Investigating the probability distribution of false negative failure alerts in HPC systems

Mohmed Slim Bouguerra, Ana Gainaru and Franck Cappello

Joint Lab workshop June 2013

Context

IBM's Sequoia

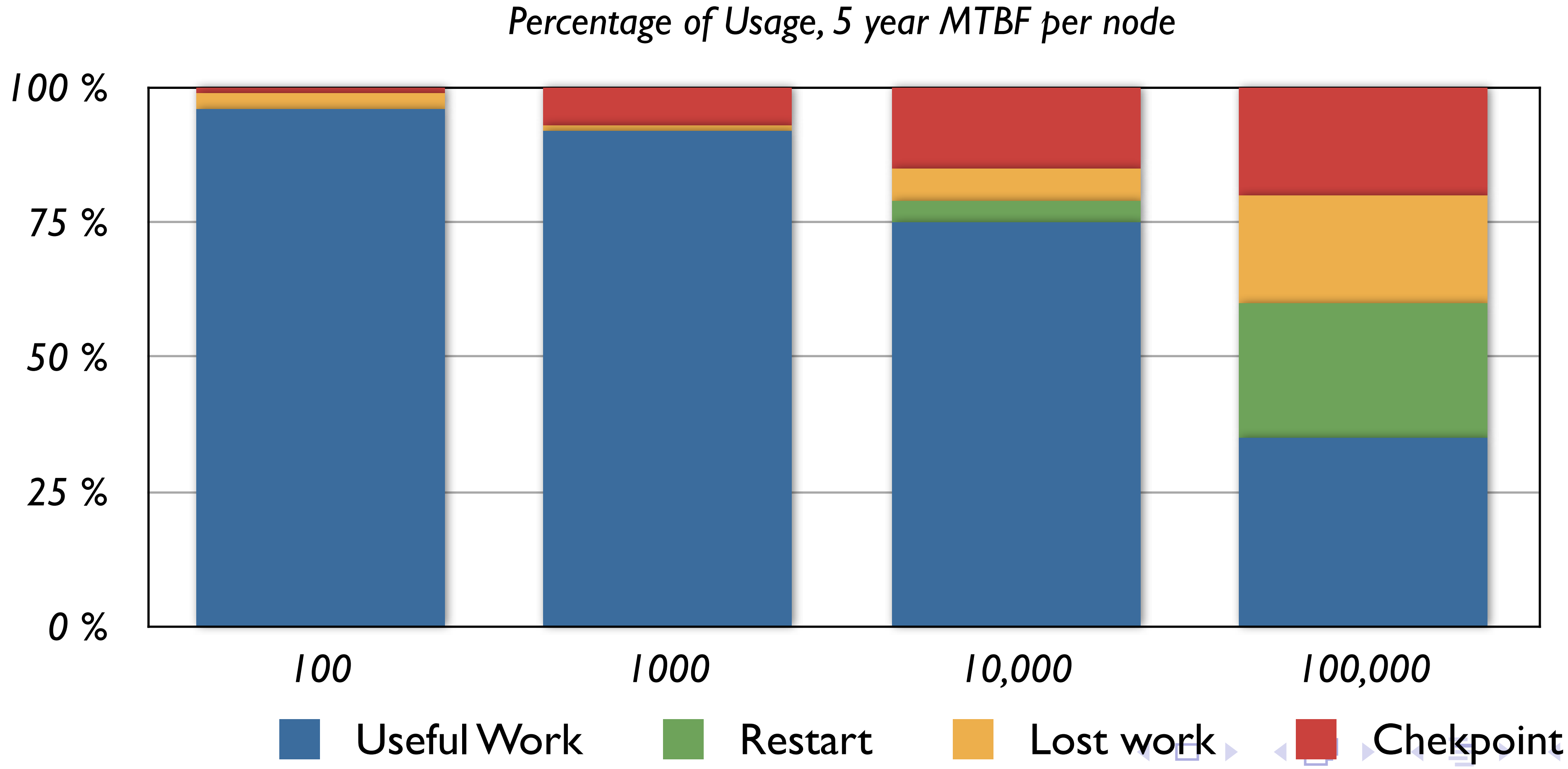
1.25 failure per day

Preventive checkpoint/restart

Context

IBM's Sequoia

1.25 failure per day



Motivations

Main Motivation

Effective and efficient combination between proactive and preventive fault tolerance strategies.

See:

Improving the Computing Efficiency of HPC Systems Using a Combination of Proactive and Preventive Checkpointing

IPDPS 2013

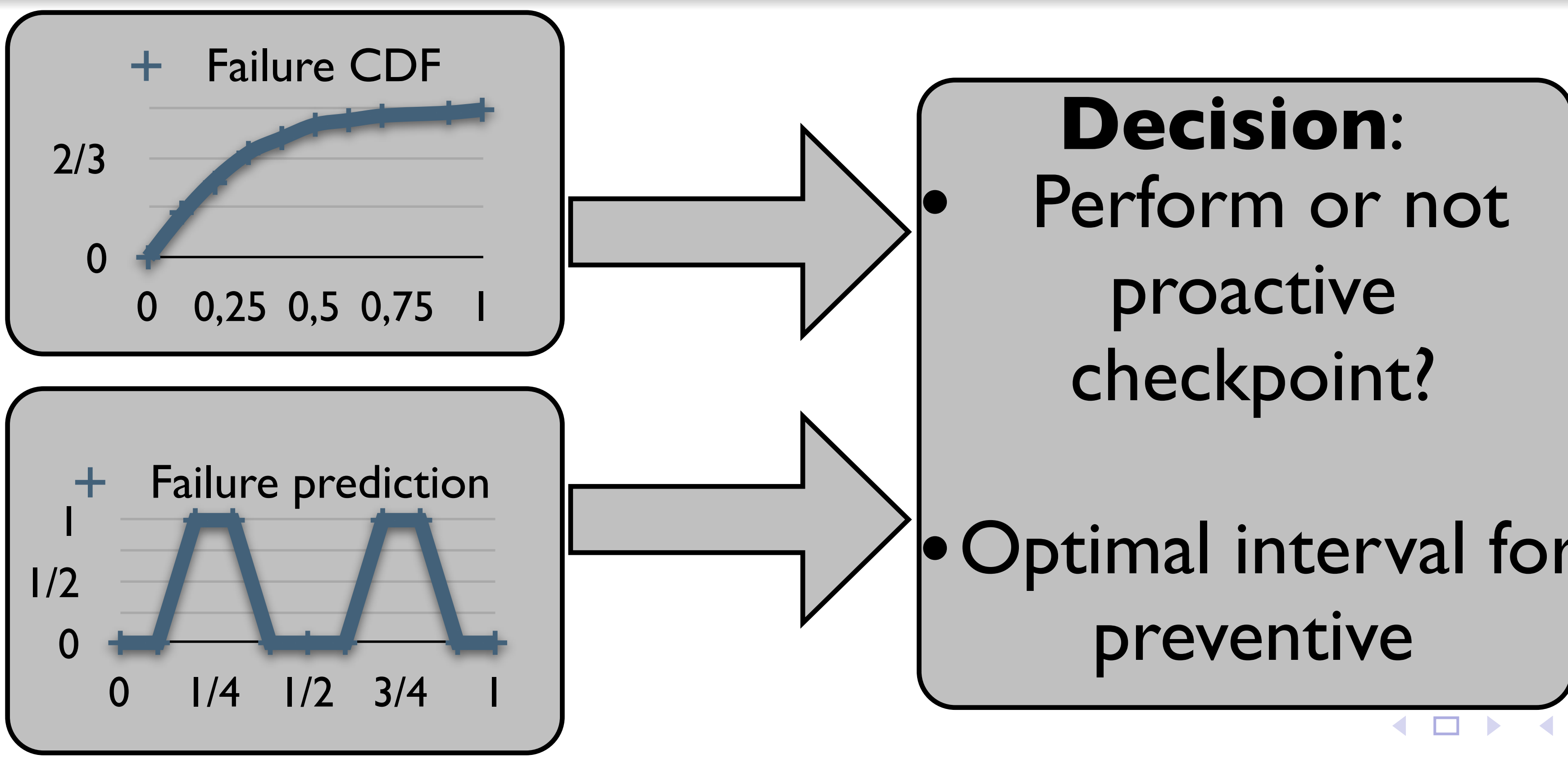
Motivations

Main Motivation

Effective and efficient combination between proactive and preventive fault tolerance strategies.

Challenge

Checkpoint interval selection problem.



Motivations

Main Motivation

Effective and efficient combination between proactive and preventive fault tolerance strategies.

Challenge

Checkpoint interval selection problem.

