Resource Use Pattern Analysis for Opportunistic Grids

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Topics

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Grids and Opportunism

- Applications for Grid Computing
  - computationally intensive
  - distributed
  - heterogeneous environments

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- InteGrade: opportunistic grid infrastructure

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- Desirable: prediction of resource availability
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- Proposed Solution:

Resource Use Pattern Analysis

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- Basic Hypothesis:

  Each **resource** has a (temporal) **"pattern"** of use

Goal

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- that automatically performs resource use pattern analysis
- for machines belonging to opportunistic grids

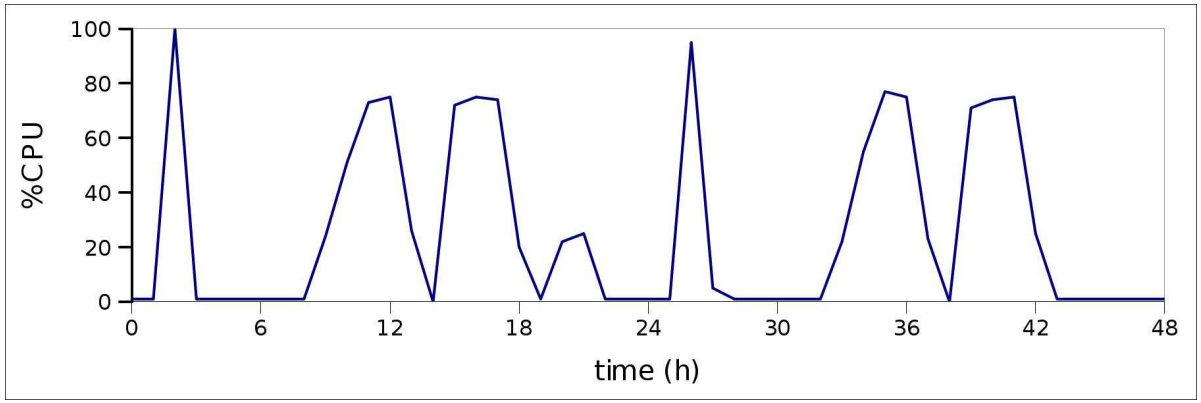
Strategy

- Discover the prototypical patterns of use (off-line)
  - Unsupervised machine learning
  - Clustering analysis
- Runtime prediction
  - Comparing prototypical with "current" pattern of use
- Development method:
  - Simulation: parameter setting
  - Implementation: LUPA module for InteGrade grid

Topics

Resource Use Objects

- A resource use object:



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- Span of 48h used for prediction
- Resources: **CPU use**, **available RAM**, disk space, swap space, network and disk I/O

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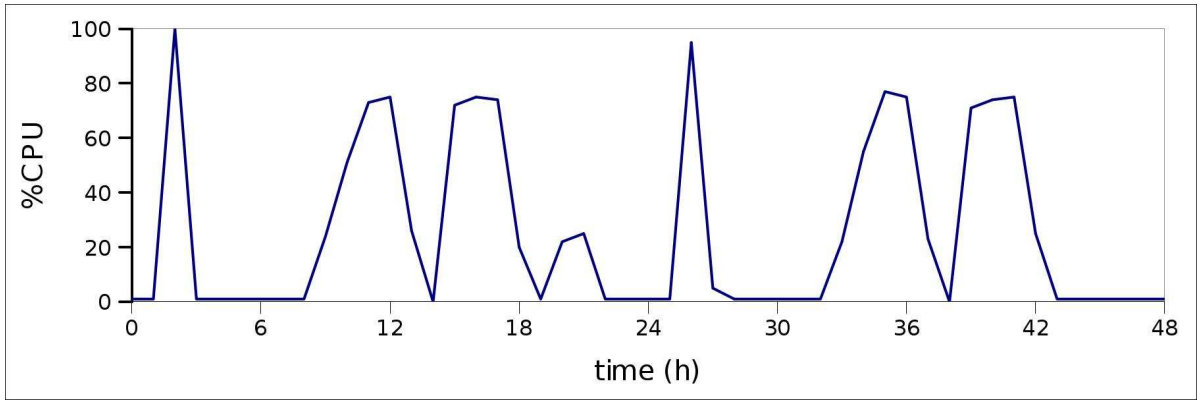

