

Scaling Resiliency and Analysis Via Machine Learning

Alok Choudhary
Northwestern University

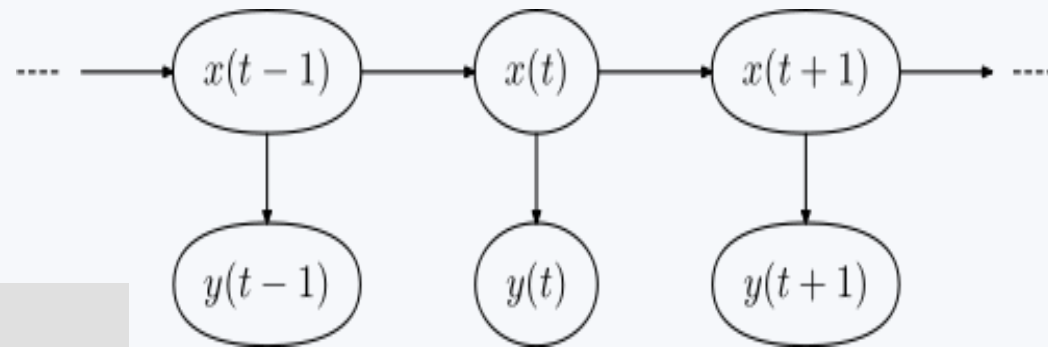
What if a Resilience and Checkpointing Solution Provided

- 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:

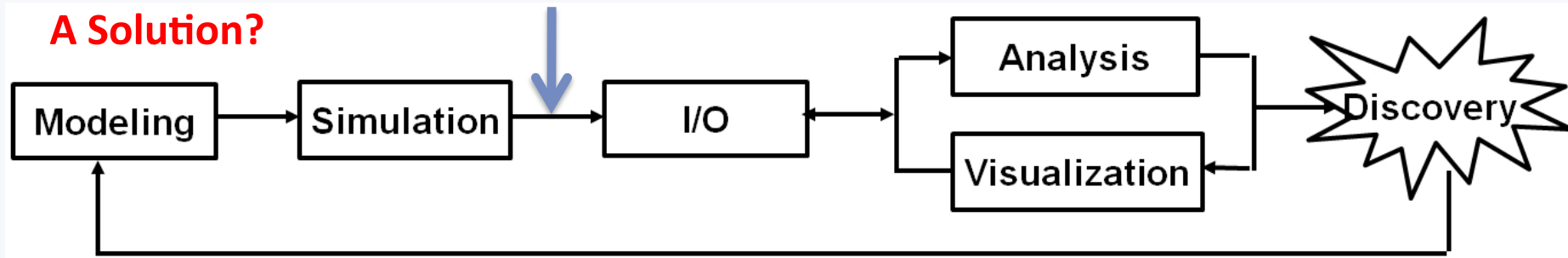
- Variable Values – distribution
- Change in Variable Value – distribution
- Relative Change in Variable Value - distribution

