Improving the Dependability of Grids via Short-Term Failure Predictions

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Motivation and Introduction

Reliability of Grids

- Grids like EGEE offer sufficient capacity for even most challenging large-scale computational experiments
- However, Grids have notoriously low reliability:
  - Data processing challenges of the **WISDOM** project (2005) have shown that only 32% (FlexX) and 57% (Autodock) of the jobs completed with "OK" status
  - A nine-month long study found that only 48% of jobs submitted in South-Eastern-Europe completed successfully (*)

(*) **Analyzing the Workload of the South-East Federation of the EGEE**. G. DaCosta, M.D. Dikaiakos, S. Orlando. *Proceedings MASCOTS 2007*.
Harvesting Large-Scale Grids for Software Resources, A. Katsifodimos, G. Pallis, M. D. Dikaiakos, *Proceedings of CCGrid 2009*.

Detecting and Managing Failures

- Detecting and managing failures is an important step to make Grids reliable
- This is an extremely complex task that relies on
  - over-provisioning of resources
  - ad-hoc monitoring
  - Sys.admin & user intervention
- Unique characteristics of Grids make it difficult to use ideas from cluster computing, Internet systems, and software systems

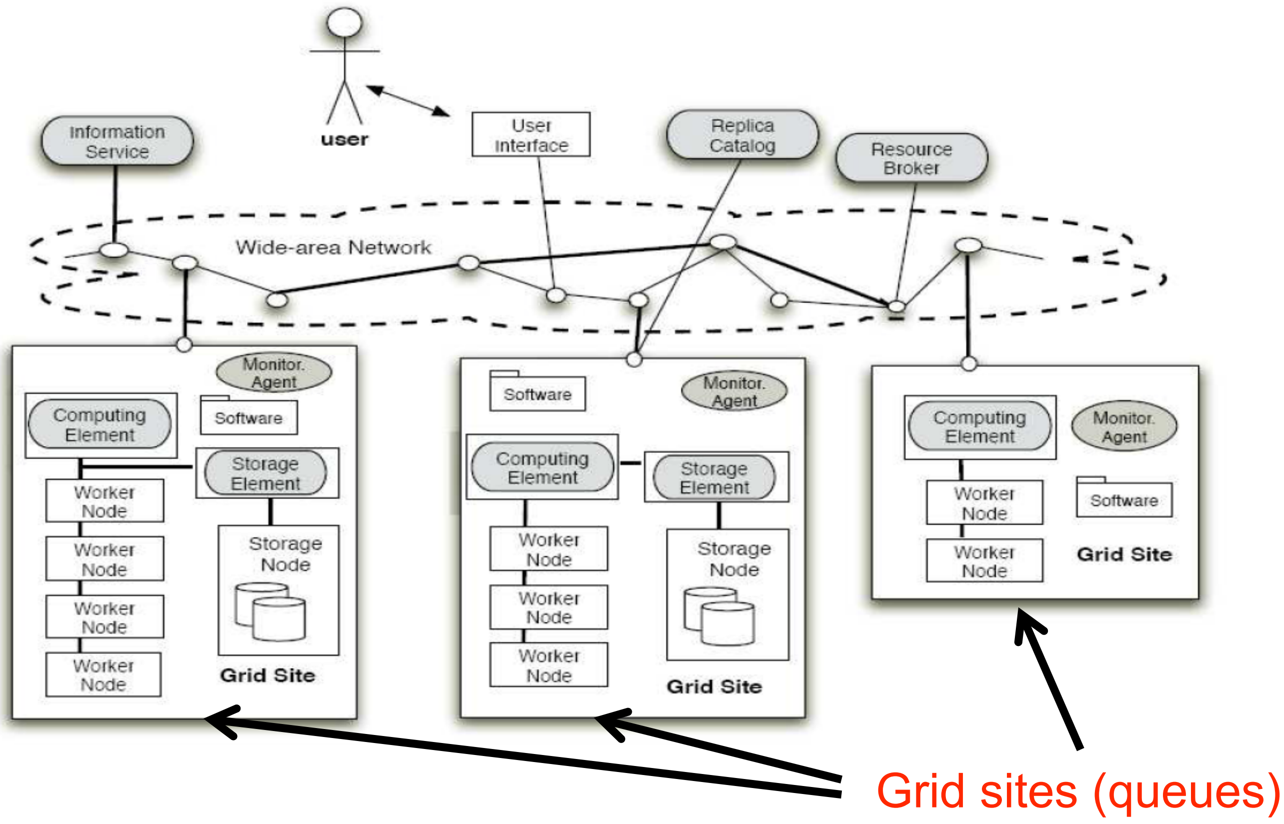
Why is Detecting Failures in Grids Hard?

