Lawrence Livermore National Laboratory

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Automatic Fault Characterization via Abnormality-Enhanced Classification

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Failures growing more common as systems become larger and more complex

- Tera/Petascale High-Performance Systems
  - ASCI Q: 26 radiation-induced errors/week
  - BlueGene/L: 3-4 L1 cache bit flips/day
  - Large scale codes encounter ~1 failures per day
  - Parallel file systems suffer frequent failures
- Problem grows worse at Exascale

Reliability a Significant Problem at Exascale

- Larger machines:
  - Sequoia system at LLNL: 1.6 million cores
  - Exascale: 200k compute chips, 3.5m DRAM chips, 300k disk drives

  [Exascale Software Study: Software Challenges in Extreme Scale Systems]
- Smaller circuit feature sizes (5-10nm)
- Predicted at Exascale:
  - 1 failure every 37 minutes or [Exascale Software Study: Software Challenges in Extreme Scale Systems] 3-26 minutes [Understanding Failures in Petascale Computers]
  - 1 cache bit flip per minute [2009 International Technology Roadmap For Semiconductors]
- At such high failure frequency, rollback isn't an option

  (applications would roll back continuously)

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Need tools to detect faults, identify causes

- Fault tolerance: requires fault detection
- System management: must know what failed
- Focus on complex system faults: reduction in capability of hardware resources

  (e.g. unexpected daemons, dropped packets, routing mis-configuration, CPU voltage scaling from overheating)
- Goal: detect fault and identify
  - Location – process most affected
  - Duration – starting and ending time
  - Fault type – e.g. CPU, Memory or Network

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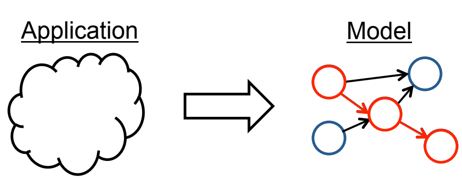
Working on Statistical Techniques to Enable Resilient Applications and Systems

- Model application behavior with and without faults
- Use models to improve fault detection and identification of fault root causes



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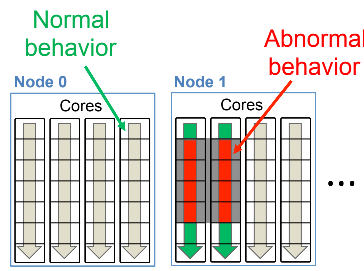
Detection and Localization of System Faults Requires Precise Models of Application Behavior

- Fault affects a fraction of application threads
- To localize fault
  - Divide execution into discrete code regions
  - Statistically model each region's normal behavior
  - Abnormally-behaving regions indicate fault location and duration
- Detect fault type by training models on example runs with known injected faults



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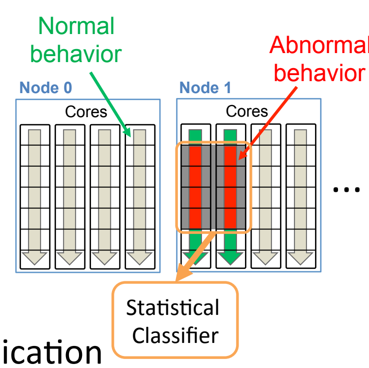
Detection and Localization of System Faults Requires Precise Models of Application Behavior

- Fault affects a fraction of application threads
- To detect fault type (CPU, Memory, Network)
  - Inject known fault types into application
  - Train statistical classifier on application behavior during each
  - Predict type based on application behavior in production



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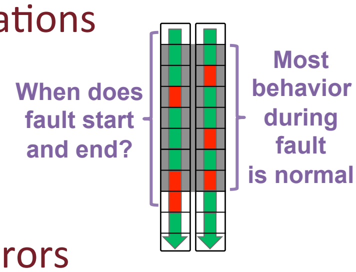
Application respond to faults in complex ways: makes fault analysis difficult

- Contribution 1: In reality faults have inconsistent effect on applications
  - CPU slowdowns only affect CPU-intensive code regions
  - Errant daemons primarily affect concurrent code



- Difficult to detect, localize errors
- Characterization becomes very hard

  Even if fault duration is known during training most events are not representative of fault

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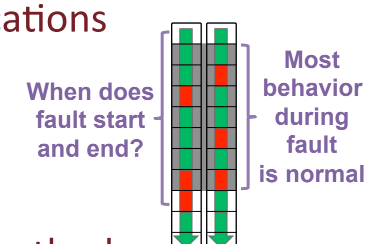