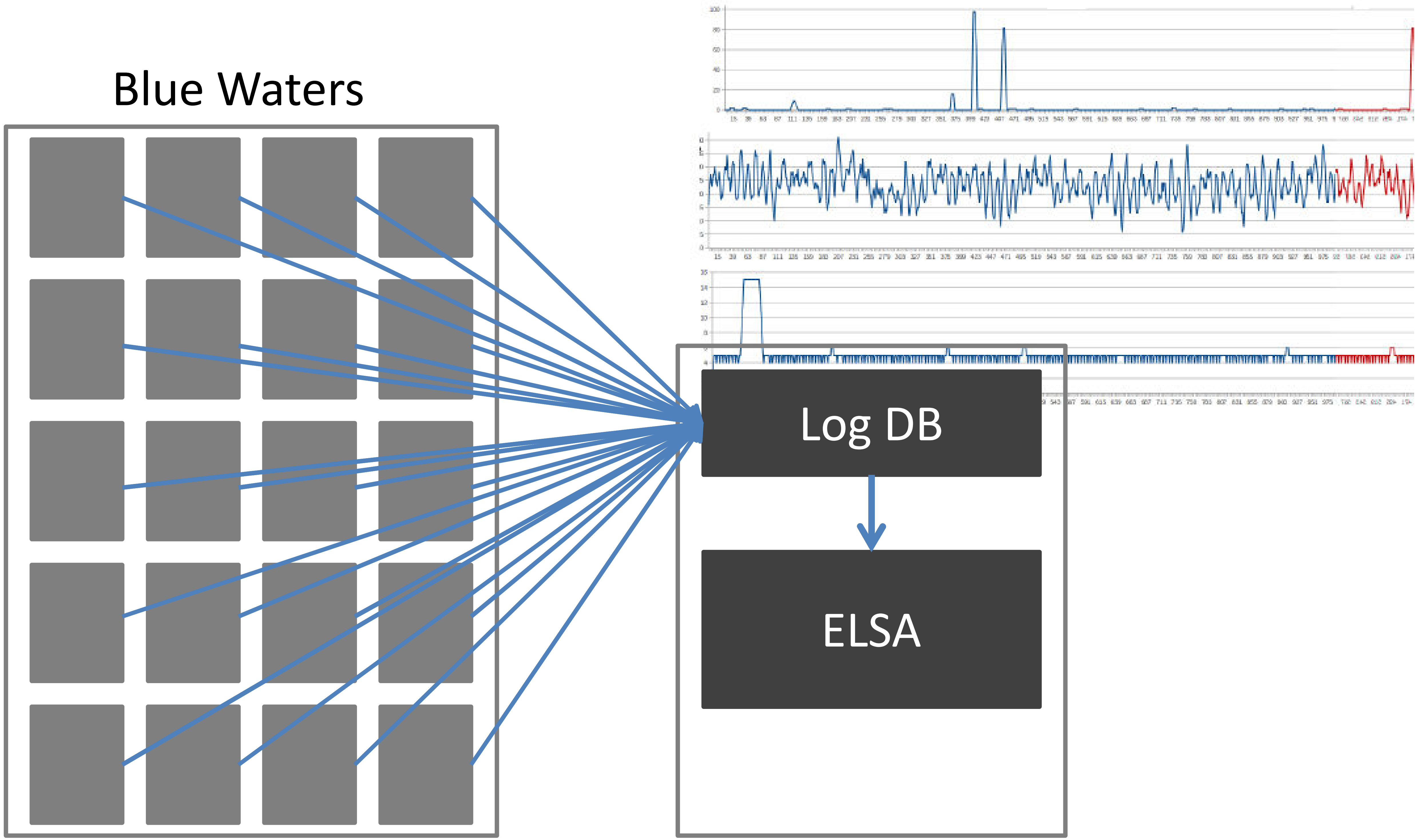
Objective

Advanced models to shape the relation between the occurrences of failures and the failure prediction mechanisms in HPC.

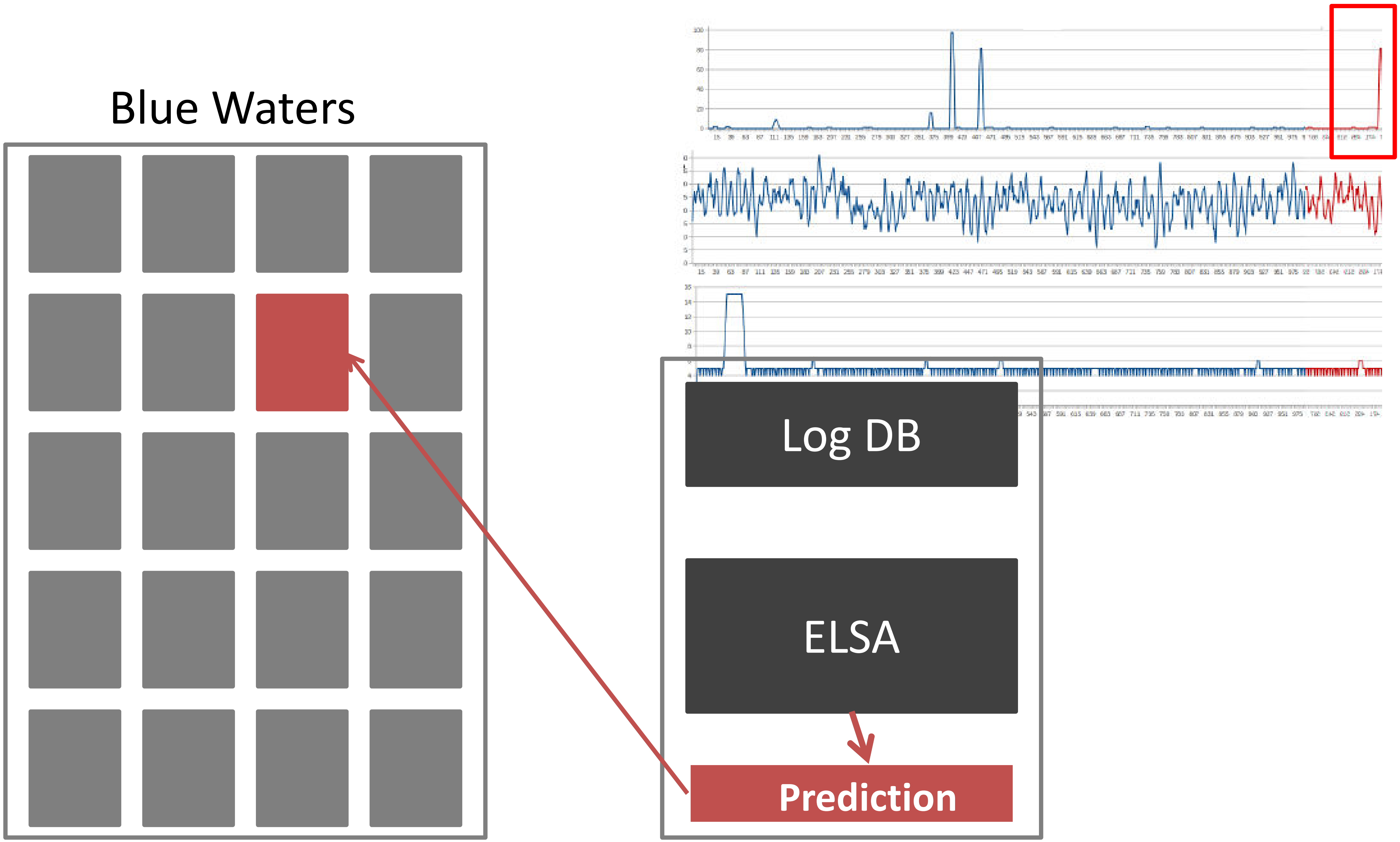
1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

Let's remember ELSA



Let’s remember ELSA



Proactive and preventive fault tolerance

Prediction is feasible

- ELSA: Signal analysis with data mining:
  - 90% precision and 45% recall.
  - At least 10 seconds of lead-time.
  - Failure location is provided.

Proactive and preventive fault tolerance

Prediction is feasible

- ELSA: Signal analysis with data mining:
  - 90% precision and 45% recall.
  - At least 10 seconds of lead-time.
  - Failure location is provided.

Fast checkpointing strategies exist

- FTI (Fault Tolerance Interface):
  - Capable of taking a checkpoint in 5s for 1GB memory.
  - Multi-level checkpoint with 8% overhead.

Online failure prediction terminology

Terminology

- True positive alert (correct prediction)
- False positive alert (misleading prediction)
- False negative alert (the failure was not predicted)

Online failure prediction terminology

Terminology

- True positive alert (correct prediction)
- False positive alert (misleading prediction)
- False negative alert (the failure was not predicted)

Metric

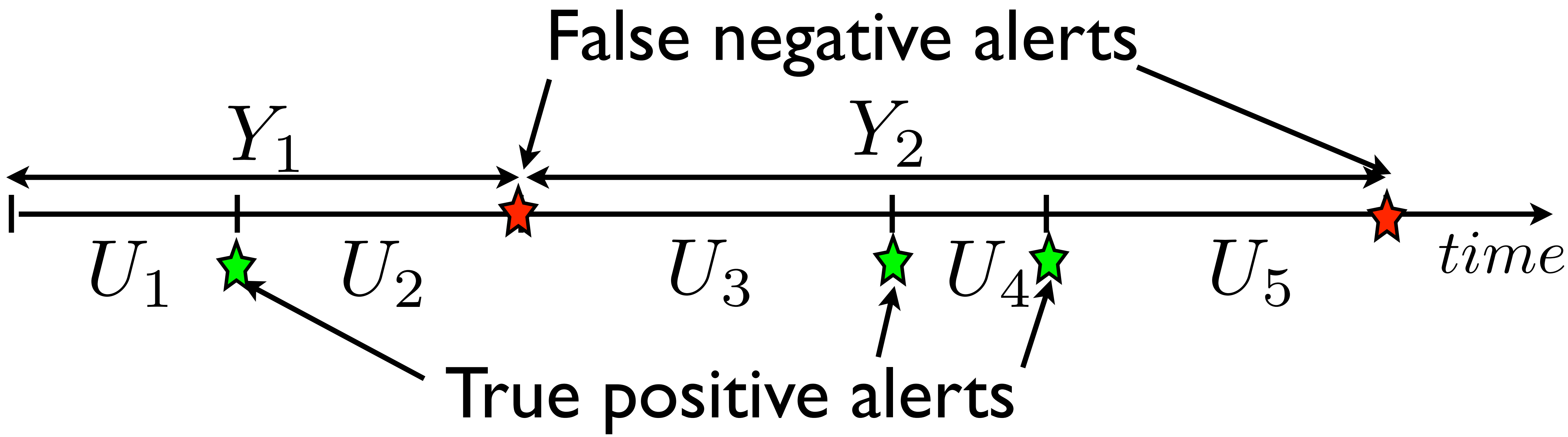
- Recall:

$$\frac{\#\text{True positive}}{\#\text{True positive} + \#\text{False negative}}$$

- Precision:

$$\frac{\#\text{True positive}}{\#\text{True positive} + \#\text{False positive}}$$

What is Modeled ?



Main focus

- The distribution of interval of time that separates false negative alerts.
- The relation between the original failure distribution and the obtained false negative distribution (relation between Y_i and U_i)

1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

Data characteristics

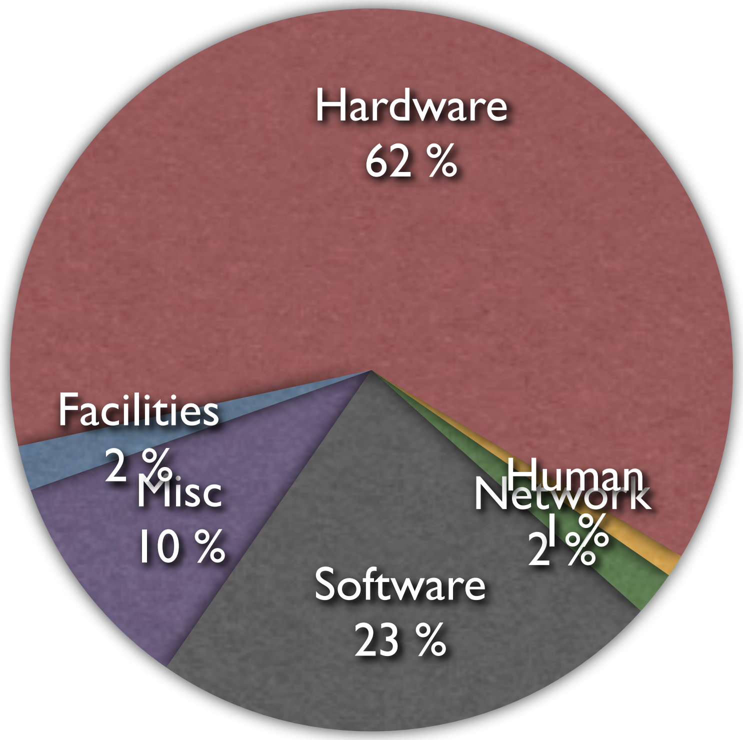
- 22 High performance computing systems from Los Alamos National Lab.
  - December 1996 - November 2005.
  - Different architectures and sizes.
  - 433,490 per system.
  - MTBF, 13 to 215 hours.
  - Failures are manually annotated.

