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# Purpose of the project

### Why data analytics at CERN?

- Lot of monitoring data stored in the past years
  - this data contains a lot of information:
    - we want to understand how to extract it

This is the purpose of the Openlab data analytics project

...to obtain added value from not so actively used data



### **Topics:**

- The R project for statistical computing
- The R Studio IDE
- Oracle R Enterprise (ORE)
- The Openlab working layout
- The CASTOR use case
  - Data sources and management
- Live demo
- Conclusions





### **About me:**

- Involved in the CASTOR monitoring
  - Developed real time Cockpit
  - Set up Hadoop cluster to store raw log data on Hadoop (10+ TB)
- Now working on data analytics in Openlab
- Found limitations of NoSQL for advanced data analysis
- Started investigating other solutions:
  - home made stuff, R and Oracle R Enterprise





# The R Project for Statistical Computing

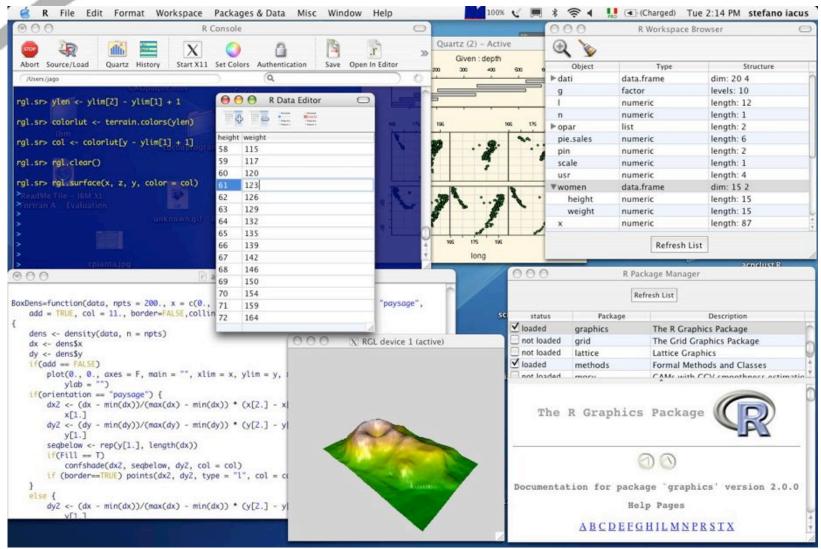


- Software environment for statistical computing and graphics
- Free and open source
- Standard and advanced statistical techniques
  - linear and nonlinear modeling
  - classical statistical tests
  - time-series analysis
  - classification, clustering
  - machine learning (neural networks, SVM, ...)
- Highly extensible

...gives a meaning to your data



# The R Project



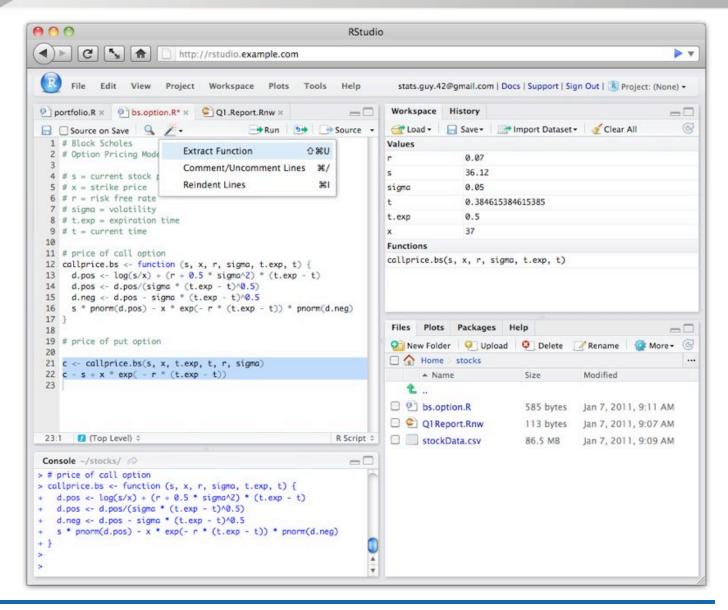


### R Studio IDE: overview

- Free and open source IDE for R
- "Take control of your R code"
- Windows, Mac Linux
- Web (RStudio server)

