Robust Computing Systems

"Sanitized" version of DataSys 2012 Keynote slides presented on Wednesday, October 24, 2012,

by

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Robust Computing Systems

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Outline

- definition of robustness
- stochastic model and metric for robustness
- integration into static resource allocation heuristics
- use of model for a dynamic environment
- conclusions

Brief Self-Introduction

- Professor, Colorado State University, USA
- BS degree: MIT
- Ph.D. degree: Princeton
- Fellow IEEE
- Fellow ACM

Applicability of Stochastic Robustness Model

- variety of computing and communication environments, such as
  - cluster
  - grid
  - cloud
  - multicore
  - content distribution networks
  - wireless networks
  - sensor networks
- design problems throughout various scientific and engineering fields
  - examples we are exploring
    - search and rescue
    - smart grids

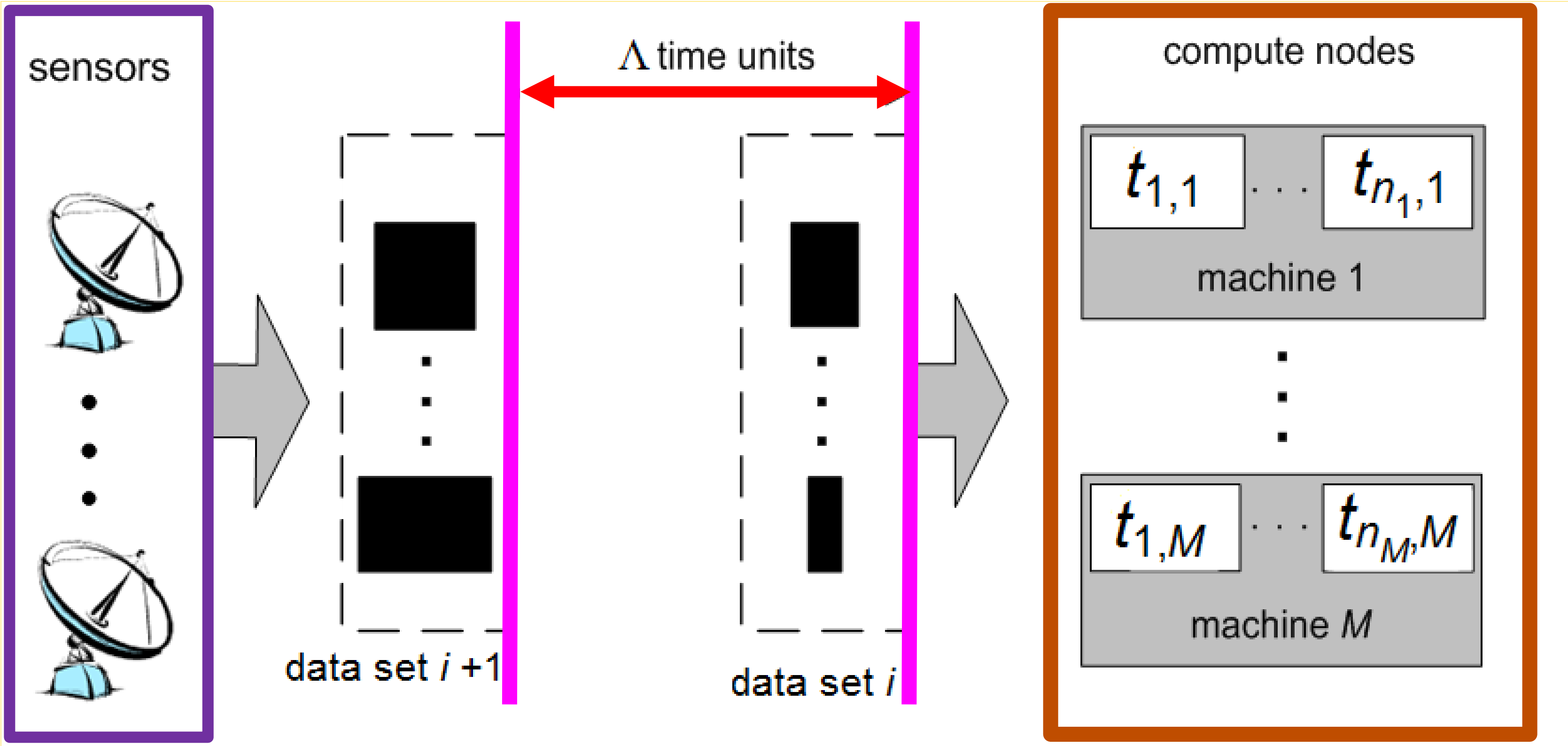
Heterogeneous Parallel Computing System

- interconnected set of different types of machines with varied computational capabilities

- workload of tasks with different computational requirements
- each task may perform differently on each machine

  - furthermore: machine A can be better than machine B for task 1 but not for task 2
- **resource allocation**:
  assign (map) tasks to machines
  to optimize some performance measure
  - NP-complete (cannot find optimal in reasonable time)
  - ex.: 5 machines and 30 tasks → 5^{30} possible assignments
    - 5^{30} nanoseconds > 1,000 years!
  - use heuristics to find near optimal allocation

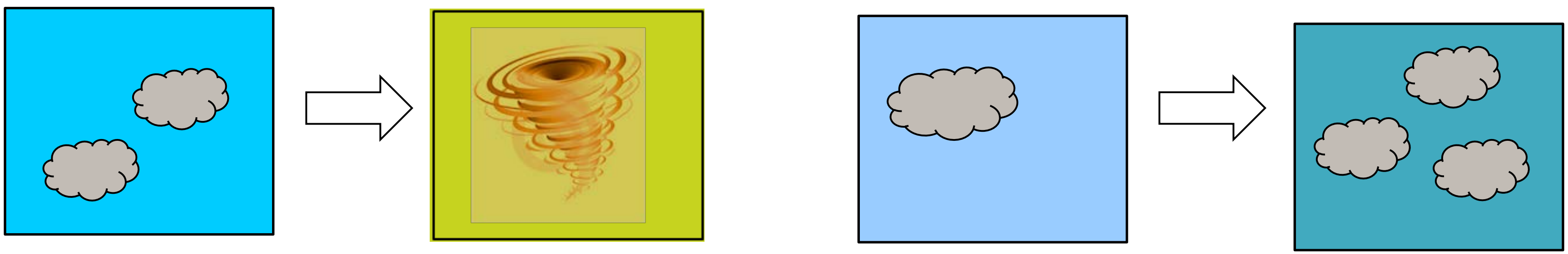
Ex.: Radar Data Processing for Weather Forecasting



- sensors produce periodic data sets, each with multiple data files
- ***N*** independent tasks process each data set within **Λ** time units
- *N* tasks **statically** assigned to ***M*** heterogeneous machines, *N*>*M*
- similar computing environments
  - satellite data sets for producing maps
  - surveillance data sets for homeland security