- Lack of central administration makes it difficult to access the remote sites in order to monitor failures
- Heterogeneity and legacy impede integration of failure feedback mechanisms in the application logic
- Huge system size make it difficult to acquire and analyze failure feedback data at a fine granularity
- It is more efficient to identify the overall state of the system and to exclude potentially unreliable sites than to identify reasons for individual failures

Failure Management in Grids: The Case of the EGEE Infrastructure.
K. Neocleous, M.D. Dikaiakos, P. Fragopoulou and E.P. Markatos, *Parallel Processing Letters*, Vol. 17, Issue 4, World Scientific, pp 391-410, December 2007

Short-Term Prediction of Site Failures

- In our approach we predict queue (site) failures on short-term time scale by deploying (off-the-shelf) machine learning algorithms



Exploiting Generic Feedback Sources

- Instead of using application-specific feedback data, we exploit a set of generic feedback sources
  - representative low-level measurements (SmokePing)
  - websites, e.g. Grid Statistics (GStat)
  - functional tests and benchmarks
- Such predictions can be used for deciding where to submit new jobs and help operators to take preventive measures

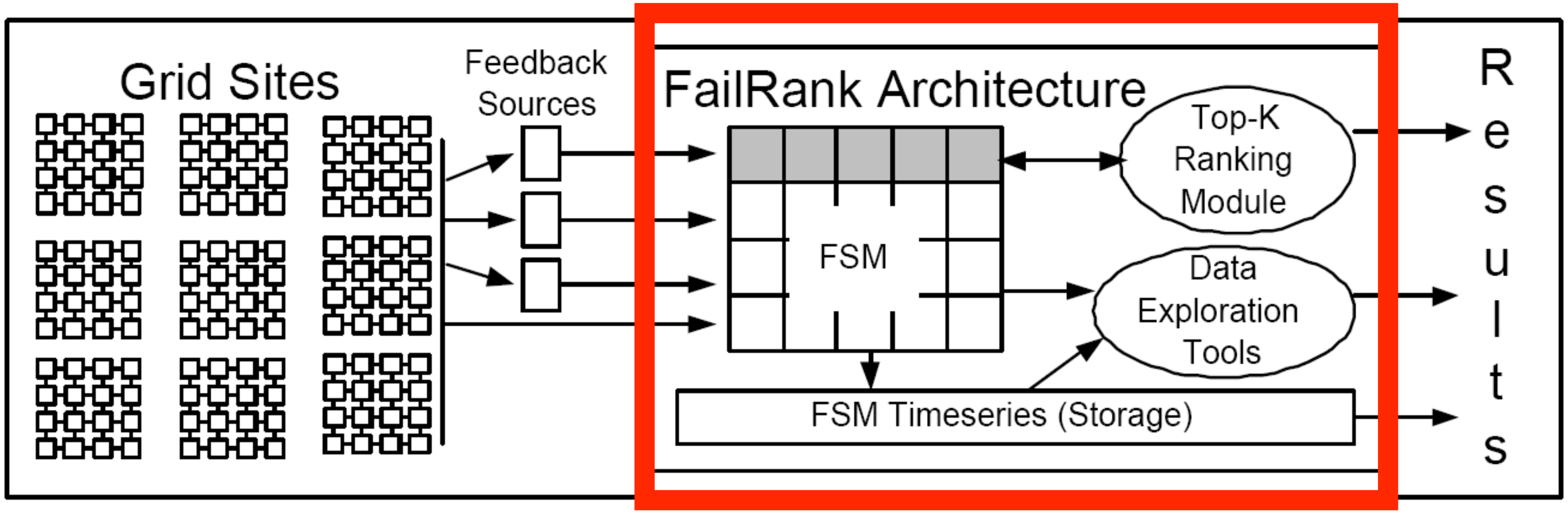
Previous Work

- In previous work – the **FailRank** system – we have used linear models of monitoring data
  - they continuously ranked K sites with the highest potential to failure
- In this study we apply individual models per queue and a more sophisticated approach, including
  - statistical selection of most meaningful sources
  - non-linear classification algorithms from machine learning

"Metadata Ranking and Pruning for Failure Detection in Grids", D. Zeinalipour-Yazti, H. Papadakis, C. Georgiou, M.D. Dikaiakos, *Parallel Processing Letters, Special Issue on Grid Architectural Issues: Scalability, Dependability, Adaptability*,Sept. 2008.

"Identifying Failures in Grids through Monitoring and Ranking." Demetrios Zeinalipour-Yazti, Kyriakos Neocleous, Chryssis Georgiou, and Marios D. Dikaiakos, in the *Proceedings of the Seventh IEEE International Symposium on Networking Computing and Applications, NCA 2008*.

FailRank Architecture



- **FailShot Matrix (FSM):** A Snapshot of all failure-related parameters at a given timestamp.
- **Top-K Ranking Module:** Efficiently finds the K sites with the highest potential to feature a failure by utilizing FSM.
- **Data Exploration Tools**: Offline tools used for exploratory data analysis, learning and prediction by utilizing FSM.