Data characteristics

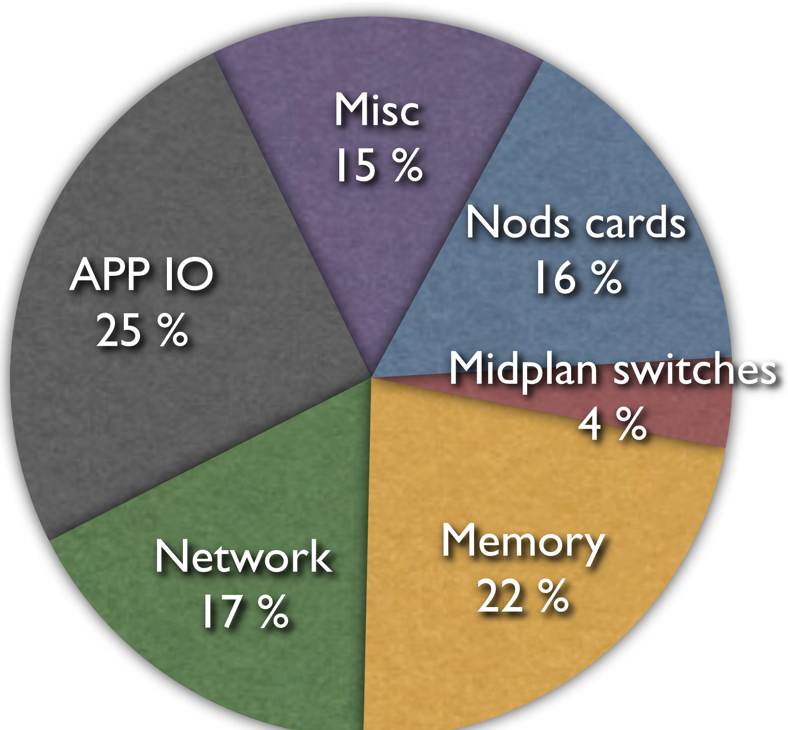
- 22 High performance computing systems from Los Alamos National Lab.
    - December 1996 - November 2005.
    - Different architectures and sizes.
    - 433,490 per system.
    - MTBF, 13 to 215 hours.
    - Failures are manually annotated.
- BlueGene/L at Lawrence Livermore National Lab.
    - June 2005 - january 2006.
    - 128K PowerPc 440 processors.
    - 4,747,963 events.
    - MTBF 24h.
    - Anomaly detection technique.

