High Performance Computing

Yusuke Nagasaka
Tokyo Institute of Technology
Dept. of mathematical and computing sciences
Matsuoka Lab.

Review Paper

- Algorithmic Approaches to Low Overhead Fault Detection for Sparse Linear Algebra [DSN2012]
  - Joseph Sloan
    - University of Illinois
  - Rakesh Kumar
    - University of Illinois
  - Greg Bronevetsky
    - Lawrence Livermore National Laboratory

Fault detection in large scale system

- HPC systems grow large and complex
  - Increase of the number of components
  - Smaller chip size
- Soft error rate will grow
  - Corrupt the computations, produce incorrect output
  - Hardware-based fault detection isn't enough
  - => Algorithm-Based Fault Tolerance

Algorithm-based fault tolerance

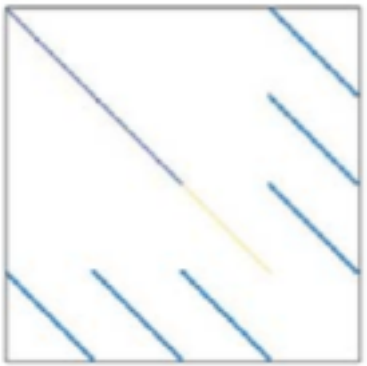
- Software or algorithmic approaches
  - Detect the soft errors with low overhead
- Check sum for matrix vector multiplication (MVM)
  - c (A x) = (c A) x : c is check vector
    - c = (1 ⋯ 1)
  - Low overhead for dense problems
    - Check : O(N^2) + O(k * N) ⇔ Dense MVM : O(k * N^2)
  - High overhead for sparse problems
    - Check : O(N) + O(k * N) ⇔ Sparse MVM : O(k * N)

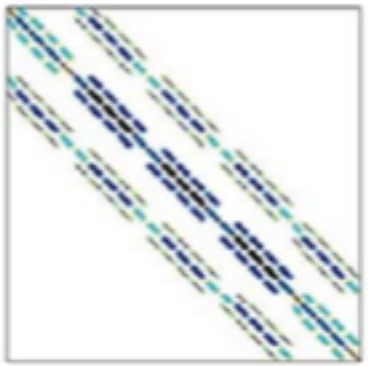
Contribution

- Reduce the check overhead by using sampling technique
  - Exploiting features of sparse matrix and algorithm
  - Approximate Random, Approximate Clustering
  - Identity Conditioning, Null Conditioning
- Compared to traditional dense check, overhead is reduced up to
  - 50% in sparse matrix vector multiplication
  - 20% in iterative linear solvers

Properties of sparse algorithm

- Sparse applications have
  - Inherent structure
    - Diagonal, banded diagonal, block diagonal
  - Significant reuse
    - Iterative methods : CG, IR





Algorithmic fault detection
Approximate Technique

- Exploiting inherent structure
- Approximate Random (AR)

$$1^T(Ax) = ((c^T A)x)s$$

  - c_i = {0,1}, s : scaling factor related to x
  - Useful for low variance of column sum
- Approximate Clustering (AC)
  - Sampling by clustering columns

Algorithmic fault detection Conditioning

- Sparse algorithms include reuse of MVM
  - Need to set the low overhead check sum
- Identify Conditioning (IC)

$$(c^T A)x = 1^T x = \sum x$$

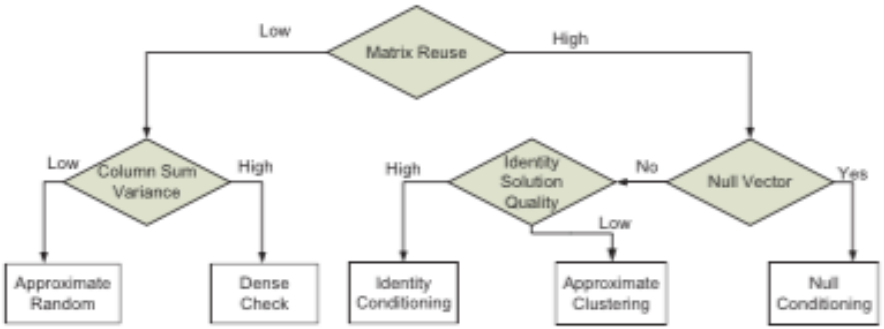
  - Solving min $|A^t x - 1|$
- Null Conditioning (NC)
  - $(c^T A)\, x = 0^T x = 0$
  - Finding a vector c by computing its smallest singular value using singular value decomposition
    - $A\, c = \sigma\, u$ (σ : singular value)