Uncertainty in Environment

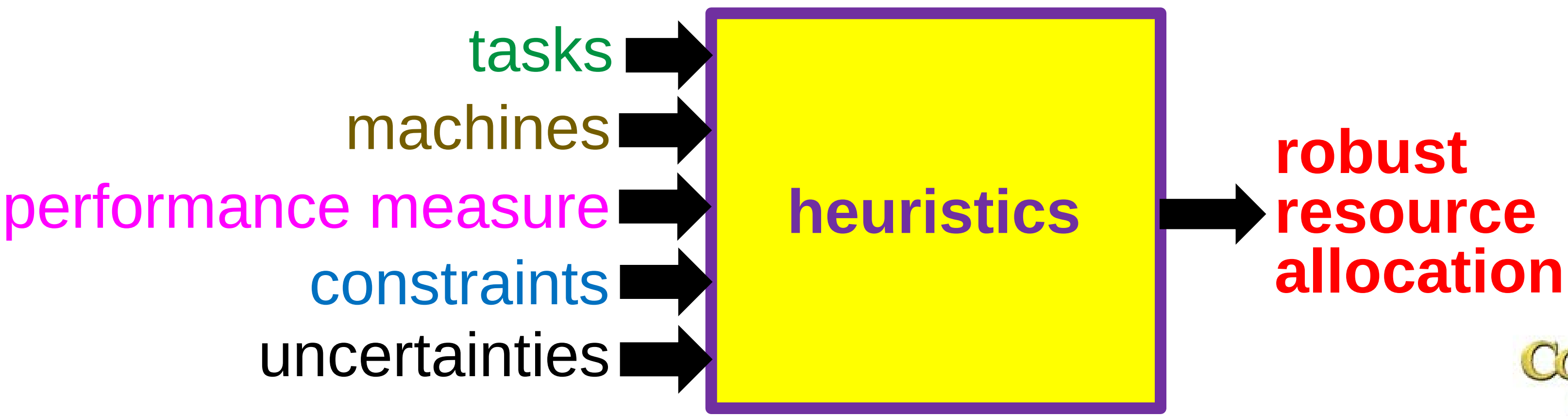
- **variability** across the data sets results in variability of the execution time of each task even on the same machine
  - examples
    - types of objects found in a radar scan data file
    - increase in number of objects in a radar scan data file



- unable to predict exact execution times of tasks
  - **uncertainty** parameters in the system
  - know **history** of task execution times on each machine over different data sets
- need to find resource allocation of tasks to machines that is **robust** against this uncertainty by using this history

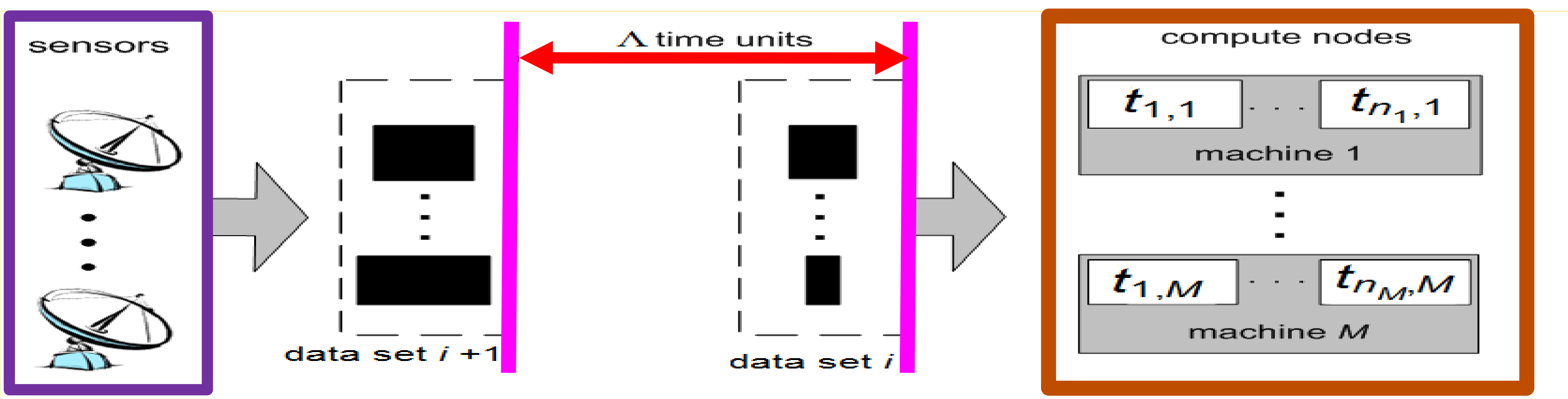
Problem Statement

- unpredictable execution times of the tasks across data sets
- calculate the probability that every data set is processed before the next data set arrives
  - have a probabilistic guarantee of performance
- <u>**problem statement**</u>
  - determine a **robust** static resource allocation
  - minimize time period (Λ) between data sets
  - constraint: a user-specified probability of 90% that all tasks will complete in Λ time units for each data set



Defining Robustness for Resource Allocation

- term "robustness" usually used without explicit definition
- **The Three Robustness Questions**
  1. what behavior of the system makes it robust?
     - ex. execute all tasks within Λ time units
  2. what uncertainty is the system robust against?
     - ex. execution times of tasks vary over different data sets
  3. how is robustness of the system quantified?
     - ex. probability that the resource allocation will execute all tasks within Λ time units for every data set