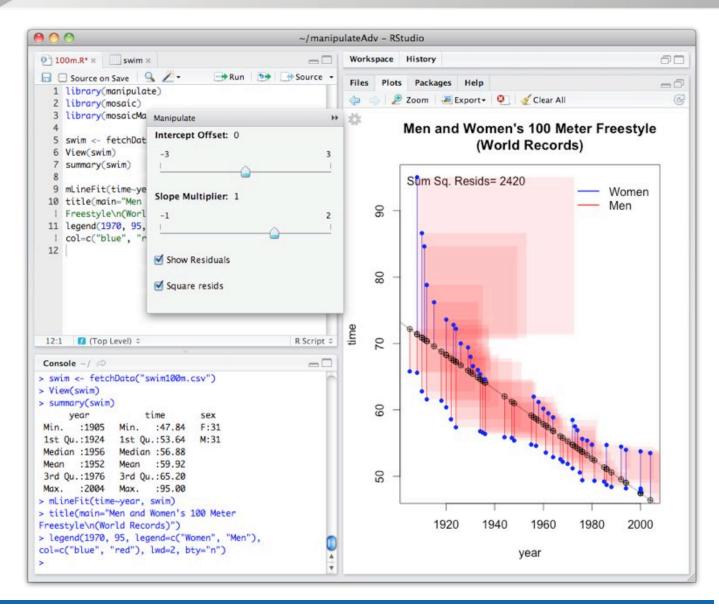


### R Studio



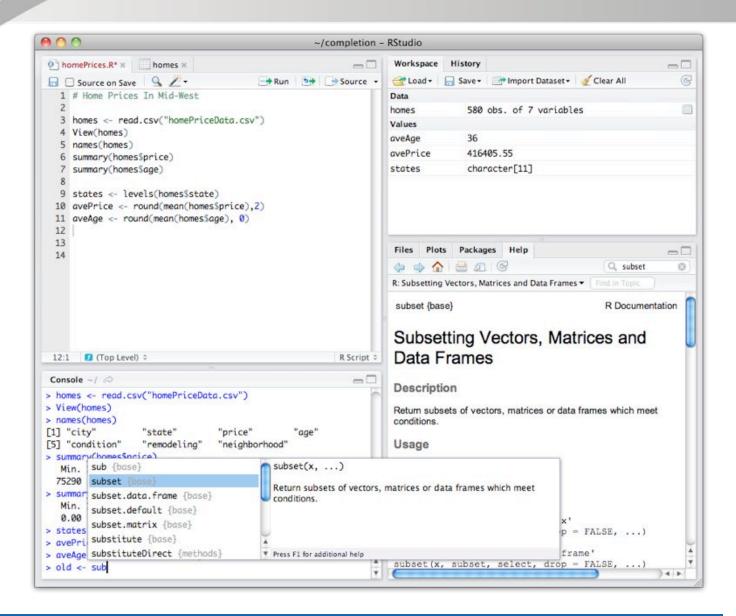








### R Studio





### **Oracle Database**

### **Oracle Database Overview**

Widely used

- ORACLE"
- At CERN since the first releases
- Scalable
- Many advanced features
  - Data consistency
  - Concurrent user support
  - PL/SQL
  - Parallel query system
  - Analytical functions
  - . . . .



### Oracle R Enterprise (ORE) overview







Leader in data management

Leader in data analysis

- R integrated in Oracle core product
  - R operates on data stored in the Oracle Database
- parallelism and scalability of the database
- automate data analysis

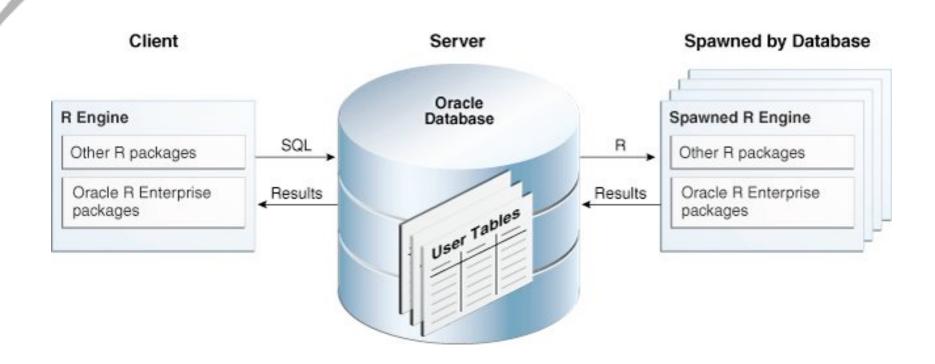


### **Features**

- Transparency Layer: allows R code and R packages run almost out of the box
  - bottom line: intercepts R functions
- Data management and organization in a DB much easier than CSV style
- R on a database approach already possible but:
  - ORE allows in-database data analysis
- Scalable and Big Data ready



### Layout





### Client



- Collection of R packages (libraries)
  - Allows connect to an Oracle Database and to interact with it
- Any R command usable
- Provides a set of highly optimized, ORE specific functions
  - corr() -> ore.cor()
  - Im() -> ore.lm()
- Functions intercept data transforms, statistical functions, and Oracle R Enterprise-specific functions



### Server



- collection of PL/SQL procedures and libraries
  - augment Oracle Database with the capabilities required to support an Oracle R Enterprise client
  - SQL query parallel execution
- embedded R execution
  - Oracle Database spawns R engines: data parallelism
- Access to tables, views, and external tables in the database