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- Resources: **CPU use**, **available RAM**, disk space, swap space, network and disk I/O
- Objects represent availability (not only use)

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    - E.g. busy work day, light work day, holiday, etc
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  - Obtain fixed number of use classes
    - A class represents a frequent use pattern
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  - Each class represented by a prototypical object
- Two phases:
  - training/learning phase: off-line
  - execution/prediction phase: runtime

Off-line Learning

- Inputs a large amount of objects
- Collected from regular operation
- Clustering is applied to training data
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- Several parameters have to be set

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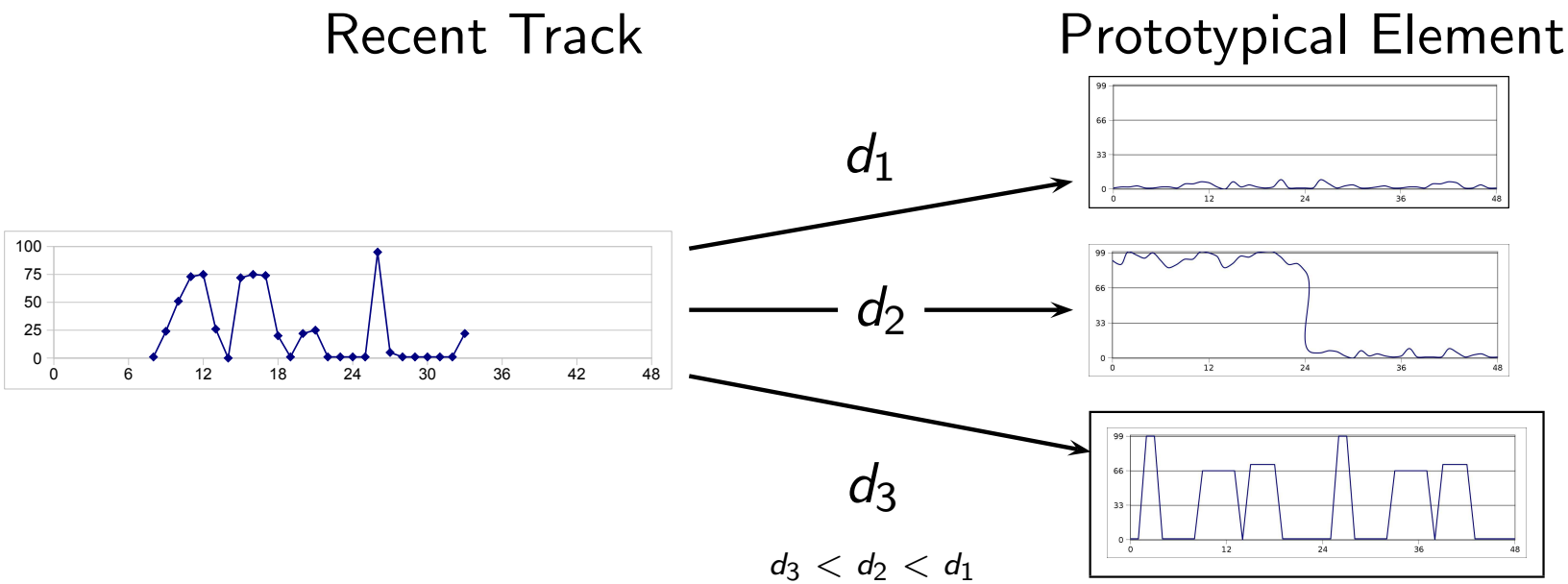
Simulation was performed to choose parameters