Failure prediction characteristics

22 HPC systems

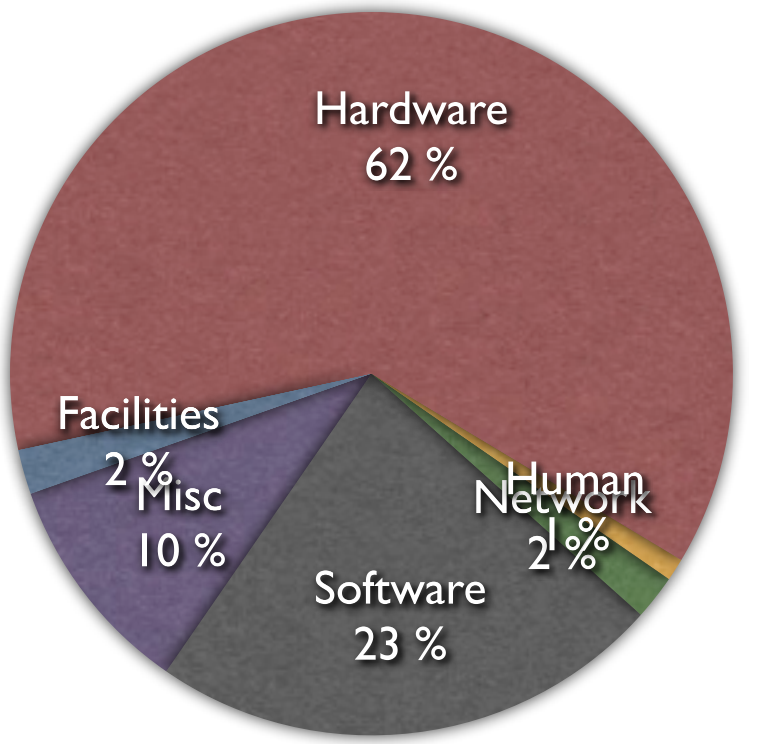


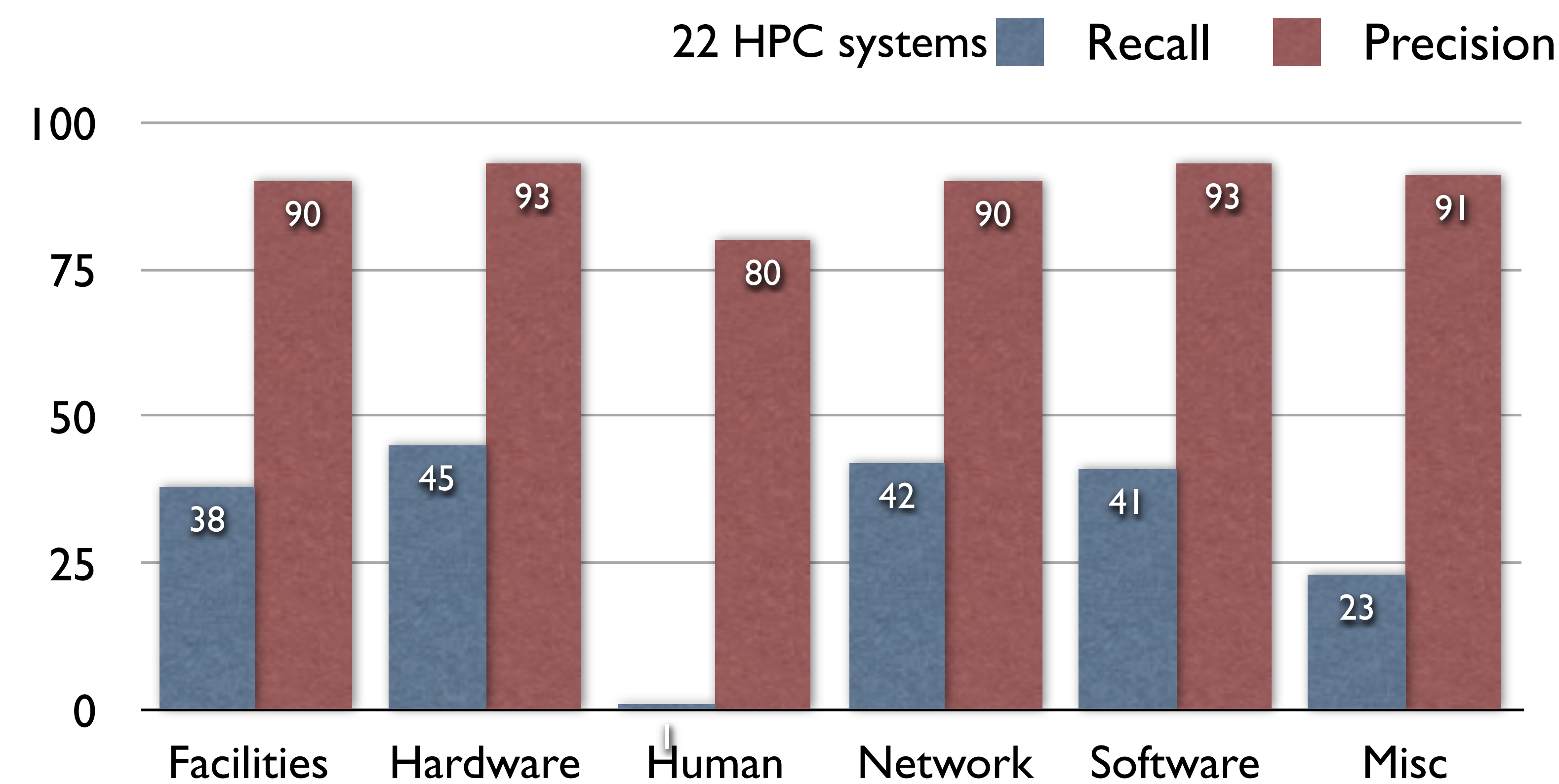
BG/L



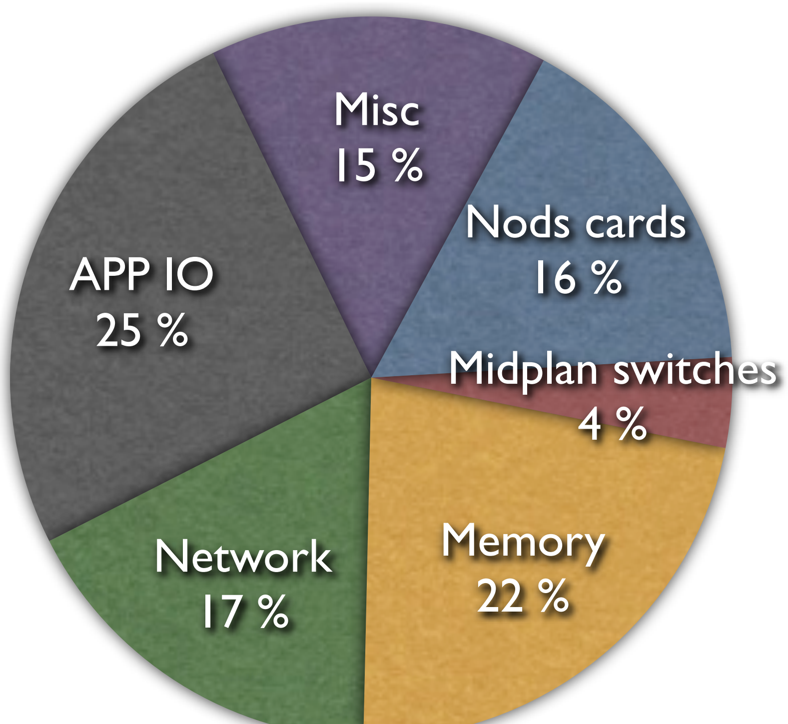
Failure prediction characteristics

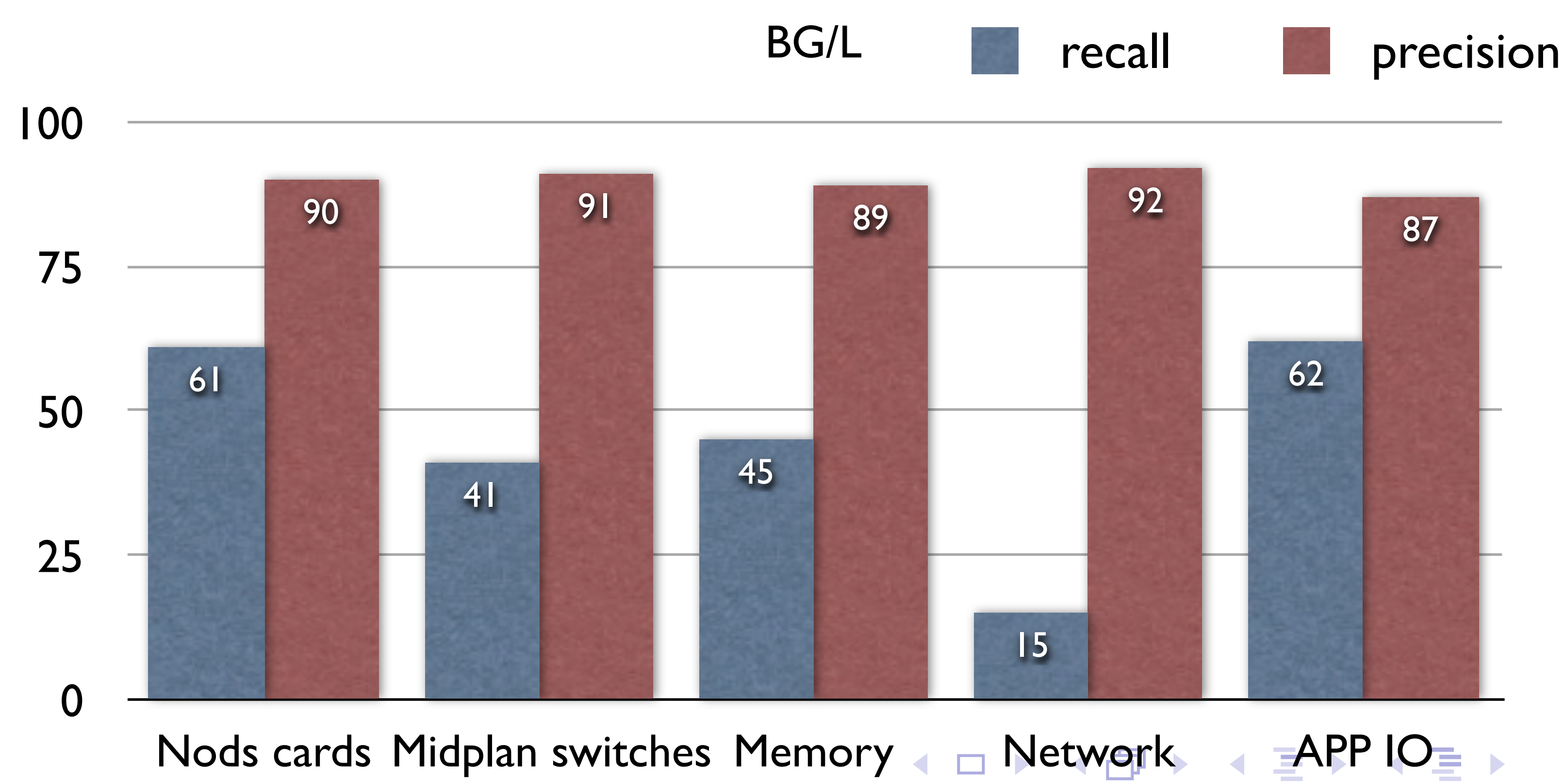
22 HPC systems





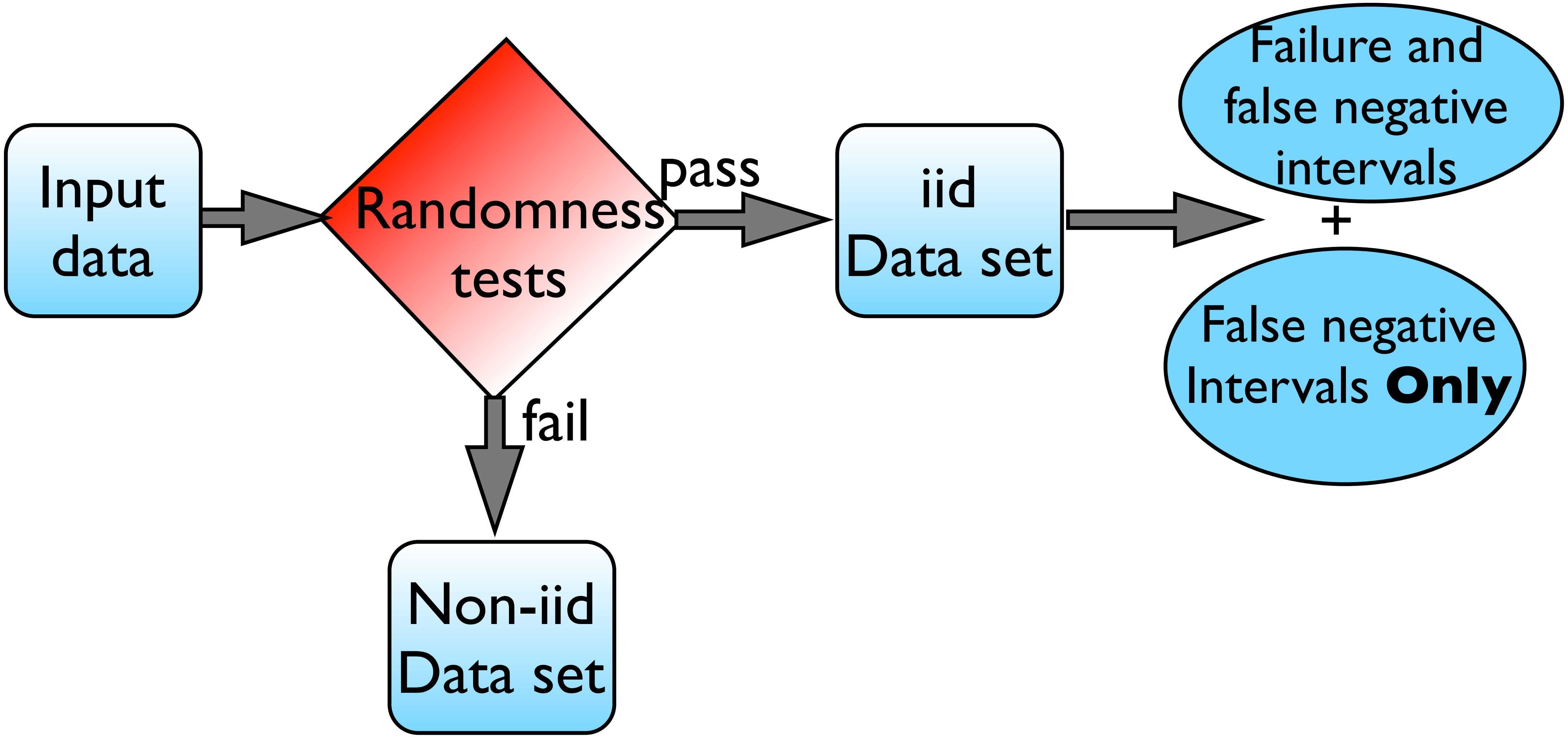
BG/L





1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

Methodology: Randomness Test



Method:

- Runs test
- Runs up/down test
- Autocorrelation function test (ACF)

Randomness tests output

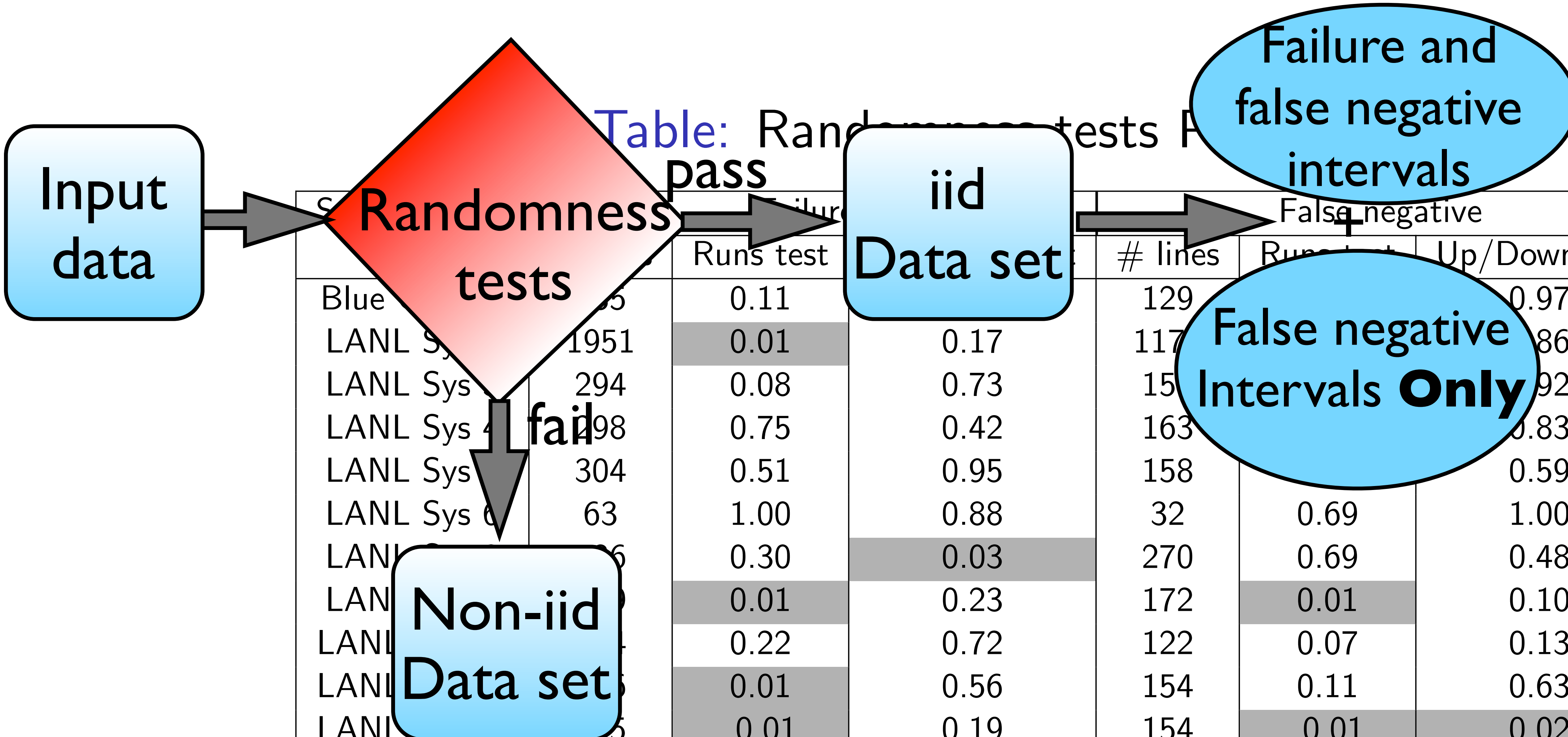


Table: Randomness tests P[illegible]

