Predicting Computer System Failures Using Support Vector Machines

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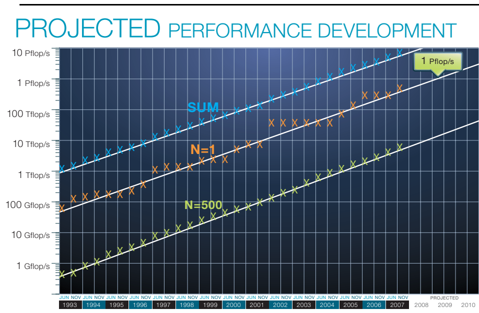
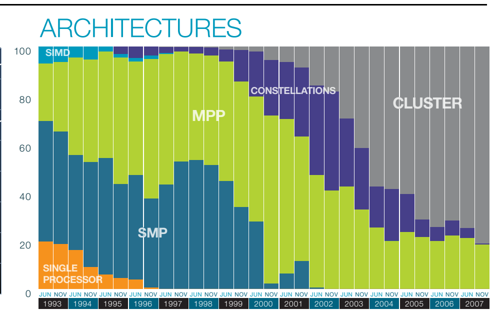
High-Performance Computing Trends





- Expected that computing will continue to double each year
  - *Petaflop systems listed on* `top500.org`
  - However CPU clock rates will see limited increases
- Computing improvements achieved with more processors
  - IBM Blue Gene at LLNL has 212,992 processors
  - System failures will become more problematic

System Events

- There are several critical system events
  - Hardware failure, software failure, and user error
  - Frequency will increase as systems become larger (cluster)
  - Resulting in lower overall system utilization
- *Cannot easily improve failure rates, can we manage failure*?
  - Smarter scheduling of applications and services
  - Minimize the impact of failure
- Accurate event predictions are key for event management
  - *Are predictions possible? How accurate?*
  - Need system status information to make predictions

System Status Information

- *Almost* every computer maintains a system log file
  - Provide information about system events
  - `syslog` is actually general-purpose logging facility [Lon01]
- An event represents a change in *system state*
  - Include hardware failures, software failures, and security

Host	Facility	Level	Tag	Time	Message
198.129.8.6	kern	alert	1	1171062692	kernel raid5: Disk failure on sde1, disabling device

- Entries contain information such as: time, message, and tag
  - Time identifies when the message was recorded
  - Message describes the event, typically natural language
  - Tag represents criticality, low values are more important