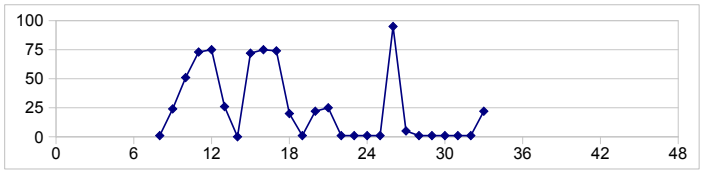
Runtime Prediction

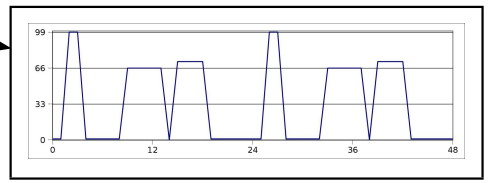


Runtime Prediction

Recent Track

Prototypical Element





Predictions

- Recent 24h record is compared against 48h use classes
- The closest class is the **current use class**.
- Predicted future in current use class: **[now–48h]**
- Request at 6am can predict 18 hours
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- Options for longer predictions:
  - Use less than 24 of current record. Predicts $<$ 48h
  - Chain of predictions (not implemented yet)

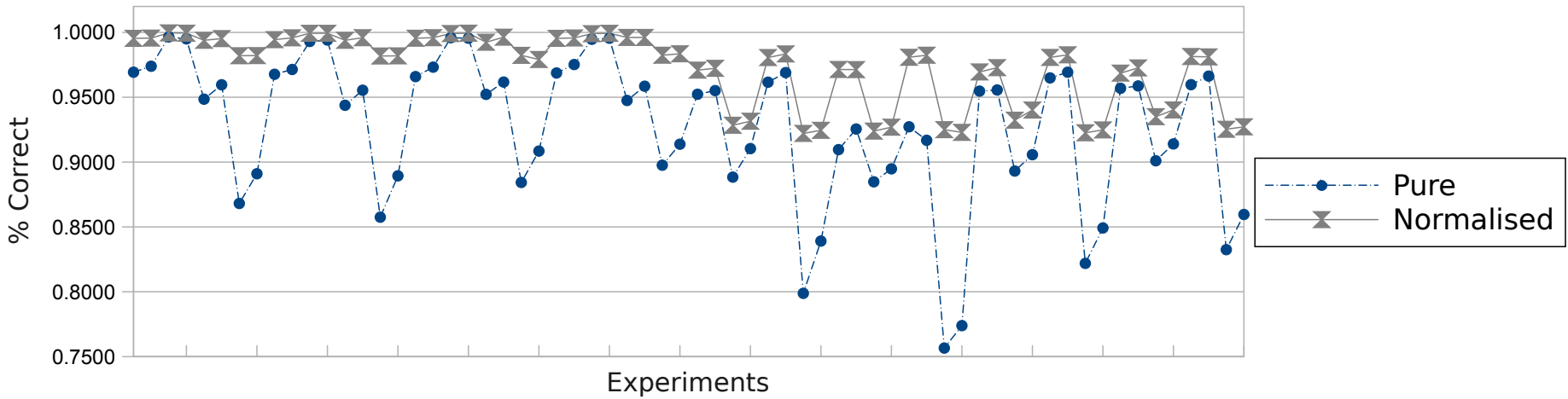
Topics

Trace-driven Simulation

- Data collected for CPU and RAM use, 120 days
- Linux machines with very different types of users:
  1. a general purpose machine with more than 30 users;
  2. a single user machine;
  3. a general purpose machine with 6 users;
  4. a multi-user machine employed for testing heavy computational linguistics programs.
- Several parameters compared

Simulation Results

Correct predictions above 75% in all parameter combinations



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Simulation validated UPA hypotheses on the use of past patterns to predict future behaviours