S[illegible]	[illegible]	Failure			False negative	
		Runs test	[illegible]	# lines	Ru[illegible]	Up/Down test
Blue [illegible]	[illegible]5	0.11	[illegible]	129	[illegible]	0.97
LANL S[illegible]	1951	0.01	0.17	117[illegible]	[illegible]	[illegible]86
LANL Sys [illegible]	294	0.08	0.73	15[illegible]	[illegible]	[illegible]92
LANL Sys 4	[illegible]98	0.75	0.42	163	[illegible]	[illegible].83
LANL Sys [illegible]	304	0.51	0.95	158	[illegible]	0.59
LANL Sys 6	63	1.00	0.88	32	0.69	1.00
LAN[illegible]	[illegible]6	0.30	0.03	270	0.69	0.48
LAN[illegible]	[illegible]	0.01	0.23	172	0.01	0.10
LANL [illegible]	[illegible]	0.22	0.72	122	0.07	0.13
LANL [illegible]	[illegible]	0.01	0.56	154	0.11	0.63
LANL [illegible]	[illegible]5	0.01	0.19	154	0.01	0.02
LANL Sys 13	194	0.04	0.74	123	0.80	0.53
LANL Sys 14	120	0.06	0.36	75	0.49	0.17
LANL Sys 15	53	0.01	0.87	32	0.50	0.51
LANL Sys 16	245	0.04	0.98	159	0.62	0.97
LANL Sys 18	3917	0.01	0.01	2195	0.66	0.74
LANL Sys 19	3235	0.03	0.54	1785	0.08	0.86
LANL Sys 20	2400	0.01	0.14	1310	0.01	0.85
LANL Sys 21	105	0.02	0.01	76	0.39	0.96
LANL Sys 22	17	not	enough	lines		
LANL Sys 23	226	0.32	0.41	129	0.15	0.55
LANL Sys 24	23	not	enough	lines		

Randomness tests output

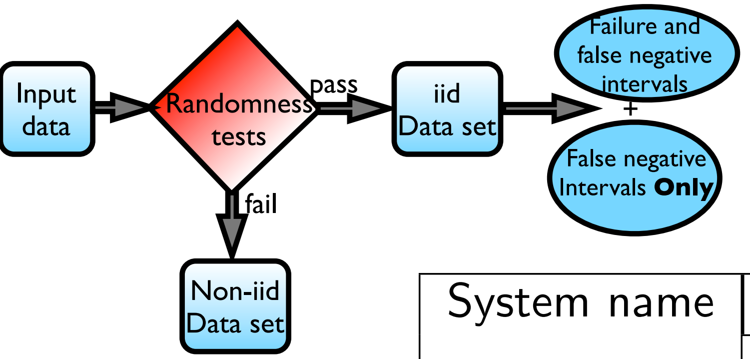
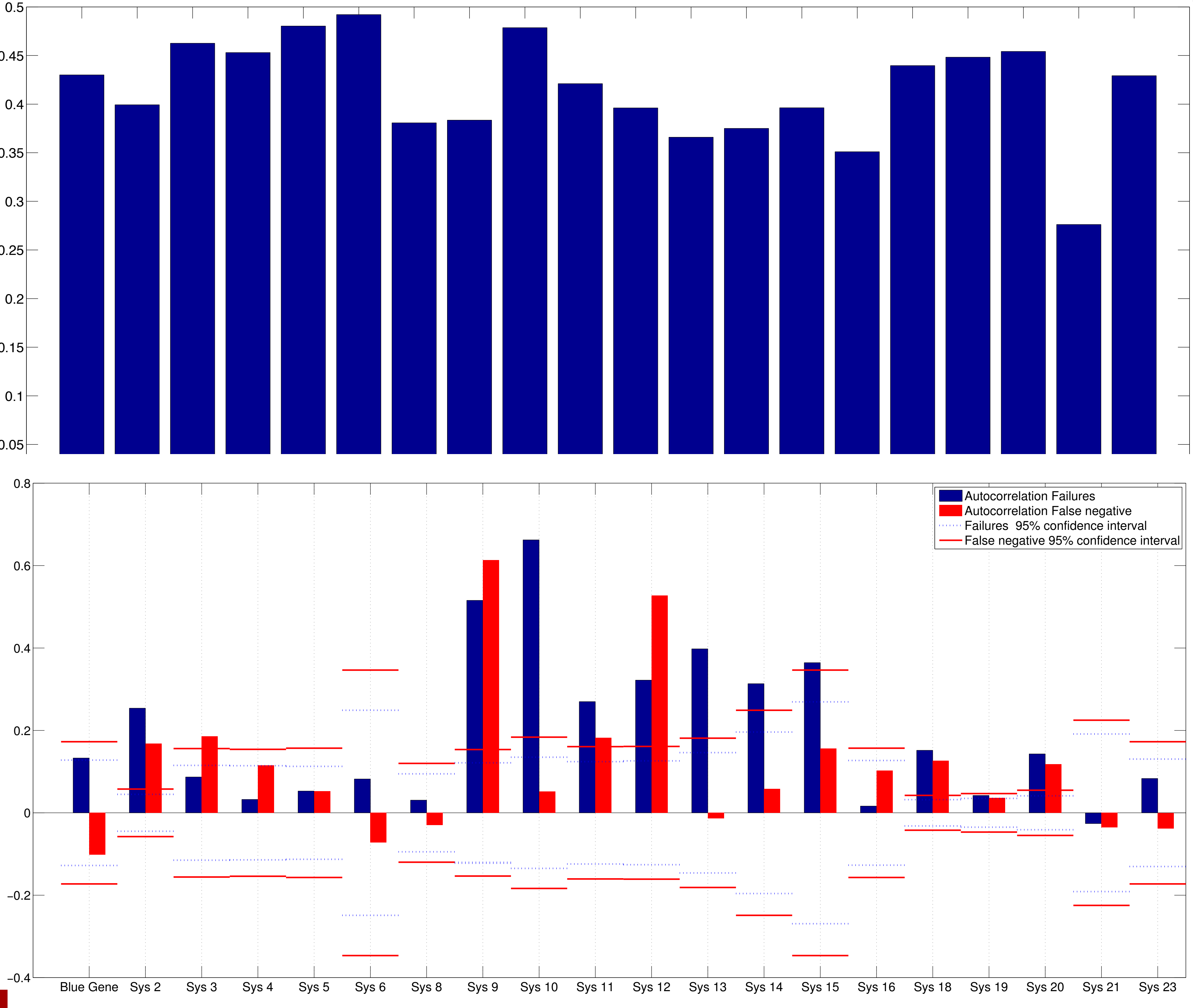