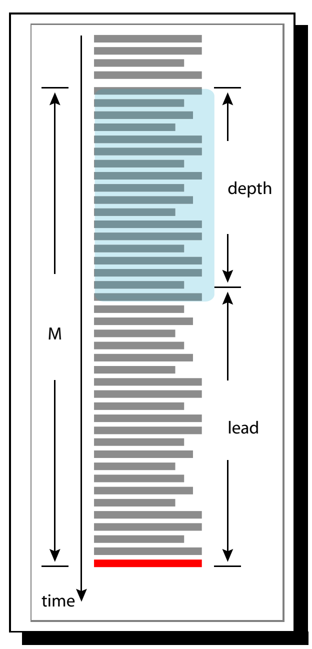
Log Files

Host	Facility	Level	Tag	Time	Message
198.129.8.6	local7	notice	189	1171061732	sysstat
198.129.8.6	kern	info	6	1171061732	kernel md: using maximum available idle IO bandwidth
198.129.8.6	cron	info	78	1171061733	crond 2500 (root) CMD (/usr/lib/sa/sa1 1 1)
198.129.8.6	auth	info	38	1171062445	rsh(pam_unix) 2215 session opened for user by (uid=0)
198.129.8.6	auth	info	38	1171062445	in.rshd 2216 root@hpcs2.cs.edu as root: cmd=/root/temps
198.129.8.6	daemon	info	30	1171062590	smartd 88 Device: /dev/twe0 SMART Prefailure Attribute
198.129.8.18	syslog	info	46	1171062590	syslogd restart.
198.129.7.282	daemon	info	30	1171062590	ntpd 2555 synchronized to 198.129.149.218, str
198.129.7.222	daemon	info	30	1171062590	ntpd 2555 synchronized to 198.129.149.218, str
198.129.7.238	daemon	info	30	1171062590	ntpd 2555 synchronized to 198.129.149.218, str
198.129.8.6	auth	notice	37	1171062590	sshd(pam_unix) 12430 auth failure; logname=el-fork-o
198.129.8.6	kern	info	6	1171062590	kernel md: using 512k, over a total of 12287936 blocks.
198.129.8.6	cron	info	78	1171062601	crond 2500 (root) CMD (/usr/lib/sa/fork-it 1 1)
198.129.8.6	kern	alert	1	1171062692	kernel raid5: Disk failure on sde1, disabling device

- Log file is a list of messages, can be analyzed for
  - Auditing, determine the cause of an event (*past*)
  - Predicting important events (*future*)

Example System Event to Predict

- An interesting event is *disk failure*
  - By 2018 [large systems] could have 300 concurrent reconstructions at any time [SG07]
  - Predicting disk failure is important
  - *Easy to identify event in the log...*
- Predict failure as **early as possible**
  - n messages $M = \{m_1, m_1, ..., m_n\}$
  - Assume m_n is the event
  - Min depth d and max lead l
- *Are all messages the same?*



SMART

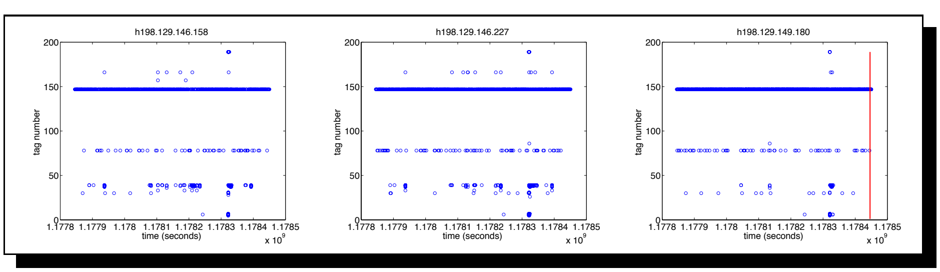
- Self-Monitoring Analysis & Reporting Technology (SMART)
  - SMART disks monitor their health and performance
  - Attributes describe current state, each attribute has unique ID
- Many different types of messages (Attribute and Value)

Attribute	Meaning
1	`Raw_Read_Error_Rate changed to` x
190	`Airflow_Temperature changed to` x
2	`Throughput_Performance`
8	`Seek_Time_Performance`
201	`Soft_Read_Error_Rate changed to` x

- Pinheiro et.al. investigated Google hard drive failure [PWB07]
  - Some SMART parameters do correlate with drive failure
  - Conclude SMART messages alone may **not** be sufficient

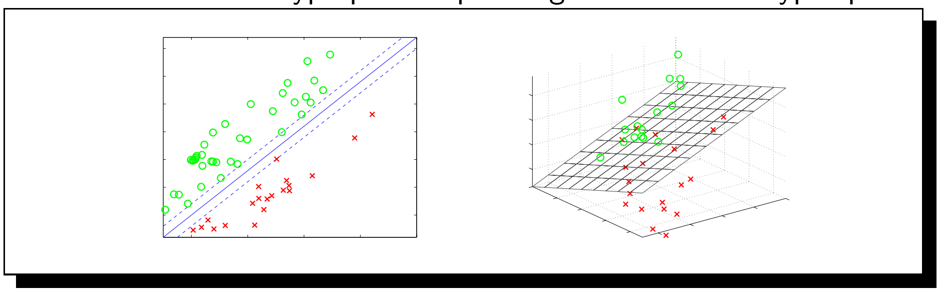
Disk Failure Prediction

- What *features* (information) should be considered?
  - A message contains criticality, message, and time
  - *Is there a series of messages that tend to be a precursor?*
- Consider a sequence of messages arriving (ordered by time)
  - *Is it possible to classify into failure and non-failure classes?*
  - Other approaches have considered Bayesian Nets and HMM