### Why ORE?

 Advanced data analysis requires advanced statistical and machine learning models

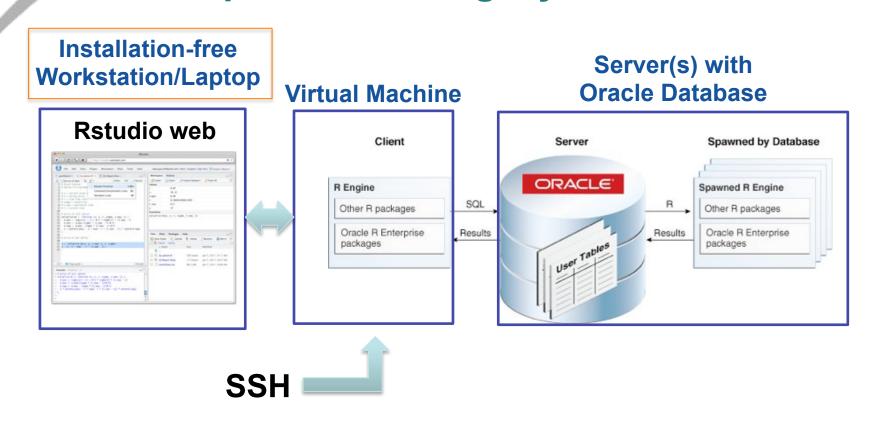
...which are ready to use in R

- If you have both many variables to evaluate and large amounts of data:
  - Management is complex with CSV-style data store
  - NoSQL solutions cannot be used for correlation analysis
  - standard R in-memory approach can fail (ORE let data be analysed inside the DB)





# The Openlab working layout



Modular, Flexible, user-friendly



A test case: the CERN Advanced STORage Manager





### **CASTOR** use case overview

- Lot of (complex) log data recorded in the past years from various systems
  - (mainly, time series)
- CASTOR TEAM: Can we obtain useful information from it?



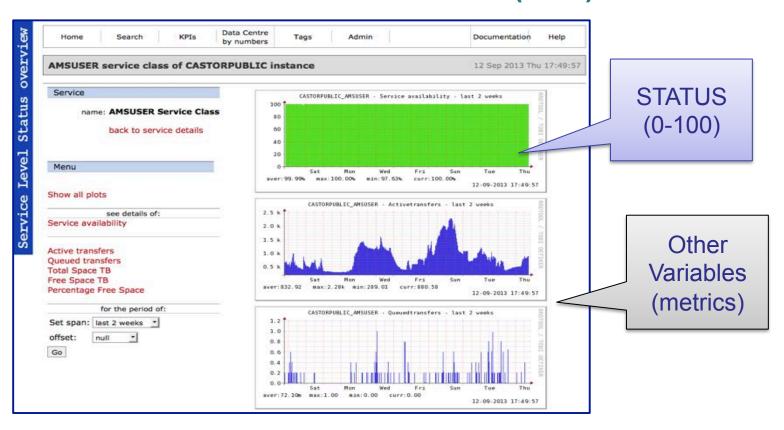
Understanding <u>if and how</u> the **anomalies** in the system are correlated with the **adverse events** would have *great value* 



- Performance
- Cause of errors
- Anomaly detection
- Predictions
- Early warning systems



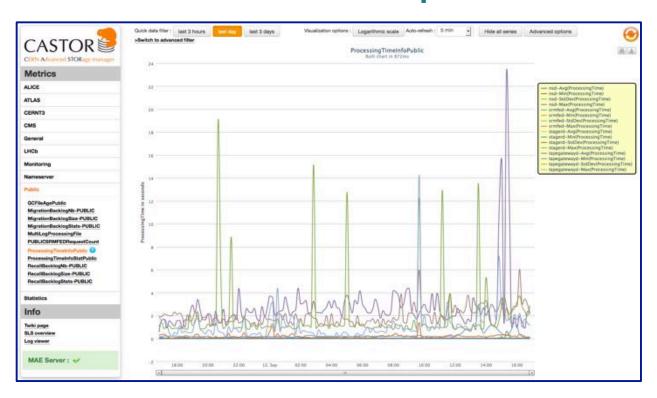
### Data source: Service Level Status (SLS)



Data format: a new data point only if the status changes



### **Data source: Castor Cockpit**



### Data format: a new data point every x seconds,

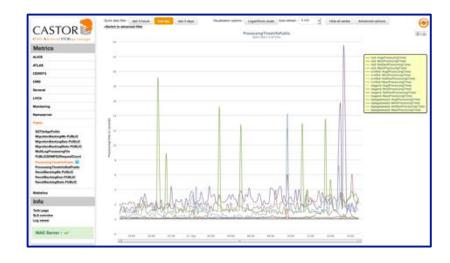
- No sync between metrics
- Missing bins



### Data source: Hadoop via Castor Cockpit

 The Castor Cockpit can load data from the Hadoop respository (Raw data, Terabytes)



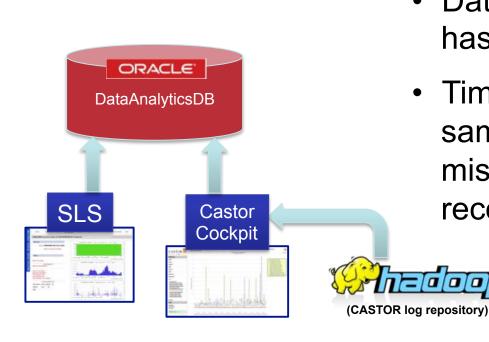




# CASTOR data mining: approach

#### APPROACH:

#### **CENTRALIZE and STANDARDIZE data**



- Data from various sources has to be standardized
- Time series must have the same frequency and missing values has to be reconstructed.