Focus on Prediction Accuracy

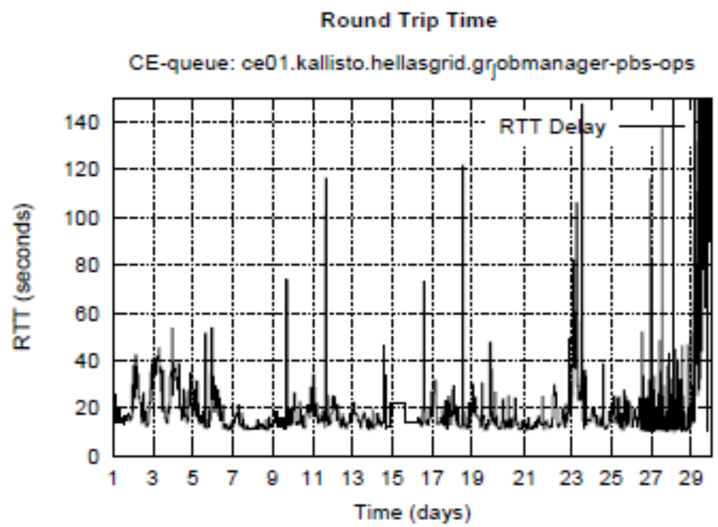
- We focus on several essential questions related to prediction accuracy:
  - *How many sources are necessary for high prediction accuracy?*
  - *Which of the sources yield the highest predictive information?*
  - *How accurately can we predict the failure of a given Grid site X minutes ahead of time?*

- Evaluation on a 30-day trace from 197 EGEE queues shows that prediction accuracy is highly dependent on:
  - the selected queue
  - the type of failure
  - the preprocessing and
  - the choice of input variables

Data and Modeling Methodology

Input Data and FailBase Repository

- Our study uses data from our FailBase Repository
  - characterizes the EGEE Grid in respect to failures between 16/3/2007 and 17/4/2007
  - maintains information for 2,565 Computing Element (CE) queues (sites accepting computing jobs)
- For our study we use a subset of 197 queues with most types of monitoring data
- For *each queue* data is a sequence of pairs (timestamp, attribute vector)
  - Each attribute vector consists of 40 measurements from to various sensors and tests
  - Sampled every 1 minute



Exemplary attribute (RTT) over time

Types of Input Data

- A. *Information Index Queries (BDII)*: 11 attributes from LDAP queries
  - e.g. number of free CPUs; max. number of running and waiting jobs
- B. *Grid Statistics (GStat)*: processed data from the monitoring web site of Academia Sinica
  - e.g. geographical region of site; available storage space
- C. *Network Statistics (SmokePing)*: Data of the gPing database from ICS-FORTH
  - average round-trip-time (RTT); the packet loss rate
- D. *Service Availability Monitoring (SAM)*: 14 attributes derived from raw html published by the CE sites
  - e.g. the version number of the middleware; results of various replica manager tests; results from test job submissions

Predictive Models

- Our prediction methods are model-based
  - A model in this sense is a function f mapping vectors of sensor values to an output (queue healthy (0) or not (1))
- We use as models classification algorithms
  - Classifiers "learn" the relationship between input data and the output ("class value") based on historical examples
  - They are well-established in data mining and have been perfected over time
- We deploy several common classifiers
  - C4.5 (decision tree), AdaBoost, Naive Bayes, LS

Learning the Model

- To predict, we need to learn the relationship between inputs (A, B) @"now" and the value of our model f @(now + T)
- First stage (training, model fitting):

@ = "at time"

  - Supply training data consisting of triples [A@x, B@x, f@(x +T)] sampled at different times x
  - Then learn a function which captures this relation
- Second stage (prediction): supply (A,B) and compute f @(x+T)]

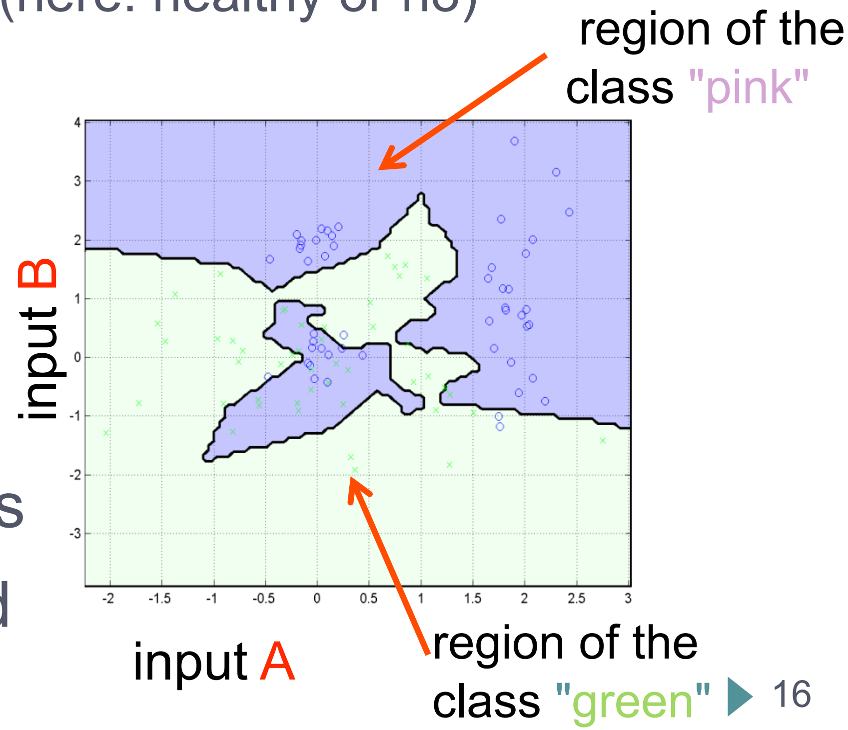
	Metric A	Metric B	f
Example 1	60	1000	[30-33]
…	…	…	…
Example k	1.4	10^6	[3-6]
Unknown Sample	30	50000	?