- Contribution 2: Automatic method to recover fault signatures from noisy application behavior data

  Enables accurate fault localization and type prediction

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Main Idea: Abstract Specification of Internal System Structure

- Statistical methods need context information about system state (features → observation)
- Relevant context often unknown to manager
- Demonstrate: can infer unknown context from observations given simple analytical model of system
- Conclusion: Division into known and inferred context very productive for modeling system behavior

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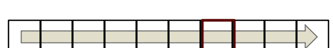
Approach:
Instrument applications with behavior monitors

- Automatically inject instrumentation points into application executable
  - Present: Start and end of each MPI call
  - Measure system state at each point
    - Time
    - Values of performance counters
- Application run divided into events

Run  (code regions)

- Elapsed Time
- Performance Counter Hits

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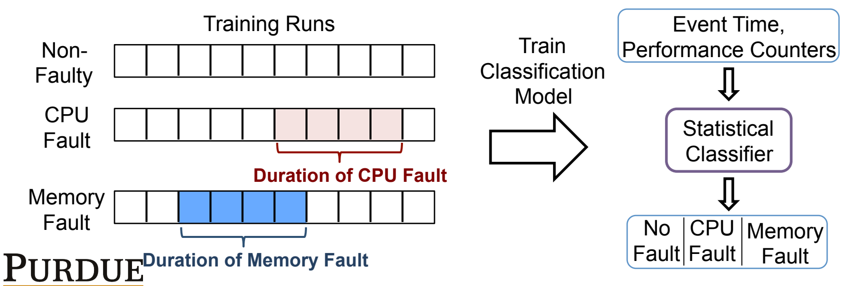
Approach: Model Application Behavior Using Traditional Statistical Classification

- Run application
  - With no faults
  - With one of several fault types injected into execution
- Build model of application's behavior in each case
- Identify each event's fault location and type using model



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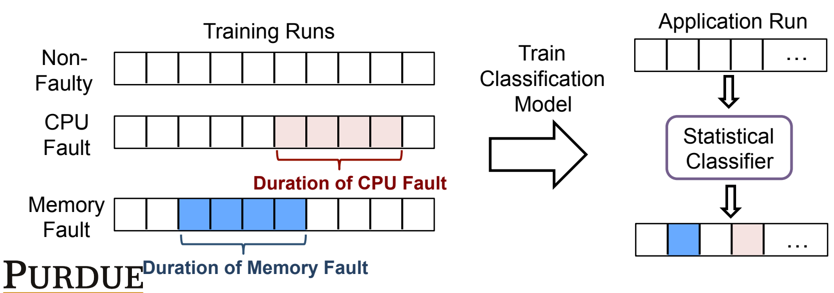

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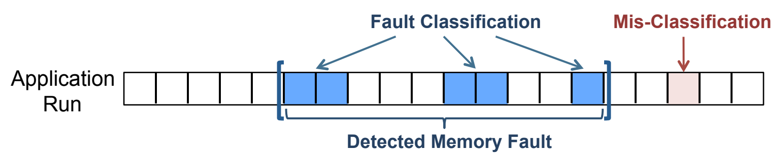
Approach: Build System Administration Tool From Single-Event Fault Predictions

- Single-event predictions too fine-grained to present to administrators
- Must be aggregated into simple fault identifications
  - On faulty runs classifier produces sequence of identical fault identifications (same location, type)
  - Aggregate entire sequence into single report to administrator



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Experimental Setup Focuses on Static Applications and Multiple Fault Types

- 16-core NAS benchmarks runs (BT, CG, LU, MG, SP)
- Injected fault thread into one application core
  - Training: Three examples of each fault type
    - CPU-intensive: arithmetic operations
    - Memory-intensive: patterns of random memory updates
    - Socket-intensive: thread communicates with self
  - Evaluation:
    - NoFault: Application runs with no faults injected
    - KnownFault: Applications injected with faults used for training
    - UnknownFault: Applications injected with faults similar to those used in training

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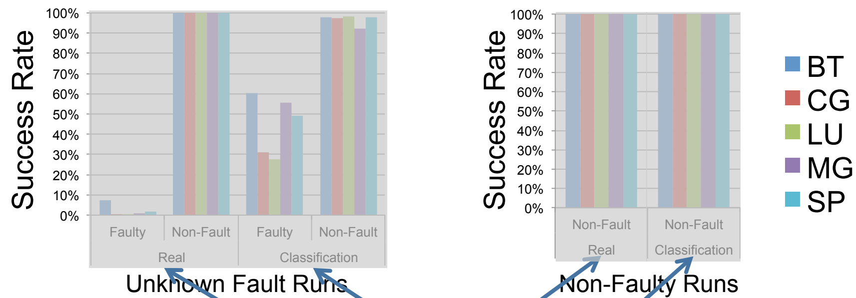
Traditional classification techniques fail for system faults