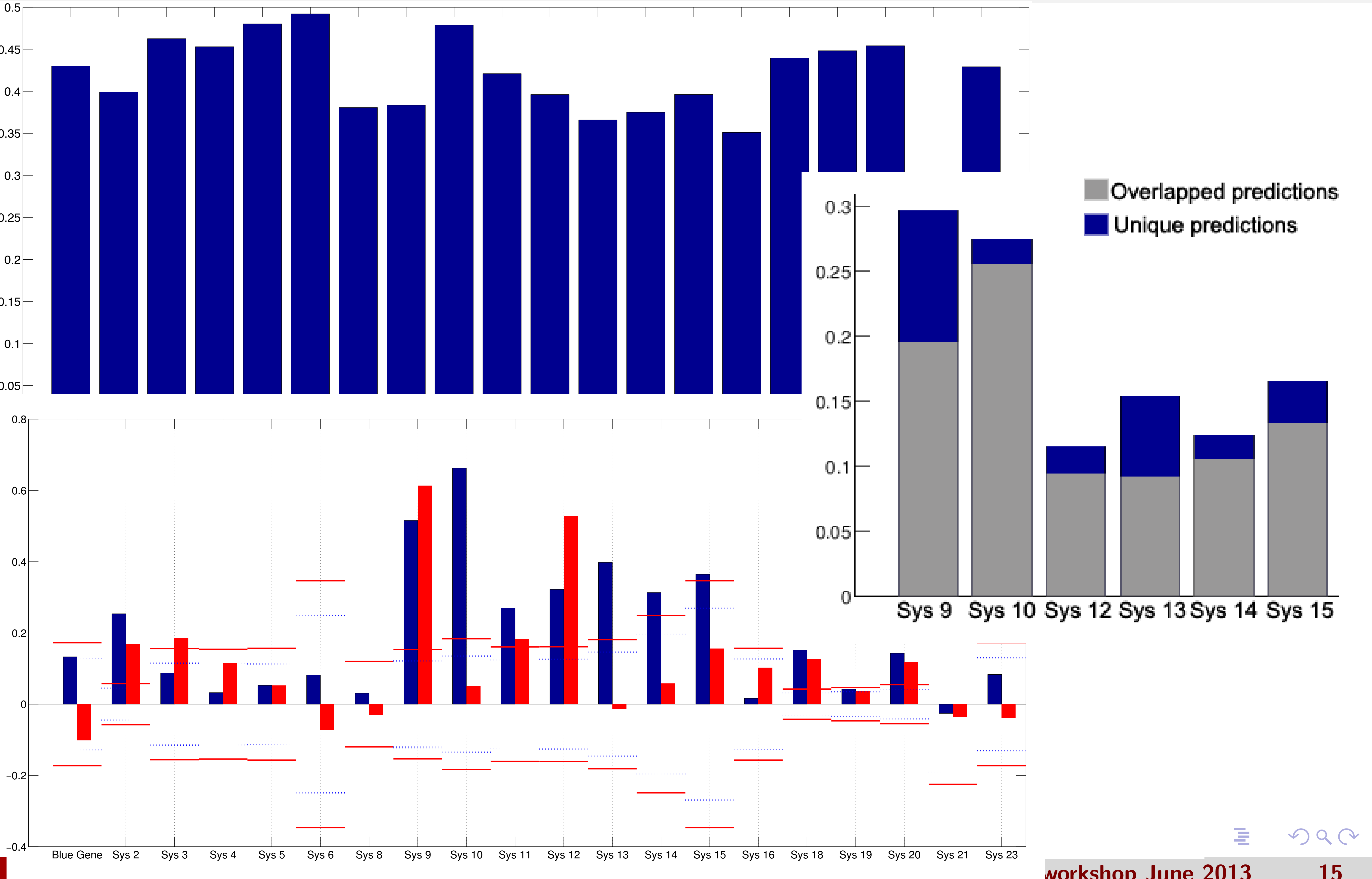
Table: Randomness tests P-values

System name	Failures			False negative		
	# lines	Runs test	Up/Down test	# lines	Runs test	Up/Down test
Blue Gene/L	235	0.11	0.17	129	0.70	0.97
LANL Sys 2	1951	0.01	0.17	1172	0.01	0.86
LANL Sys 3	294	0.08	0.73	158	0.36	0.92
LANL Sys 4	298	0.75	0.42	163	0.15	0.83
LANL Sys 5	304	0.51	0.95	158	0.83	0.59
LANL Sys 6	63	1.00	0.88	32	0.69	1.00
LANL Sys 8	436	0.30	0.03	270	0.69	0.48
LANL Sys 9	279	0.01	0.23	172	0.01	0.10
LANL Sys 10	234	0.22	0.72	122	0.07	0.13
LANL Sys 11	266	0.01	0.56	154	0.11	0.63
LANL Sys 12	255	0.01	0.19	154	0.01	0.02
LANL Sys 13	194	0.04	0.74	123	0.80	0.53
LANL Sys 14	120	0.06	0.36	75	0.49	0.17
LANL Sys 15	53	0.01	0.87	32	0.50	0.51
LANL Sys 16	245	0.04	0.98	159	0.62	0.97
LANL Sys 18	3917	0.01	0.01	2195	0.66	0.74
LANL Sys 19	3235	0.03	0.54	1785	0.08	0.86
LANL Sys 20	2400	0.01	0.14	1310	0.01	0.85
LANL Sys 21	105	0.02	0.01	76	0.39	0.96
LANL Sys 22	17	not	enough	lines		
LANL Sys 23	226	0.32	0.41	129	0.15	0.55
LANL Sys 24	23	not	enough	lines		

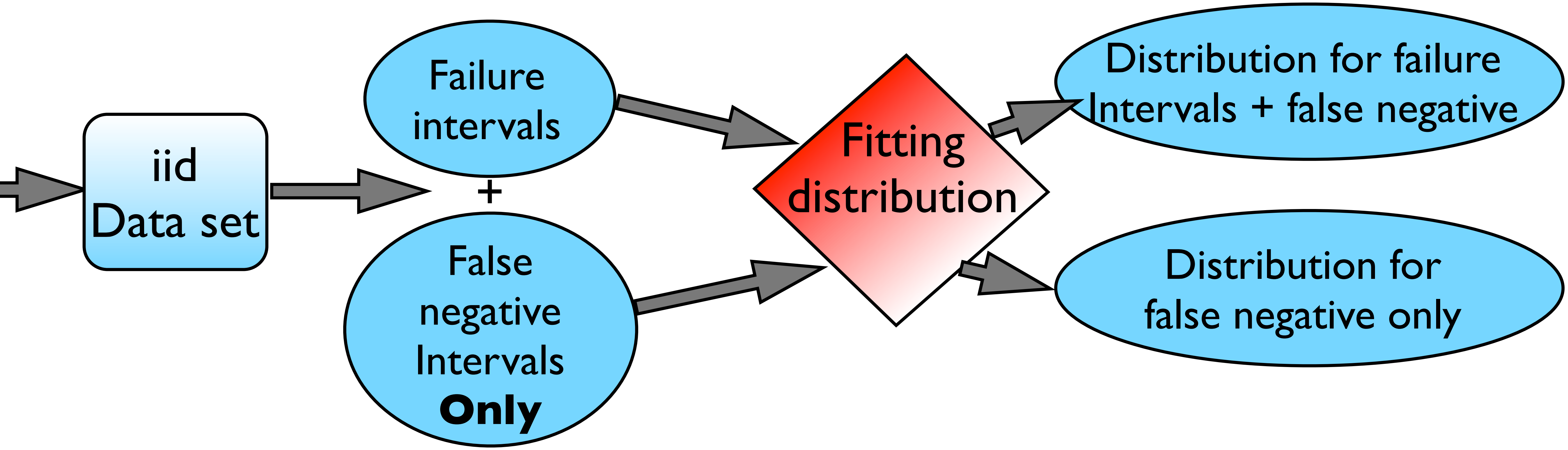
Randomness tests output



Randomness tests output



Methodology: Fitting



Method:

- Maximum Likelihood Estimation (MLE)

Target Distributions: Exponential, Weibull, Log-normal and Gamma.

Fitting output

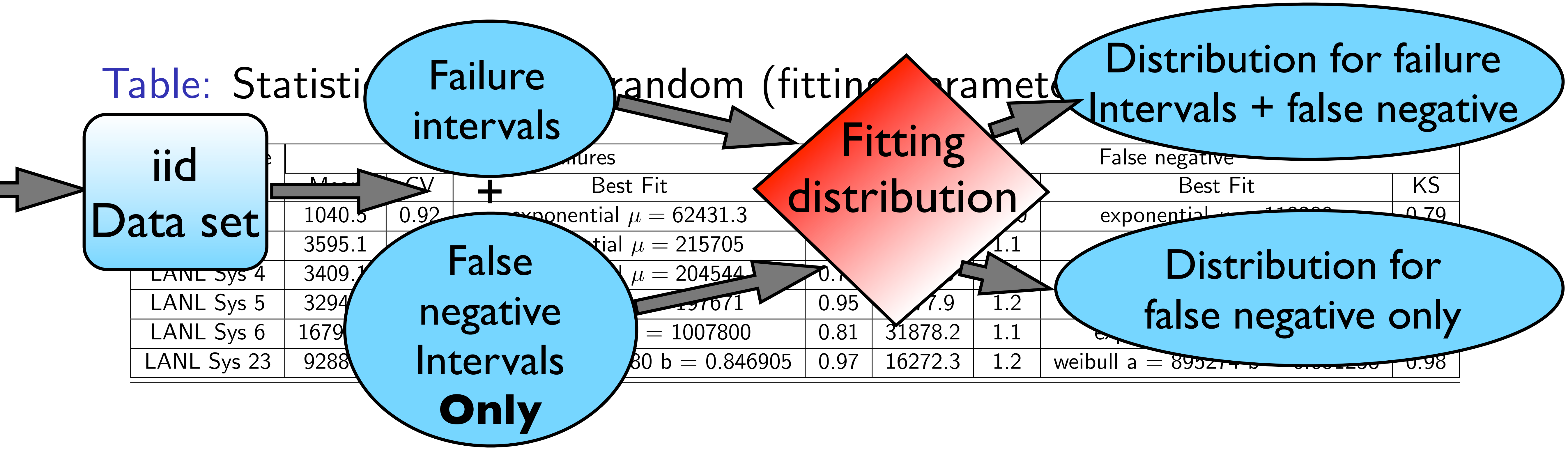


Table: Statistical Fitting false negative random

System name	False negative			
	Mean	CV	Best Fit	KS
LANL Sys 8	7859.6	1.4	weibull a = 401499 b = 0.767798	0.74
LANL Sys 10	8247.0	3.6	weibull a = 318087 b = 0.647838	0.29
LANL Sys 11	6353.5	3.0	weibull a = 232647 b = 0.609348	0.61
LANL Sys 13	8164.3	3.9	lognormal μ = 11.5257 σ = 1.87004	0.14
LANL Sys 14	11351.0	2.5	weibull a = 391931 b = 0.559039	0.77
LANL Sys 15	12136.7	1.2	exponential μ = 728203	0.17
LANL Sys 16	3430.6	1.3	weibull a = 182624 b = 0.810939	0.69
LANL Sys 18	818.6	1.5	lognormal μ = 10.1123 σ = 1.28677	0.37
LANL Sys 19	863.6	1.4	exponential μ = 29000.5	0.18
LANL Sys 21	1986.9	2.3	lognormal μ = 10.6382 σ = 1.46402	0.85