1. fit model

2. predict

Classifiers Explained Visually

- Assume that you have two metrics, and want to use them for predicting some (discrete) value - a class
  - Interpret inputs as coordinates of points in the plane
- Then training data = multicolored points in R^2
  - color corresponds to a class (here: healthy or no)
- Training: *finding a suitable subdivision of the plane*
  - model = a compact representation of a colored subdivision
- Prediction: given a new sample, find its color = class
- We have 40 metrics instead of 2 (R^{40}), but same idea



Attribute Selection

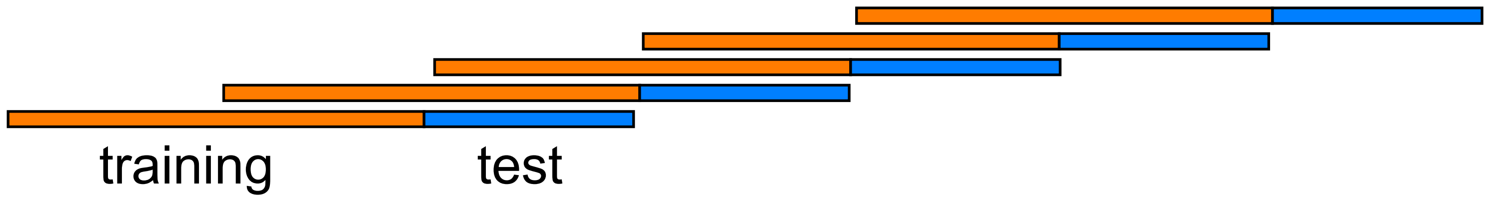
- Initially, we do not know which of the 40 metrics (= attributes) contain most predictive information
- Keeping all create some serious problems
  - Overfitting
  - Inefficiency: memory "explodes" at training phase
  - We don't learn which metrics are really relevant
- Therefore we use attribute selection
  - Learn and evaluate "probe models" on training data with various subsets of attributes
  - Then use attribute sets with lowest errors
  - *For specialists*: we use forward or backward branch-and-bound selection with C4.5 (decision tree)

Evaluation Metrics

- To quantify prediction errors we use
  - Recall = probability that a (randomly selected) failure is indeed predicted
  - Precision = probability that a (randomly selected) failure prediction indicated a true failure
- These metrics are then averaged over all 197 queues for most diagrams

Model Updates

- Models are periodically updated to ensure adaptability to profile changes
  - How? Train model on the orange part and test on the blue part, then advance by the blue part etc.



- The used values are:
  - training interval: 15 days (21600 of 1-minute samples)
  - update interval = test interval = 10 days (14400 samples)
  - why? – will be shown later