Support Vector Machines

- Support Vector Machine (SVM) is a classification algorithm
  - Consider a set of samples from two different classes
  - Each vector consists of features describing the sample
  - SVM finds a hyperplane separating the classes in hyperspace



  - The vectors closest to the plane are the *support vectors*
- Great for aggregate statistics, *what about series?*
  - Interested in using *sequences of messages* as features

Spectrum Kernel

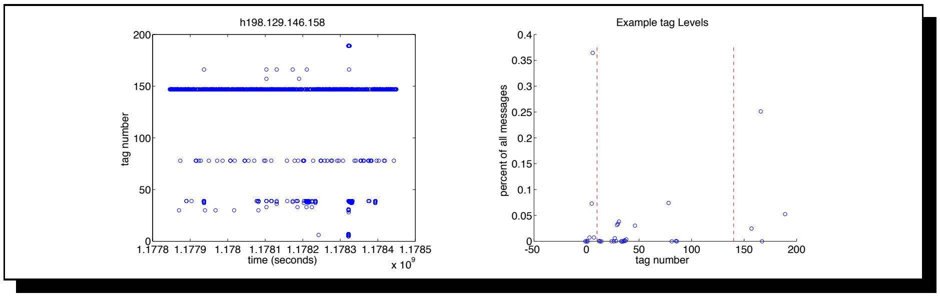
- A spectrum kernel considers k length sequences as features
  - The frequency of the sequence is the feature value
- Assume two symbols $\{A, B\}$ and sequence length $k = 2$
  - There are 2^k possible sequences (features) (AA, AB, BA, BB)
  - Value of a feature is the number of occurrences

$M = \{A, A, B, A, A, B, B, A\}$
AA: 2
AB: 2
BA: 2
BB: 1

  - There are b^k possible sequences, were b is number of symbols
- *How does this work for syslog messages?*

tag Sequences

- Each message has a `tag` that indicates criticality
  - Sequence of messages represented by sequence of `tag` values



  - Need to reduce number of symbols, assume three levels
  - high (`tag` < 10), medium ($10 <$`tag`< 140), low (`tag`> 140)
- Given a series of messages M, process using a *sliding window*
  - Count the number of occurrences of k-length sequences

Example tag Processing

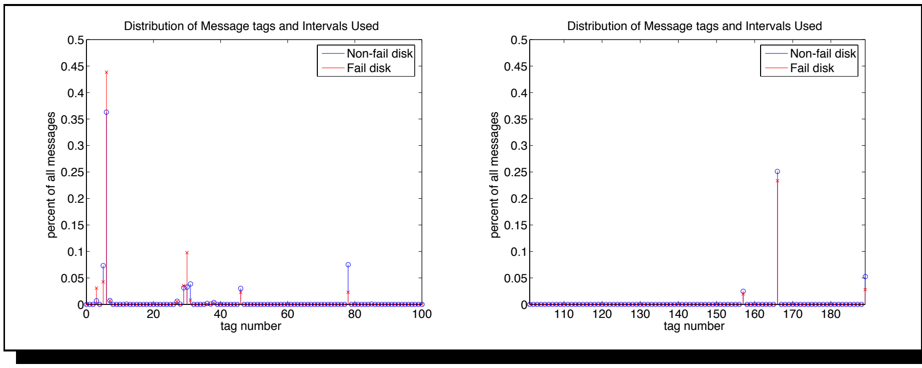
- Let $M = \{148, 148, 158, 40, 158, 188, 188, 88, 158, 188\}$
- Assume $b = 3$ and $k = 5$, then $3^5 = 243$ possible features

`tag`	**Encoding** (e)	**Sequence**	f (base 10)
148	2	2	
148	2	22	
158	2	222	
40	1	2221	
158	2	22212	239
188	2	22122	233
188	2	21222	215
88	1	12221	160
158	2	22212	239
188	2	22122	215

