of data to be stored by an order of magnitude, and
- Guaranteeing **user-specified** tolerable maximum error rate for each data point, and
- an order of magnitude smaller mean error for each data set, and
- reduced I/O time by an order of magnitude, and
- Enabling faster restart and faster convergence after restart, while
- Providing data for effective analysis and visualization

Simulation Represents a State Transition Model - *What if we analyze the Change in Value?*



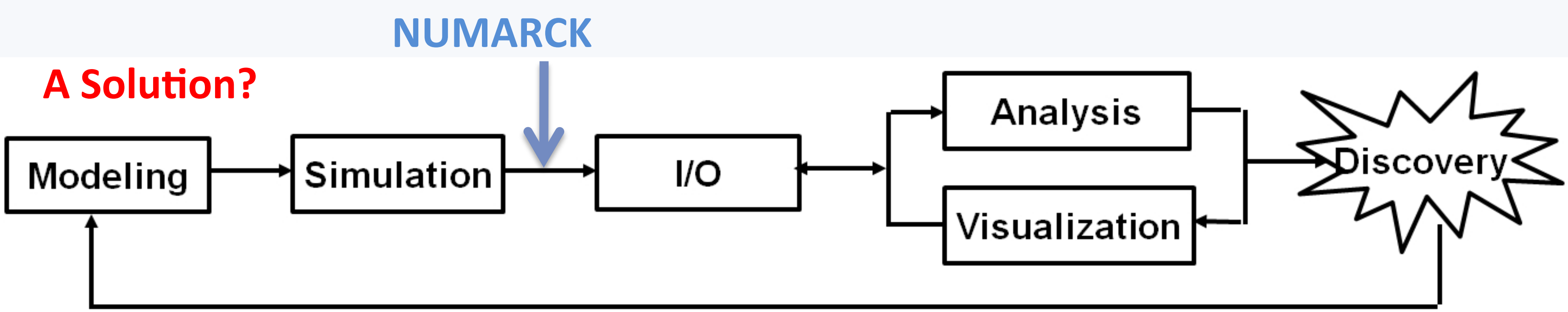
Observations:

- Variable Values – distribution
- Change in Variable Value – distribution
- Relative Change in Variable Value - distribution

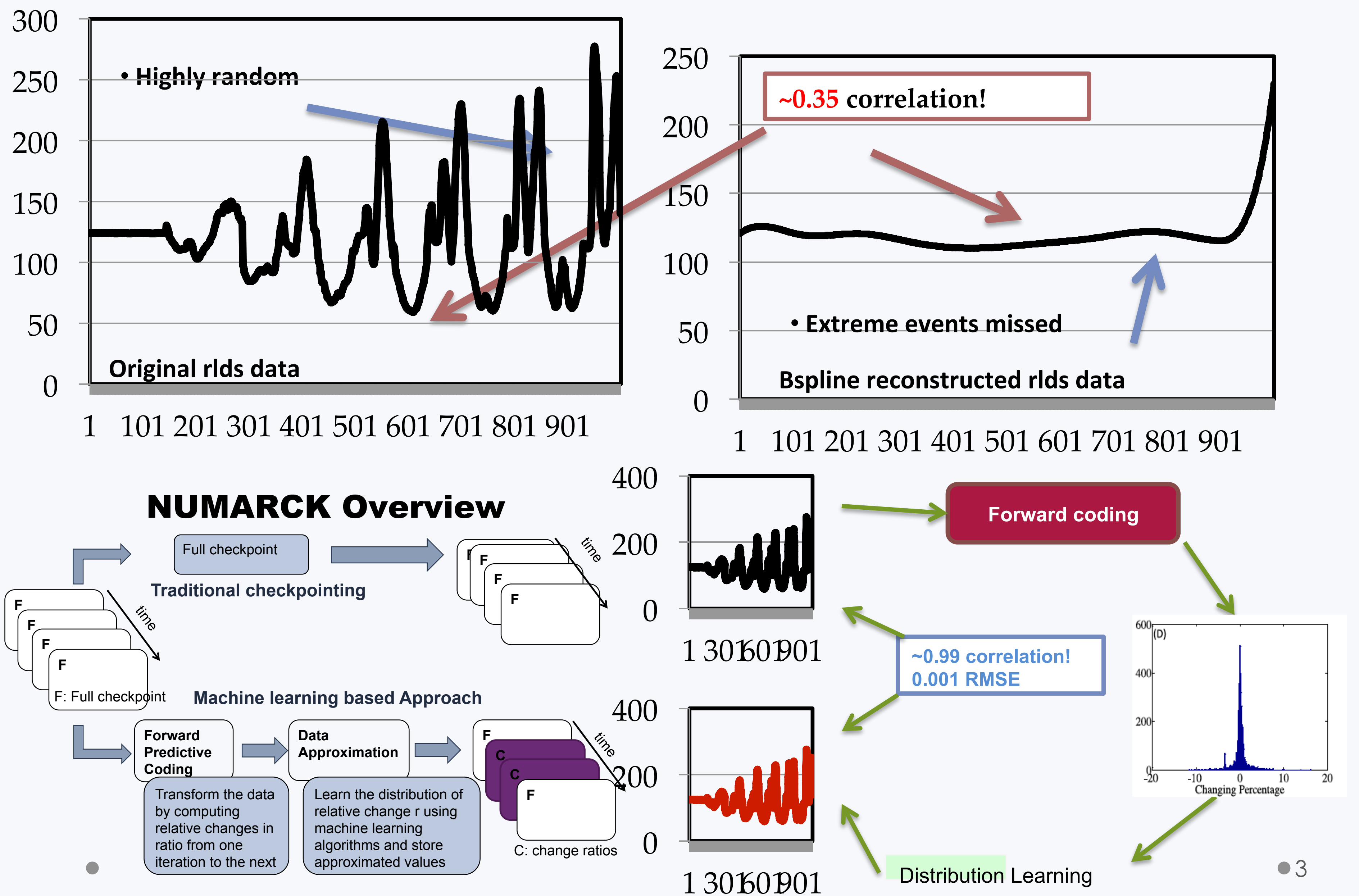
$$\Delta D_{i,j} = \frac{D_{i,j} - D_{i-1,j}}{D_{i-1,j}}$$