Fitting output

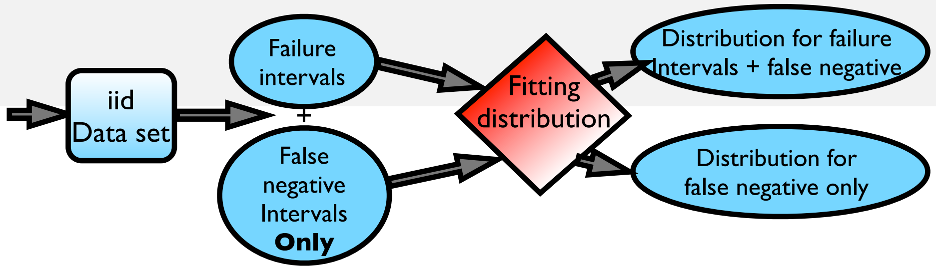


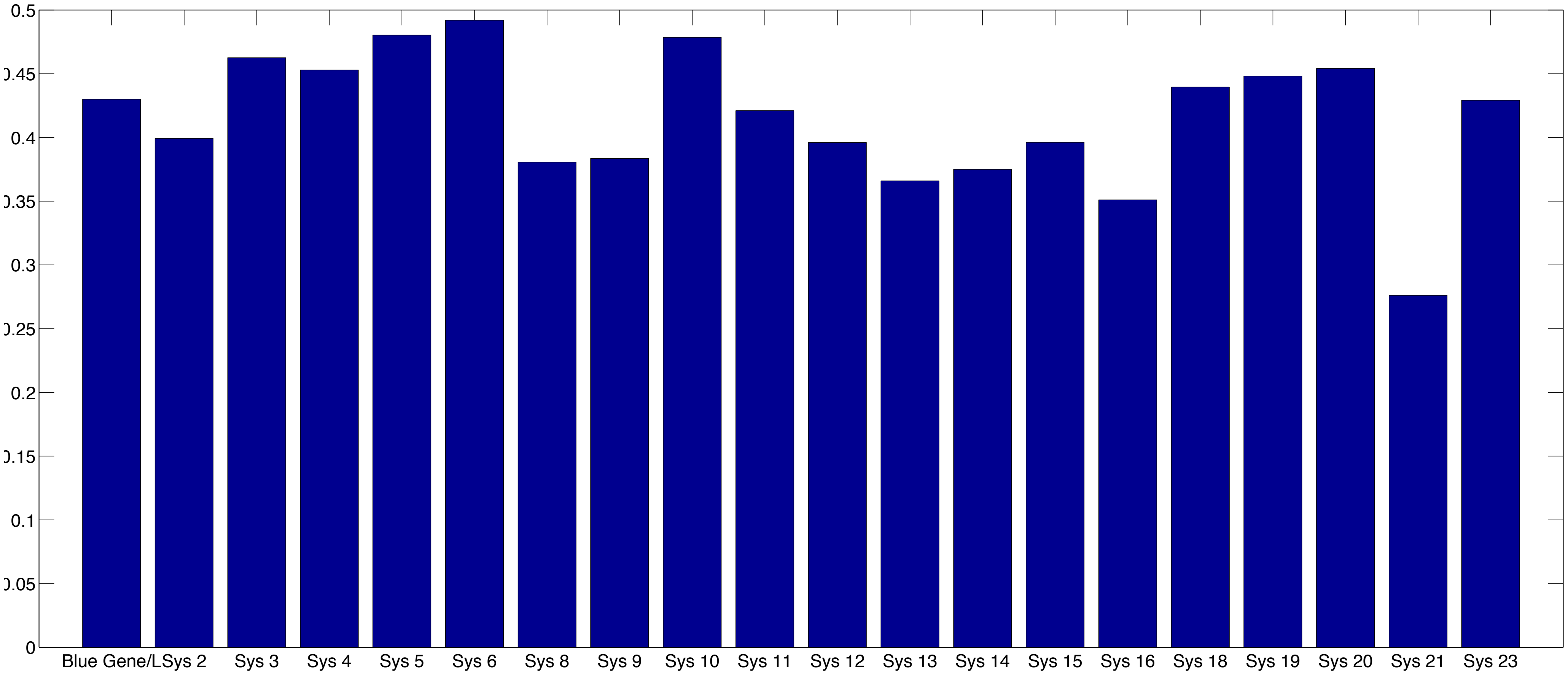
Table: Statistical fitting all random (fitting parameters scale are in seconds)

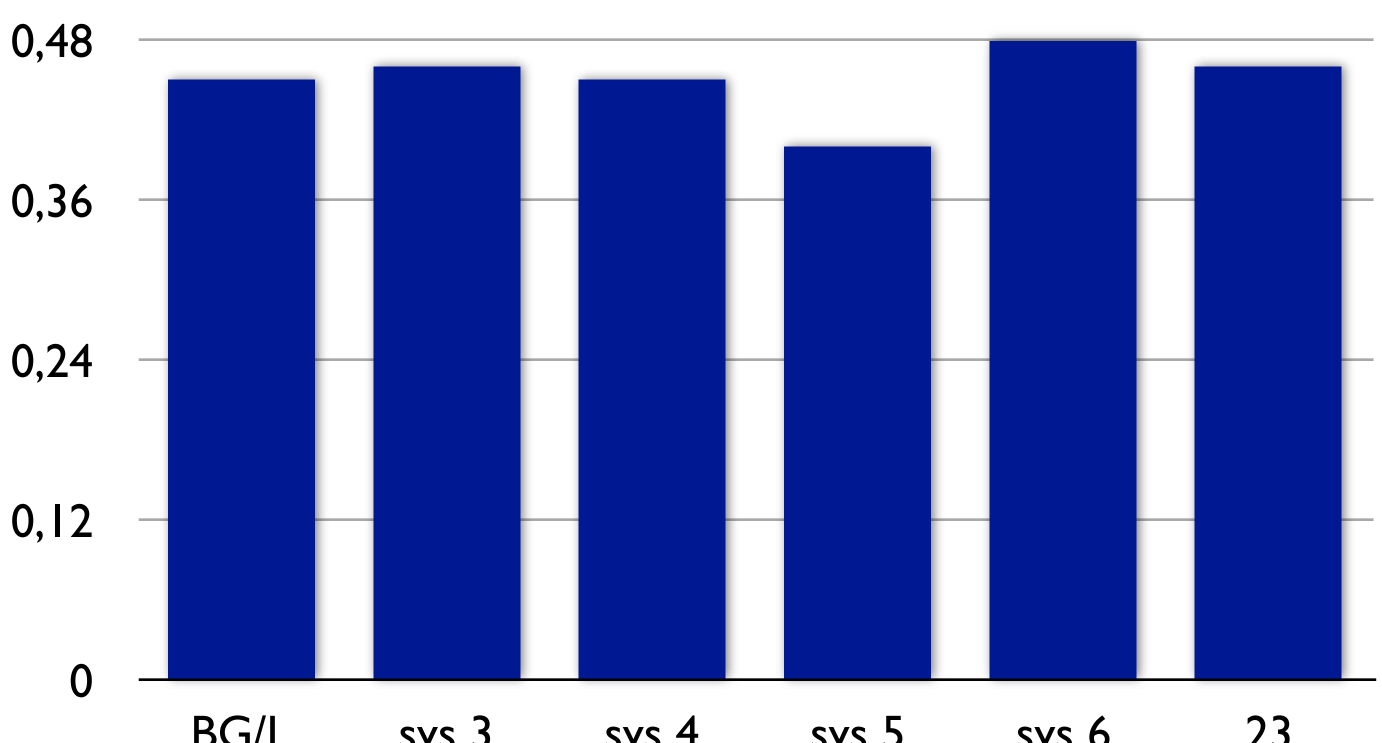
System name	Failures				False negative			
	Mean	CV	Best Fit	KS	Mean	CV	Best Fit	KS
Blue Gene/L	1040.5	0.92	exponential $\mu = 62431.3$	0.10	1888.1	1.10	exponential $\mu = 113289$	0.79
LANL Sys 3	3595.1	1.1	exponential $\mu = 215705$	0.98	6559.0	1.1	exponential $\mu = 393538$	0.70
LANL Sys 4	3409.1	1.1	exponential $\mu = 204544$	0.77	6187.0	1.1	exponential $\mu = 371218$	0.99
LANL Sys 5	3294.5	1.1	exponential $\mu = 197671$	0.95	6377.9	1.2	exponential $\mu = 382671$	0.35
LANL Sys 6	16796.7	0.9	exponential $\mu = 1007800$	0.81	31878.2	1.1	exponential $\mu = 1912690$	0.99
LANL Sys 23	9288.2	1.3	weibull a = 509380 b = 0.846905	0.97	16272.3	1.2	weibull a = 895274 b = 0.851258	0.98

Table: Statistical Fitting false negative random

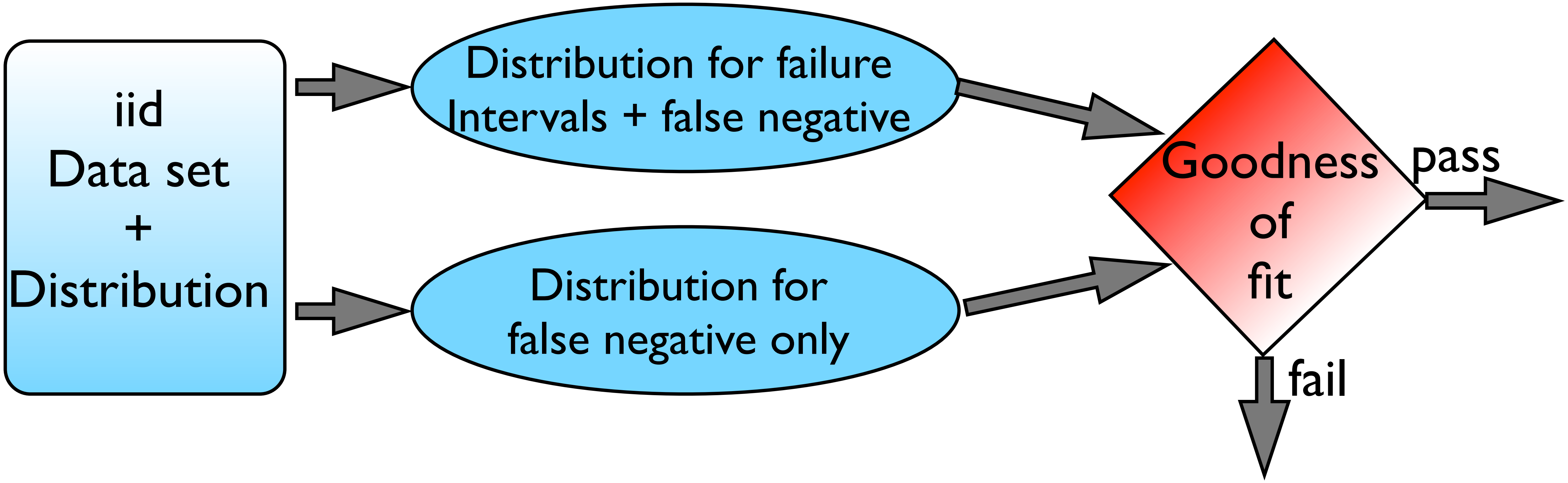
System name	False negative			
	Mean	CV	Best Fit	KS
LANL Sys 8	7859.6	1.4	weibull a = 401499 b = 0.767798	0.74
LANL Sys 10	8247.0	3.6	weibull a = 318087 b = 0.647838	0.29
LANL Sys 11	6353.5	3.0	weibull a = 232647 b = 0.609348	0.61
LANL Sys 13	8164.3	3.9	lognormal $\mu = 11.5257$ $\sigma = 1.87004$	0.14
LANL Sys 14	11351.0	2.5	weibull a = 391931 b = 0.559039	0.77
LANL Sys 15	12136.7	1.2	exponential $\mu = 728203$	0.17
LANL Sys 16	3430.6	1.3	weibull a = 182624 b = 0.810939	0.69
LANL Sys 18	818.6	1.5	lognormal $\mu = 10.1123$ $\sigma = 1.28677$	0.37
LANL Sys 19	863.6	1.4	exponential $\mu = 29000.5$	0.18
LANL Sys 21	1986.9	2.3	lognormal $\mu = 10.6382$ $\sigma = 1.46402$	0.85

