Towards energy-aware scheduling in data centers using machine learning

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Context: Energy, Autonomic Computing and Machine Learning

- Keywords:
  - Autonomic Computing (AC): Automation of management
  - Machine Learning (ML): Learning patterns and predict them

- Applying AC and ML to energy control:
  - **Self-management** must include **energy policies**
  - **Optimization** mechanisms are becoming more **complex**
  - … and they can be improved through **automation** and **adaption**

- Challenges for autonomic energetic management:
  - Datacenters policies require adaption towards constant optimization
  - Complexity can be saved through modeling and learning
  - If a system follows any pattern, maybe ML can find an accurate model to help the decision makers and improve policies

Introduction

- Self-management looking towards Energy Saving:
  - Apply the well-known consolidation strategy

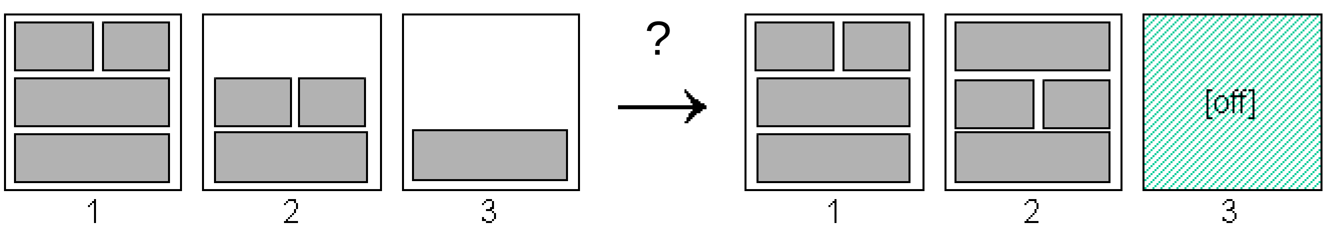
- Consolidation strategy:
  - Reduce the turned on machines grouping tasks in less machines
  - Turn off as many IDLE machines as possible (but not all!)

- Main Contributions
  - Consolidate tasks in a datacenter environment
  - Predict information *a priori* to solve uncertainty and “play it safe”
  - Design adequate metrics to compare consolidation solutions
  - Turn on/off machines from SLA vs. Power trade-off method

Energy Aware Scheduling

- Consolidation
  - Execute all tasks with the minimum amount of machines
  - Unused machines are turned off
  - Known policies: Random, Greedy policies, (Dynamic) Backfilling

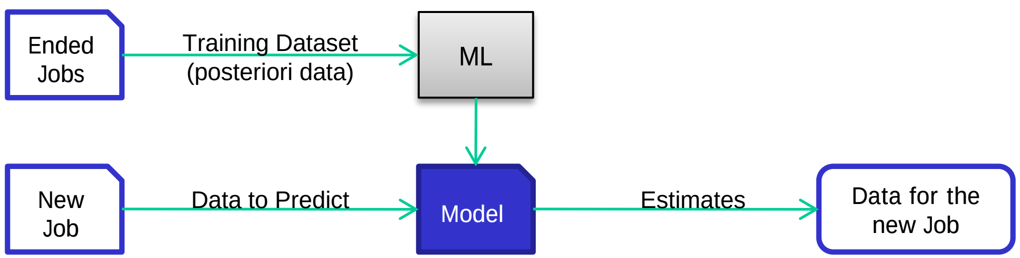
- Policies and Constraints
  - SLA fulfillments must not degrade excessively
  - Operations must reduce or maintain energy consumption
  - Turn off as many machines as possible



EAS: Machine Learning application (I)

- Prediction *a priori* :
  - Deal with uncertainty
  - Anticipate *future* information

- Applying Machine Learning:
  - Relevant variables for decision making only available *a posteriori*
  - ML creates a model from past examples



- Desired information *a priori* :
  - SLA fulfillment level: i.e. we don’t know the exact finish time per task
  - Consumption: i.e. we don’t know the consumption before placing a task

- Learn a model to induce:
  - <Info. Running tasks, Info. Host> → <SLA fulfillment, Power Consumption>

EAS: Machine Learning application (II)

- Information “a posteriori”
  - R_h: Average SLA fulfillment level of jobs in host
  - C_h: Host consumption
  - Finished jobs: Information about ended jobs
  - Host: Information about host capabilities

- Learn a model to induce
  - $<\text{Running jobs, Host}> \rightarrow <R_h, C_h>$

- Used Variables
  - “Post-mortem” data:
    - Finished Job: $<Job_{Info}, T_{start}, T_{end}, T_{user}, SLA_{Fact}> \rightarrow R_j$
    - Host Consumption: $<Usage_{Res}> \rightarrow C_h$
  - Available data:
    - Running Job: $<CPU_{Usage}, T_{start}, T_{now}, T_{user}, SLA_{Fact}> \rightarrow R_j$
    - Host Consumption: $<CPU_{Available}> \rightarrow C_h$
    - Host SLA fulfillment: aggregation of $R_j \rightarrow R_h$

