ÉCOLE POLYTECHNIQUE MONTRÉAL

Predicting Software Defects Through Time Series

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Contents

- The aim
- Background on time series
- How we proceed
- Case study and results

The aim

- Identifying relevant characteristics (periods, trends, etc)
- Analyze and understand trends
- Predicting the defects (or other parameters) can be a significant help to manage software evolution

Time Series

- A collection of observations made sequentially in time
  - number of defects, size, people, average age of modification, complexity, …
- Each observation is a realization of a stochastic process
- Assumptions of stationarity and ergodicity

Objectives

- Understand the underlying stochastic process

  (Trend, saisonality, periods, etc.)

- Predict futures values

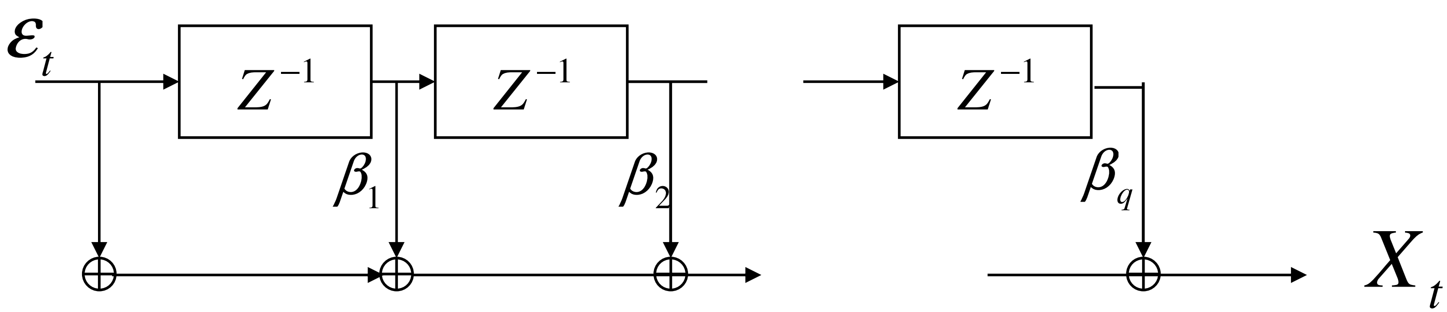
  - $$X_t = T_t + C_t + \varepsilon_t$$

  - Identify a model

Moving Average

Suppose that $\{\varepsilon_t\}$ is a white noise (discrete purely random process with zero mean and variance σ^2) then a process $\{X_t\}$ is said to be a moving average process of order q, MA(q), if:

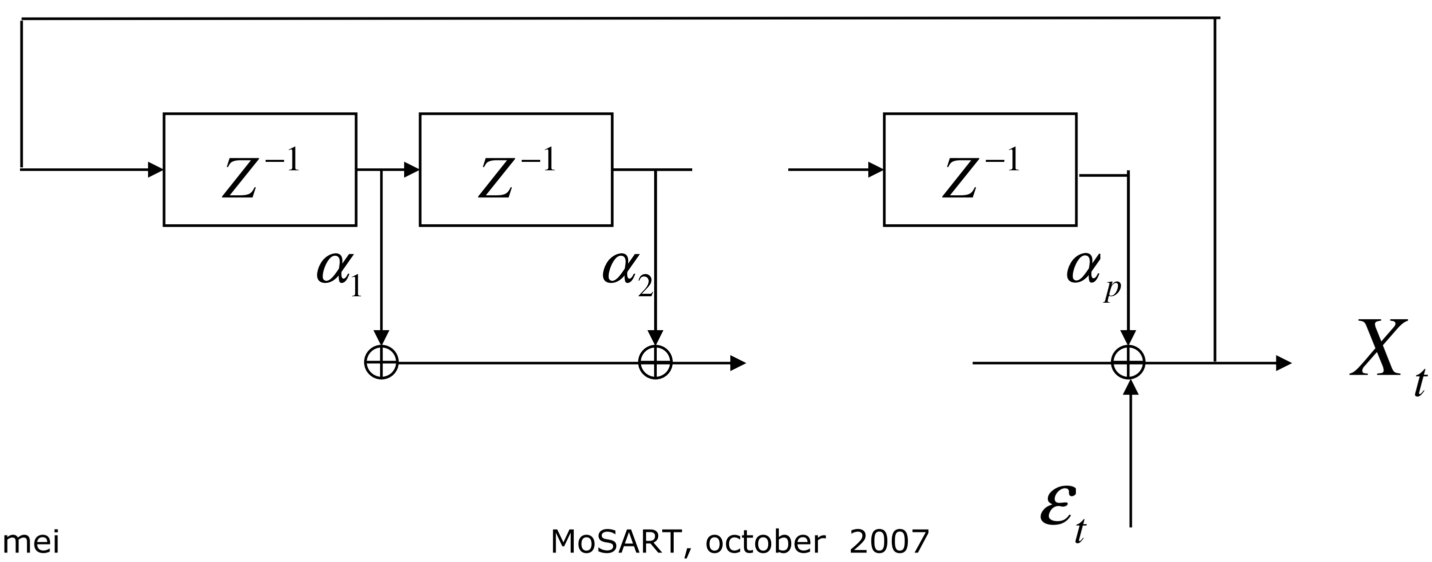
$$X_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q}$$