Parameter space

- Fault injection
  - Into the arithmetic operation and check operation
  - Various fault models
  - Fault rates : 0, 1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1
- Sample rate (AR, AC)
  - 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, … ,1.0

Metrics

- F-Score
  - Used to summarize an algorithm's effectiveness
  - F-Score = 2 * TP / (2 * TP + FP + FN)
    - TP : True positives, detect the fault
    - FP : False positives, detector signals when no fault
    - FN : False negatives, not detect the fault
- Choose the best technique
  - Oracle : so that F-Score is best
  - Decision Tree
    - More practical



Results and Analysis

Experiment condition

- Datasets
  - University of Florida Sparse Matrix Collection
- Benchmarks
  - Matrix vector multiplication (MVM)
  - Iterative linear solver
    - Conjugate Gradient (CG)
    - Iterative Refinement (IR)

Evaluation
MVM

- Compare each detection technique
  - AR, AC and IC show same accuracy as traditional dense check
  - NC achieved F-Score above 0.9 for less than 10%
    - Smallest singular value is large
    - Eigenvectors have many zeros
      - Faults is masked

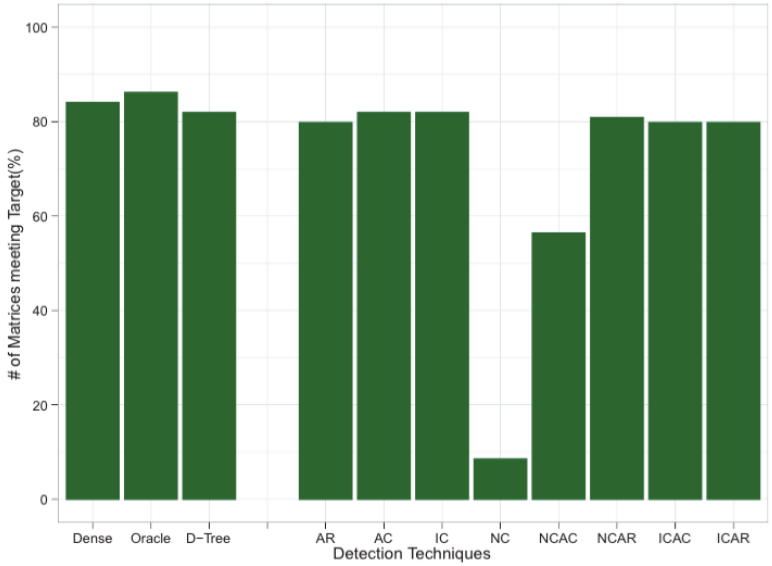


Fig. 7. Number of problems meeting F-Score target. F-Score target=0.9, Fault Rate=$1e-3$, FaultModel=1

Evaluation
MVM

- Compare each detection technique
  - Overhead of AR was 50% lower
  - AC was useful for lower variance pattern matrix
  - NC was useful for what contain small singular values

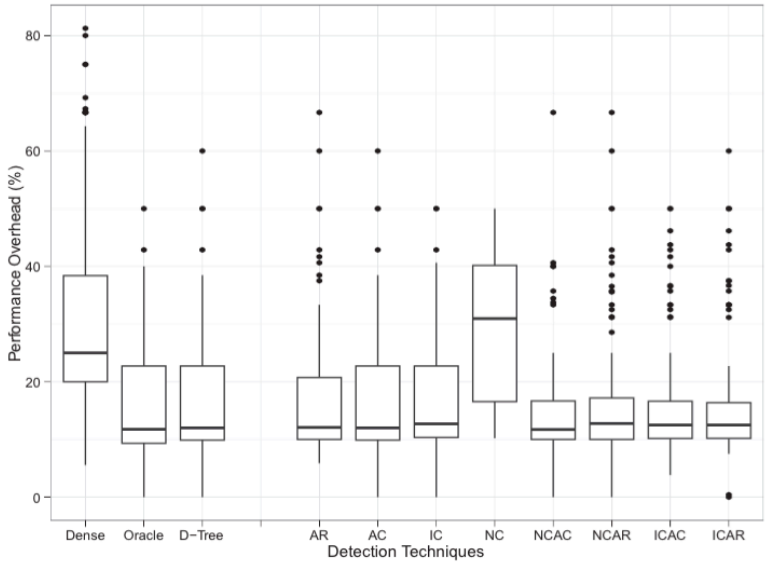


Fig. 6. Runtime overhead of each technique. F-Score target=0.9, Fault Rate=$1e-3$, FaultModel=1