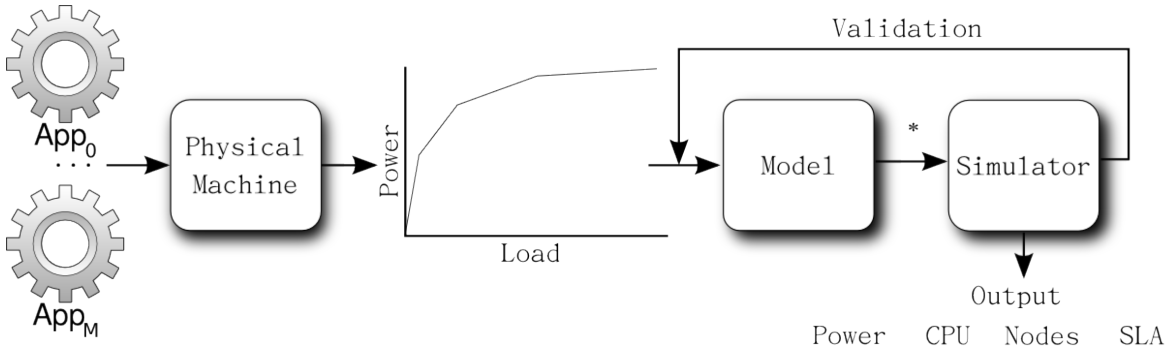
EAS: Machine Learning application (III)

- Backfilling and Dynamic Backfilling policies:
  - Purpose: fill turned on hosts before starting off-line ones
  - When a task enters, it is always put on the most fillable host
  - At each scheduling round, move tasks to get more consolidation

- Applying Machine Learning:
  - We learn the SLA fulfillment impact and consumption impact, for each past schedule
  - For each possible task allocation <host, jobs on host+new job>:
    - Estimation of resulting SLA fulfillment
    - Estimation of resulting power consumption
    - If they don't degrade, allocation is viable
  - Dynamic Backfilling: Change the static data by estimated data

Simulation and Metrics

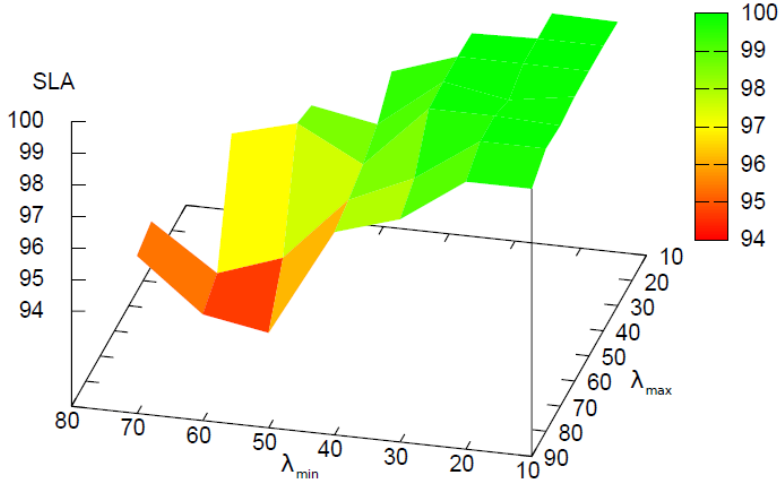
- Self-created simulator:
  - Simulates a data center able to execute tasks according to different scheduling policies
  - Takes into account CPU consumption and energy
  - Able to turn on/off simulated machines

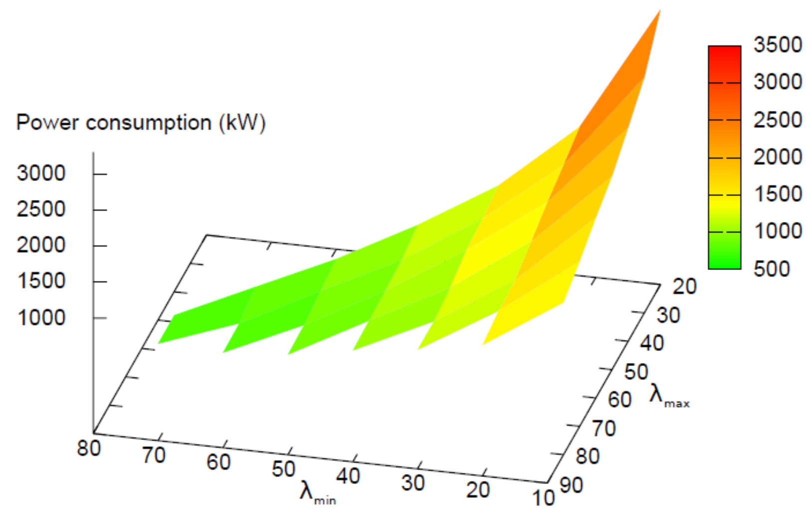


- Metrics:
  - There is no standard approach to compare power efficiency
  - We introduce metrics to compare adaptive solutions:
    - Working nodes, Running nodes, CPU usage, Power consumption, SLA fulfillment level…