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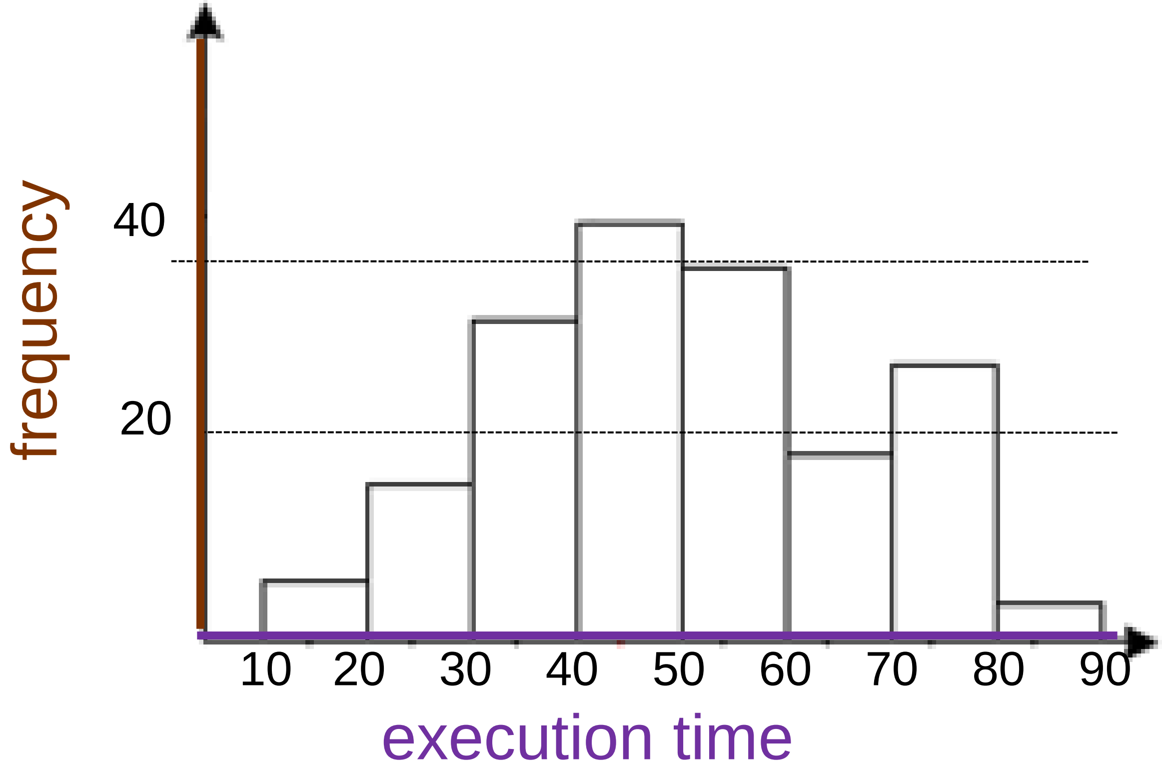
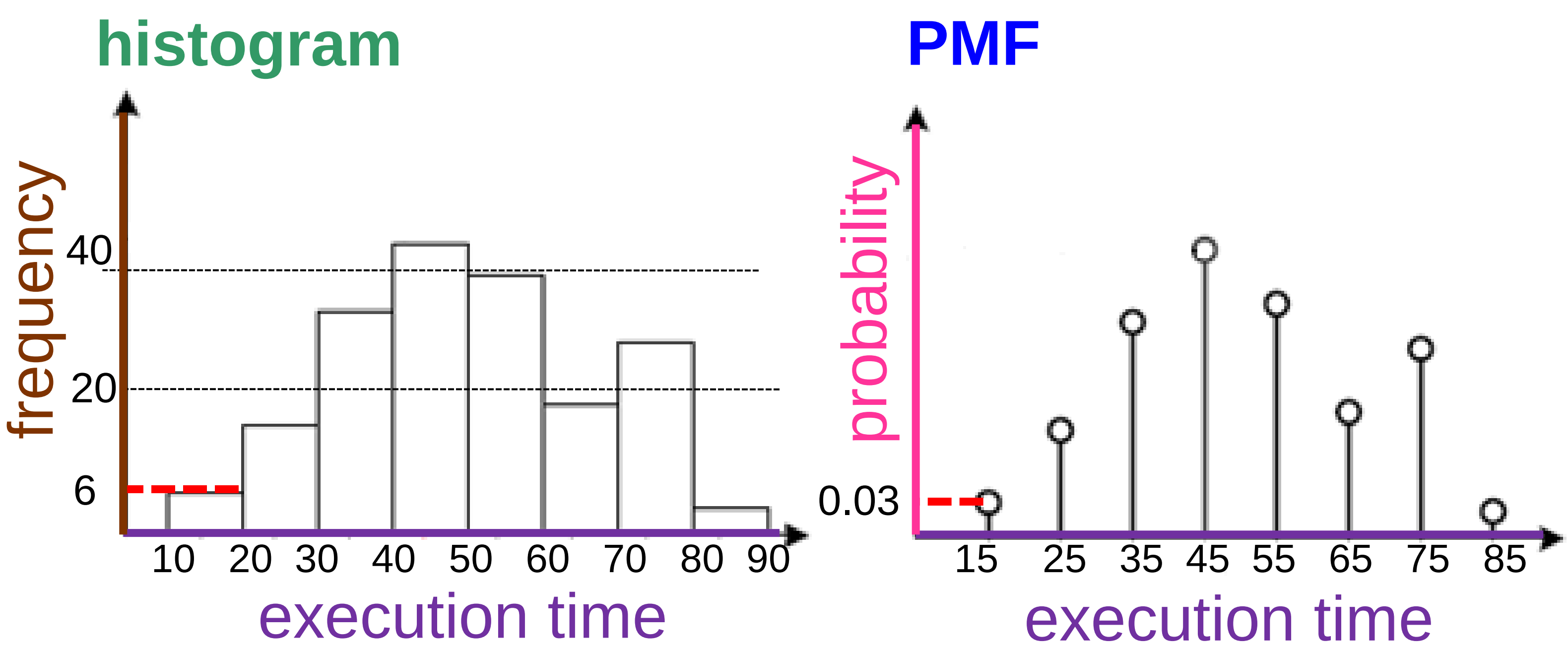
Construct Histogram from Collected Information

- know **history** of task execution times on each machine over different data sets
- consider collecting samples of how long a given task has taken to execute on a given machine in a **histogram**
  - x-axis: execution time within 10 second interval bins
  - y-axis: frequency = height of bar for a given interval



Generating a PMF from a Histogram

- a probability mass function (PMF) can be generated using a histogram
- convert the frequency to a probability to create PMF
  - probability = frequency/total # samples
- example: probability of value from 10 to 19 = 6/200 = 3%



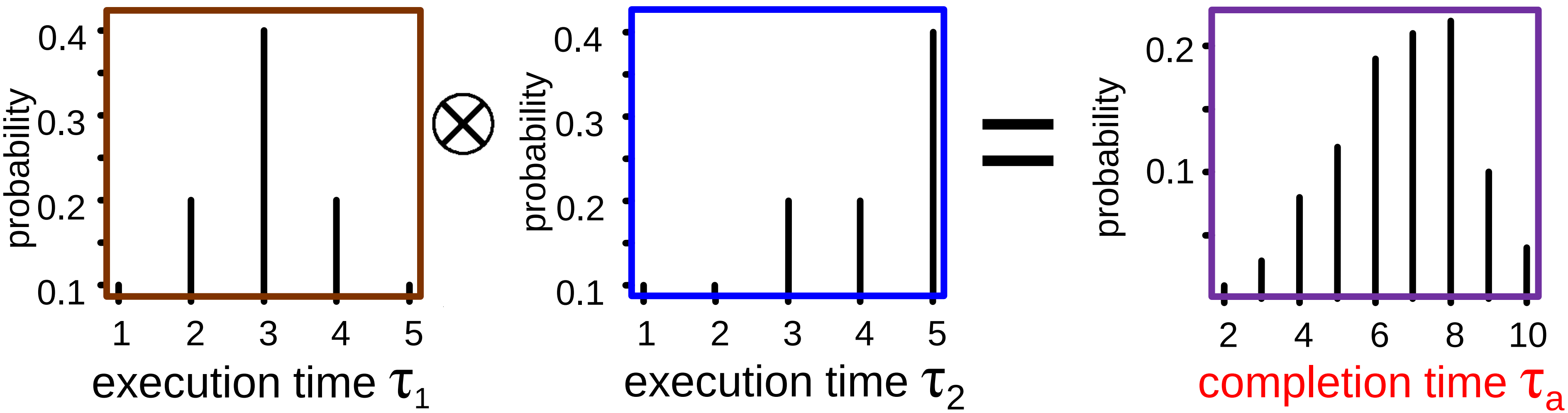
PMF for Completion Time of Machine

- assume task 1 and task 2 only tasks assigned to machine A
  - can find completion time PMF for machine A to do both tasks
  - if tasks independent, it is the "discrete convolution" (combination) of the execution time PMFs for the two tasks