- Accuracy of Boosted Logit classifier in detecting and localizing faulty events

(same results for other classifiers)



Detection success rate

If eve If event was Predicted to be Faulty/Non-Faulty

Precision

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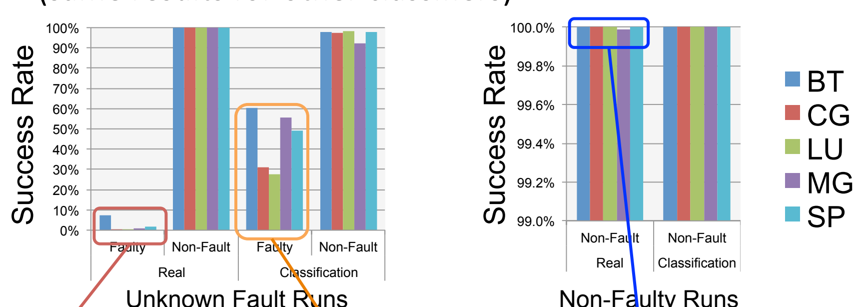

Most faults missed

Majority of Fault Detections Incorrect

Low false-positive rate

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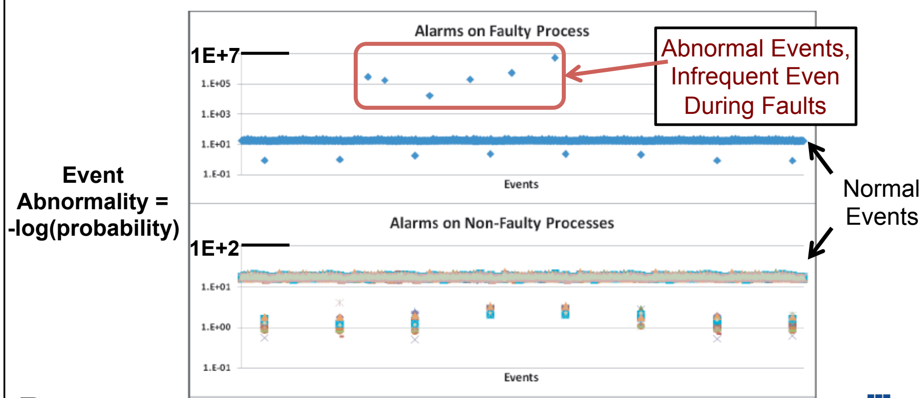
Accuracy of Naïve Method is Low Because System Faults Have Erratic Effects

- Can train probability distributions as above to measure probability each state



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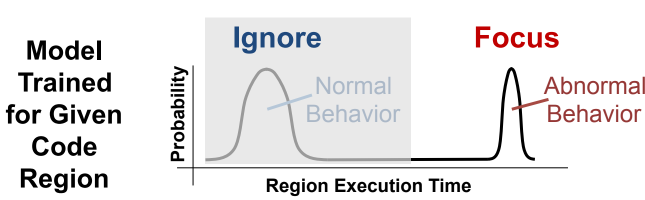
Can Improve Accuracy by Combining Probability and Classifier Models

- During fault only few events are abnormal
- These events truly representative of the fault
- Filter events in faulty runs to label only abnormal events as Faulty
- Other events labeled as Non-Faulty



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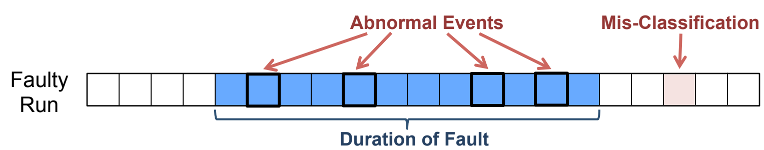
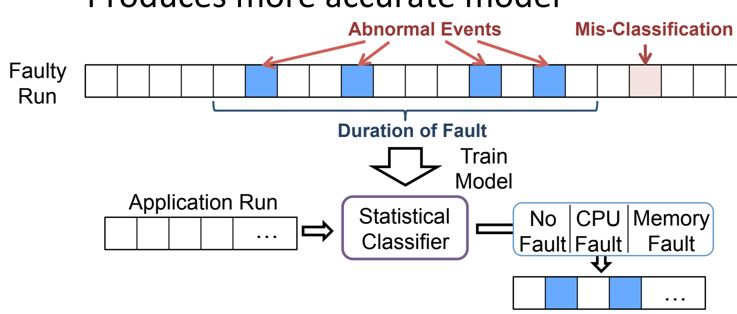


