Modeling Techniques Towards Resilience

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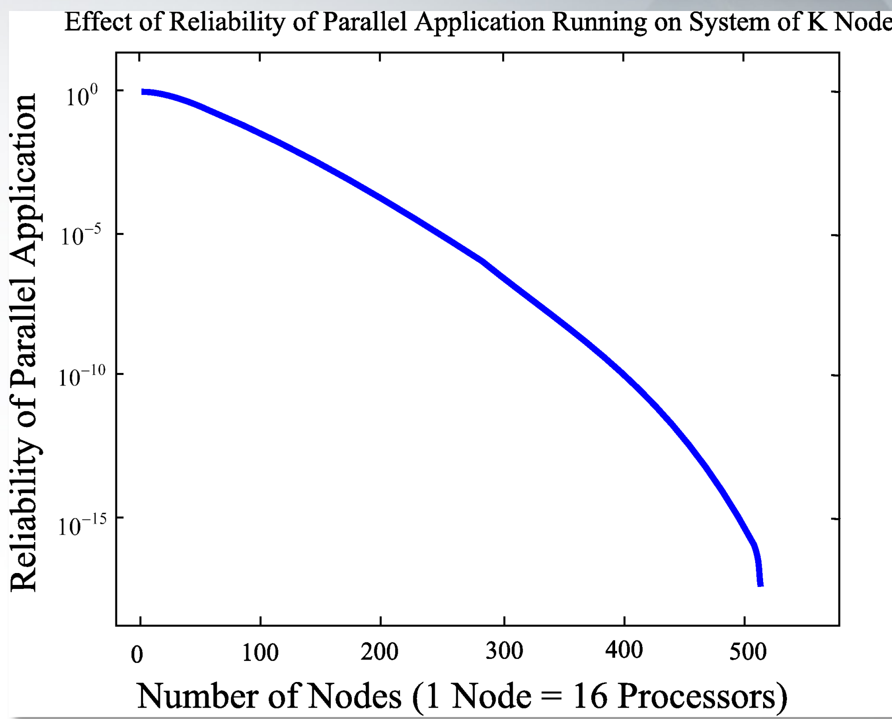
Outline

- Motivation
- Resilience and resilience modeling
- Existing models
  - Fundamental models
  - Resilience supporting models
- Conclusion

Motivation: Failures Happen (Often)

- Even the most reliable system will fail at some point
- Scaling up in components reduces a system's reliability
- The 1,000,000-node example:
  - Desired system MTTF: 12h
  - Needed node MTTF: 12,000,000h (that's 1,370 years)
- We need to learn to live with failures as they happen (often)



Resilience and Resilience Modeling

- Resilience:
  - Continuous, progressive computing despite failures
  - Extends beyond traditional fault tolerance approaches
- Resilience modeling:
  - Mathematical representation of system behavior
    - Failure mode, root cause, impact and probability
    - Resilience mechanism type, capabilities and impact
  - Optimization towards “resilience computing”