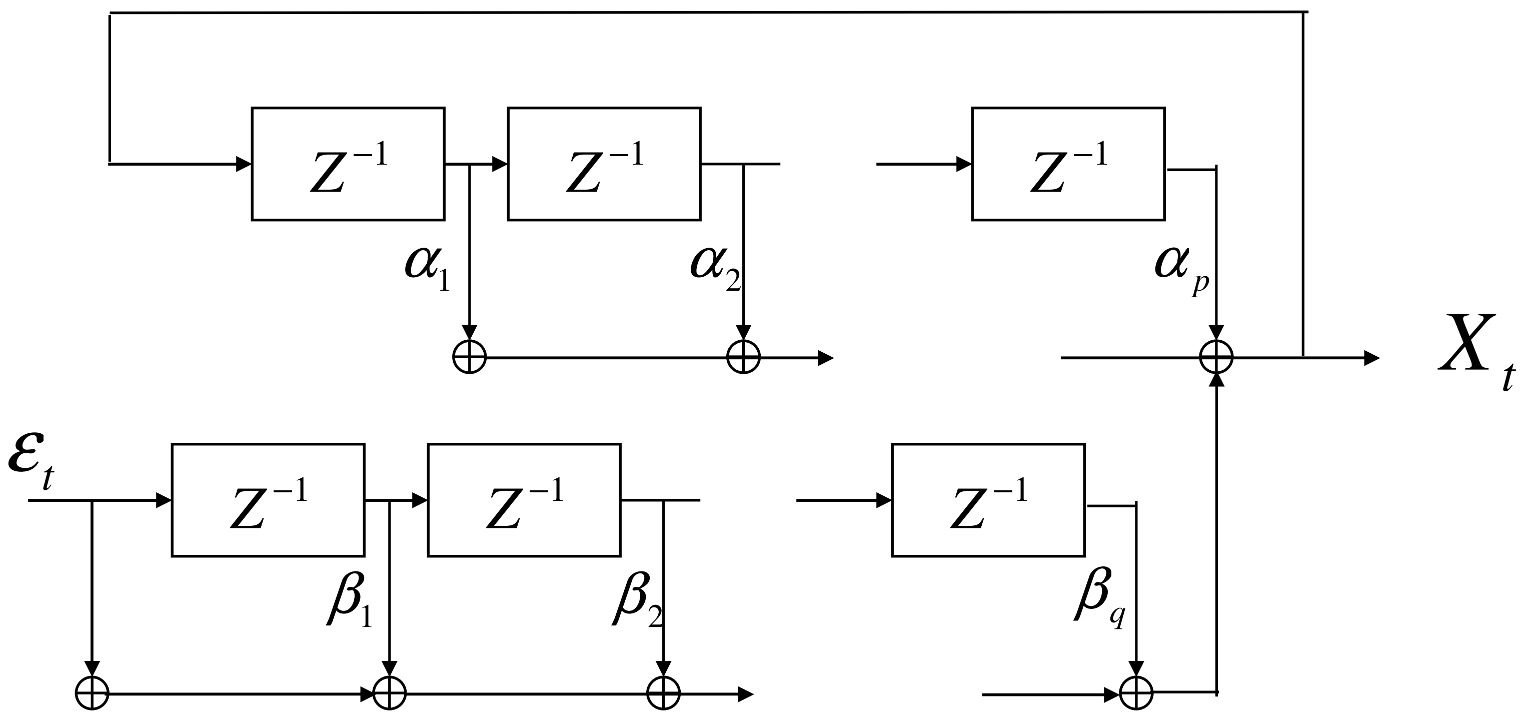
Auto-regressive

Suppose that $\{\varepsilon_t\}$ is white noise, then a process $\{X_t\}$ is said to be an autoregressive process of order p, AR(p), if:

$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + \varepsilon_t$$



ARMA(p,q)



$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + Z_t + \beta_1 Z_{t-1} + \dots + \beta_q Z_{t-q}$$

Time Series Modeling

1. Model identification: ARIMA(p,d,q) i.e., determine p,d,q
   - d=0 means ARMA
   - d>0 means a non-stationary process

2. Estimation: given the model order p,d,q, estimate the coefficients $\{\alpha_i\}$ $\{\beta_j\}$