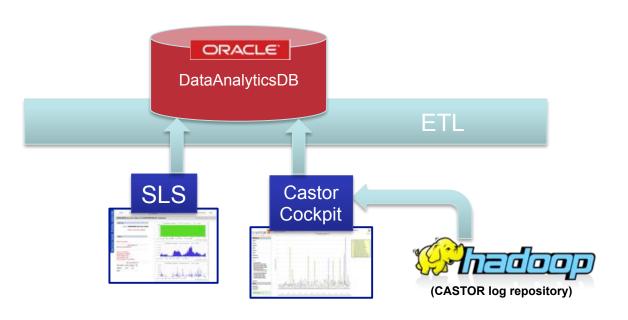


# CASTOR data mining: approach

#### APPROACH:

### **CENTRALIZE and STANDARDIZE data**

### **Home made ETL process**



- Extract
- Transform
- Load

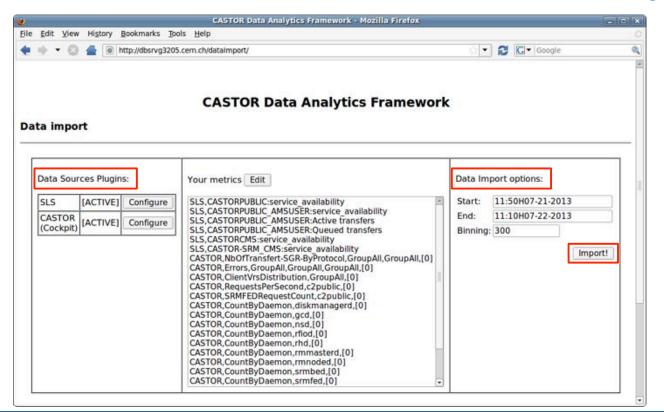


# CASTOR data mining: approach

#### APPROACH:

### **CENTRALIZE and STANDARDIZE data**

### Home made ETL process



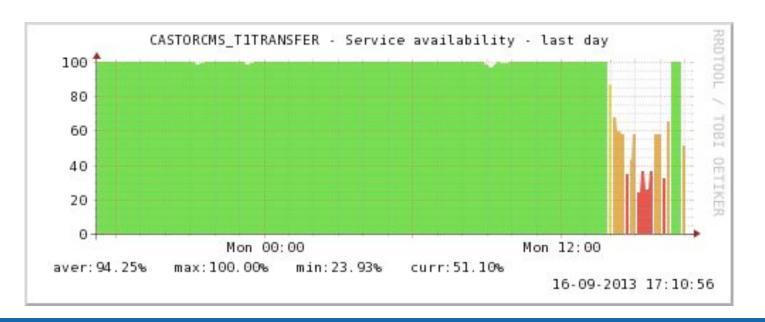
- Extract
- Transform
- Load

Python backend



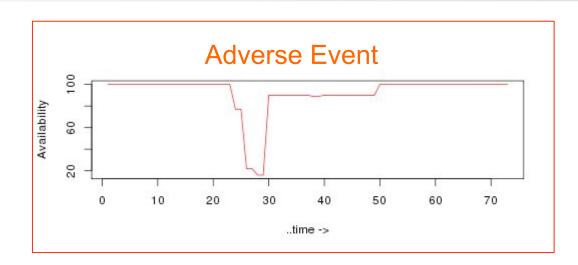
### "Adverse Events"

- An adverse event is a downtime/problem/failure in the CASTOR system
- The SLS service availability metric identifies in first approximation the "adverse events":