- A1(t) = 100, A1(t+1) = 110 => change = 10, rel change = 10%
- A2(t) = 5, A2(t+1) = 5.5 => change = .5, rel change = 10%

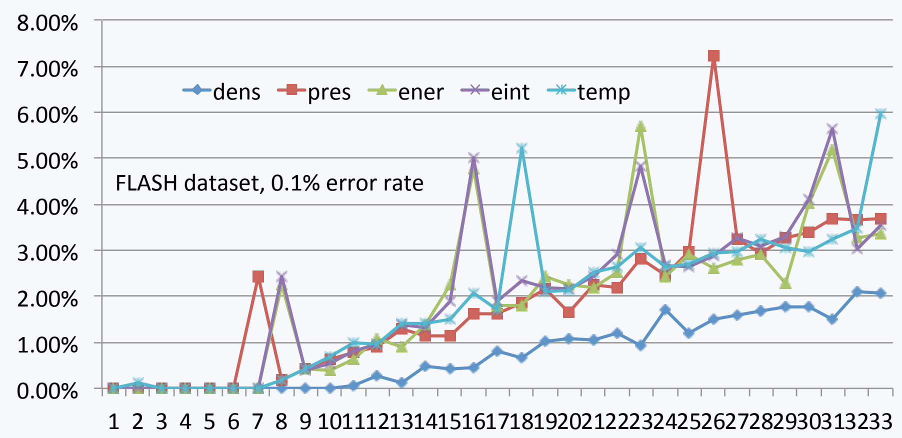
1. Relative change is more predictable. 2. The relative changes in variable values can be learned (ML) and represented in a much smaller state space (compressions). 3. Anomalies are preserved.