- Feature number is $f_{t+1} = \mod (b \cdot f_t, b^k) + e$
- Vector for M would be (160:1, 215:2, 233:1, 239:2)

System Data used for Experiments

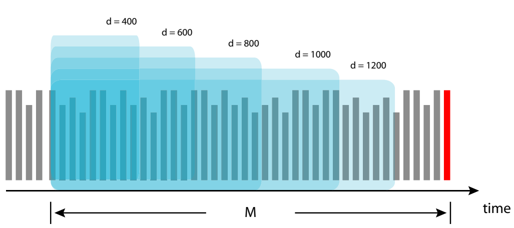
- About 24 months of syslog files from 1024 node Linux cluster
  - Averaged 3.24 messages an hour (78 a day) per machine
  - Observed 120 disk failure events

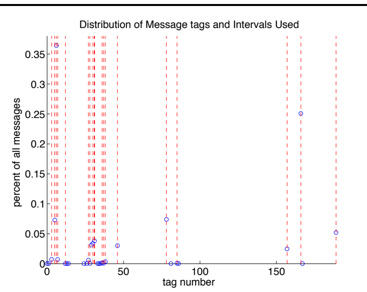


- Tag values ranged from 0 to 189
  - 61 unique tag messages were observed during this time

Prediction Experiments

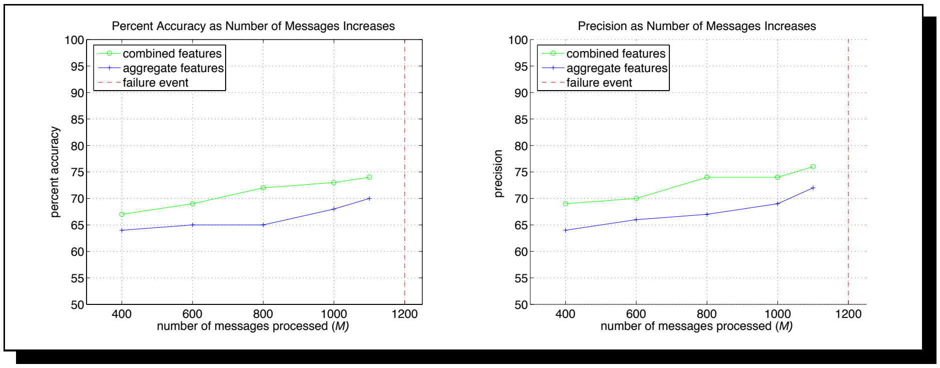
- Sets of M =1200 messages (15 days) collected per machine
  - From first message, processed $d = \{400, 600, 800, 1000, 1100\}$
- One SVM considered aggregate features occurring within d
  - Number of occurrences for each tag value
- Another SVM also considered tag sequences occurring within d
  - Sequences consisted of 5 messages, there were 19 tag ranges





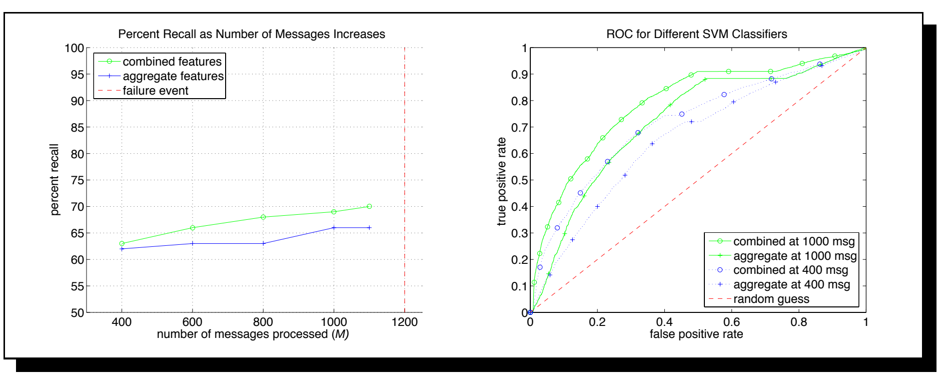
Prediction Results

- Accuracy, precision, recall, and ROC recorded per experiment
  - Where acc=$\frac{TP+TN}{P+N}$, prec= $\frac{TP}{TP+FP}$, and recall= $\frac{TP}{P}$