PMF for t_1 on machine A

PMF for t_2 on machine A

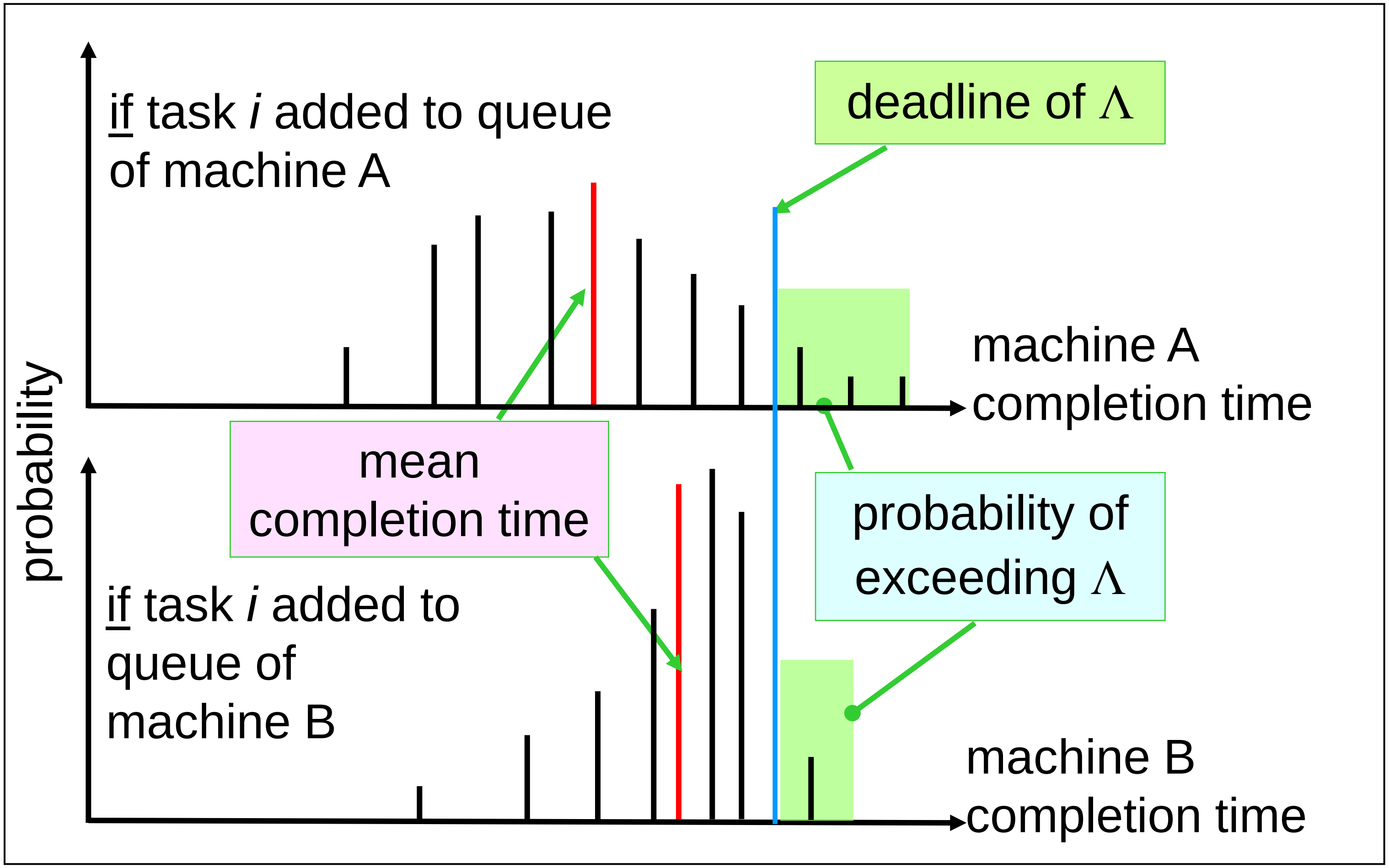
PMF for completion time of machine A



- $$p(\tau_a = k) = \sum_{\tau_1 + \tau_2 = k} (p(\tau_1) \cdot p(\tau_2))$$

Intuitive View of Stochastic Robustness

- PMFs for machine completion time based on
  - (1) PMFs for tasks already assigned to that machine, and
  - (2) PMF for task *i* – which may be assigned to that machine



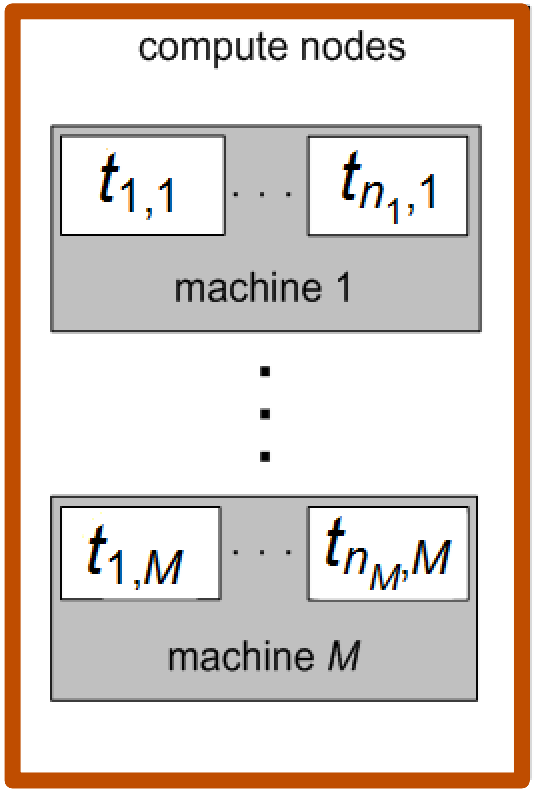
- assign task *i* to machine A or B?
- mean → A
- sum of heights of pulses > deadline → B

Stochastic Robustness Heuristic Goals

- T_{ij} : execution time random variable for task *i* on machine *j*
- S_j : stochastic completion time for machine *j* (tasks independent) $S_j = \sum_{i=1}^{n_j} T_{ij}$
- Λ : deadline for completing all tasks
- machine *j* stochastic robustness Prob[$S_j \leq \Lambda$]
- **Stochastic Robustness Metric (SRM)**
  - assuming independence of machines

$$\text{SRM} = \prod_{j=1}^{M} \text{Prob}[S_j \leq \Lambda]$$

- **goal of heuristics** – two possible robustness situations
  - maximize <u>SRM</u> for a given <u>Λ</u> value
  - minimize <u>Λ</u> for a given <u>SRM</u> value



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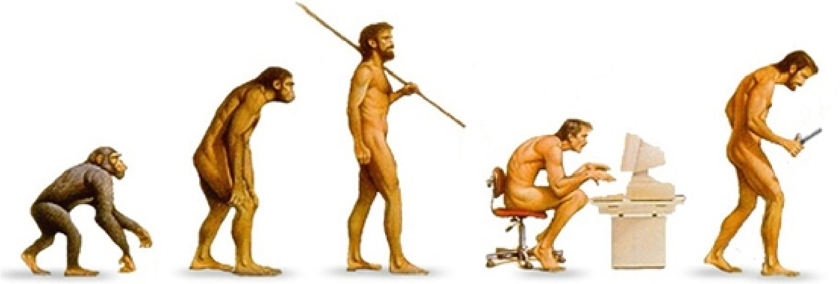
Static Resource Allocation Heuristics

- goal: static assignment of *N* tasks to *M* machines
  - minimize Λ for a given SRM value, for example 90%
- greedy heuristics
  - example: Two-Phase
  - allocation made with locally optimal decisions

- global heuristics
  - example: Genitor – steady-state genetic (evolutionary) algorithm
  - improve allocation over iterations