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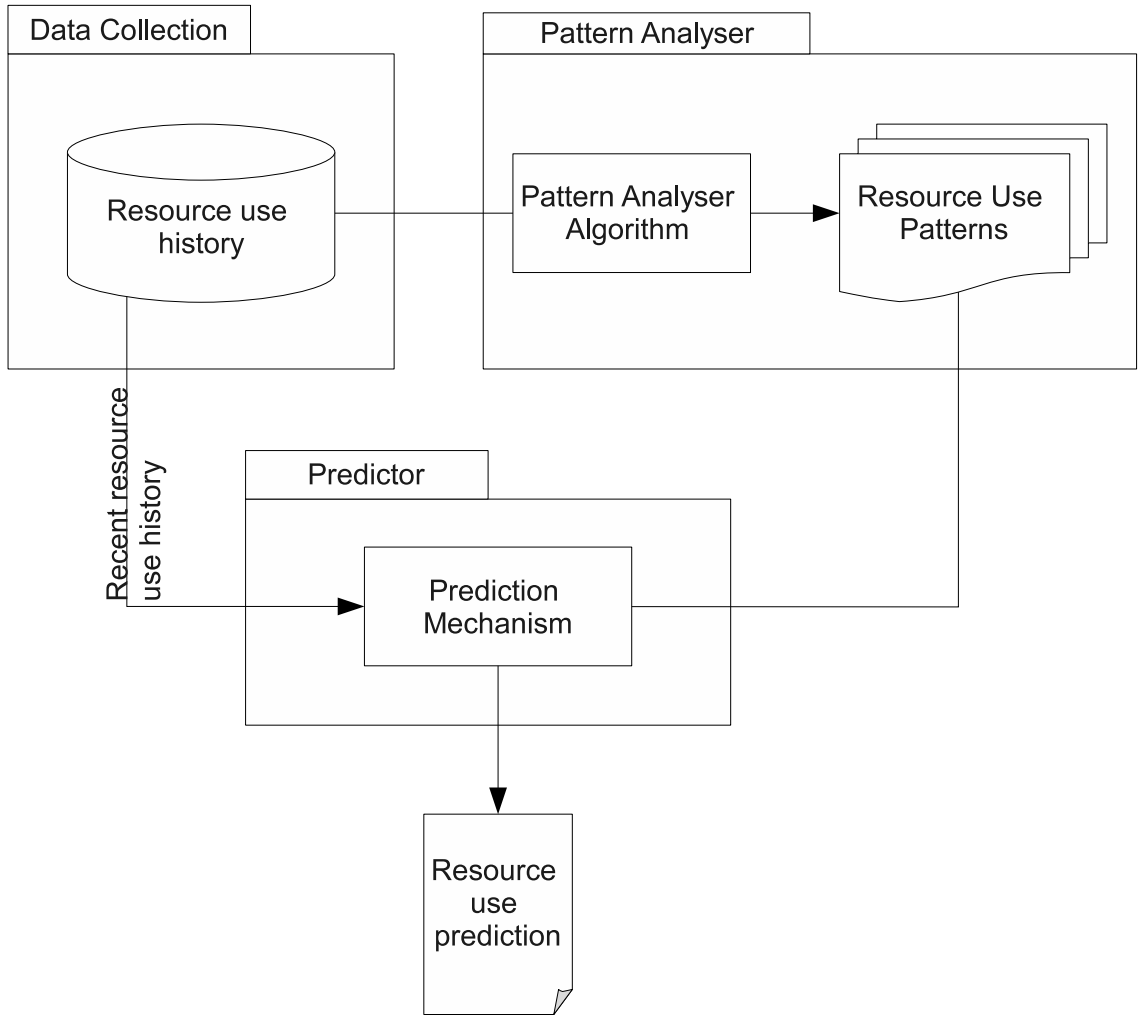
- Compare UPA scheduling with other methods
- Identify initialisation strategies
  - because UPA needs a few months of resource use data collection to be reliable

