PREDICTING COMMUNICATION PERFORMANCE

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SUPERCOMPUTERS

48 GB/s, 1-2 microsec

40 GB/s, 1-3 microsec

150 GB/s, 0.8 microsec

420 GB/s, 1-2 microsec
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40 GB/s, 1-3 microsec

150 GB/s, 0.8 microsec

Larger Bandwidth
Lower Latency
Fewer hops

420 GB/s, 1-2 microsec
WHY STUDY NETWORK PERFORMANCE?
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WHY STUDY NETWORK PERFORMANCE?

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- High raw bandwidth does not guarantee proportionate observed performance
  - Blue Gene vs Cray’s Gemini
- Savings are proportionate to core-count
- Most importantly, as a graduate student, I do what I am asked to do!
QUANTIFYING IMPACT

Mapping via logical operations in Rubik

What about others mappings?

How far are we from the best?

ALTERNATIVES

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- Simulations: too slow
  - 15 days to simulate one use case*

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- Theoretically: NP hard
- Simulations: too slow
  - 15 days to simulate one use case*
- Real runs: very expensive
  - Application/allocation specific information

<table>
<thead>
<tr>
<th></th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intrepid</td>
<td>4.16M</td>
<td>0.73M</td>
</tr>
<tr>
<td>Mira</td>
<td>0.17M</td>
<td>7.67M</td>
</tr>
<tr>
<td>Total</td>
<td>4.33M</td>
<td>8.40M</td>
</tr>
</tbody>
</table>

13 million core hours!

2D-Halo: predicting performance using a linear regression model for known metrics
SUPERVISED LEARNING

- Collect/generate data and summarize
- Build models: train performance prediction based on independent metrics
- Predict
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COMMUNICATION

Source node  Intermediate router/switch  Destination node

Memory  MU  Network Device  Receiver

Memory

Network Device

Network Device

Network Device

Memory
COMMUNICATION

Injection FIFO
Contention
COMMUNICATION

Injection FIFO Contention

Link Contention
COMMUNICATION
COMMUNICATION

Injection FIFO Contention

Receive Buffer Contention

Reception FIFO Contention

Link Contention
NETWORK COUNTERS OF BLUEGENE/Q
A PMPI based BGQ-Counter collection module
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- Packets sent on links in specific directions: A, B, C, D, E
- Deterministic, dynamic
A PMPI based BGQ-Counter collection module

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- Packets received on a link
- Packets in buffers
ANALYTICAL TOOL

- Simulate the injection mechanism

  - Selection of memory injection FIFO

  - Mapping of memory FIFO to network injection FIFO
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- Simulate the injection mechanism
  - Selection of memory injection FIFO
  - Mapping of memory FIFO to network injection FIFO
- Simulate routing to obtain hops/dilation
SUPERVISED LEARNING

- Collect raw data - various entities, e.g. bytes on a link, and the observed performance.
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- Derive metrics from the raw data on entities, e.g. average of bytes on links.
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- Derive metrics from the raw data on entities, e.g. average of bytes on links.

- Create a database of derived metrics and performance; we have used 100 mappings.

- Select two-third entries as training set; includes derived metrics and performance.
The training set is used to create a model for prediction.
SUPERVISED LEARNING

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http://scikit-learn.org
SUPERVISED LEARNING
SUPERVISED LEARNING

Decision trees

X[1] <= 0.4295

X[0] <= 0.0082

X[0] <= 0.2857

X[1] <= 0.0077

X[0] <= 0.0176

X[0] <= 0.1905

leaf

leaf

leaf

leaf

Rest of the tree
SUPERVISED LEARNING

Decision trees

Randomized forest of trees

Decision surfaces of a random forest
HOW TO JUDGE A PREDICTION

- Rank Correlation Coefficient (RCC): fraction of the number of pairs of task mappings whose ranks are in the same partial order in predicted and observed performance list

\[
concord_{ij} = \begin{cases} 
1, & \text{if } x_i \geq x_j \text{ & } y_i \geq y_j \\
1, & \text{if } x_i < x_j \text{ & } y_i < y_j \\
0, & \text{otherwise}
\end{cases}
\]

\[
RCC = \left( \sum_{0 \leq i < n} \sum_{0 \leq j < i} concord_{ij} \right) / \left( \frac{n(n-1)}{2} \right)
\]

- Absolute Correlation

\[
R^2(y, \hat{y}) = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}
\]