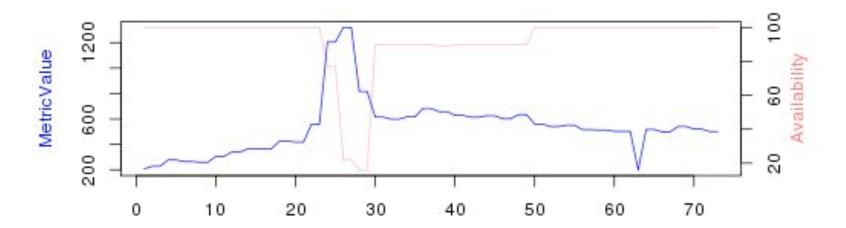




# **Correlating Anomalies**

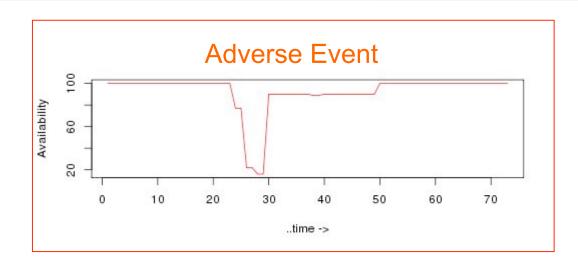


### Easy to correlate:

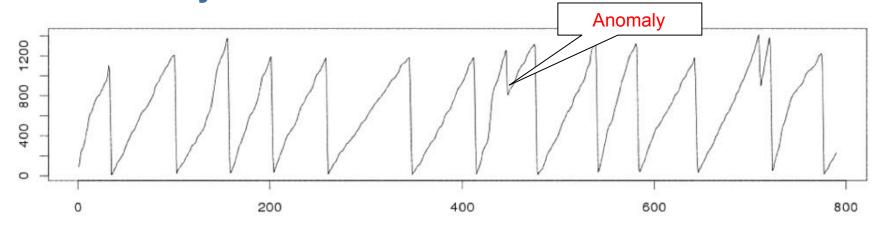




# **Correlating Anomalies**



Not so easy:



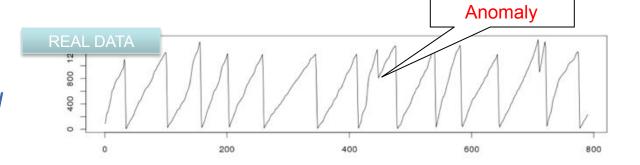
Example algorithm: data to be transferred to tape.

Queue data, then transfer to tape in one-go



## **Anomaly detection**

- 1) Build a **SVM** (*Neural Network like*) **model** 
  - self trained
  - no supervision

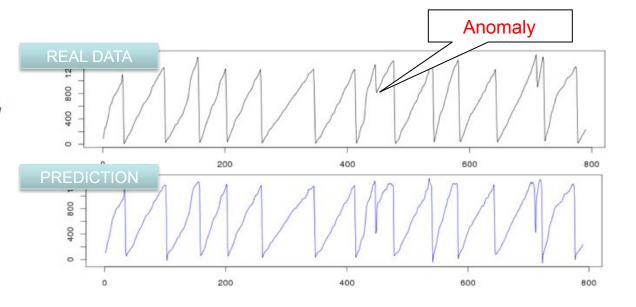


\_\_\_\_\_\_ Time \_\_\_\_\_



# **Anomaly detection**

- 1) Build a **SVM** (*Neural Network like*) **model** 
  - self trained
  - no supervision
- 2) Predict



— Time ————

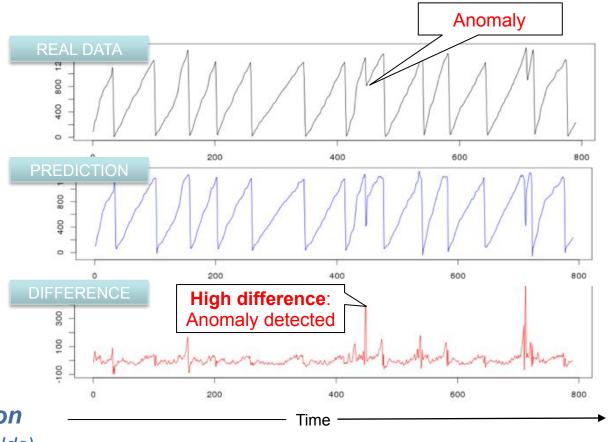


## **Anomaly detection**

- 1) Build a **SVM** (*Neural Network like*) **model** 
  - self trained
  - no supervision
- 2) Predict and compare:

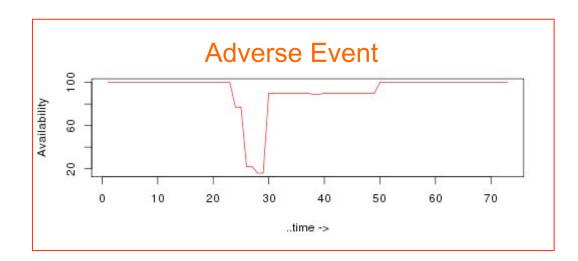
#### **Real data Vs Prediction**

- Blindly recognize anomalies
- No other information required (i.e. thresholds)

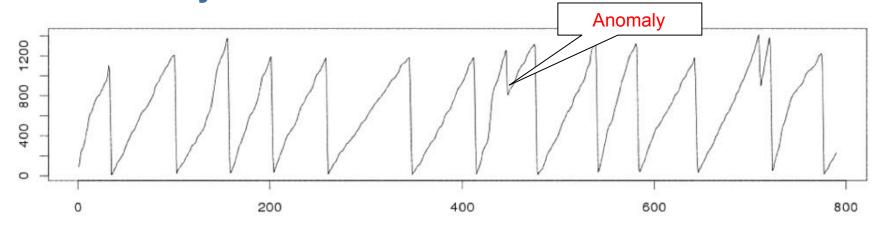




# **Correlating Anomalies**



Not so easy:

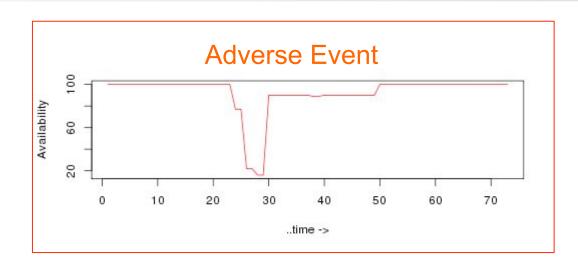


Example algorithm: data to be transferred to tape.

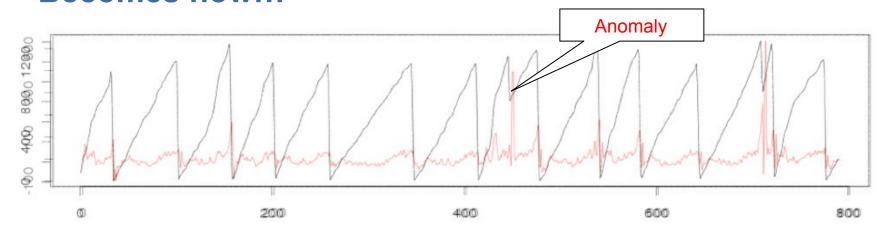
Queue data, then transfer to tape in one-go



# **Correlating Anomalies**



Becomes now...

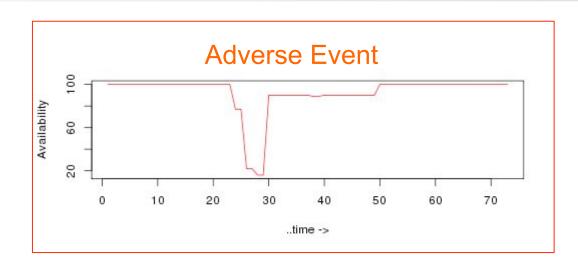


Example algorithm: data to be transferred to tape.

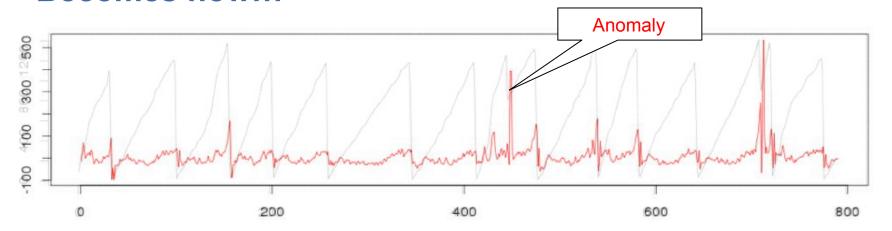
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# **Correlating Anomalies**



Becomes now...

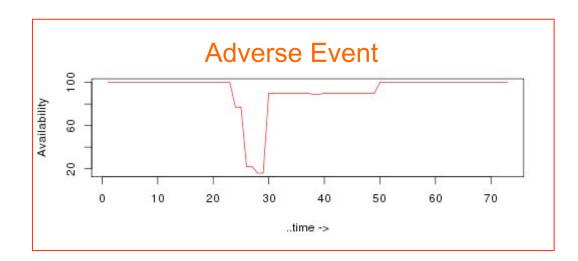


Example algorithm: data to be transferred to tape.

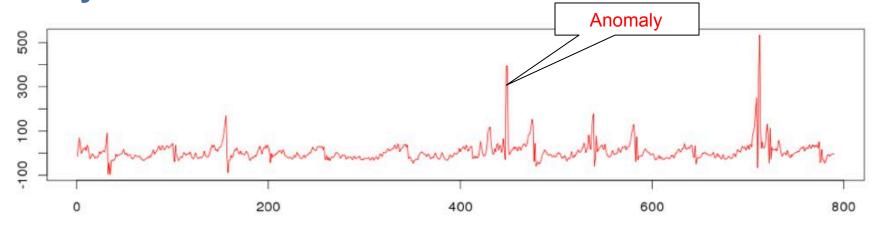
Queue data, then transfer to tape in one-go



# **Correlating Anomalies**



### Way easier:



Example algorithm: data to be transferred to tape.

