Forecasting for Grid and Cloud Computing
On-Demand Resources Based on Pattern Matching

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Outline

1. Introduction
2. Related work
3. Our approach
4. Experiments
5. Conclusions and future work
A typical Cloud client

- Provides a form of Web Service
- Deploys a user-interactive application
A typical Cloud client

- Provides a form of Web Service
- Deploys a user-interactive application

Cloud client goals

- Take advantage of the Cloud’s flexibility
- Have a higher resource usage efficiency
- Scale his application according to need
- Reduce expenses
The situation

+ IaaS Cloud providers have APIs for platform manipulation
- Virtual resources have a setup time
  \( \approx 1 \text{ min } 22 \text{ sec} \) for an EC2 m1.small instance

Setup time The total time it takes for the virtual resource to be usable since the request was issued.
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Our starting point

Jonathan Kupferman, Jeff Silverman, Patricio Jara, Jeff Browne. UCSB. “Scaling Into The Cloud”

- Analyzed three algorithms for dynamic Cloud Client resource scaling
- Proposed a new scoring metric for auto-scaling algorithms

Conclusions

- Dynamic provisioning provides large improvements over static allocation
- Predictive approaches tend to respond more rapidly to sharp changes
What can currently be found in practice as auto-scaling algorithms

**Reactive:** scaling decisions are made as a function of the current platform’s state

**Predictive:** considers past platform states as a discrete function and constructs a mathematical model to extrapolate
Reactive approaches

Examples:
- The Rightscale algorithm
- Elasticity rules based scaling

Pros / cons:
- Offered by most Cloud providers
- Simple to setup and use
  - Immune to platform repetitive behavior
  - Virtual resource setup time is still a problem
Predictive approaches

Examples:
- Regressive approaches
- Moving averages
- Neural network
- ...
- [our pattern-based approach]

Pros / cons:
- Can compensate for virtual resource setup time
- Periodic repetitive behavior
- More insight than reactive approaches
  - Non-periodic repetitive behavior *
  - Prediction accuracy can be a problem
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What we propose

- A pattern-based predictive approach
- Compensate for the virtual resource setup time
- Predict future Cloud client application load by identifying similar past usage patterns
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Self-similarity in web traffic

- Technically documented
- Macro level: yearly similarities
- Micro level: serving a file multiple times has a similar load pattern
- Implication: repetitive, non-periodic behavior
Our methodology

- Consider a measure of Cloud client platform usage (CPU count, total RAM used, etc.)
- Consider a history of the Cloud client’s platform usage of size $n$
- Consider the last $m$ instances of the measure – the last usage pattern
- Identify $p$ similar usage patterns in the history
- Do a weighted interpolation on the $p$ similar patterns

The resulting values give us an insight into future platform usage.
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Side-note

This approach can be used for predicting any measure that has a pattern-like repetitive behavior.
Figure: Mock example #1: historic data; pattern
Figure: Mock example #2: identified 3 similar patterns
Figure: Mock example #3: interpolate found candidate patterns
Knuth-Morris-Pratt string matching algorithm

- Used for identifying a substring of length $m$ inside a string of length $n$
- Fast running time: $\theta(m + n)$
- Can be trivially convertible to parallel code if we consider $n \gg m$
- Good for exact matches
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Knuth-Morris-Pratt algorithm adaptation

- Find approximate matches
- Changed running time to $O(m \times n)$ in the worst case
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### Data sources

- Animoto Cloud application
- Large Hadron Collider Compute Grid (LCG)
- Nordugrid
- SHARCNET
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Call for Cloud Traces
- Cloud traces are needed
- Cloud traces are difficult to obtain
- Open archive would be useful to the community
Experimental methodology

- Used time slices of 100 seconds
- Considered the total number of used CPUs per time slice
- Pattern length of 100 time slices ($\approx 2.7$ hours)
- Predicted 1 time slice ($\approx 1$ minute 30 seconds)
- Used traces from one platform to predict
  - its own usage (self-prediction)
  - usage of another platform
- Measured
  - Prediction error
  - Score by using a metric proposed Kupferman et al. (UCSB)
UCSB scoring metric

\[
\frac{(A_{\log})^\alpha}{C} - \frac{\gamma C}{A_{\log}} + \beta
\]  

\(A = \frac{\text{\#serviced \_requests}}{\text{\#of \_requests}}\) represents the availability of the platform

\(A_{\log} = -\log(1 + \delta_a - A), \delta_a < 1\) represents the availability in logarithmic scale

\(C = \frac{\text{\#CPU}}{\text{hours} \times 0.10}\) represents the cost

\(\alpha, \beta, \gamma, \delta_a\) have been chosen through experimentation
<table>
<thead>
<tr>
<th><strong>Metric</strong></th>
<th>A w/ A</th>
<th>A w/ L</th>
<th>L w/ L</th>
<th>L w/ N</th>
<th>N w/ L</th>
<th>S w/ N</th>
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<tbody>
<tr>
<td>Min err (%)</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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<tr>
<td>Max err (%)</td>
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<td>53.4</td>
<td>100.0</td>
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<tr>
<td>Med err (%)</td>
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<td>1.2</td>
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<td>1.749</td>
<td>7.32</td>
<td>35.38</td>
<td>375.65</td>
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<tr>
<td>UCSB</td>
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<td>-15.95</td>
<td>10.66</td>
<td>3.43</td>
<td>30.64</td>
<td>-3.23</td>
</tr>
<tr>
<td>Time (ms)</td>
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<td>27</td>
<td>41</td>
<td>514</td>
<td>162</td>
<td>528</td>
</tr>
</tbody>
</table>

Table: Prediction results. **A w/ B** – predicting A’s usage by using B as historic data. Possible platforms are: Animoto, LCG, NorduGrid and SHARCNET
Table: The prediction error obtained for various lengths of historic data and pattern lengths for the LCG platform.
Conclusions

- The current work presents a resource usageprediction approach based on pattern matching.
- Results are good when presented with historic data that is relevant to the current domain.
- Results can be improved by:
  - increasing historic data size
  - determining the appropriate pattern length
- There is a need for freely-available Cloud platform traces.

Future work

- Integrate our proposed approach into a grid and Cloud middleware - DIET http://graal.ens-lyon.fr/DIET/