

# Grid models: challenges and examples

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- ✓ Once upon a time...
- ✓ Scientific challenges
- Towards realistic behavioural models
- Conclusion and questions



## The Grid Observatory

- Digital curation of the behavioural data of the EGI grid: observe and publish
- Complex systems description
- Models, optimization, Autonomics
- This talk is about some lessons learned









### Remember tomorrow

A computational grid is a hardware and software infrastructure that provides dependable, consistent, pervasive, and inexpensive access to high-end computational capabilities

lan Foster, 1998





### Still a long way to go



### Consistent

### Dependable

#### Amazon's Cloud Crash Disaster Permanently Destroyed Many Customers' Data

### Henry Blodget | Apr. 28, 2011, 7:10 AM | 6, 77,816 | 📮 76

In addition to taking down the sites of dozens of high-profile companies for hours (and, in some cases, days), Amazon's huge EC2 cloud services crash permanently destroyed some data.

The data loss was apparently small relative to the total data stored, but anyone who runs a web site can immediately understand how terrifying a prospect any data loss is.

(And a small loss on a percentage basis for Amazon, obviously, could be catastrophic Um... for some companies).



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AAA

### Remember tomorrow (5 years later)

Systems manage themselves according to an administrator's goals. New components integrate as effortlessly as a new cell establishes itself in the human body

J. Kephart and David M. Chess, the Autonomic Computing Manifesto, 2003





## The challenge

- How much of Computer Science, and specifically Autonomics research went to the real world?
- We need to show that the research has verifiable and positive impact on production systems





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### AC Paper Trends 2001-2010: Self-\*, Benchmarks

 David Patterson warned us that we needed benchmarks for self-{C,H,P} in order to drive work in the field

- It appears that he was right
- We need to revive the benchmark work

 We need more work on self-{C,H,P}



June 15, 2011

## A fairy tale







- 1979: Patterson went for a sabbatical at DEC. He worked on the implementation of the VAX machine on a single chip. This turned out to be impossible because of the extreme complexity of the microcode.
- With J. Hennessy he built the RISC I and **demonstrated** it better than its competitor from experience
- And a new era in Computer architecture began



## The challenge

- We need to show that the research has verifiable and positive impact on production systems
- Not Yet Implemented. Why? Sociology e.g. research vs production is a real, but minor issue
- This talk is about:

Demonstrating on complex systems raises serious scientific issues





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### Issue I: Uncertainty

- As a dynamic(al) system
  - Entities change behavior as an effect of unexpected feedbacks, emergent behavior
  - Organized self-criticality, minority games,...
- Lack of complete and common knowledge – Information uncertainty
  - Monitoring is distributed too
  - Resolution and calibration







### Unexpected behavior



## Issue II: Fundamentals in statistics

- Statistical significance
- Which metrics?
- Are our systems stationary?



## Statistical significance

### Extreme values may dominate the statistics

	At	las	Biomed			
	ART ERT		ART	ERT		
Mean	1.33E3	2.74E4	3.01E2	2.66E2		
Median	11	1	11	1		
Std	1.09E4	7.41E4	4.33E3	5.99E3		
RMSE	7.94	4E4	7.21E3			
$q_{90\%}$	1.35E2	1.16E5	25	4		
Over. fraction	22	%	3%			
Over. median	9.34	4E4	228			
Under. fraction	77%		96%			
Under. median	9.0	1E0	9.00E0			



## Statistical significance

### Can we predict anything? Maybe as difficult as earthquakes and markets

	Atlas		Biomed		
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### Metrics

### Root Mean Squared Error is inadequate

	Atlas		Biomed		
	ART	ERT	ART	ERT	
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### Metrics

### Should make sense for the end user

	Atlas		Biomed		
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### A few keywords





### Do naïve statistics make sense?

# Non-stationarity and heavy-tailedness can easily be confused

- The Hurst effect under trends. J. Appl. Probab., 20(3), 1983.
- Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. J. Empirical Finance, 11(3), 2004.
- Testing for long-range dependence in the presence of shifting means or a slowly declining trend, using a variance-type estimator. J. Time Ser. Anal., 18(3), 1997.
- Long memory and regime switching. J. Econometrics, 105(1), 2001.