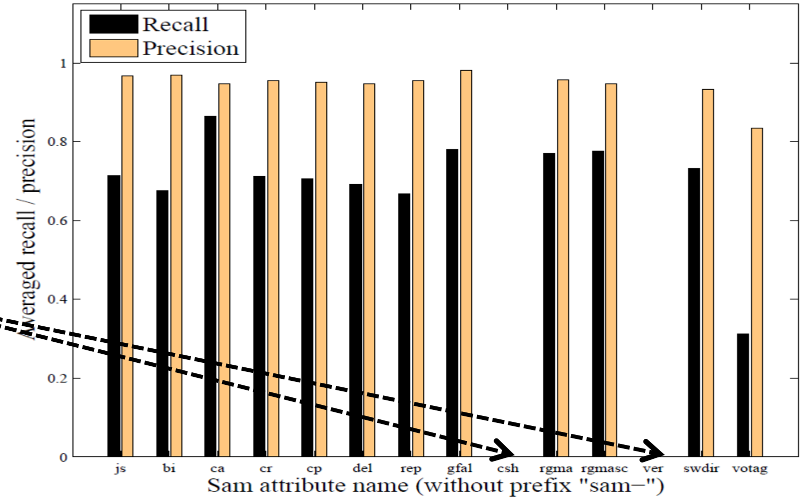
Experimental Results

Identifying Failure Indicators

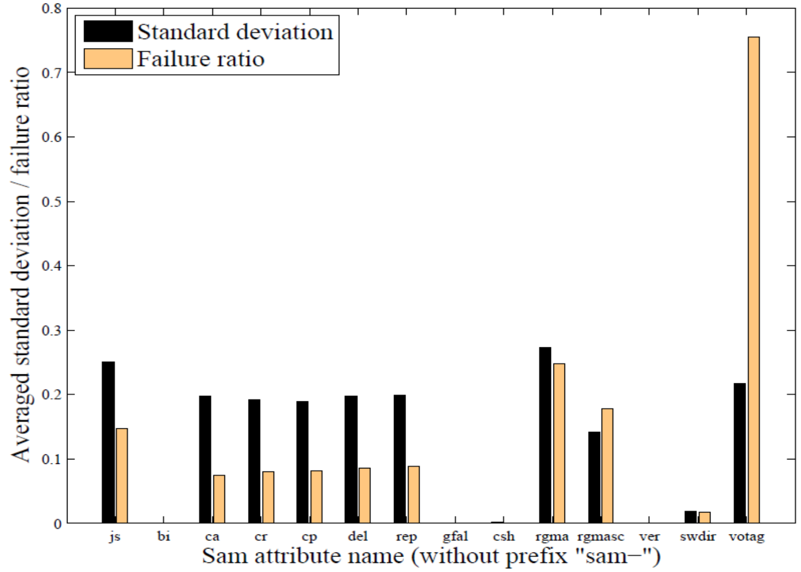
- Unfortunately, we do not have any additional data whether jobs on a site have failed or not
- As a substitute, we used as failure indicators two metrics from the Service Availability Monitoring (SAM) measurements (group D):
  - sam-js: a test that submits a simple job for execution to the Grid and then seeks to retrieve that job's output from the UI
  - sam-rgma: R-GMA makes all Grid monitoring data appear like one large DB; this test insert a tuple and run a query for that tuple
- *Values (0/1) of each of these 2 metrics are assumed to mean "queue failed" or "queue healthy"*

Why sam-js and sam-rgma?

- First: we computed averaged recall / precision for all 14 SAM (group D) attributes
- This eliminated only two of them

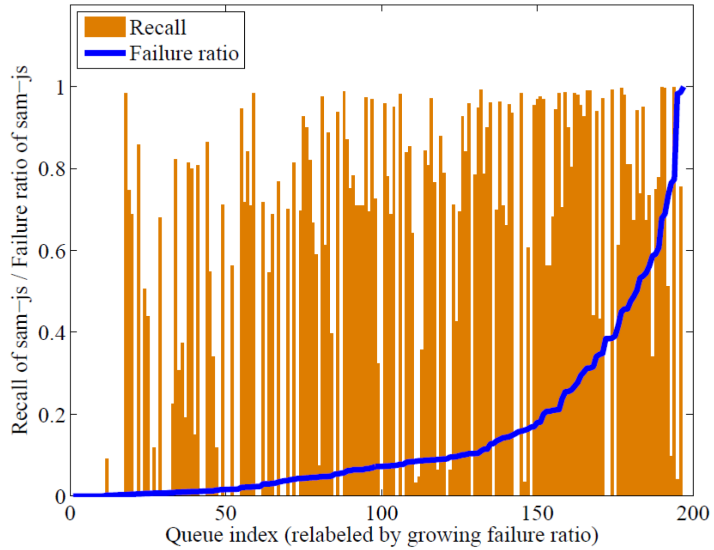


- We then looked *per attribute* at:
  - standard deviation - more changes = more information
  - failure ratio = (#all samples indicating a failure) / (# all samples)
  - low FR = not enough "bad cases" to train a predictor
- From the remainder ones we selected these 2 by importance of representing failures

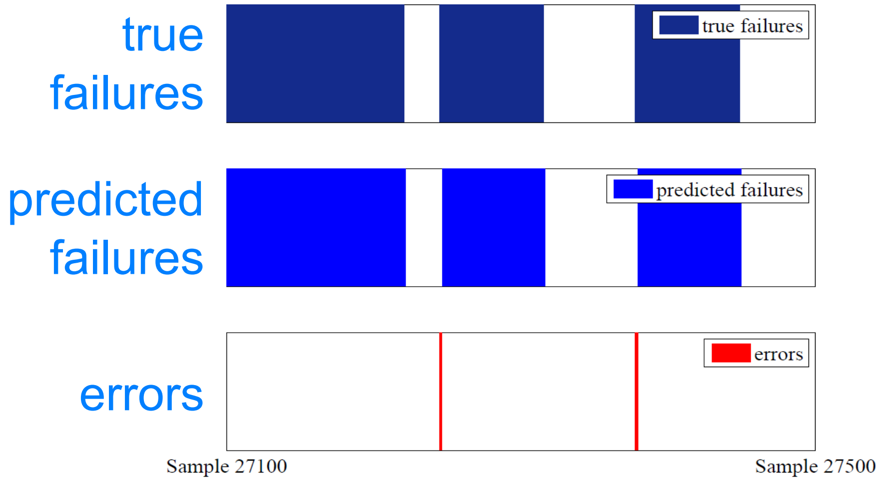


Data Characteristics

- *A. Is there a relationship between failure ratio (FR) and accuracy?*
  - FR = (#all samples indicating a failure) / (# all samples)
- Plot: recall of sam-js (bars) sorted by FR or sam-js (line)
- **No!** => Models are "non-trivial"