3. Diagnostic checking: verify if the identified model is adequate

   (white noise test of the residuals, normality)

How we proceed

- We use different parameters from software databases
  - CVS and bug tracking
- Not only bugs, but also
  - Patches
  - People
  - System size
  - Average age of the system, etc.

Data extraction

- Software : Mozilla, Jboss, Eclipse
- Every 2 weeks
- From 2002 to 2005
- Temporal features are being considered

Case Study

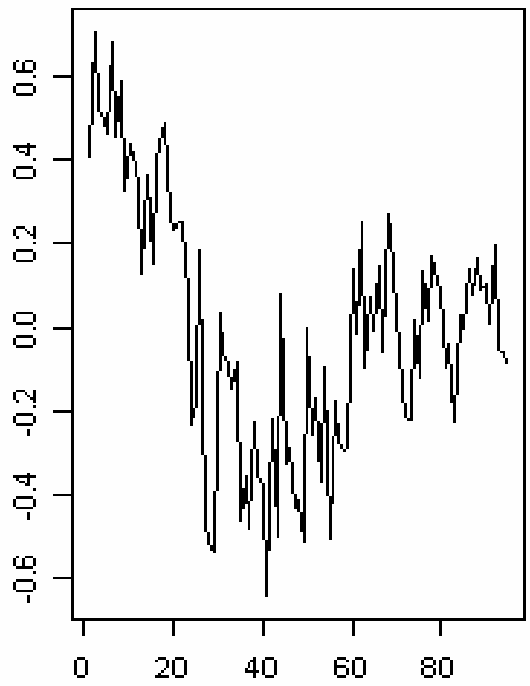
- Prediction error measured as:

$$100\frac{|x_t - \hat{x}_t|}{x_t}$$

- Statistical comparisons with naive models (ARIMA(0,1,0), ...)