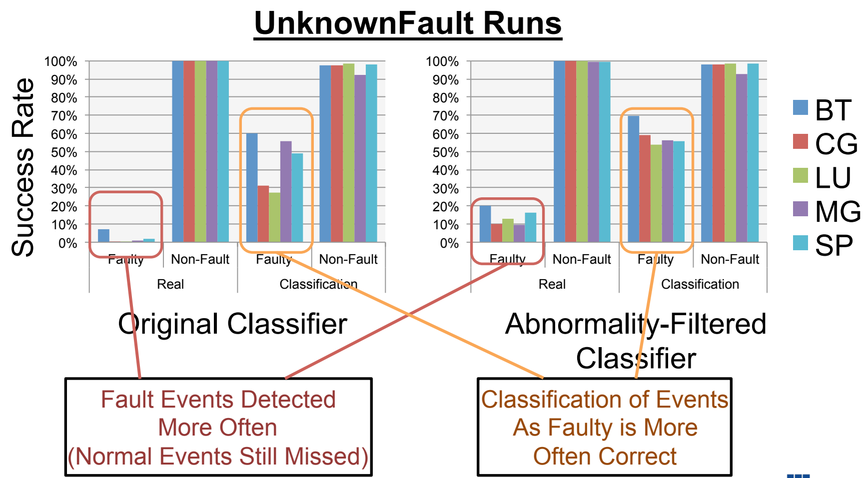
Can Improve Accuracy by Combining Probability and Classifier Models

- Filtered labeling
  - Significantly improves data to noise ratio of training data
  - Produces more accurate model



Abnormality-Filtered Classifier Detects Faults More Accurately

Using Relative Rather than Absolute Counter Measurements Improves Accuracy Further



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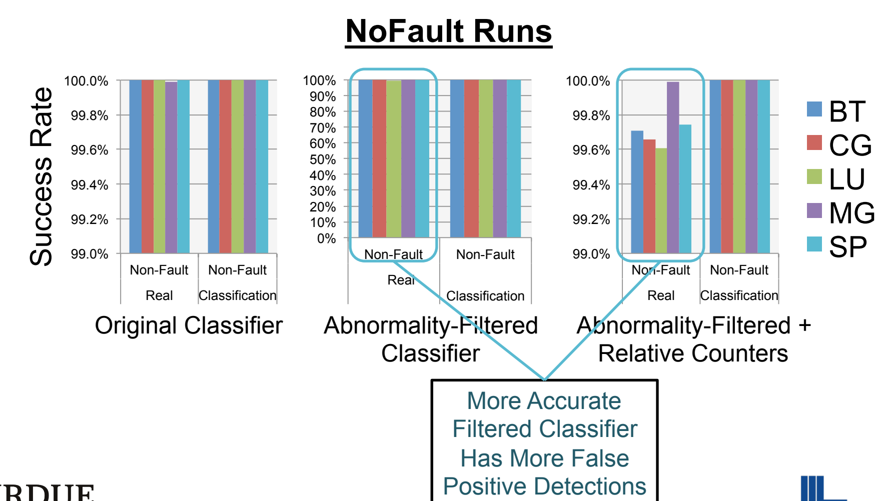
Abnormality-Filtered Classifiers Have More False Positives



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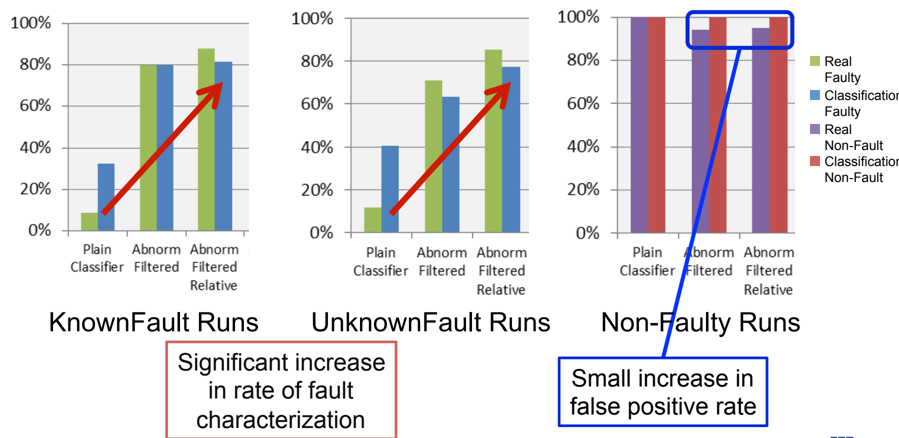
Improved Technique Detects Fault's Location, Time and Type