### **NON-STATIONARITY IS A REASONABLE ALTERNATIVE**



### Issue III: Intelligibility





## Issue III: Intelligibility

### How to build the knowledge?

- No Gold Standard, too rare experts
- Let's go to unsupervised learning, model-free policies eg Reinforcement Learning!
- Unfortunately, tabula rasa policies and vanilla ML methods are too often defeated



Exploration/exploitation tradeoff





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### The ROC metrics: à la BQP



[C. Germain-Renaud et al. The Grid Observatory. CCGRID 2011]



### 1. Statistical testing

- Sequential jump detection
- Theoretical guarantees for known distributions
- Predictive, not generative
- Example: blackhole detection
- Calibration and Validation: by the Expert





### 2. Segmentation

- Fit a piecewise timeseries: infer the parameters of the local models and the breakpoints
- Model selection: AIC, MDL,... – based
- a priori hypotheses on the segment models: AR, ARMA, FARMA,...



[T. Elteto et al. Towards non stationary Grid Models, to appear in JoGC Dec. 2011]



### 2. Segmentation

- Mostly off-line and computationally expensive: generative, explanatory models
- Validation is not trivial
  - Fit quality
  - Stability: bootstrapping
  - Randomized optimization: clustering the results
- Hints at global behavior





### 3. Adaptive clustering:

- Clustering with Affinity Propagation (Frey & Dueck): the exemplars are the model
- Feedback from analysis to curation: feature selection instead of a priori

[X. Zhang et al. Toward Autonomic Grids: Analyzing the Job Flow with Affinity Streaming". SIGKDD'2009]







### 3. Adaptive clustering:

- Adaptive: on-line rupture detection
- Back to statistical testing, but on the model, not on the data





## Issue III: Intelligibility

- No Gold Standard, too rare experts: unsupervised learning, model-free policies eg Reinforcement learning
- Tabula Rasa policies, vanilla ML methods are too often defeated
- Exploration/exploitation tradeoff
- Ongoing work: infer causes from data as latent topics, in the spirit of text mining
- [Y. Kim et al. Characterizing E-Science File Access Behavior via Latent Dirichlet Allocation, to appear un UCC 2011]



## Conclusion





## The collaboration

- Born in EGEE-III, now a collaborative effort of
  - CNRS/UPS Laboratoire de Recherche en Informatique
  - CNRS/UPS Laboratoire de l'Accélérateur Linéaire
  - Imperial College London
  - France Grilles French NGI of EGI
  - EGI-Inspire
  - Ile de France council
  - (Software and Complex Systems programme)
  - INRIA Saclay (ADT programme)
  - CNRS (PEPS programme)
  - University Paris Sud (MRM programme)
- Scientific Collaborations
  - NSF Center for Autonomic Computing
  - European Middleware Initiative
  - Institut des Systèmes Complexes
  - Cardiff University













Grid Observatory

## The digital data

Component	Range	Scope	Format	Size
RTM	Comprehensive	gLite	Spec.	200MB
IS	Comprehensive	EGI	LDIF	300MB
L&B	Partial	gLite	SQL	2GB
Accounting	Local	gLite	PBS	6MB
CondorG	Partial	gLite	Spec.	15 KB
JobController	Partial	gLite	Spec.	40MB
LogMonitor	Partial	gLite	Spec.	70 MB
WorkloadManager	Partial	gLite	Spec.	70MB
GridFTP	Partial	EGI	Spec.	11 <b>MB</b>



## The GO Portal





Traces available through the portal: no grid certificate



Use and users both increasing steadily



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### Let's take a closer look at how AC is doing as a field

- Run Harzing's Publish or Perish with queries "Autonomic Computing" and "International Conference on Autonomic Computing"
  - Uses Google Scholar; finds top 1000 papers in terms of citation counts
- Put structured data in spreadsheet
- Cleanse the data
- Identify interesting trends

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