Fitting output





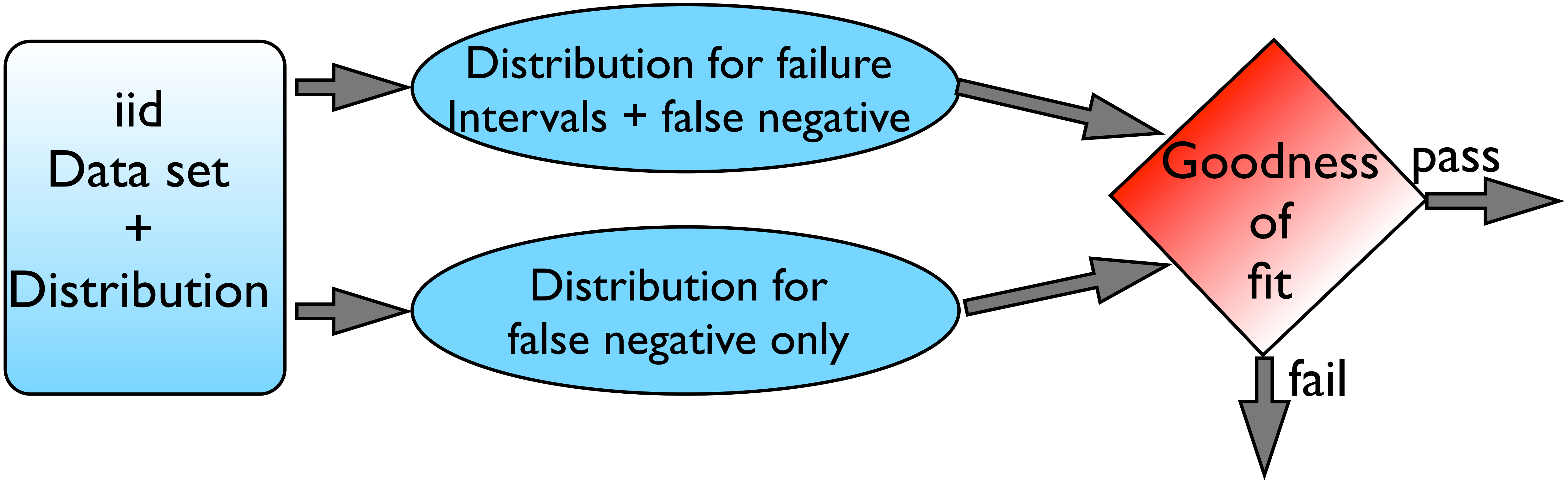
Methodology: Goodness of fit



Method:

- Kolmogorov-Smirnov test
- Probability-Probability plot (PP-plot).

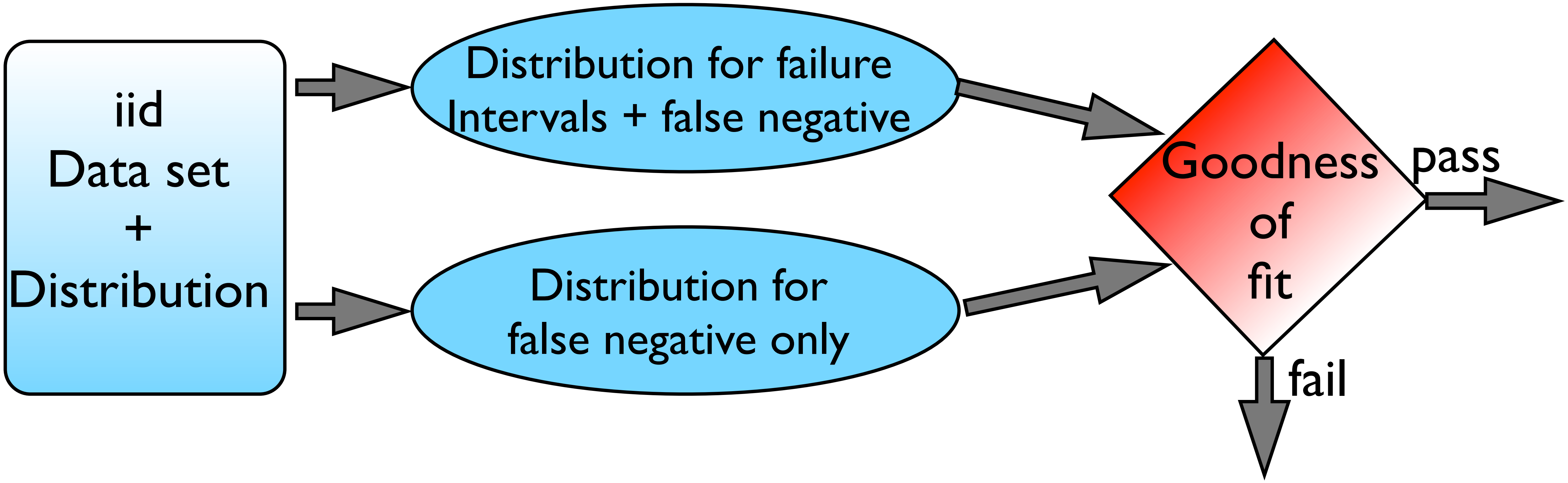
Goodness of fit outputs



System name	Failures				False negative			
	Mean	CV	Best Fit	KS	Mean	CV	Best Fit	KS
Blue Gene/L	1040.5	0.92	exponential $\mu = 62431.3$	0.10	1888.1	1.10	exponential $\mu = 113289$	0.79
LANL Sys 3	3595.1	1.1	exponential $\mu = 215705$	0.98	6559.0	1.1	exponential $\mu = 393538$	0.70
LANL Sys 4	3409.1	1.1	exponential $\mu = 204544$	0.77	6187.0	1.1	exponential $\mu = 371218$	0.99
LANL Sys 5	3294.5	1.1	exponential $\mu = 197671$	0.95	6377.9	1.2	exponential $\mu = 382671$	0.35
LANL Sys 6	16796.7	0.9	exponential $\mu = 1007800$	0.81	31878.2	1.1	exponential $\mu = 1912690$	0.99
LANL Sys 23	9288.2	1.3	weibull a = 509380 b = 0.846905	0.97	16272.3	1.2	weibull a = 895274 b = 0.851258	0.98

System name	False negative			
	Mean	CV	Best Fit	KS
LANL Sys 8	7859.6	1.4	weibull a = 401499 b = 0.767798	0.74
LANL Sys 10	8247.0	3.6	weibull a = 318087 b = 0.647838	0.29
LANL Sys 11	6353.5	3.0	weibull a = 232647 b = 0.609348	0.61
LANL Sys 13	8164.3	3.9	lognormal $\mu = 11.5257$ $\sigma = 1.87004$	0.14
LANL Sys 14	11351.0	2.5	weibull a = 391931 b = 0.559039	0.77
LANL Sys 15	12136.7	1.2	exponential $\mu = 728203$	0.17
LANL Sys 16	3430.6	1.3	weibull a = 182624 b = 0.810939	0.69
LANL Sys 18	818.6	1.5	lognormal $\mu = 10.1123$ $\sigma = 1.28677$	0.37
LANL Sys 19	863.6	1.4	exponential $\mu = 29000.5$	0.18
LANL Sys 21	1986.9	2.3	lognormal $\mu = 10.6382$ $\sigma = 1.46402$	0.85

Goodness of fit outputs



System name	Failures				False negative			
	Mean	CV	Best Fit	KS	Mean	CV	Best Fit	KS
Blue Gene/L	1040.5	0.92	exponential $\mu = 62431.3$	0.10	1888.1	1.10	exponential $\mu = 113289$	0.79
LANL Sys 3	3595.1	1.1	exponential $\mu = 215705$	0.98	6559.0	1.1	exponential $\mu = 393538$	0.70
LANL Sys 4	3409.1	1.1	exponential $\mu = 204544$	0.77	6187.0	1.1	exponential $\mu = 371218$	0.99
LANL Sys 5	3294.5	1.1	exponential $\mu = 197671$	0.95	6377.9	1.2	exponential $\mu = 382671$	0.35
LANL Sys 6	16796.7	0.9	exponential $\mu = 1007800$	0.81	31878.2	1.1	exponential $\mu = 1912690$	0.99
LANL Sys 23	9288.2	1.3	weibull a = 509380 b = 0.846905	0.97	16272.3	1.2	weibull a = 895274 b = 0.851258	0.98

System name	False negative			
	Mean	CV	Best Fit	KS
LANL Sys 8	7859.6	1.4	weibull a = 401499 b = 0.767798	0.74
LANL Sys 10	8247.0	3.6	weibull a = 318087 b = 0.647838	0.29
LANL Sys 11	6353.5	3.0	weibull a = 232647 b = 0.609348	0.61
LANL Sys 13	8164.3	3.9	lognormal $\mu = 11.5257$ $\sigma = 1.87004$	0.14
LANL Sys 14	11351.0	2.5	weibull a = 391931 b = 0.559039	0.77
LANL Sys 15	12136.7	1.2	exponential $\mu = 728203$	0.17
LANL Sys 16	3430.6	1.3	weibull a = 182624 b = 0.810939	0.69
LANL Sys 18	818.6	1.5	lognormal $\mu = 10.1123$ $\sigma = 1.28677$	0.37
LANL Sys 19	863.6	1.4	exponential $\mu = 29000.5$	0.18
LANL Sys 21	1986.9	2.3	lognormal $\mu = 10.6382$ $\sigma = 1.46402$	0.85

1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

1. Failure prediction terminology and concepts
2. Data source and characteristics
3. Modeling and fitting methodology
4. Conclusion and future work

Conclusion

- Classication based on the randomness tests (iid vs non-iid)

Conclusion

- Classication based on the randomness tests (iid vs non-iid)
- Most of the available failure traces are not random and so are suitable for use as empirical data for probability fitting.

Conclusion

- Classication based on the randomness tests (iid vs non-iid)
- Most of the available failure traces are not random and so are suitable for use as empirical data for probability fitting.
- Failure prediction mechanism is a good tool to catch the non randomness and correlation.

Conclusion

- Classication based on the randomness tests (iid vs non-iid)
- Most of the available failure traces are not random and so are suitable for use as empirical data for probability fitting.
- Failure prediction mechanism is a good tool to catch the non randomness and correlation.
- The failure prediction mechanism acts as a scale function and it affects only the scale parameter.

Conclusion

- Classication based on the randomness tests (iid vs non-iid)
- Most of the available failure traces are not random and so are suitable for use as empirical data for probability fitting.
- Failure prediction mechanism is a good tool to catch the non randomness and correlation.
- The failure prediction mechanism acts as a scale function and it affects only the scale parameter.
- The peak of correlation on the initial traces has an important impact on the prediction results, specifically on the recall value

Future Work

- Analyze more deeply the set of systems with a high correlation like system 2 or 20 and isolate sources of non-randomness.

Future Work

- Analyze more deeply the set of systems with a high correlation like system 2 or 20 and isolate sources of non-randomness.
- Investigate if a cross-correlation of different time scale has an impact of the prediction mechanism.

Future Work

- Analyze more deeply the set of systems with a high correlation like system 2 or 20 and isolate sources of non-randomness.
- Investigate if a cross-correlation of different time scale has an impact of the prediction mechanism.
- Manage the tradeoff between the precision and the recall.

Future Work

- Analyze more deeply the set of systems with a high correlation like system 2 or 20 and isolate sources of non-randomness.
- Investigate if a cross-correlation of different time scale has an impact of the prediction mechanism.
- Manage the tradeoff between the precision and the recall.
- Use different sources of failure prediction that concerns different component of the machine.

Thank You