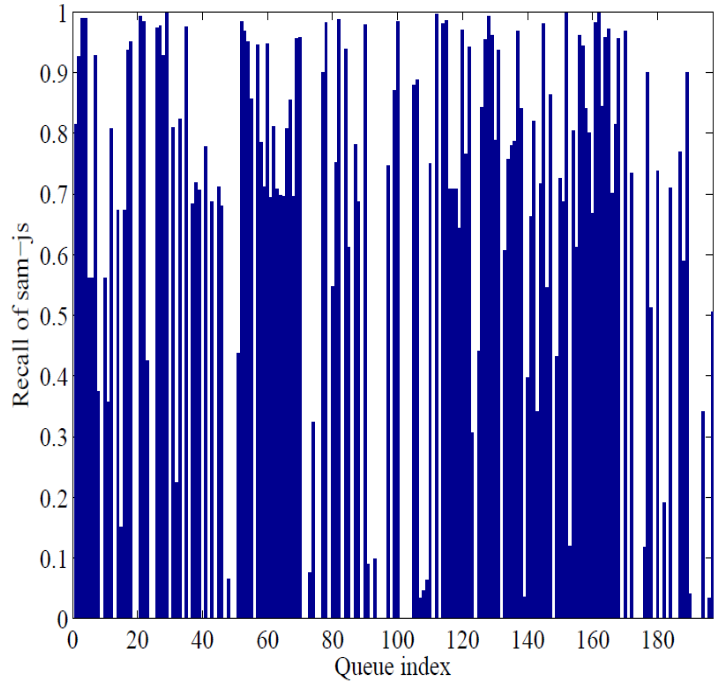
- *B. What are the failure patterns in our data?*
- Typically, the failure state does not change frequently (long "runs" of failures / non-failures
- Prediction errors occur frequently right after the change of failure state



Are Individual Models (per Queue) Useful?

- We have created separate model (trained classifier) per queue
- This is a lot of effort – is it useful?
- It turns out that prediction accuracy varies hugely between queues!
- Lessons:
  - "Aggregated models" of reliability (i.e. one model for many queues) can be severely inappropriate
  - Scheduling decisions should take into account confidence of the model *per queue*
    - How likely is to predict a failure for *this* queue?
    - If confidence is low, increase redundancy / overprovision for this queue *preemptively*

recall of sam-js

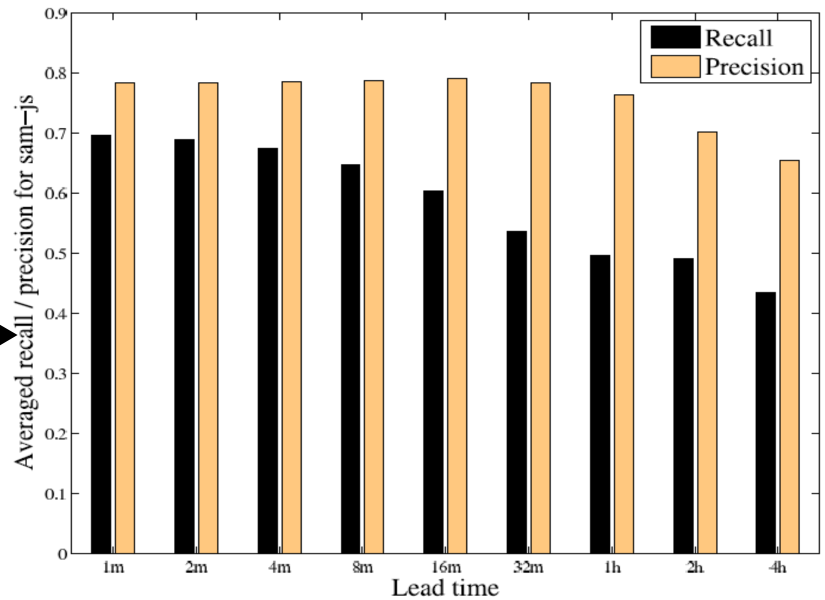


queue index – 0 to 196

Lead Time vs. Accuracy

- How much into future can we predict?
  - we set the lead time to 15 minutes
  - lead times of 1-8 minutes were slightly more accurate
    - but not very useful – might not give enough time to react
  - lead times above 30 minutes yielded larger errors