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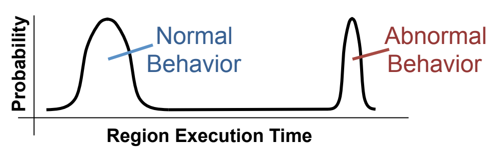
Application behavior is a random process managed by hidden state

- Behavior of each code region depends on separate probability distribution



- Composition of multiple sub-behaviors
- Choice controlled by hidden process

  e.g. region vulnerable/invulnerable to fault

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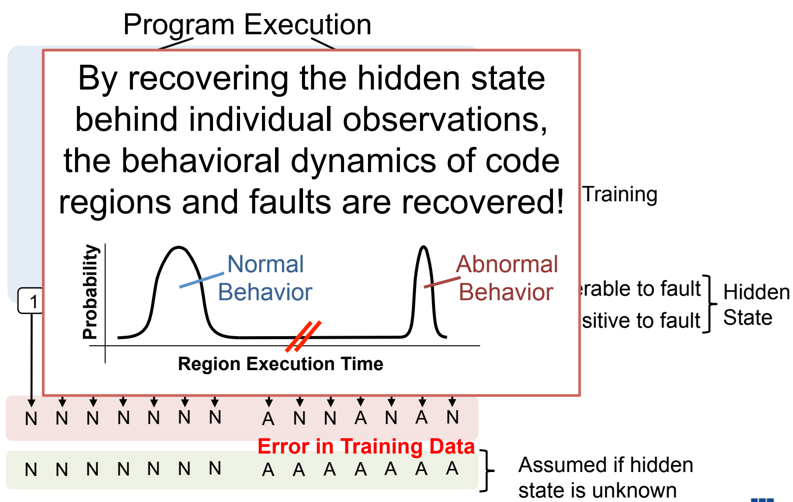
To train accurate models we must extract hidden state and explicitly represent it



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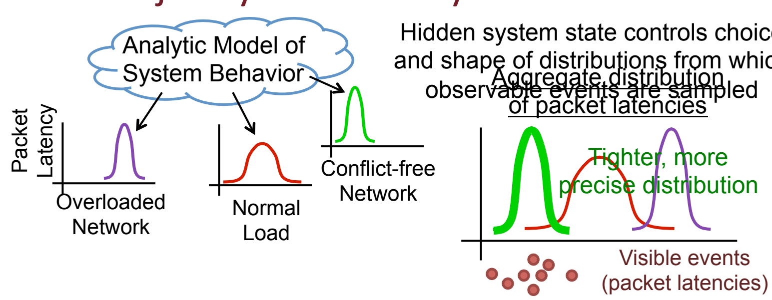
Hidden variable inference: general approach to modeling system behavior

- Human manager: specifies analytical model for major dynamics of system behavior



- Infer system state from observed events

Observed events more constrained and predictable

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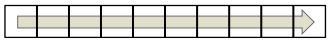
Proposal: New Way for Administrators to Interact with Statistical System Models

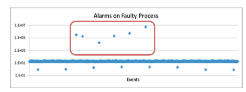
- Known context: specify directly

  (e.g. node/core ID, code region, input data details)

   (code regions)

- Unknown context:

  (e.g. code region vulnerability, effective network load)

  - Specify implicitly via approximate analytic model of system behavior
  - Infer current state within model from observations

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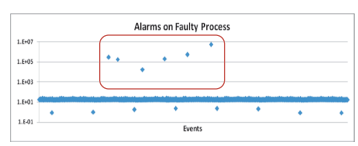
Developed statistical modeling technique focused on complexities of system faults

- Traditional modeling approaches fail on system faults because they can't capture internal system state
- Developed filtering approach to infer hidden state from observed events



- General modeling approach:
  - System administrators develop simple analytical models of system behavior
  - Modelers infer current model parameters from observations

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Developed statistical technique to localize and characterize complex system faults

- Traditional modeling approaches fail on system faults because they ignore internal system state
- Developed statistical modeling technique to accurately detect and localize system faults
- Developed filtering approach to infer hidden state from observed events
- Significant improvement in detection and localization accuracy over naïve classifier
  - Small increase in false alarm incidences

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