Design Decisions

- UPA data analysed locally, not centrally
  - Advantages: privacy, no network traffic due to UPA processing
- Local resource Use Pattern Analyser (LUPA) module installed in all grid machines
- LUPA module is part of InteGrade middleware
- C++, on several Linuxes

LUPA Architecture



LUPA Submodules

- **Data Collection**: resource use sampling.
- **Pattern Analyser**: off-line clustering.
  Patterns are recomputed once a day.
- **Predictor**: runtime predictions. Interface

```
double[] getPrediction(resource r, int hours);
```

  returns a vector of values representing the `r`-use prediction for the next `hours`, in 5-minute intervals.

LUPA is not yet integrated with the scheduler.

Topics

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Compare UPA scheduling with other methods

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- **UPA**

Experiment Goals

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Scheduling methods for choosing n machines for h hours:

- **RR**: round robin. No prediction
- **last4**: Predicts to the future average of last 4h.
- **UPA**

Predicting methods choose n machines with highest prediction of CPU availability for the next h hours

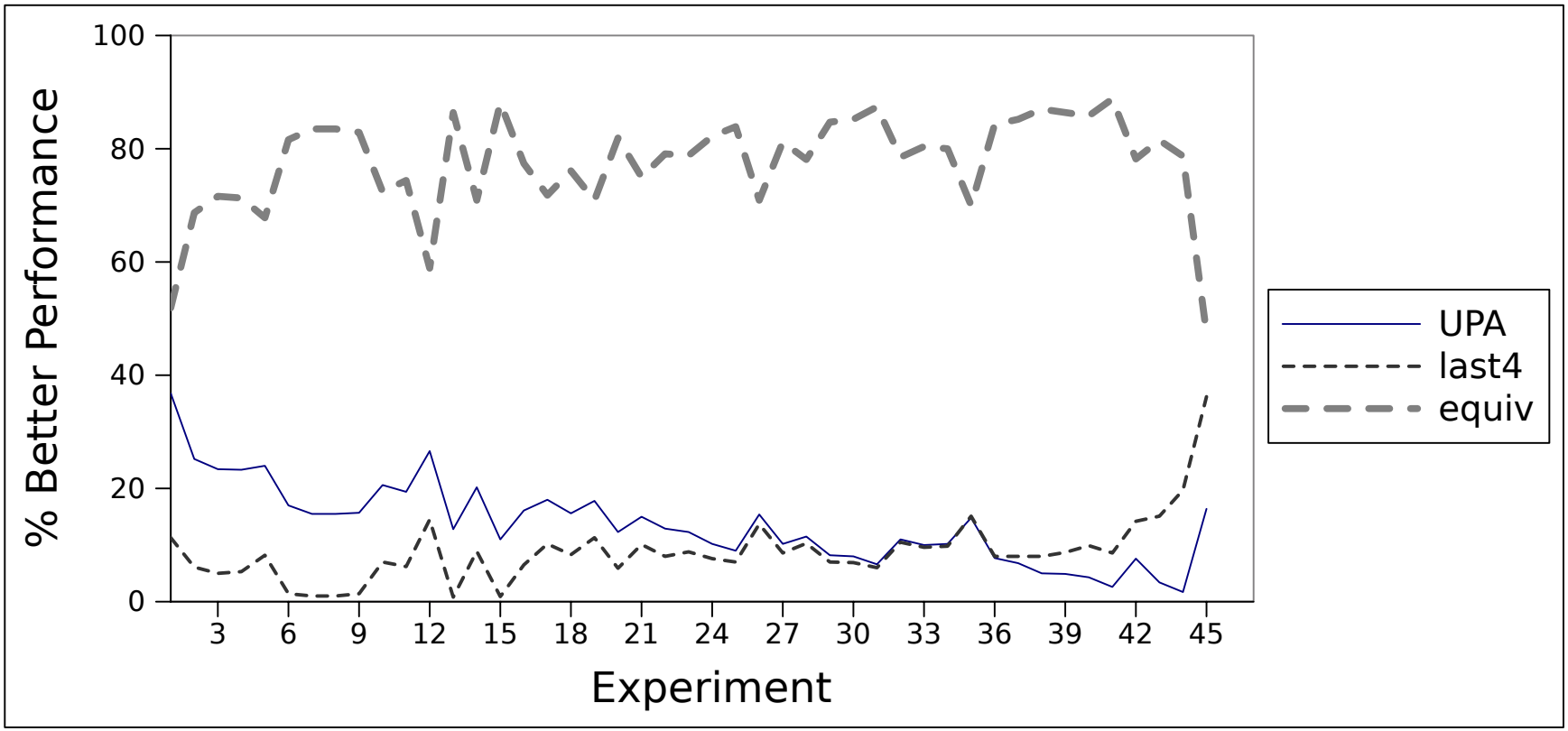
Experiment Description

- 15 machines, logs of 41–120 days
- Sequence of tests for a fixed set of parameters: n, h
- Instant tests (1 experiment $\approx$ 527 tests)
  - Choose a day with m valid machines
  - 24 tests are executed for 3 methods, each for an hour of the day

$$performance_s(t) = 1 - \frac{\sum_{i=1}^{n} use(m_i, t, h)}{n}$$

  - s: scheduling algorithm
  - n: number of chosen machines
  - m_i: machine chose to run for h hours starting at t
  - $use(m_i, t, h)$: average CPU at m_i for $[t, t + h]$

UPA *versus* last4



Comparison of Scheduling Methods

	UPA	**last4**
Performance	Similar to **last4**, but better	Similar to **UPA**, but worse
Impact of $\uparrow m/n$	$\uparrow$ performance	no effect
Impact of $\uparrow h$	no effect	no effect

Performance of **RR** consistently below both **last4** and **UPA**

Adaptative UPA Method

- Use **UPA** if more than 21 days of data collection is available; else
- Use **last4** if more than 4 hours of data collection is available; else