Evaluation
MVM (Less frequent fault rate)

- Dense check becomes worse
  - Faults are likely to occur in the check operations
- Approximate checks work well

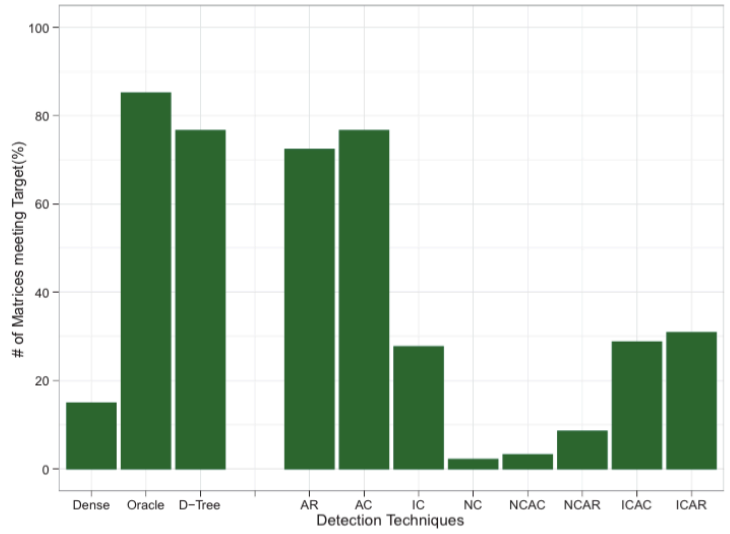


Fig. 9. Number of problems meeting F-Score target. F-Score target=0.9, Fault Rate=1e-6, FaultModel=1