Averaged recall & precision for sam-js

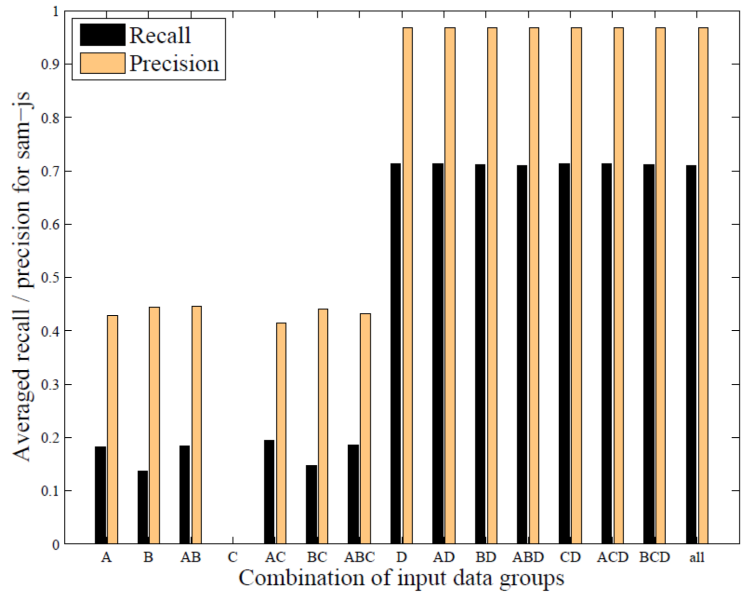


lead time (in minutes) 1 4 16 60 4*60

Most Relevant Types of Input Metrics

- Which of the input types (A, B, C, D) provide most predictive information?
- We tested all input combinations A, B,.., AB, AC,…, ABCD
- Group D (SAM = functional tests) is most relevant
  - In fact, groups A, B, C do not carry any additional information

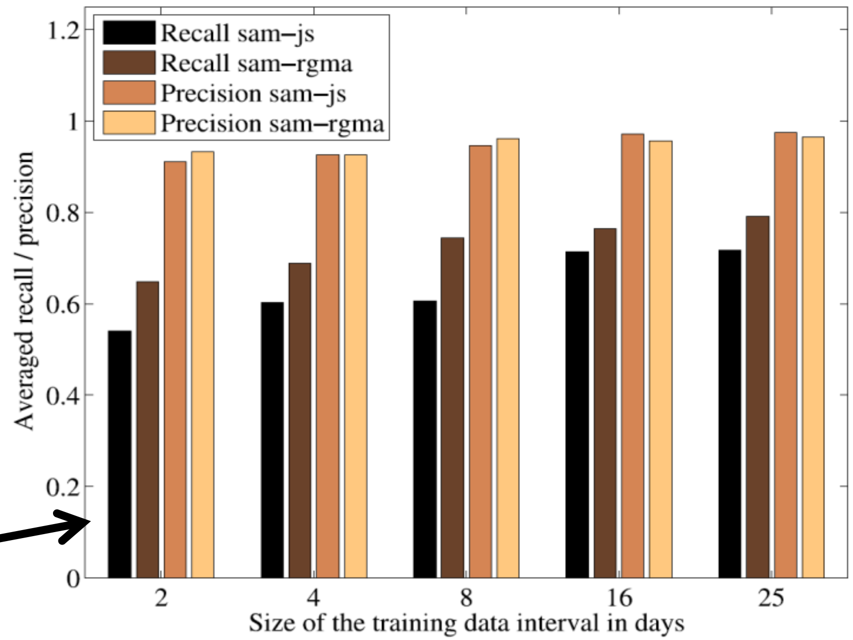
Averaged recall & precision for sam-js



Group combination A B AB C AC BC ABC D ... BCD.all

Training Data Size

- How much training data (# samples) is needed for accurate models?
- In general, the less the better
  - Higher adaptability to changes, less "waiting time" until first results
  - But too little data decreases accuracy
- Training interval of 15 days turned out optimal
- Test interval = Model update interval was irrelevant



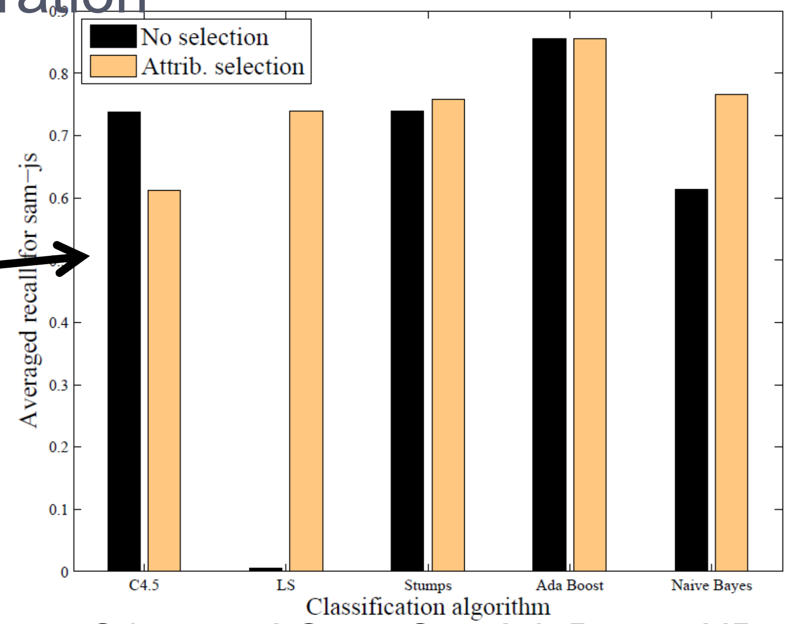
2 4 8 16 25

Averaged recall & precision vs. training time (days)