- Predict that resource use at request time persists.

Overhead Analysis

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- Running time for prediction calls was always below 3ms
- Measurements made on notebook [AMD Turion 64 1.8GHz CPU, 1GB RAM running Kubuntu 7.10 (32 bits) Linux]
- Running pattern analysis once a day poses negligible overhead

Topics

Correlated Availability

- BOINC: Volunteer computing
- Correlated Availability in Internet-Distributed Systems (Kondo, Andrzejak & Anderson, 2008)
- Computes patterns of simultaneous **CPU availability** via clustering

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- Monitors 112,268 hosts
- Global monitoring and pattern discovery
- Several interesting clusters of machines discovered, with potential applications.
- Not originally intended for scheduling

Preemptive Resume Scheduling
[Roy and Livny, 2003]

- Condor:
  - Combination of dedicated and opportunistic scheduling
  - Opportunistic scheduling based on checkpointing
  - Preemptive resume scheduling
  - No prediction

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  - No prediction
  - **No need to predict job duration**

Predictive Scheduling
[Yang, Schopf and Foster, 2003]

- One-step-ahead CPU load prediction
  - Load Tendency Prediction
  - Increase/decrease adaptation processes
- Interval Load Prediction
  - Average over aggregated CPU load time series
- Load Variance Prediction
  - Standard deviation time series
  - Combined with one-step-ahead prediction
- Conservative scheduling: combines interval and variance load prediction

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- UPA method compares favourably w.r.t. other methods
- Small overheads involved
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- UPA method compares favourably w.r.t. other methods
- Small overheads involved
- Method can be used for practical grid scheduling
  - but needs task duration prediction

Ongoing and Future Works

- Scheduler using LUPA information
- Automated learning of task duration prediction
- Long term predictions
- Preemptive task migration using UPA
- Automated "booking" of machine resources for future executions using UPA

www.integrade.org.br

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