- More messages improved prediction results
- Combined were better, 73% accuracy with 200 message lead

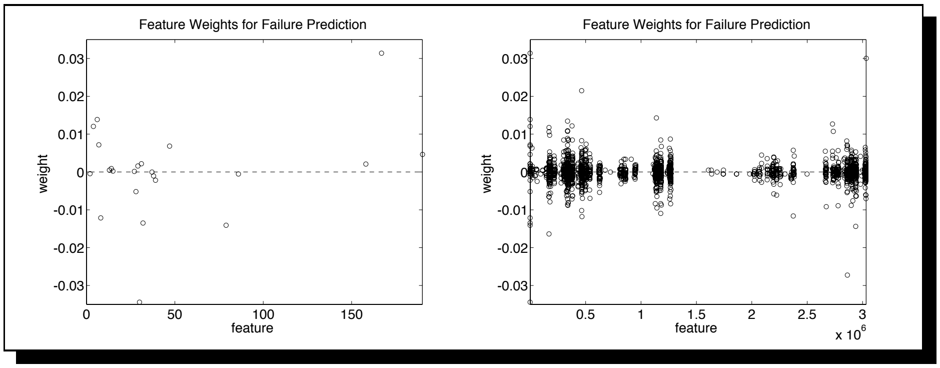
Prediction Results



- ROC curve can be used to compare classifiers/predictions [Faw06]
  - Closer to the *north-west*, the better the performance
  - Some issues with false negatives
- Combined features performed better, typically 4% to 5% increase

Feature Weights

- Use of a *linear kernel* for the SVM allows for feature analysis
  - Larger weight (positive or negative) indicates a feature useful



- Of 2,476,289 features, only 2,251 were useful
  - Of the useful features 22 were aggregate, remaining were sequences

Runtime Performance

- For the combined feature experiments
  - Training time averaged 7 minutes 38 seconds
  - Tesing time averaged 0.21 seconds

Conclusions and Future Work

- Using syslog data to predict disk failures
  - Spectrum-kernel SVM predicted with 73% 100 msg lead
  - Message sequences did improve performance
- Several areas for improvement
  - determine k and b, add new features, ...
  - *How does message rate impact performance?*
  - Need more and different data
- Consider other *interesting* events
  - Other failures, since disk failure $\neq$ node failure
  - *Can this be useful for security?*
  - Multi-system analysis
- Possible to create a *reduced message system?* [YM05]

References

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[PWB07] Eduardo Pinheiro, Wolf-Dietrich Weber, and Luiz André Barroso. Failure trends in a large disk drive population. In *Proceedings of the USENIX Conference on File and Storage Technologies*, pages 17–29, 2007.

[SG07] Bianca Schroeder and Garth A Gibson. Understanding failures in petascale computers. *Journal of Physics: Conference Series*, (28), 2007.

[YM05] Kenji Yamanishi and Yuko Maruyama. Dynamic syslog mining for network failure monitoring. In *Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery in Data Mining*, pages 499–508, 2005.

Other Prediction Stats

Accuracy

$M =$	400	600	800	1000	1100
Agg	64	65	65	68	70
Comb	67	69	72	73	74

Precision

$M =$	400	600	800	1000	1100
Agg	64	66	67	69	72
Comb	67	69	72	73	74

Recall

$M =$	400	600	800	1000	1100
Agg	62	63	63	66	66
Comb	63	66	68	69	70

F-score

$M =$	400	600	800	1000	1100
Agg	63	64	65	67	69
Comb	66	68	71	71	73