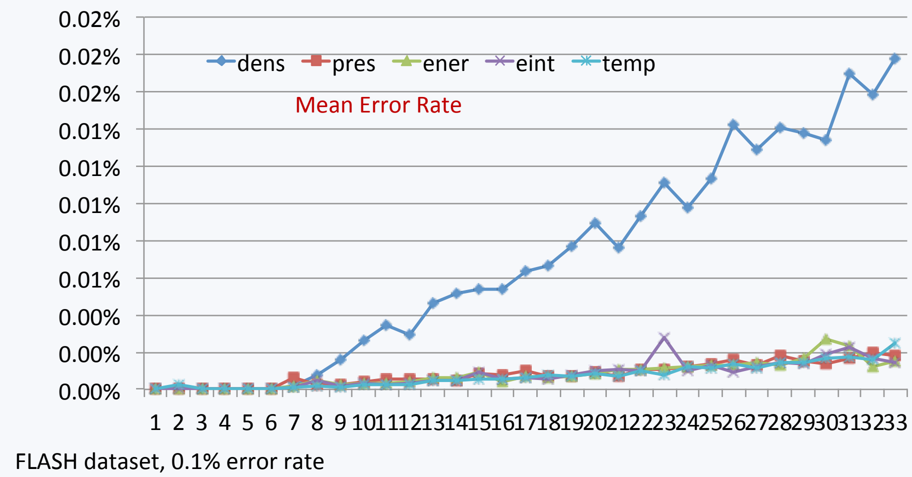


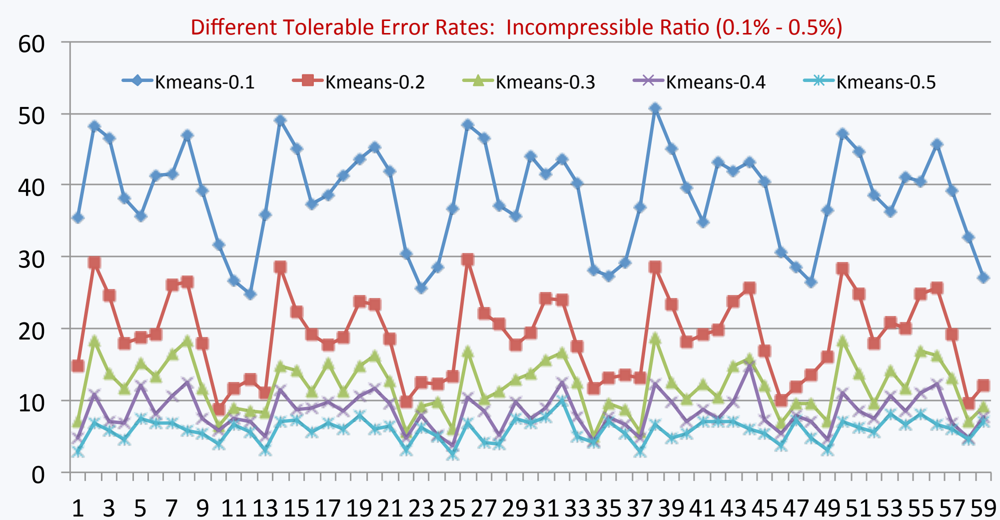
“Incompressible” with Lossy Encoding

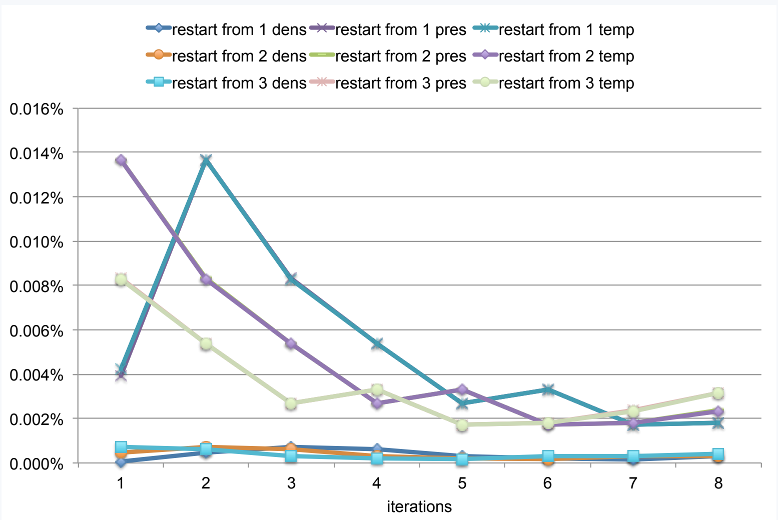


Examples


dens
pres
ener
eint
temp
FLASH dataset, 0.1% error rate
8.00%
7.00%
6.00%
5.00%
4.00%
3.00%
2.00%
1.00%
0.00%


dens
pres
ener
eint
temp
Mean Error Rate
0.02%
0.01%
0.00%
FLASH dataset, 0.1% error rate


Different Tolerable Error Rates: Incompressible Ratio (0.1% - 0.5%)
Kmeans-0.1
Kmeans-0.2
Kmeans-0.3
Kmeans-0.4
Kmeans-0.5
60
50
40
30
20
10
0


restart from 1 dens
restart from 1 pres
restart from 1 temp
restart from 2 dens
restart from 2 pres
restart from 2 temp
restart from 3 dens
restart from 3 pres
restart from 3 temp
0.016%
0.014%
0.012%
0.010%
0.008%
0.006%
0.004%
0.002%
0.000%
iterations