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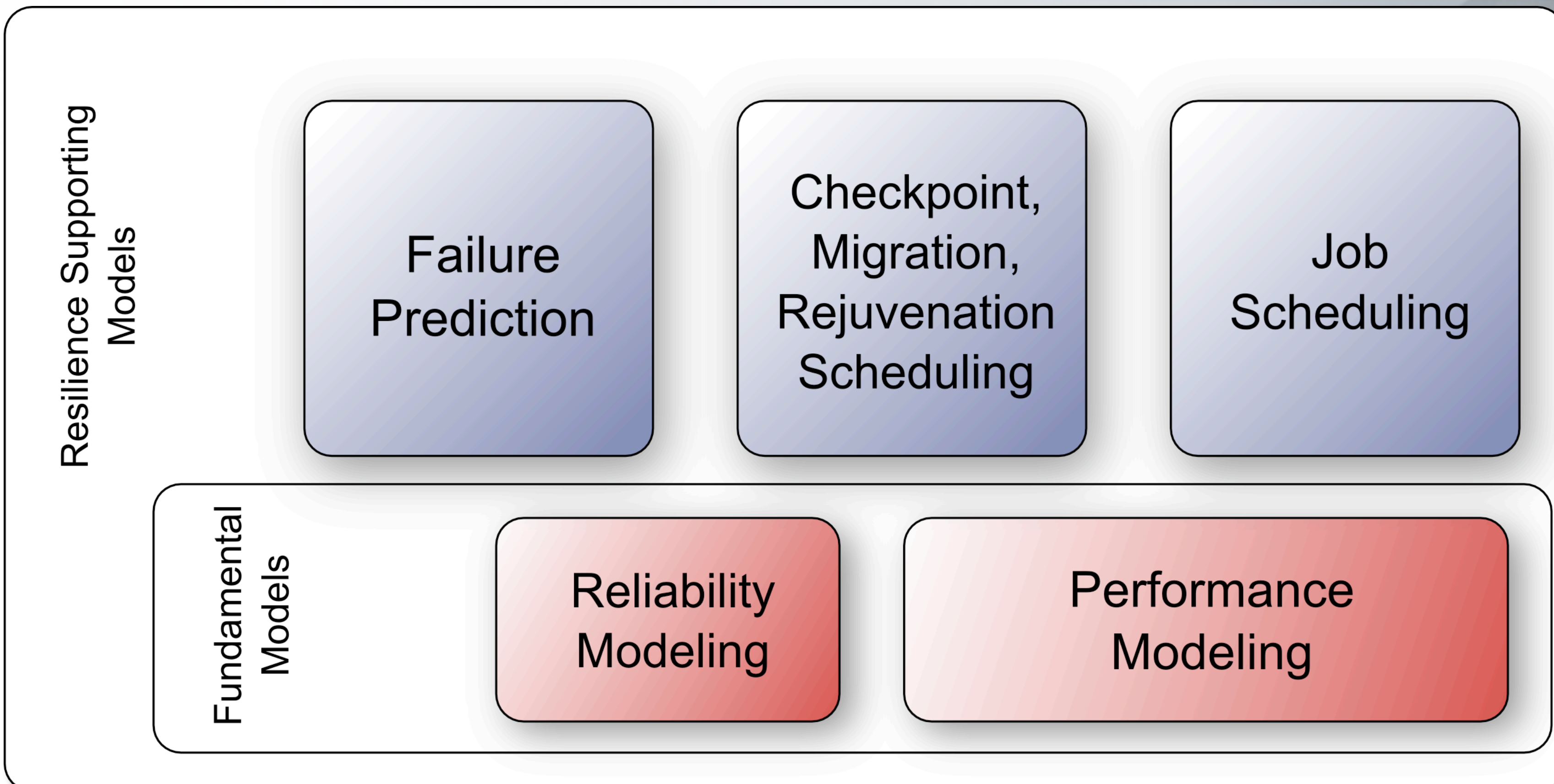
Resilience Models



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Fundamental Models

- Study of failure distribution in HPC systems, e.g., Exponential vs. Weibull distributions
  - Schroeder and Gibson ’06, Y. Liu ’08
- Scalable stochastic HPC system reliability model
  - Gottumukkala ’09
- RAS models for specific HPC system components
  - Tang ’08

Resilience Supporting Models

- Checkpoint scheduling
- Migration scheduling
- Rejuvenation scheduling
- Job scheduling
- Failure prediction
- Runtime decision for optimization

Checkpoint, Migration and Rejuvenation Scheduling

- Objective:
  - Reduce waste time due to failure occurrences
- Use model to:
  - Minimize mechanism overhead
  - Minimize waste time
- Important modeling factors:
  - Reliability of the entire system and of individual nodes
  - Availability of the entire system
  - Overhead induced by mechanism