Classifier Type & Attribute Selection

- Are some classifiers more accurate than others?
  - Except for the least sophisticated algorithm (LS = linear perceptron, a hyperplane in R^d) accuracy is comparable
- How much attribute selection matters
  - Mixed results: for LS & Naïve Bayes improvement, for C4.5 (decision tree) deterioration

Averaged recall for sam-js
(no selection /
with attribute selection)



C4.5 LS St. AdaBoost NB

Conclusions

- Short-term prediction of failures in Grid queues can yield high accuracy (precision / recall)
- However, this accuracy varies hugely among queues
  - Individual queue modeling is essential
- Some metrics (like *Service Availability Monitoring (SAM)*) are more informative than all others together
  - Consider this for "economical" metric collection
- Sophisticated classification algorithms yield comparable accuracy

Future work

- Direct comparison with FailRank (linear models)
- Scheduling strategies with consideration of model confidence

Additional Slides

Why is Detecting Failures in Grids Hard?

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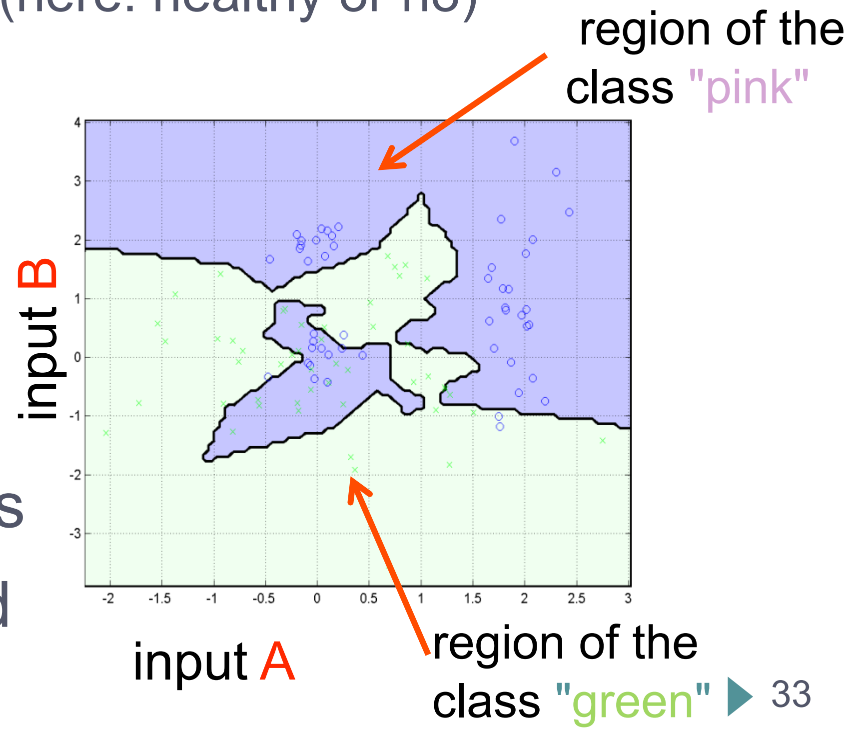

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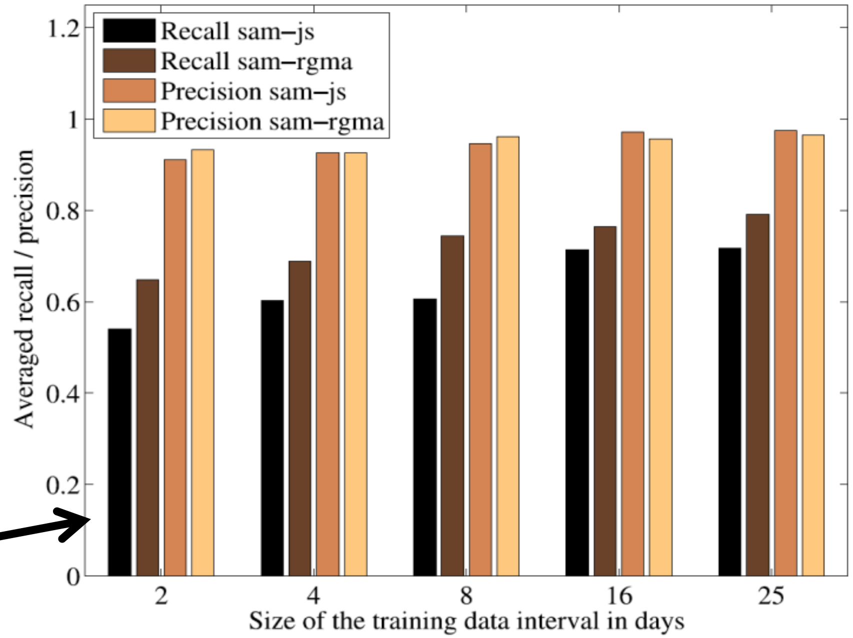

2 4 8 16 25

Averaged recall & precision vs. training time (days)