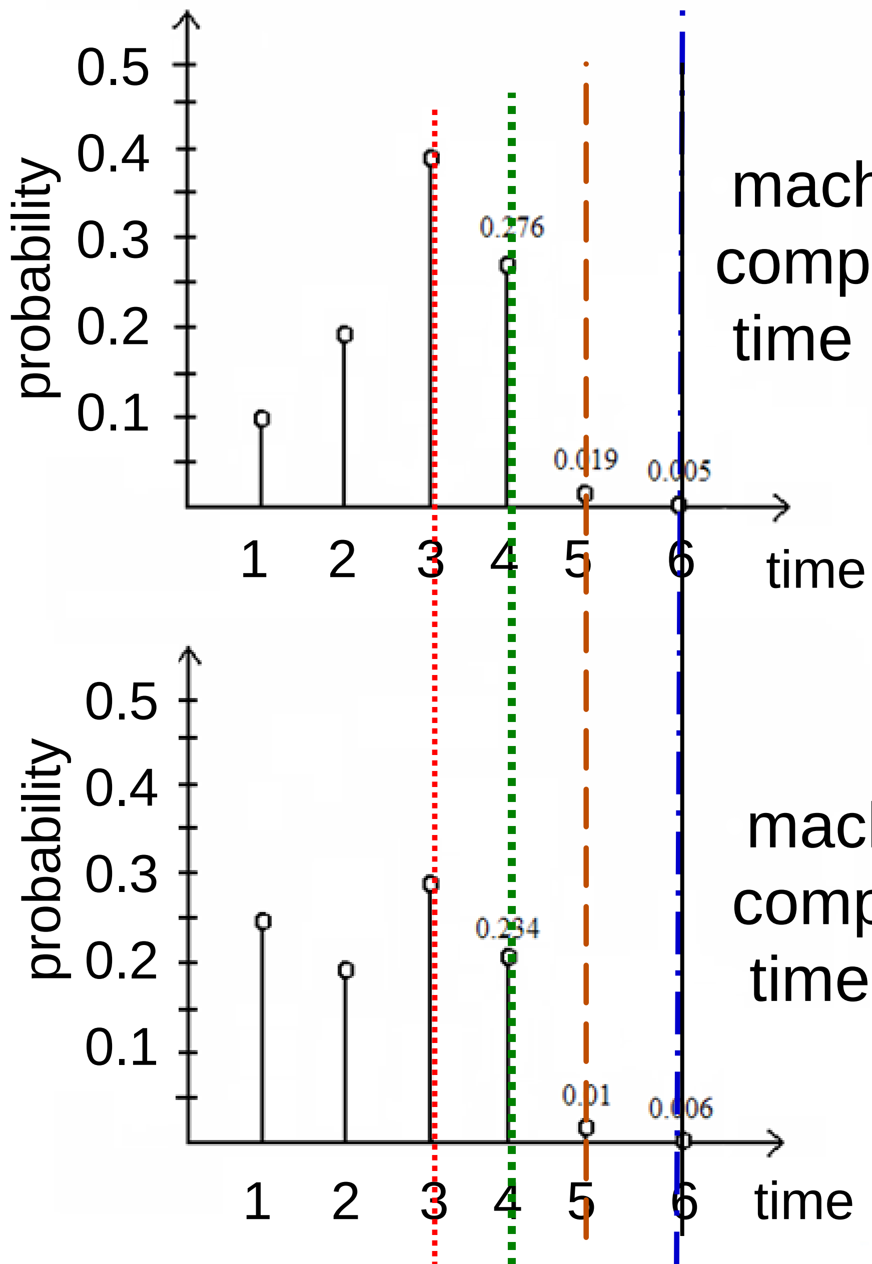
- greedy heuristic generally derives allocation faster than global
- global heuristics can improve upon greedy results
- use Lambda Minimization Routine (LMR) to find for a <u>given resource allocation</u> the minimum Λ is for SRM value of 90%

Lambda Minimization Routine (LMR)

- determines minimum Λ
  - for a given resource allocation
  - at required SRM (probability)
  - $$\prod_{j=1}^{M} \text{Prob}[S_j \le \Lambda] \ge 90\%$$
- ex.: SRM = 90%

SRM = 1 (Λ = 6)
0.97 (Λ = 5)
0.96 (Λ = 4)
0.525 (Λ = 3)

therefore
Λ = 4



machine A completion time PMF

machine B completion time PMF

Two-Phase Greedy Heuristic

- based on the concept of the Min-min heuristic
- $\Lambda(t_i,m_j)$ call to LMR function for minimum Λ **if** task t_i is added to machine m_j

Two-Phase Greedy procedure

- **while** there are still unmapped tasks
  - **phase 1:** for each of the unmapped tasks
    - j value that minimizes $\Lambda(t_i,m_j)$, $1 \le j \le M$
  - **phase 2:** among these task/machine pairs
    - find pair with minimum $\Lambda(t_i,m_j)$
    - map this task to its associated machine

Genitor Steady State Genetic Algorithm (GA)

- chromosome of length *N* (number of tasks) = a mapping (solution)
  - *i* th element identifies the **machine** assigned to **task *i***

1	2	3	4	5	6	7	8	9	10	. . .
2	1	2	3	1	2	3	1	2	2	. . .

- population size of 200 (decided empirically)

Genitor
Population: 200

- initial population generation
  - one chromosome: solution from the Two-Phase Greedy heuristic ("seed")
  - other 199: simple greedy heuristic

- population is put in ascending order based on minimum Λ value for the given SRM (probability)
  - LMR (Lambda Minimization Routine) is used to find minimum Λ value

Procedure for Genitor

- generate initial population
- **while** stopping criterion
  - select two parent chromosomes from the population
  - perform crossover
  - **for** each offspring chromosome
    - perform mutation
    - apply local search
  - insert offspring into population based on minimum Λ order
  - trim population to population size
- **end of while**
- output the best solution

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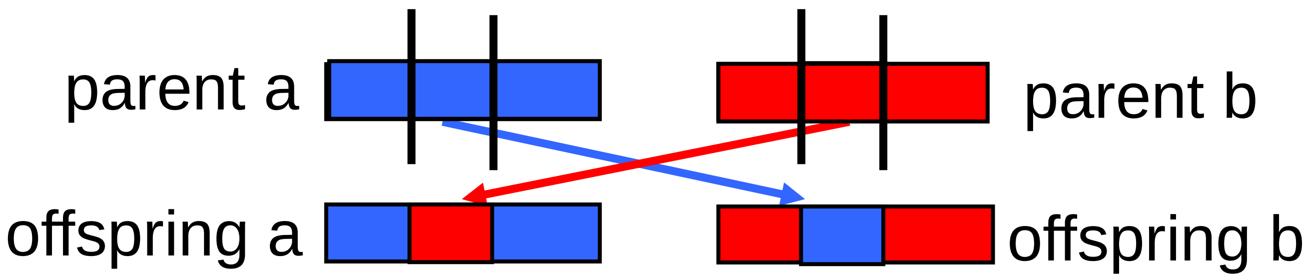
Genitor: Crossover

- selection of parents is done probabilistically
- crossover is “two point reduced surrogate”
  - crossover points are randomly selected
    so that at least one element is different
  - elements between crossover points are exchanged
  - generates two offspring