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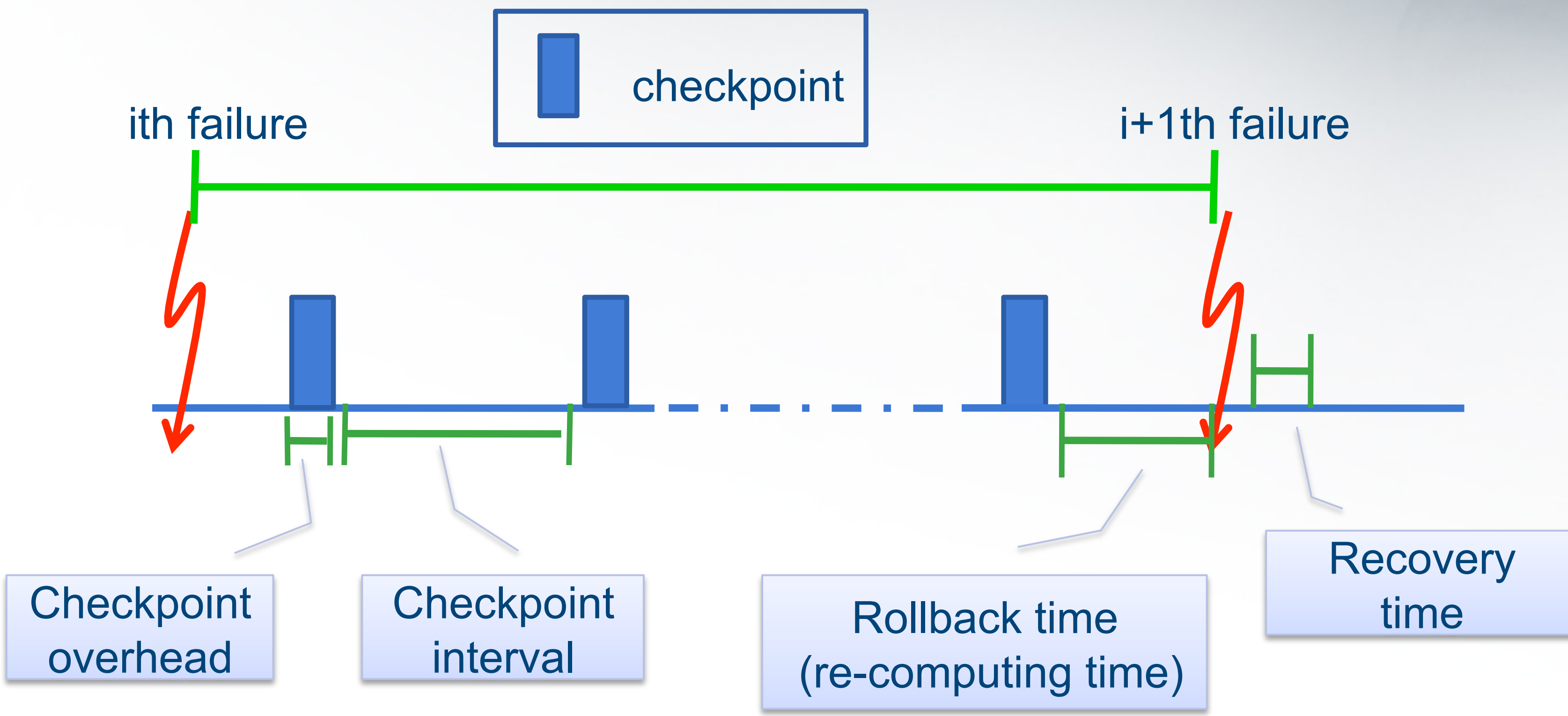
Checkpoint Scheduling



Checkpoint Scheduling Models (1/2)

- Globally optimal checkpoint placement for balancing overhead and re-computing time
  - Consider the expected total waste time and expected re-computing time
  - Plank ’74, Daly ’04, Ling ’01, Osaki ’06, Y. Liu ’07
- Locally optimal checkpoint placements
  - Decide whether to perform the current/requested checkpoint or not by probability of failure occurrence
  - Oliner ’06

Checkpoint Scheduling Models (2/2)

- Checkpoint scheduling that maximizes overall system availability
  - Geist ’88, Plank ’99, Wong ’93
- Incremental checkpoint placement
  - When to perform regular/incremental checkpoints
  - Palaniswamy and Wilsey ’93, S. Yi ’06, Naksinehaboon ’08

Missing in Checkpoint Scheduling Models

- Some need better checkpoint overhead accuracy
  - Constant vs. non-constant overheads
- Some are only for single nodes or small systems
  - Effects in large-scale systems
- Some are impractical
  - Too complex mathematics
  - Too many considered factors

Migration Scheduling

- Objective:
  – Determine appropriate time to migrate process or VM
- Use model to:
  – Co-relate system behavior with failure events
  – Support proactive, preventative approaches
- Important modeling factors:
  – Reliability of the entire system and of individual nodes
  – Environmental monitoring data and system log analysis
  – Failure prediction