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

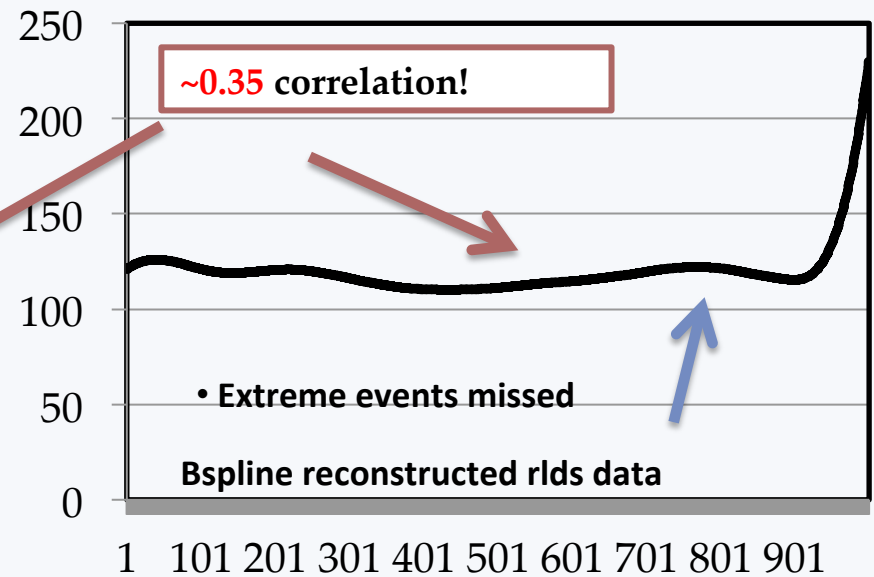
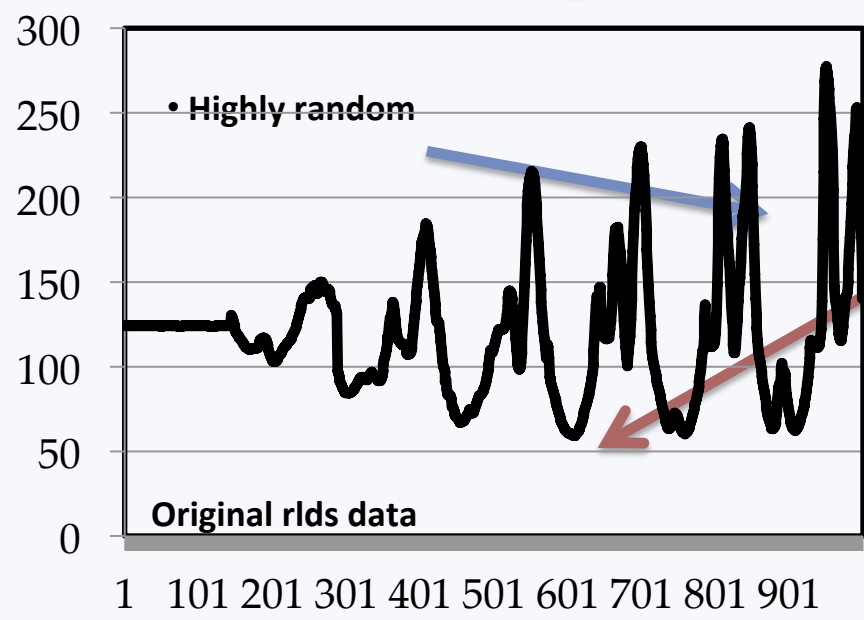
- A1(t) = 100, A1(t+1) = 110 => change = 10, rel change = 10%
- A2(t) = 5, A2(t+1) = 5.5 => change = .5, rel change = 10%

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.

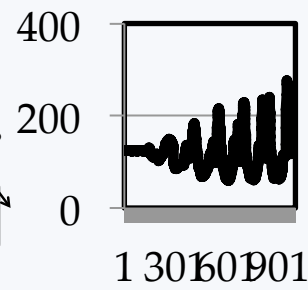
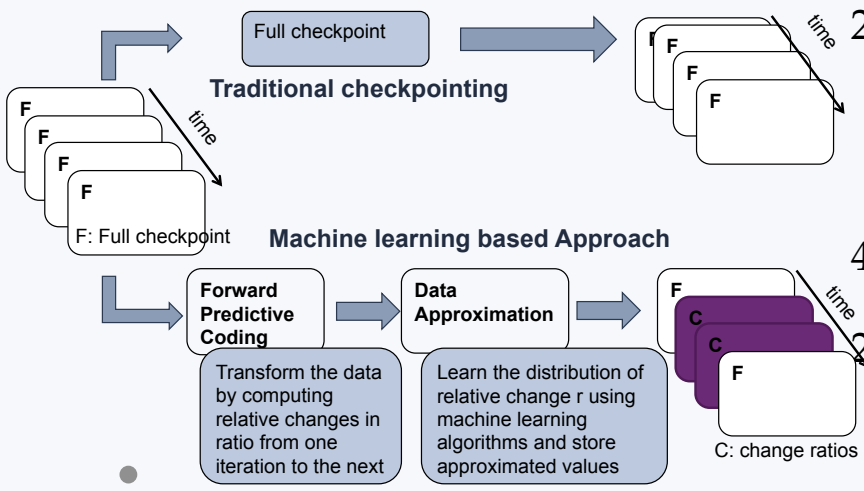
NUMARCK



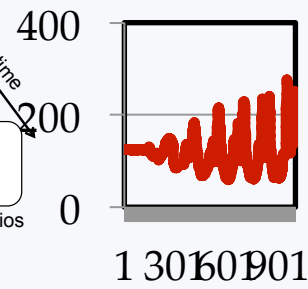
“Incompressible” with Lossy Encoding



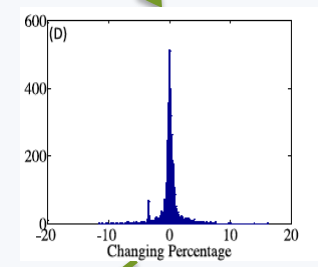
NUMARCK Overview



Forward coding



**~0.99 correlation!
0.001 RMSE**



Distribution Learning

Examples