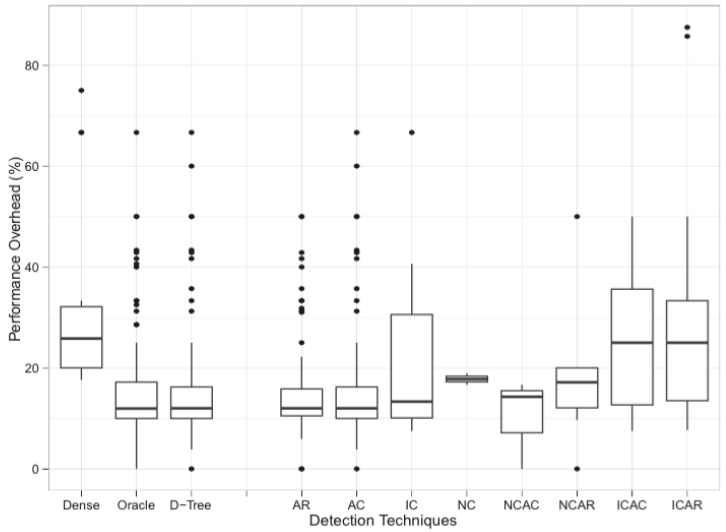
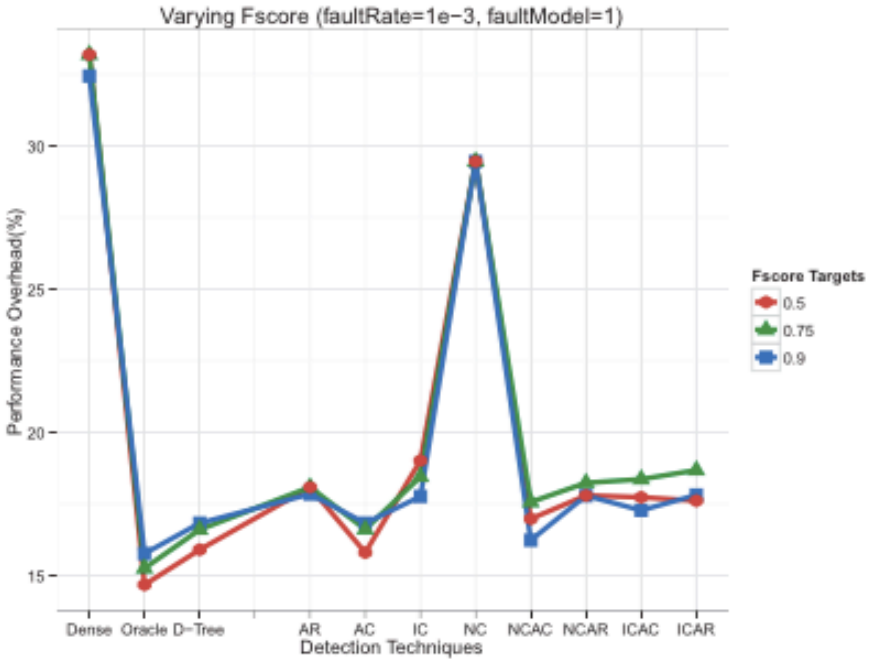
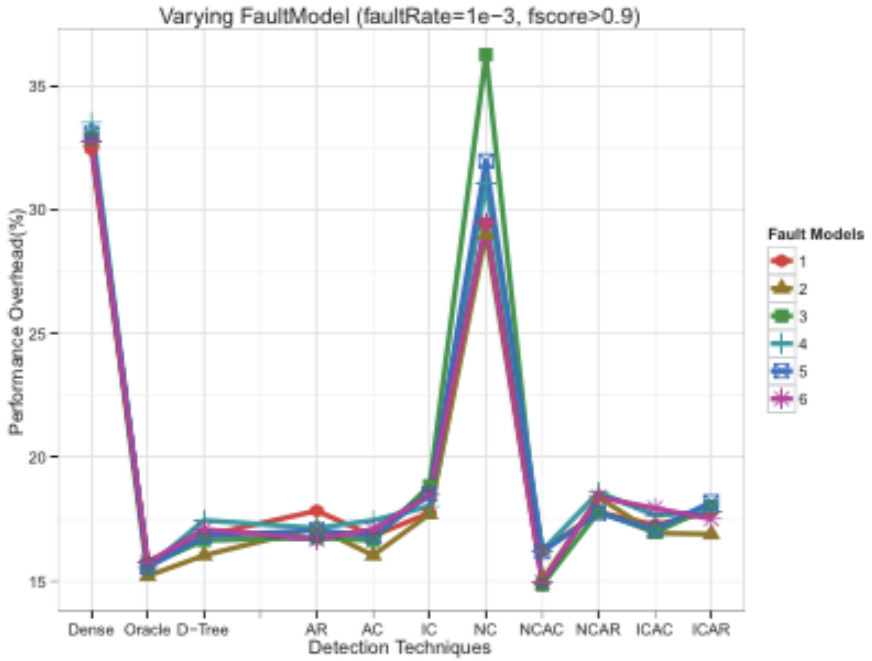


Fig. 8. Runtime overhead of each technique. F-Score target=0.9, Fault Rate=1e-6, FaultModel=1

Evaluation
MVM

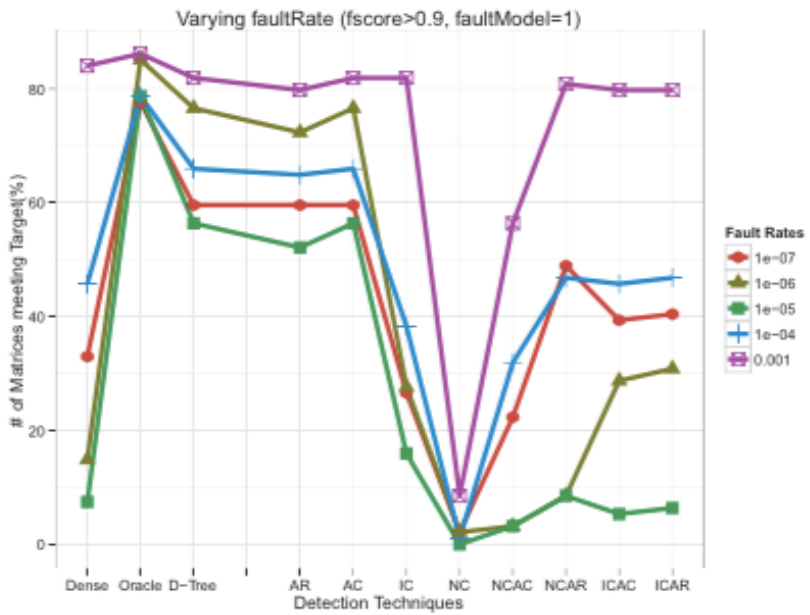
- Across different F-Score targets, fault models
  - Overhead is not sensitive to these parameters