Queue data, then transfer to tape in one-go



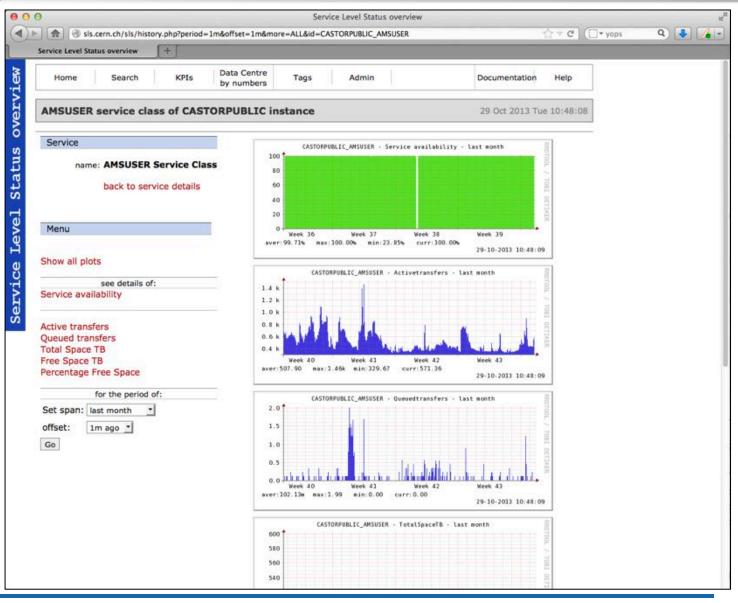
### Why ORE for the CASTOR use case?

- Detecting anomalies requires advanced statistical and machine learning models: ready to use in R
- The CASTOR use case involves two challenges:
  - Many variables to evaluate (management is complex)
    - SLS Status broken down by instance and service class
    - Several other SLS variables for every instance and service class
    - Cockpit data broken down by many other fields (i.e. daemon, message, hostname)
  - Large amounts of data to process
    - Correlations cannot be computed over NoSQL solutions (Hadoop)
    - standard R in-memory approach can fail

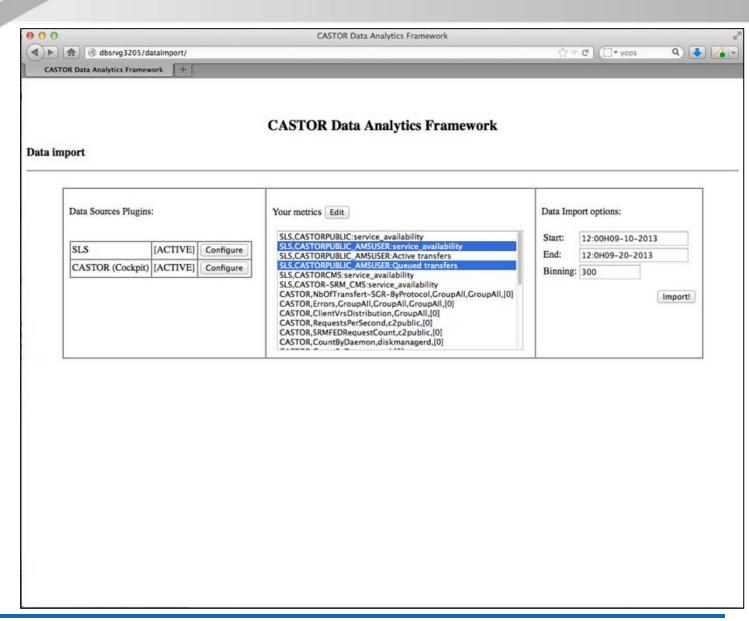
In-database R (ORE) solves all these problems