- Higher the better!
RESULTS

- Three communication kernel
  - Five-point 2D stencil
  - 14-point 3D stencil
  - Sub-communicator all-to-all
- Four message sizes to span MPI and routing protocols
KNOWN METRICS

- Entities
  - Bytes on a link
  - Dilation
- Derivation Methods
  - Maximum
  - Average
  - Sum

![Graph showing the relationship between Maximum bytes on a link and another metric. The x-axis represents maximum bytes on a link, with values ranging from $10^9$ to $9 \times 10^9$. The y-axis ranges from 20 to 60. The data points are scattered across the graph, indicating variability in the relationship.]
RESULTS

KNOWN METRICS

- Rank correlation coefficient
- Absolute performance correlation

Graphs showing correlation coefficients for 2D-Halo, 3D-Halo, and Sub-A2A.
RESULTS

KNOWN METRICS

max bytes is good, but incorrect in 10% cases
NEW METRICS
NEW METRICS

- Entities
  - Buffer length (on intermediate nodes)
  - FIFO length (packets in injection FIFO)
  - Delay per link (packets in buffer / packets received)
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- Entities
  - Buffer length (on intermediate nodes)
  - FIFO length (packets in injection FIFO)
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- Derivation methods
  - Average Outliers (AO)
  - Top Outliers (TO)
RESULTS
NEW METRICS

Rank correlation coefficient

Absolute performance correlation

2D-Halo  3D-Halo  Sub-A2A

max dilation  avg buffer  avg bytes AO
avg bytes  avg buffer TO  avg bytes TO
max bytes  sum dilation AO
HYBRID METRICS

- Combine multiple metrics to complement each other
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- Some combinations
  - avg bytes + max bytes + max FIFO
  - avg bytes + max bytes + avg buffer + max FIFO
  - avg bytes + avg buffer + avg delay AO + sum hops
  - avg bytes TO + avg buffer TO + avg delay TO + sum hops
RESULTS
HYBRID METRICS

Rank correlation coefficient

Absolute performance correlation

2D-Halo 3D-Halo Sub-A2A
max dilation sum dilation AO avg bytes avg bytes AO avg bytes
max bytes avg buffer avg bytes TO H1 avg buffer TO H2 H3 H4 H5 H6
RESULTS

HYBRID METRICS

 hybrid metrics provide high accuracy
Figure 7: Prediction success based on hybrid features from Table 3. We obtain RCC and $R^2$ values exceeding 0.99 for 3D Halo and Sub A2A. Prediction success improves significantly for 2D Halo also.

0.93 to 0.975 and 0.955 for the 16 KB and 4 MB message sizes respectively. For the more communication intensive benchmarks, we obtained $R^2$ values as high as 0.99 in general. Hence, the use of hybrid features not only predicts the correct pairwise ordering of mapping pairs but also does so with high accuracy in predicting their absolute performance.

5.5 Summary

Figure 8 presents the scatter-plot of predicted performance for the three benchmarks for the 4 MB message size. On the x-axis are the task mappings sorted by observed performance, while the y-axis is the predicted performance. The feature set $H_3$: avg bytes, max bytes, avg buffer, max FIFO was used for these predictions. It is evident from the figure that an almost perfect ordering is achieved for all three benchmarks.

Figure 9 shows the prediction success for the three benchmarks on 65,536 cores of BG/Q. From all the previously presented features (prior, new and hybrid), we selected the ones with the highest RCC scores for 16,384 cores, and present only those in this figure. We obtain significant improvements in the prediction scores using hybrid features for prediction in comparison to single features such as max bytes to avg bytes. For Sub A2A, RCC improved by 14% from 0.86 to 0.98, with a RCC value of 1.00 for both 512 bytes and 4 MB message sizes. For 2D Halo and 3D Halo, an improvement of up to 8% was observed in the prediction success. Similar trends were observed for $R^2$ values.

6. COMBINING ALL TRAINING SETS

In the previous section, we presented high correlation for predicting performance of the three benchmarks. For the prediction of individual benchmarks, the training and testing sets were generated from the 84 different mappings of the same benchmark for a particular message size on a fixed core count. In this section, we relax these requirements, and explore the space where the training and testing sets are a mix of different benchmarks, message sizes and core counts.