Genitor: Mutation

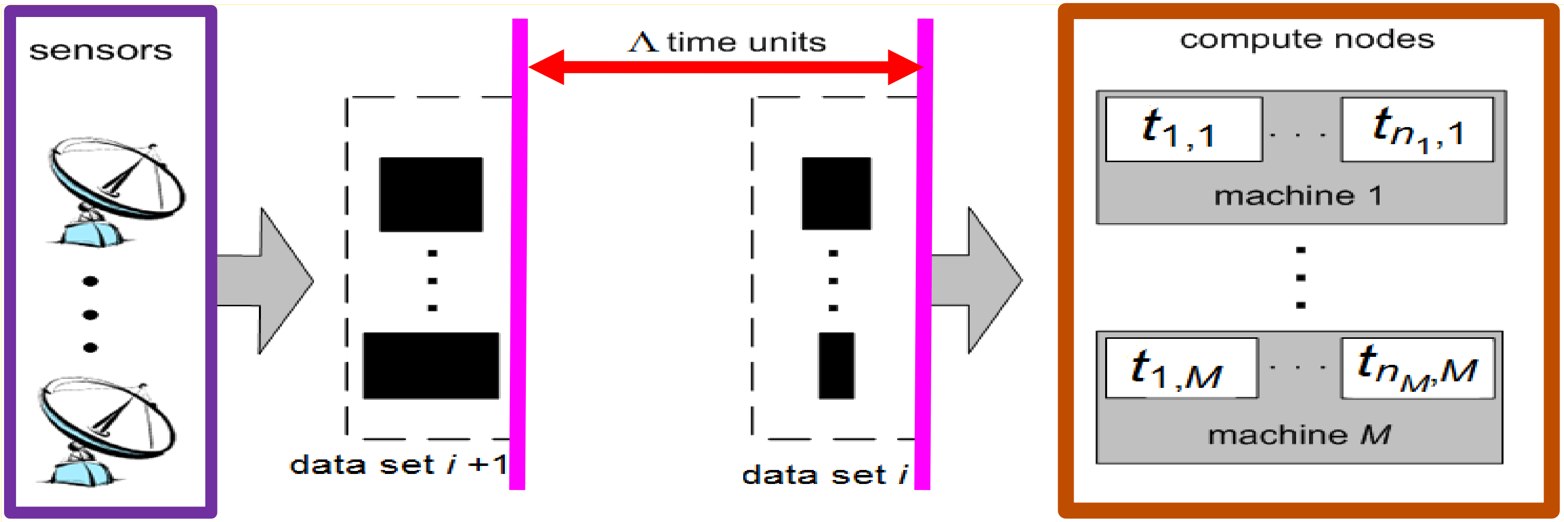
1	2	3	4	5	6	7	8	9	10	...
2	1	2	3	1	2	3	1	2	2	...

5

- mutation applied to offspring obtained from the crossover
  - for each element of each offspring chromosome
    - assignment has a 1% probability of mutation
  - mutation randomly selects a different machine

Genitor: Local Search

- local search applied to each offspring
  - 1. for machine with individual highest Λ
    - consider moving each task to other machines
    - if improvement, move the task that gives smallest overall system Λ
  - 2. repeat 1 until no more improvement



Recall: Procedure for Genitor

- generate initial population
- **while** stopping criterion
  - select two parent chromosomes from the population
  - perform crossover
  - **for** each offspring chromosome
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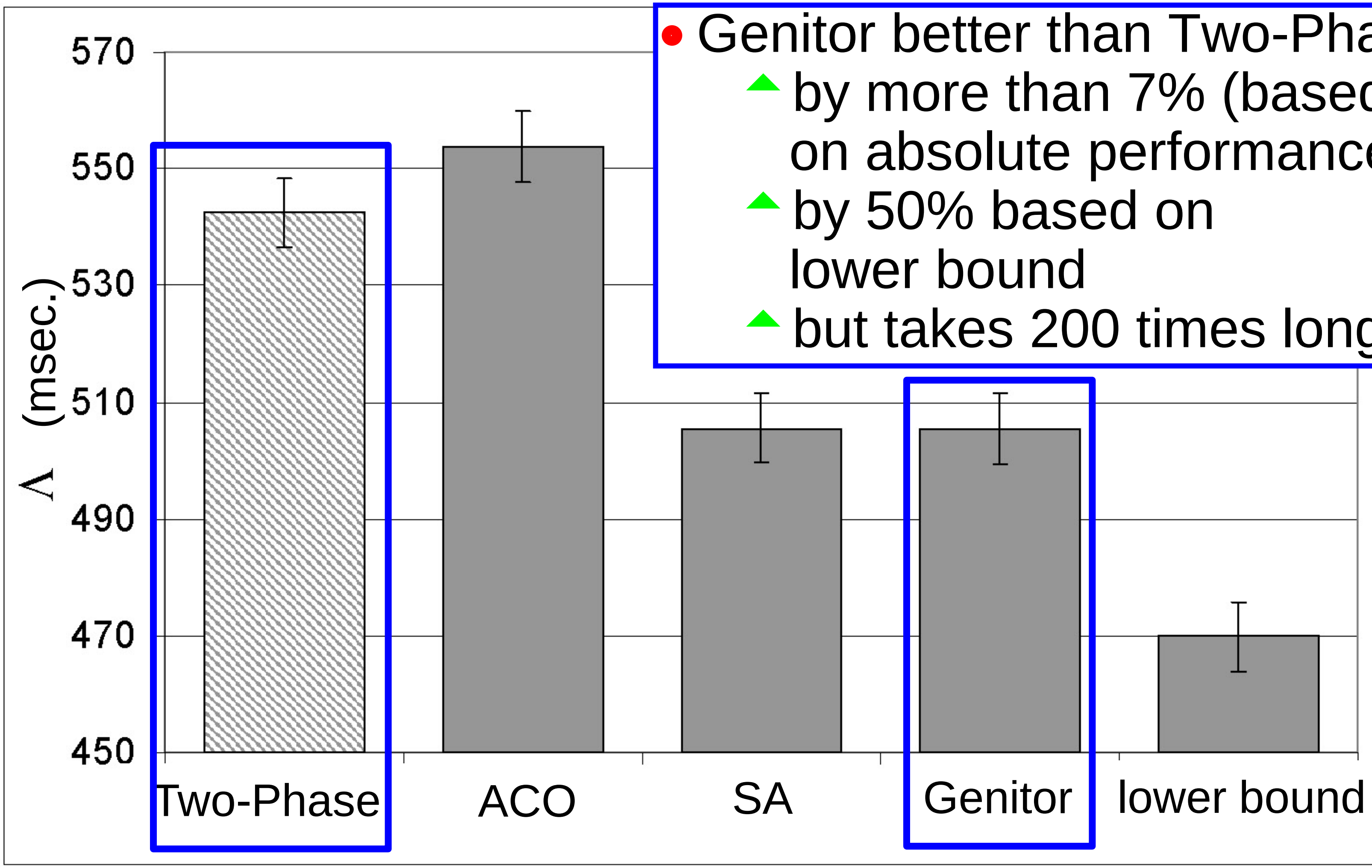
Simulations: Performance of Static Heuristics



- Genitor better than Two-Phase
  - by more than 7% (based on absolute performance)
  - by 50% based on lower bound
  - but takes 200 times longer

- N = 128 tasks, M = 8 machines, SRM value set to 90%
- 50 simulation trials, different PMFs for task/machine pairs
- 95% confidence intervals shown