Migration Scheduling Models

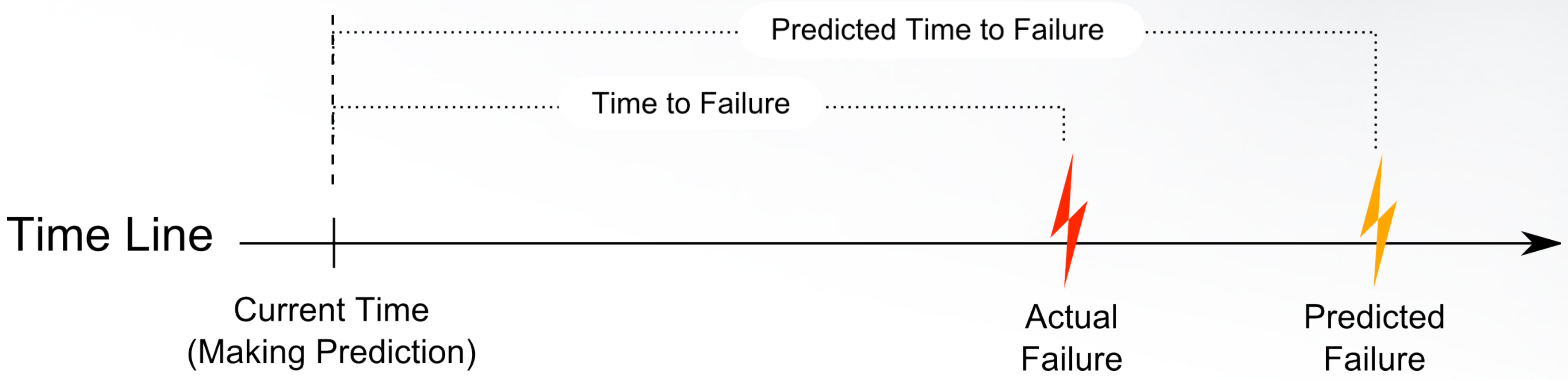
- Load balancing
  - R. Fernandes and L. Senger ‘04, M. Harchol-Balter and A. Downey ’95
- Scheduling for checkpoint-enabled systems
  - Z. Lan and Y. Li ’08
- Network-aware migration scheduling
  - A. Stage and T. Setzer ’09

Failure Prediction

- Failure:
  - Inability of an item to perform a required function
  - Item can be a component, set, or the entire system
- Goal:
  - To know a failure before hand, so that we can handle it
  - Predict ***time*** to failure
  - Predict failure emergence in some ***time interval***

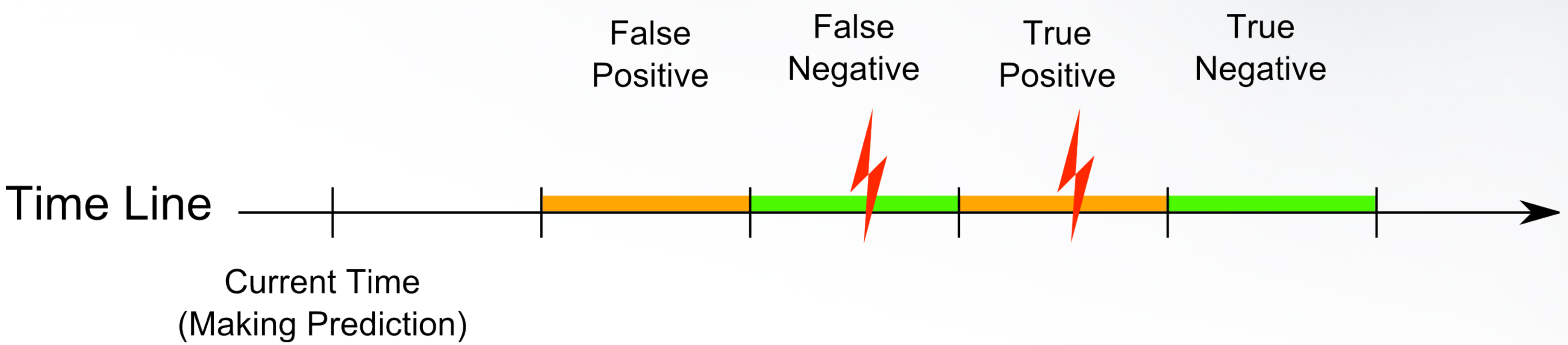
Time to Failure Prediction

(Obviously, predict time to failure)



Failure Emergence Prediction

(Predict if a failure will emerge in the time interval)



Failure Prediction Models

- Using historical failure data and other related data
- Solely based on TTF or UP/DOWN time
  - Univariate Time Series Analysis (Sahoo '03)
  - Markov Model (with two states: up and down) (Kang '07)
- Incorporating additional data, e.g. system event logs
  - Association Rule Mining (Sahoo '03)
  - Markov Model (F. Salfner '06)
  - Neural Network (Charoenpornwattana '08)
  - Naïve Bayes (Hamerly '01)

Missing in Failure Prediction Models

- System failure modeling with more factors
  - More data is needed, more accurate data is needed
    - Resource consumption: CPU, network, file I/O, …
    - Resource exhaustion: Out of memory, file I/O overload, ...
    - Hardware (IPMI) data: Temperatures, voltages, …
- More sophisticated causality analysis
- More job/application-specific modeling
- Trade off between prediction accuracy, incurred overheads and provided resiliency

Conclusion

- Existing models address only a few problems
- There are many opportunities in modeling
- How can we bring “resilience computing” to life:
  - Make runtime and applications smarter and adaptive
  - Collect more data in standardized format
  - Beware of inaccurate data: garbage in = garbage out
  - Explore more modeling techniques (e.g., adv. statistics)
- Resilience computing = modeling + mechanisms

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