Scheduling Stochastic Jobs on HPC Platforms (and Beyond)

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HPC Batch Scheduler

- **Reservation-Based:**
  - Relies on (reasonably) accurate runtime estimation from the user/application
  - Intended for HPC jobs with (relatively) deterministic and predictive behavior

- **Resource under-estimation**
  - Job killed; need to resubmit; prolonged completion time
  - Waste of system resources

- **Resource over-estimation**
  - Job completed early; but may have waited longer in queue than needed
  - May waste system resources (if no backfilling possible)
Computing in HPC

Execution Time = Wait Time + Runtime

Figure: Average wait times of jobs run on Intrepid (2009) as a function of requested runtime (data: Parallel Workload Archive).
Stochastic Jobs

• Many scientific applications are **stochastic** and **unpredictable**
  - Execution time is *input-dependent* (stochastic)
  - Unpredictable even for *same input-size* (quality matters)
  - *Large variations* (order of magnitude difference)
  - Common in *many domains* (e.g. neuroscience, adaptive mesh refinement)

![Graphs of fMRIQA, VBMQA, and dtiQA execution time distributions](image)

Figure: Traces [2013-2016] of neuroscience apps (Vanderbilt’s medical imaging database).
Neuroscience Applications

Range of execution times and I/O traffics for 31 representative neuroscience applications
Coping with Stochastic Jobs

• **Scheduling Options:**
  - **System-level solution:**
    - Abandon reservation-based batch scheduling
    - Use online (on-the-fly) scheduling → **not practical**
  - **Application-level solution:**
    - Develop optimized code to reduce stochasticity
    - Better resource estimation (e.g., using ML methods) → **difficult**
Coping with Stochastic Jobs

• **Scheduling Options:**
  - **System-level solution:**
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  - **Our approach:**
    - Optimization of expected job execution times
    - **Non-disruptive** to existing HPC scheduling model and application development process
Computing in the Cloud

• **Several Pricing Models** *(e.g., using Amazon AWS)*
  - **On-Demand (OD) = pay-what-you-use:**
    
    “you pay for compute capacity by the hour or second depending on which instances you run”
  - **Reserved-Instances (RI) = Pay-what-you-reserve:**
    
    “provide you with a significant discount (up to 75%) compared to On-Demand pricing”

<table>
<thead>
<tr>
<th>Payment Option</th>
<th>Upfront</th>
<th>Monthly*</th>
<th>Effective Hourly**</th>
<th>Savings over On-Demand</th>
<th>On-Demand Hourly</th>
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</thead>
<tbody>
<tr>
<td>No Upfront</td>
<td>$0.00</td>
<td>$8.03</td>
<td>$0.011</td>
<td>57%</td>
<td></td>
</tr>
<tr>
<td>Partial Upfront</td>
<td>$134.00</td>
<td>$3.72</td>
<td>$0.01</td>
<td>60%</td>
<td>$0.0255</td>
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<tr>
<td>All Upfront</td>
<td>$252.00</td>
<td>$0.00</td>
<td>$0.01</td>
<td>62%</td>
<td></td>
</tr>
</tbody>
</table>

Data extracted from AWS website
Models

• **Job Model**: Execution time modeled by a random variable $X$ that follows:
  - Known probability distribution $D$
  - PDF $= f(t)$ and CDF $= F(t)$
  - Positive support: $X \in [\min D, \max D]$
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- **Cost Model**: If reserve $t_1$ time and actual execution is $t$ time:
  \[
  \text{Cost} = \alpha t_1 + \beta \min(t_1, t) + \gamma
  \]
  - If $t_1 \geq t$, then reservation is enough and job succeeds
  - If $t_1 < t$, then job is killed; a new reservation ($t_2 > t_1$) is needed
Optimization Objective

• The objective is to compute a sequence of increasing reservations:

\[ S = (t_1, t_2, \ldots, t_i, t_{i+1}, \ldots) \]

that minimizes the total expected cost:

\[
E(S) = \beta \cdot E[X] + \sum_{i=0}^{\infty} (\alpha t_{i+1} + \beta t_i + \gamma) \mathbb{P}(X \geq t_i)
\]

- Expected total usage cost
- Extra cost incurred for each failed reservation
Solution 1: Characterizing Optimal Sequence

• **Existence**: optimal sequence (with finite expected cost) exists for distributions with bounded mean and variance
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• **Property**: optimal sequence satisfies the following recursive relationship for smooth distributions:

\[
t_i^o = \frac{1 - F(t_{i-2}^o)}{f(t_{i-1}^o)} + \frac{\beta}{\alpha} \left( \frac{1 - F(t_{i-1}^o)}{f(t_{i-1}^o)} - t_{i-1}^o \right) - \frac{\gamma}{\alpha}
\]

- Compute \( t_i \) based on \( t_{i-1} \) and \( t_{i-2} \) (as in Fibonacci numbers)
- By default \( t_0 = 0 \), it remains to compute \( t_1 \)
- Bounded search range: \( t_1^o \in [\min_D, O(\text{mean} + \text{var})] \)
- Complexity of computing optimal \( t_1^o \) is unclear (rational solution)
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- **Heuristic (Brute-Force)**: Numerical search of optimal \( t_1^o \) in the range
Solution 2: Approximating via Discretization