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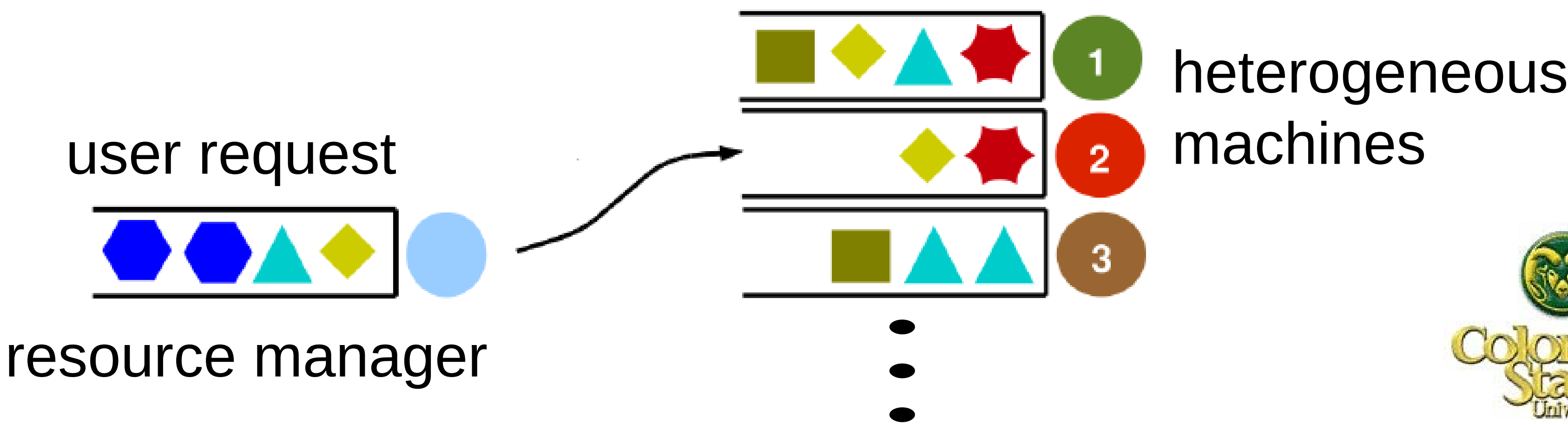
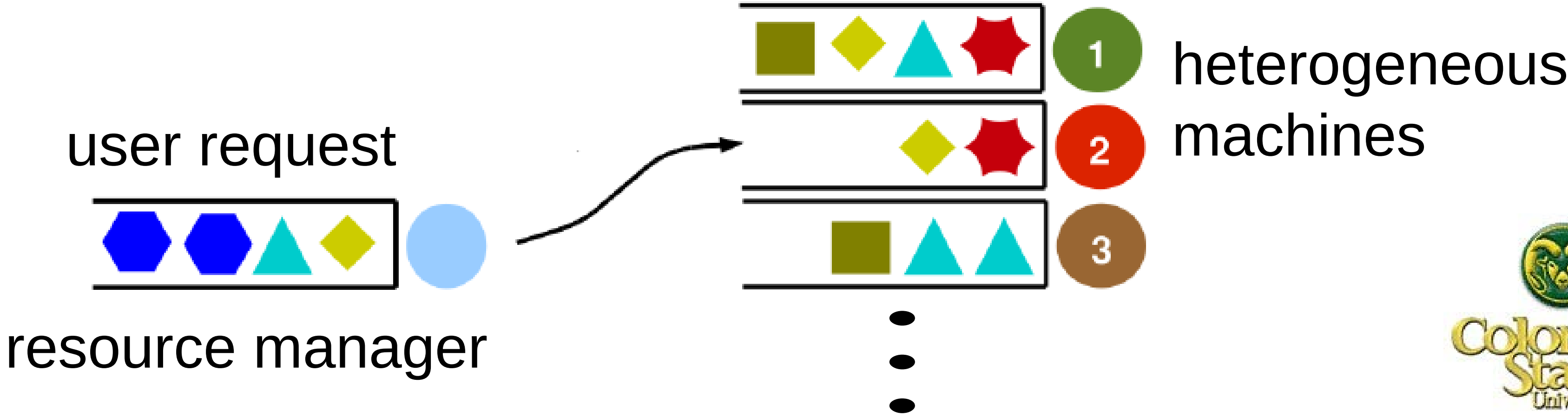
Dynamic System Model

- modeled after real-world satellite imagery processing system
- cluster of *M* heterogeneous machines
- each dynamically arriving user request has three elements
  - which existing utility application to be executed
  - archived data to be processed by that application
  - individual deadline for completing that particular request
    - agreement between service provider and customer
      - if miss deadline, complete on a “best effort” basis
- resource manager assigns requests to machines



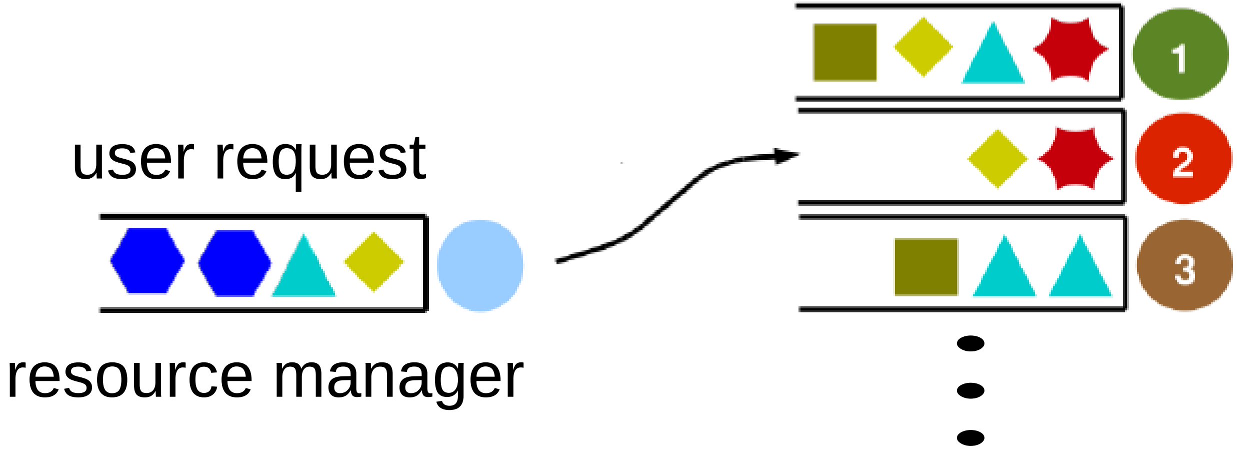
Dynamic System Performance Goal

- application execution time dependent on data size and content
- probability mass functions (PMFs) for each application's execution time on each machine, based on experiential data
- no inter-application communication
- requests cannot be re-assigned
- assume data needed for request is staged to machine while request in queue
- **goal:** complete all requests by their individual deadlines
  - late requests will be completed on "best effort" basis



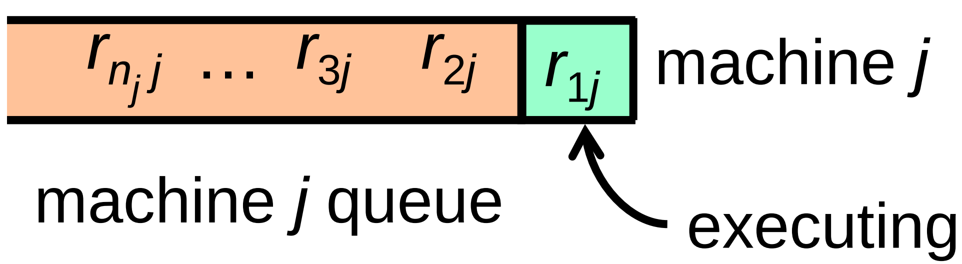
Three Robustness Questions for Dynamic System

- what behavior makes the system robust?
  - completing all requests by their individual deadlines
- what uncertainty is the system is robust against?
  - application execution times may vary substantially
- how is robustness of the system quantified?
  - probability of completing all requests by their individual deadlines