Evaluation (I): Shutting down machines

- Power vs SLA fulfillment trade-off
  - Determine when to shut down IDLE nodes, and turn on new ones
- Find the adequate number of IDLE on machines
  - It depends on the number of running tasks
  - Determine range of IDLE machines (minimum and maximum)
- Trade-off between energy and required resources
  - At what load start off-line machines, or shut down IDLE ones

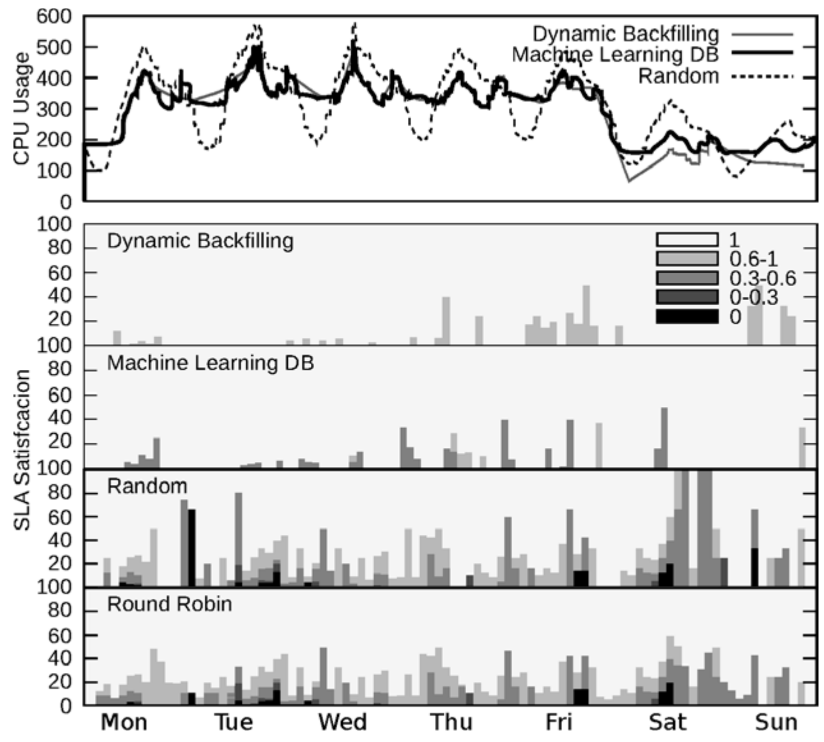




Evaluation (II): Consolidation

- Experimental Environment
  - Simulated datacenter with 400 hosts (4 CPU per host)
  - Workload: fixed CPU size tasks and variable CPU size tasks
  - Use of Linear Regression and M5P for SLA and Power prediction

- Experimental Results
  - Consolidation techniques perform better than the other techniques:
    - Backfilling & Dynamic BF
  - SLA fulfillment around 99%
  - CPU utilization more stable and lower power consumption



Evaluation (III): Machine Learning

- Experimentation Results (II)
  - Dynamic BF + ML performs better, having uncertainty (service and heterogeneous workloads)
  - Accuracy around 98.5% on predictions
  - Detail: Values with highest estimation always had highest accuracy

	Working nodes (avg)	Running nodes (avg)	Power (kwh)	SLA (%)
		Grid workload		
Round Robin	16.11	41.37	1696.66	85.99
Dynamic Backfilling	$\boxed{9.91}$	$\boxed{26.46}$	$\boxed{1118.86}$	100.00
Machine Learning DB	15.04	37.92	1574.78	99.69
		Service workload		
Round Robin	290.99	400.00	19761.54	100.00
Dynamic Backfilling	108.79	352.88	16229.22	100.00
Machine Learning DB	$\boxed{99.61}$	$\boxed{270.50}$	$\boxed{13673.71}$	100.00
		Heterogeneous workload		
Round Robin	260.66	400.00	19713.72	94.20
Dynamic Backfilling	$\boxed{111.03}$	$\boxed{329.07}$	16214.49	99.59
Machine Learning DB	$\boxed{124.20}$	$\boxed{307.89}$	$\boxed{15110.33}$	98.63

Conclusions and Future Work

- Challenge and Contribution
  - Vertical and “intelligent” consolidation methodology
  - Metrics to evaluate different consolidation approaches
  - Predict application SLA timings and power consumption to decide scheduling
- Experimentation Results
  - Consolidation aware techniques:
    - Improve power efficiency
    - Compare backfilling with “standard” techniques
  - Machine Learning method:
    - Close to consolidation techniques
    - Better when information is inaccurate
- Current and Future Work
  - More complex SLA fulfillment (response time, throughput, ...)
  - More complex Resource elements (CPU, memory, I/O elements)
  - More elaborated Policy optimization (utility functions)
  - Addition of virtualization overheads

Thank you for your attention