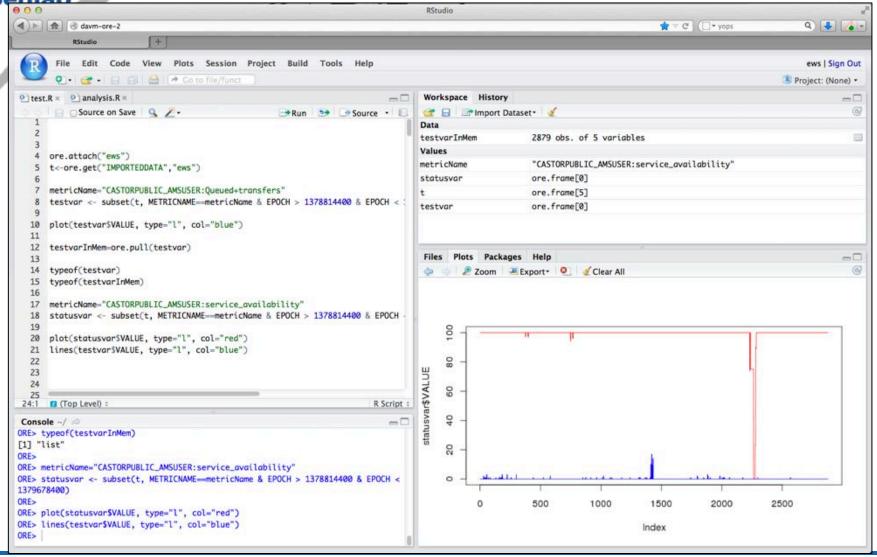




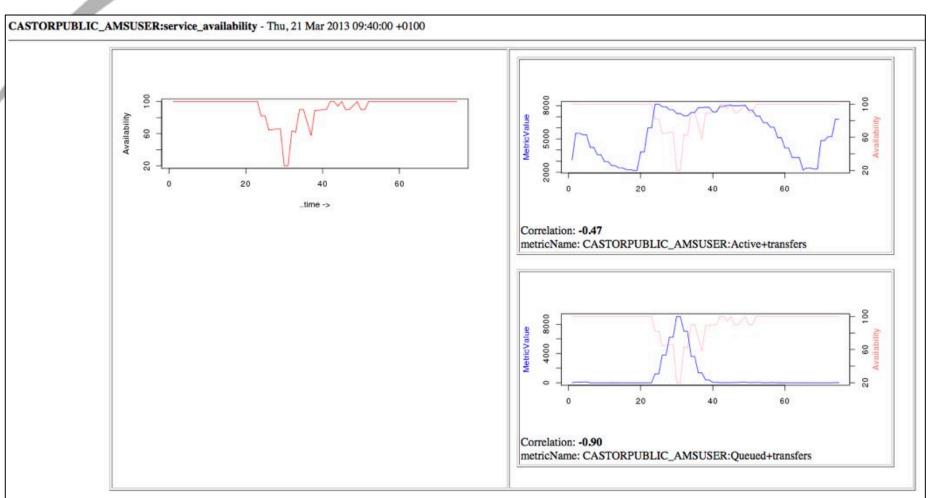




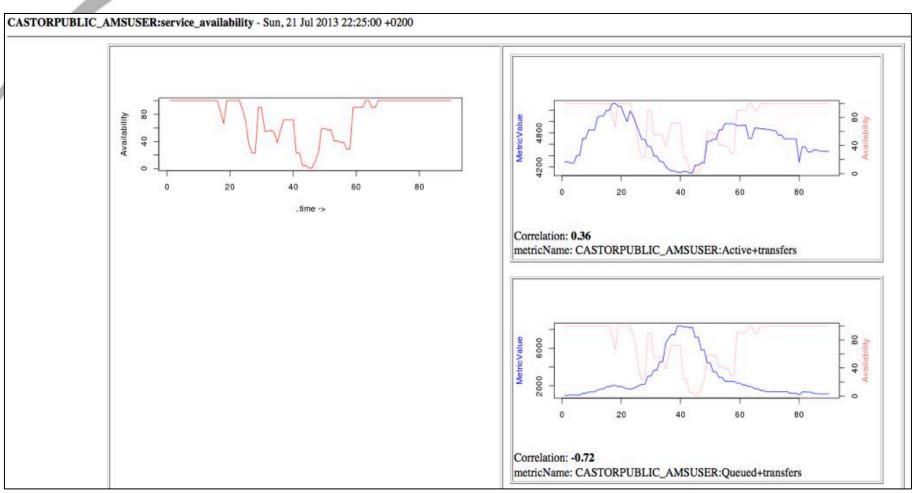












# CERN

### Conclusions

### **Conclusions**

- R is a powerful and interesting tool for data analysis
- ORE brings R into a scalable DB engine (solving problems of data management, analysis and scalability)
- We actually can obtain information and added value from not so actively used data
- Lesson learnt: The more you aggregate, the more you can give a meaning to your data:

3<sup>rd</sup> aggregation: correlate results

2<sup>nd</sup> aggregation: DB, ORE

1st aggregation: SLS / CASTOR Cockpit

RAW Data





### **Future plans**

- Work with castor team to deliver daily reports of CASTOR analysis
- Extend to other use cases
- Promote the data analytics project
  - 20<sup>th</sup> November: CERN data analytics use cases workshop
  - February 2014: II Openlab Workshop on Big Data Analytics

### Thanks to the CASTOR team and Oracle!





- II Openlab Workshop on Big Data Analytics (February 2014)
  - Big Data Solutions
  - Big Data Analytics Technologies
    - Advance Analytics
    - Information Discovery
    - In-Database Analytics
    - Logs Analysis
    - Advance Visualization
  - Main Challenges

M.Sc. in Soft-computing and Intelligence Information Systems in 2011 both at the University of Granada, Spain. He is a member of the "Soft Computing and Intelligent Information Systems" (SCI2S) research group and the "Distributed Computational Intelligence and Time Series" research lab (DICITS). In 2007 he joined the Beam department of the European Centre for Nuclear Research (CERN). A that time he was coleading the Control Configuration Database and the database integration of the Front-End Software Architecture. Both projects of critical importance for improving the CERN's accelerators complex control systems. Currently, Manuel is part of the CERN IT

architects from Oracle Development. In this role he h: the honor to work with companies like Amazon, Yaho Mastercard, Nielsen, Bank of America, Allianz, BN Paribas, Deutsche Bank, Turkcell, Garanti Bank, S Telekom and many more. He started as Consultant, the moved into Project Management, Presales and final Business Development.





## Thank you for your attention!

• Questions..?