- **Discrete Transformation**: truncate and discretize continuous distribution
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• **Dynamic Programming**: for discrete distribution $X \sim (v_i, f_i)_{i=1..n}$

$$E^*_i = \min_{i \leq j \leq n} \left( \alpha v_j + \gamma + \sum_{k=i}^{j} f'_k \cdot \beta v_k + \left( \sum_{k=j+1}^{n} f'_k \right) (\beta v_j + E^*_{j+1}) \right)$$

- Cost of successful reservation
- Cost of failure

- **Initialization:**
  $$E^*_n = \alpha v_n + \beta v_n + \gamma$$

- **Complexity:** $O(n^2)$
### Performance (Common Prob. Distributions)

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Bf($t_1$)</th>
<th>DP(ET)</th>
<th>DP(EP)</th>
<th>Mean-by-Mean</th>
<th>Mean-Stdev</th>
<th>Mean-Doub.</th>
<th>Med-by-Med</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>2.15</td>
<td>2.31 (1.07)</td>
<td>2.36 (1.10)</td>
<td>2.36 (1.10)</td>
<td>2.39 (1.11)</td>
<td>2.42 (1.13)</td>
<td>2.83 (1.32)</td>
</tr>
<tr>
<td>Weibull</td>
<td>2.12</td>
<td>2.40 (1.13)</td>
<td>2.22 (1.05)</td>
<td>2.76 (1.30)</td>
<td>3.58 (1.69)</td>
<td>3.03 (1.43)</td>
<td>3.05 (1.44)</td>
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<tr>
<td>Gamma</td>
<td>2.02</td>
<td>2.20 (1.09)</td>
<td>2.13 (1.05)</td>
<td>2.26 (1.12)</td>
<td>2.18 (1.08)</td>
<td>2.24 (1.11)</td>
<td>2.51 (1.24)</td>
</tr>
<tr>
<td>Lognormal</td>
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<td>1.87 (1.01)</td>
<td>1.93 (1.04)</td>
<td>2.19 (1.19)</td>
<td>2.09 (1.13)</td>
<td>1.95 (1.06)</td>
<td>2.30 (1.24)</td>
</tr>
<tr>
<td>TruncatedNormal</td>
<td>1.36</td>
<td>1.38 (1.02)</td>
<td>1.36 (1.00)</td>
<td>1.98 (1.46)</td>
<td>1.83 (1.35)</td>
<td>1.98 (1.46)</td>
<td>2.16 (1.60)</td>
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<tr>
<td>Pareto</td>
<td>1.62</td>
<td>1.71 (1.05)</td>
<td>1.66 (1.03)</td>
<td>1.82 (1.12)</td>
<td>2.18 (1.34)</td>
<td>1.75 (1.08)</td>
<td>2.26 (1.39)</td>
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<tr>
<td>Uniform</td>
<td>1.33</td>
<td>1.33 (1.00)</td>
<td>1.33 (1.00)</td>
<td>2.21 (1.66)</td>
<td>1.90 (1.43)</td>
<td>1.67 (1.26)</td>
<td>2.21 (1.66)</td>
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<tr>
<td>Beta</td>
<td>1.75</td>
<td>1.79 (1.02)</td>
<td>1.80 (1.02)</td>
<td>2.02 (1.15)</td>
<td>2.11 (1.20)</td>
<td>1.98 (1.13)</td>
<td>2.45 (1.40)</td>
</tr>
<tr>
<td>BoundedPareto</td>
<td>1.80</td>
<td>2.00 (1.11)</td>
<td>1.91 (1.06)</td>
<td>1.84 (1.02)</td>
<td>2.09 (1.16)</td>
<td>1.83 (1.01)</td>
<td>2.81 (1.56)</td>
</tr>
</tbody>
</table>

- **Brute-Force ($t_1$)** heuristic has best performance (around 2x of offline optimal)
- **Discretization-based heuristics** have close performance, much better than other naïve heuristics
Performance (Realistic Workloads)

(a) Fitted \textbf{LogNormal} execution-time distribution for the VBMQA jobs

(b) Fitted \textbf{affine} waiting time function based on logs from the Intrepid data

(c) Performance of all heuristics with impact of varying mean and standard deviation
Future Work

• From User’s Perspective (Single Job):
  - How to request runtime along with other resources (#nodes, memory)?
  - Is checkpointing at the end of some/all reservations useful?

  Related to HPC fault tolerance: Trade-off between time wasted due to checkpointing and time saved for not having to start from scratch
Future Work

• From User’s Perspective (Single Job):
  - How to request runtime along with other resources (#nodes, memory)?
  - Is checkpointing at the end of some/all reservations useful?
    Related to HPC fault tolerance: Trade-off between time wasted due to checkpointing and time saved for not having to start from scratch

• From System’s Perspective (Set of Jobs):
  - Are reservation-based schedulers still suitable for stochastic workloads?
  - How should scheduling and backfilling be performed (under uncertainty)?
  - Is it time to consider new scheduling paradigms (e.g., online, hybrid)?
    Preliminary results: on-the-fly scheduling better for both system-level performance (utilization) and user-level performance (average response time) for single-node stochastic jobs; work-in-progress for multi-node jobs.
Thank you!

Hongyang Sun

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References