6.1 Combining samples from different kernels

We first explore the use of training and testing sets that are a combination of all three benchmarks and both 16 KB and 4 MB message sizes.
RESULTS

![Graph showing execution time for different mappings]

- FFT Predicted
- 3D Halo Predicted
- FFT Observed
- 3D Halo Observed
- 2D Halo Predicted
- 2D Halo Observed
RESULTS
Figure 9: Prediction success: summary for all benchmarks on 65,536 cores of BG/Q. H3: avg bytes & max bytes & avg buffer & max FIFO; H5: avg bytes TO & avg buffer TO & avg delay AO & sum hops A0 & max FIFO sizes. It is to be noted that the training and testing sets are now six times the size of individual sets (336 vs. 56 for the training set and 168 vs. 28 for the testing set). Figure 10 presents the prediction success and the absolute number of mispredictions for this experiment. We present selected prior, new and hybrid features in this experiment.

High RCC values, such as 0.97 for avg bytes, suggests that the combination of training sets results in a better prediction than the individual cases. A comparison of the total number of mispredictions, presented in Figure 10, with the sum of mispredictions for individual cases results in similar values. This suggests that scikit was successful in classifying the sample data from different kinds of communication patterns and message sizes and in making good predictions using them. This suggests that if a large database consisting of different communication patterns and message sizes is created, predicting performance of different classes of applications (possibly with unknown communication structure) may be feasible. We leave an in-depth study of this aspect for future work.

6.2 Predicting performance on 65,536 cores using 16,384-core samples

We also experimented with predicting the performance on 65,536 cores using the same combined training set for 16,384 cores from the section above. We obtained a maximum RCC value of 0.975 using the feature set H3: avg bytes, max bytes, avg buffer, max FIFO. In terms of absolute number of pairs with the wrong ordering, ⇐ 3200 pairs was mispredicted among a full set of 126756.

We find these results to be very encouraging since a strong correlation for predicting performance on large node counts using data from smaller jobs may provide a scalable method for performance prediction. Using smaller systems to predict performance at scale has several advantages. First, generating data sets is more feasible in this regime because it consumes less resources. Second, manually generating various mappings for large systems is impractical, but using prediction on smaller node counts, a large number of mappings can be explored with low overhead.

7. RESULTS WITH PF3D

PF3D [17] is a multi-physics code used for studying laser plasma-interactions in the National Ignition Facility (NIF) experiments at LLNL. PF3D is a communication-heavy application and has been shown to benefit significantly from task mapping on Blue Gene/P [6]. This is the first attempt at mapping PF3D on Blue Gene/Q.

PF3D simulations consist of three distinct phases: wave propagation and coupling, advecting light, and solving the hydrodynamic equations. The MPI processes are arranged in a 3D Cartesian grid.
RESULTS

Predicting performance on 65,536 cores using 16,384 cores data for training
RESULTS - PF3D

Rank correlation coefficient

Absolute performance correlation
RESULTS - PF3D

Rank correlation coefficient

<table>
<thead>
<tr>
<th>Metric</th>
<th>RCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>avg bytes</td>
<td>1.0</td>
</tr>
<tr>
<td>max bytes</td>
<td>0.9</td>
</tr>
<tr>
<td>sum dilation AO</td>
<td>0.8</td>
</tr>
<tr>
<td>avg buffer</td>
<td>0.7</td>
</tr>
<tr>
<td>H1</td>
<td>0.6</td>
</tr>
<tr>
<td>H3</td>
<td>0.9</td>
</tr>
<tr>
<td>H4</td>
<td>1.0</td>
</tr>
<tr>
<td>H5</td>
<td>0.9</td>
</tr>
<tr>
<td>H6</td>
<td>1.0</td>
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</table>

Absolute performance correlation

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<tr>
<th>Metric</th>
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<td>H1</td>
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<tr>
<td>H3</td>
<td>0.9</td>
</tr>
<tr>
<td>H4</td>
<td>1.0</td>
</tr>
<tr>
<td>H5</td>
<td>0.9</td>
</tr>
<tr>
<td>H6</td>
<td>1.0</td>
</tr>
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Blue Gene/Q (16,384 cores)

Execution Time (s)

Mappings sorted by actual execution times

pf3D Observed - pF3D Predicted
SUMMARY

- Communication is not just about peak latency / bandwidth
- Simultaneous analysis of various aspects of network is important
- Complex models are required for accurate prediction
- There are patterns waiting to be identified!
FUTURE WORK

- More applications!
- More metrics
- Weighted analysis
- Offline prediction of entities
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Questions?