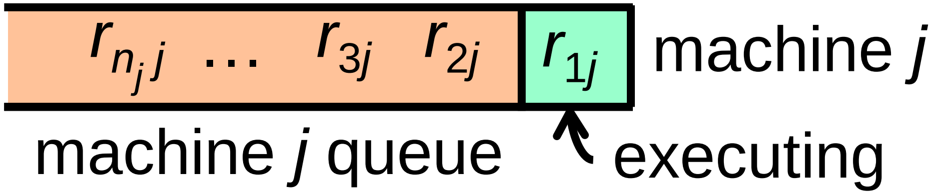


Probability of Completing All Requests by Deadlines

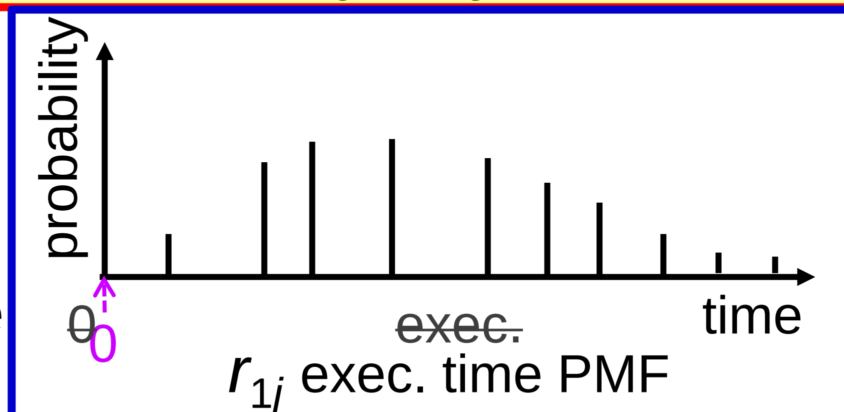
- a new mapping event is to occur at time-step $t^{(k)}$
- r_{ij} – i th request assigned to machine j at time-step $t^{(k)}$
- p(r_{ij}) – probability of completing r_{ij} by its deadline
- n_j – number of requests assigned to machine j at time-step $t^{(k)}$
- p(r_{1j} , r_{2j} , … , $r_{n_j j}$) – joint probability of completing all requests assigned to machine j by their individual deadlines

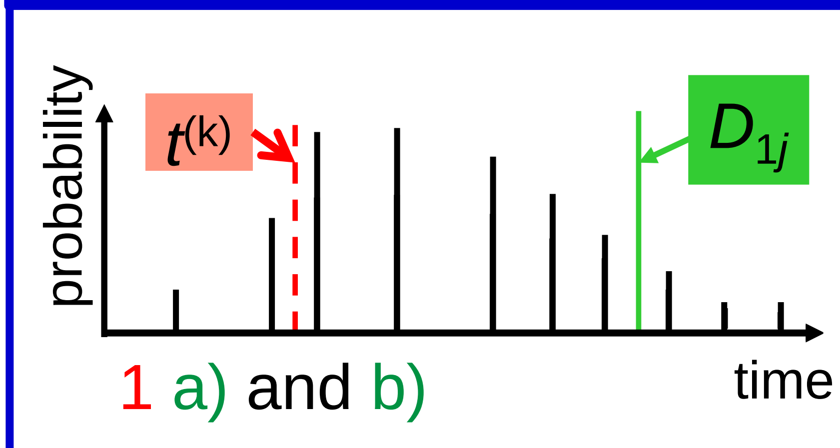


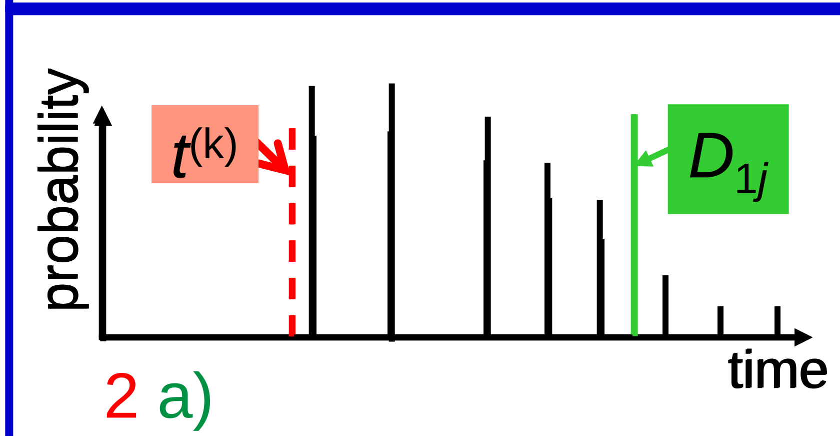
Calculating Joint Probabilities — p(r_{1j} , r_{2j})



1. find p(r_{1j}): prob. r_{1j} meets deadline
   a) $t^{(k)}$ = current time
      - drop pulses < $t^{(k)}$
      - renormalize
   b) sum pulses < deadline D_{1j}
2. find p(r_{1j}, r_{2j}) = p(r_{1j}) · p(r_{2j} | r_{1j})
   a) find PMF for r_{1j} meeting D_{1j}
      - drop pulses > deadline D_{1j}
      - renormalize
   b) convolve with execution time PMF for r_{2j}
   c) p(r_{2j} | r_{1j}) = [sum pulses < deadline D_{2j}]







Dynamic Stochastic Robustness Metric

$r_{n_j j}$ … r_{3j} r_{2j}	r_{1j}	machine j
machine j queue	executing	

- find probability to complete all requests $p(r_{1j}, r_{2j}, \ldots, r_{n_j j})$

$$p(r_{1j}, r_{2j}) = p(r_{1j}) \cdot p(r_{2j} \mid r_{1j})$$

$$p(r_{1j}, r_{2j}, r_{3j}) = p(r_{1j}, r_{2j}) \cdot p(r_{3j} \mid r_{1j}, r_{2j})$$

$$\vdots \quad = \quad \vdots$$

$$p(r_{1j}, r_{2j}, \ldots, r_{n_j j}) = p(r_{1j}, r_{2j}, \ldots, r_{n_j - 1\, j}) \cdot p(r_{n_j j} \mid r_{1j}, r_{2j}, \ldots, r_{n_j - 1\, j})$$

- $\rho^{(k)}$ – stochastic robustness metric at time-step $t^{(k)}$

$$\rho^{(k)} = \prod_{1 \le j \le M} p(\ _{1j}\ \ _{2j}\ \ \ _{n_j j})$$

- we use $\rho^{(k)}$ in dynamic resource allocation heuristics

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Current and Future Research

- methods to build the **initial PMFs**
- **update PMFs** using experiential data
- effective techniques for **convolving** PMFs
- incorporating stochastic robustness into static and dynamic resource allocation **heuristics** for different environments
- considering **energy** or power as a performance or constraint
- combining PMFs and probabilities when **not independent**
  - ex. **DAG** of communicating tasks
- use **relative probabilistic** information about uncertainty values
- how to combine the PMFs from **multiple uncertainties** to calculate single SRM
- how to be robust with respect to **inaccuracies** in the PMFs

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Concluding Remarks

- **The Three Robustness Questions**
  1. what behavior of the system makes it robust?
  2. what uncertainties is the system robust against?
  3. how is robustness of the system quantified?
- devised a stochastic model for robust resource allocation
- used stochastic robustness in resource allocation heuristics
- listed areas for future research in robustness
- please see our papers listed at
  www.engr.colostate.edu/~hj/Robust_Papers.pdf
  for more information and references to other relevant research

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