# Predicting Performance Characteristics of Distributed Simulator for Scale-free Networks

Christopher L. Hood, George F. Riley

Georgia Institute of Technology

13 May 2015



Long run time  $\iff$  Large-scale  $\iff$  Parallel simulation

- Parallel and distributed simulations maximize usage of available computational resources in an effort to minimize total run time.
- We only care about distributing computation when the run time is going to be significant, i.e. large-scale simulations.
- Can we use information about the model to infer the best way to set-up the parallel simulation?

# Terminology



"Glues" the two together: ns3::Event.

#### **Description of Problem**

Given a description of an experiment and a history of previous experiments and their associated performance metrics (run time, memory usage, energy consumption, etc.), can we accurately **predict** how to set-up the simulator executive in order to achieve the best performance?

i.e. can we form a **performance characterization** for how to set-up the simulator executive based on the model configuration?

# Synchronization Algorithms in ns-3

- Event causality constraint  $\implies$  synchronization.
- Optimistic vs. conservative synchronization.
- Synchronous (Allgather) vs. asynchronous (null-message).
- Naïve characterization: do not take into account how the synchronization actually works.

# Ways We Can Set-up the Executive in ns-3

- Allgather vs. null-message.
- Different scheduling schemes (not considered).
- "Intelligent" automatic segregation of model components across LPs (not currently viable in ns-3).

# Simulation Meta-data in ns-3

- ns3::MpiStatsAggregator to assist in gathering simulation meta-data, e.g. various wallclock intervals, number of events scheduled, number of messages sent, etc.
  - ::AddClock (clkName, clockType)
  - ::{Reset,Start,End,Pause}Clock (clock)
  - ::{Add,Set,Get}Stat (...)
  - Leverages ns3::GlobalValue so values are accessible outside of the mpi module.
  - Leverages MPI windowed communications for asynchronous access of values from any LP.
- Abstract a ns3::WallClock class:
  - ns3::SystemWallClockMs uses system clock.
  - ns3::TscWallClock leverages x86 CPU clock counter.

#### Learning a Performance Characterization

- Problem:
  - Many ways to set-up the executive (many independent variables).
  - Infinite number of ways to configure the model.
  - The model configurations we care about (large-scale models) take a long time to simulate.
- Solution: constrain both the number of independent variables and model configuration and see if we can find a characterization then.
  - Independent variable: synchronization algorithm  $\in$  {Allgather, null-message}.
  - Model configuration: constrain topology, network size, traffic, etc.

### Experimental Set-up

- Number of router nodes,  $N_R \in \{64, 128, 256, 512, 1024, 4096, 8192, 65536\}.$
- Number of LPs,  $N_A \in \{64, 128, 256, 512, 1024\}$ .
- Mean link delay,  $E[\ell] \in \{1, 10, 100\}$  ms.
- Traffic: on-off UDP traffic bursting at 50% duty cycle.
- Random topology generation using BRITE.

#### Example Topology—64 router nodes, 64 LPs



- ● ● ●

э

### Running the Experiments

- Using the different combinations of number of routers, LPs and different mean link delays, as well as using different random seeds for the topology, 450 unique model configurations created.
- For each model configuration, experiment run using both Allgather and null-message synchronization, total of 900 different experiments.
- Wallclock run time measured for each experiment.
- Run on LLNL's Cab, Intel Xeon 2.6 GHz, 16 cores and 32 GB memory per node.



# Recast as a Classification Problem

- For each pair of experiments corresponding to a unique model configuration (there are 450), there are two components:
  - The data vector x<sub>i</sub> consisting of features (simulation meta-data).
  - **②** The label  $z_i$ , which is 1 if the null-message algorithm produced a faster run-time than Allgather and -1 if the opposite.
- Then, the goal become thus: given pairs of (x<sub>i</sub>, z<sub>i</sub>) for i in some subset (the training data set), and given only the x<sub>j</sub> for j in a non-intersecting subset (the testing data set), predict what z<sub>j</sub> is (compute the prediction 2̂<sub>j</sub>).
- Simply used random permutations (half and half) of the 450 data points as the training and testing data sets.