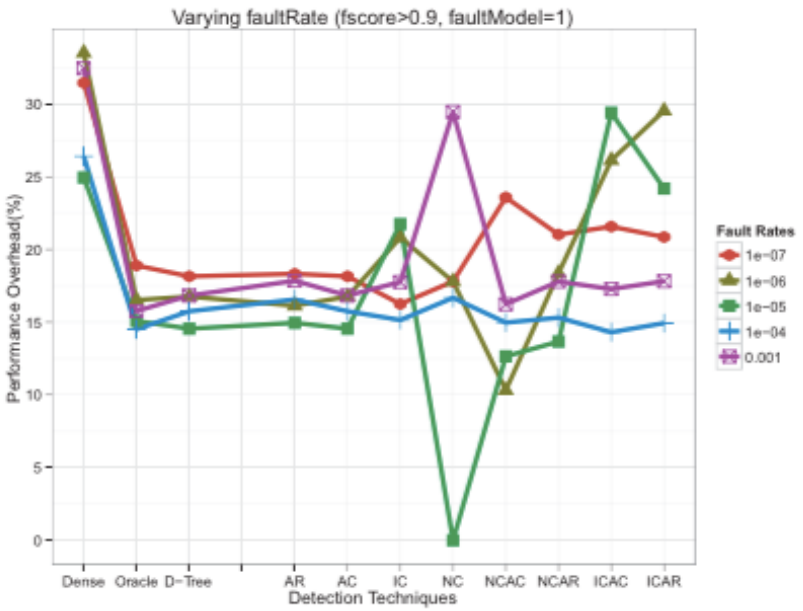




Evaluation
MVM

- Across different fault rates
  - Detection is most difficult in the middle fault rate
  - Tree algorithm is resilient





Evaluation
Linear solvers

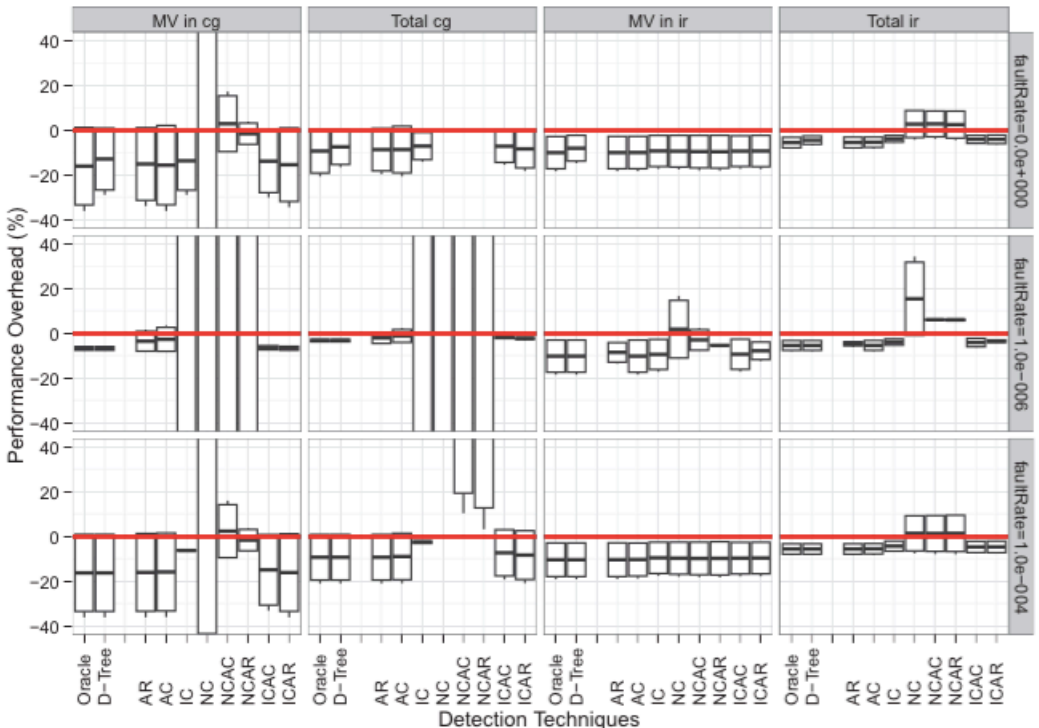
- Evaluation of iterative method
  - CG and IR
- Overhead includes set up
  - Conditioning