## Recast as a Classification Problem

• In this work, the following features are used:

$$\mathbf{x}_{i} = \begin{bmatrix} \text{number LPs} \\ \text{number routers} \\ \text{lookahead mean} \\ \text{lookahead std.} \\ \text{lookahead min.} \\ \text{lookahead max.} \\ \text{outdegree mean} \\ \text{outdegree std.} \\ \text{outdegree max.} \end{bmatrix} \in \mathbb{R}^{9}$$

- Note the following definitions:
  - outdegree: number of edges from a router to other routers
  - mean, std., min., and max.,: the sample mean, standard deviation, minimum, and maximum of a certain measurement over all LPs in an experiment.

#### Performance Characterization

How to compute the estimate  $\hat{z}_j$  given  $\mathbf{x}_j$  for j in the testing data set?

 $\implies$  simplest to use a linear classifier:

$$\hat{z}_j = \operatorname{sign}(\mathbf{w}^T \mathbf{x}_j + b)$$

where  $\mathbf{w}$  and b are determined from the training data.

#### Is There an Apparent Pattern?



# Is There an Apparent Pattern?

Data points, colored by truth 2 1.5 lookaheadMax 1 × × faster × NMS 0.5 Θ Allgather faster 0 -0.5 -1 -0.5 0 0.5 1.5 2 2.5 -1 1

numAs

# Is There an Apparent Pattern?

Data points, colored by truth



Christopher L. Hood, George F. Riley Georgia Tech ECE

P

# Principal Components Analysis

• Given the training data feature vectors **x**<sub>i</sub>, apply a linear transformation

$$\tilde{\mathbf{x}}_i = P\mathbf{x}_i$$

so that the first feature of  $\tilde{\mathbf{x}}_i$  represents the highest variance, the second feature the second-highest variance whilst being orthogonal to the first feature, etc.

- Consequences:
  - Each feature of  $\tilde{\mathbf{x}}_i$  is uncorrelated with the others.
  - Provides a principled way of dimensionality reduction, which helps prevent over-fitting.

### Is There an Apparent Pattern?

Transformed data points, first two principal components



#### Performance Characterization

- Simple but principled way to compute **w** and *b* from the training data: linear discriminant analysis.
- Assume the training data points corresponding to each label come from Gaussian distributions of identical covariance.
- Compute **w** and *b* by constructing hyperplanes of equal likelihood.

### LDA



#### Training Data Results

PCA training data colored by truth, LDA classifier line



#### Testing Data Results: 93% Classification Success

PCA testing data colored by truth, LDA classifier line





# Conclusions

- Strict constraints on model configuration  $\implies$  high degree of success in performance characterization.
- More general characterization may or may not exist.
- Results of experiments not immediately useful, but framework is indispensible.

# Next Steps

- Repeat procedure using a wider range of model configurations, using more continuously-varying parameters.
  - Larger and finer range of number of LPs, number of routers, link delay, etc.
  - Different (possibly non-random) topologies.
  - Different traffic configuration.
- Include testing data points from model configurations outside of the range of training configurations (see if we can predict via extrapolation).
- Integrate training data gathering and decision framework into ns-3 codebase so we don't have to do everything in Matlab.

# Questions

æ

э

◆ 同 ▶ ◆ 三



- vol. 6. pp. 1617-1622. December 1988.

Î

ì

K. Chandy and J. Misra, "Distributed simulation: A case study in design and verification of distributed programs," IEEE Transactions on Software Engineering, vol. SE-5, pp. 440-452, September 1979.



R. E. Bryant, "Simulation of packet communication architecture computer systems," tech. rep., Cambridge, MA. USA. 1977.

Image: A mathematical states and a mathem

э

R. M. Fujimoto, Parallel and distributed simulation systems.



New York, NY: John Wiley & Sons, 2000.

- S. Theodoris and K. Koutroumbas, *Pattern Recognition*. Burlington, MA: Academic Press, 4th ed., 2009.
- B. University, "Boston university representative internet topology generator," 2002.
- A. Medina, A. Lakhina, I. Matta, and J. Byers, "Brite: Universal topology generation from a user's perspective," January 2001.
- ns-3 Project, ns-3 Manual, 3.22 ed., 2015.

- ns-3 Project, ns-3 API Documentation, 3.22 ed., 2015.
- ns-3 Project, ns-3 Model Library, 3.22 ed., 2015.
- Message Passing Interface Forum, MPI: A Message-Passing Interface Version 3.0, September 2012.

< □ > < 同 >