$$Overhead = \frac{Time\_sparse - Time\_dense}{Time\_dense}$$

- Problems used with preconditioning solvers achieved significant benefits (> 2x)
  - 5 problems for CG, 1 problem for IR

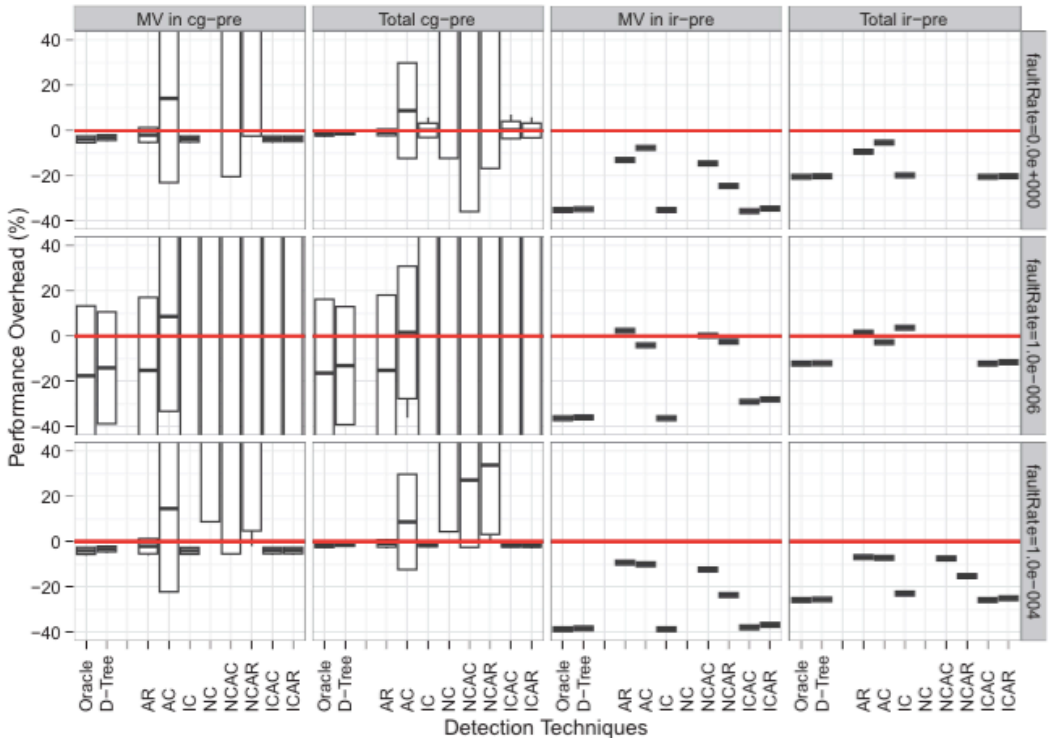
Evaluation
Linear solvers

- Sparse check reduce the overhead
  - 17% less time in MVM for CG on average
  - 9% less time in total for CG



Evaluation
Linear solvers with preconditioning

- Sparse checks with small overhead on average
  - CG-pre : - 5% ~ - 10%
  - IR-pre : - 30% ~ - 40%



Conclusion

- Sparse check technique reduce the overhead of fault detection from traditional dense check exploiting the properties of sparse algorithms
  - Approximate check : AR, AC
  - Conditioning : IC, NC
  - Up to 2x over in MVM
  - Effective for the iterative solver

Discussion

- Apply sparse check technique to
  - Unstructured sparse matrix
  - Dense matrix
- Result of CG-per and IR-pre are not enough
  - Few dataset
- Not enough information about
  - Datasets
  - Experiment environment