Mozilla

95 observations open bugs bi-weekly, stationary



$$X_t : ARIMA(2,0,3)$$

Let m1 be the errors of ARIMA(0,1,0) model and m2 the errors from our model

H0 : m1=m2

H1: m1>m2

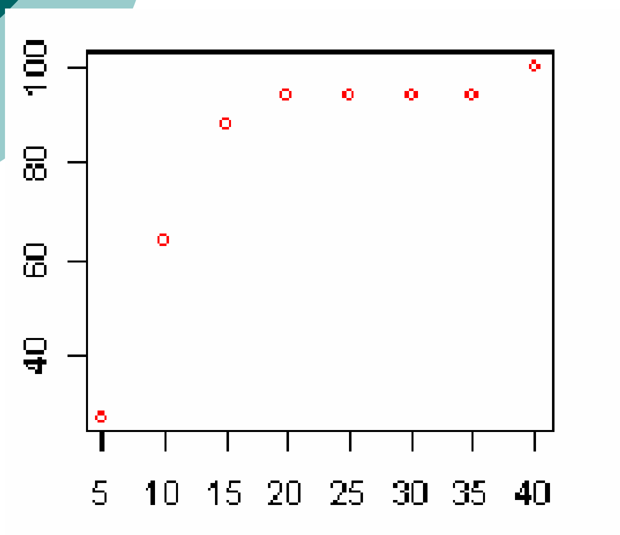
Mozilla : models comparison

	h=1	h=2	h=3
S=20	T=0.006	T=0.090	T=0.000
S=40	T=0.000	T=0.034	T=0.000
S=60	T=0.019	T=0.206	T=0.005
S=70	T=0.025	T=0.507	T=0.038

With a threshold of 95%, m1>m2 in all cases when h=1,3

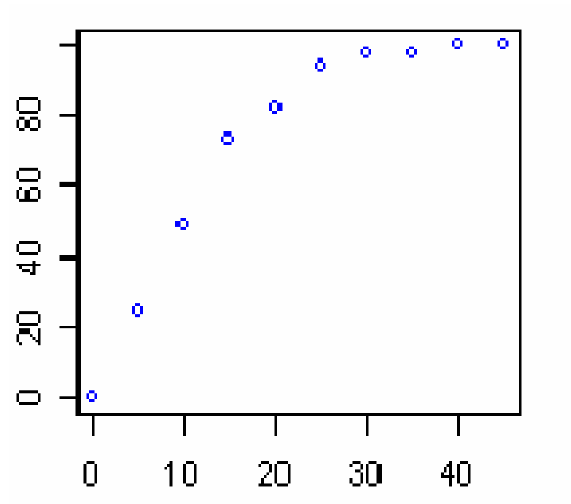
Mozilla : prediction performance

learning size : 60



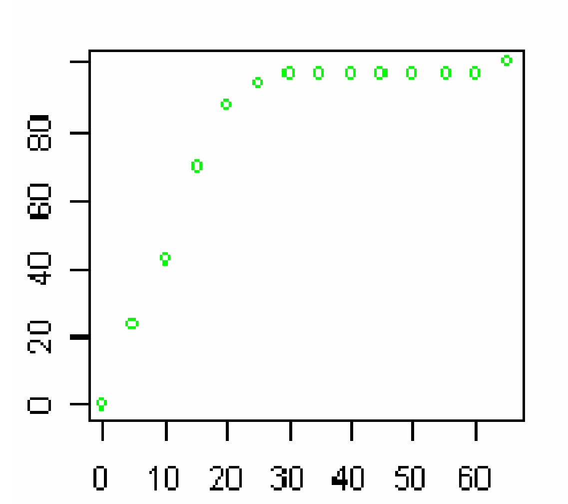
H=1

90%<15%



H=2

90%<25%

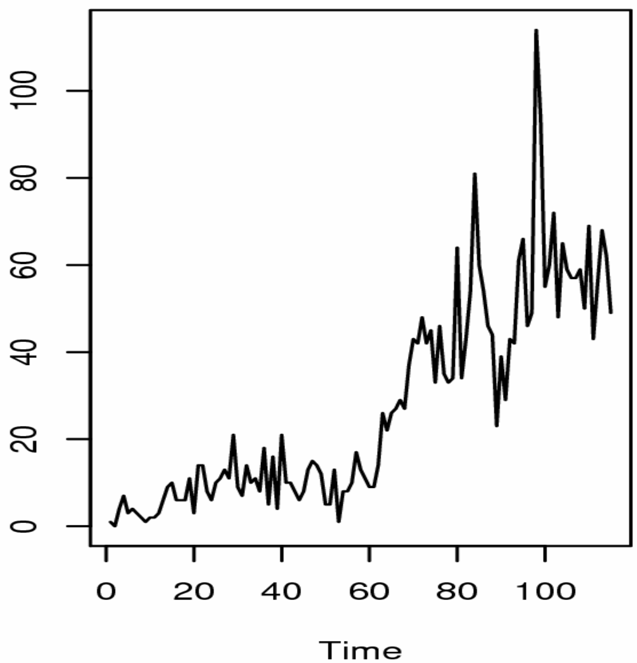


H=3

90%<25%

Jboss

115 observations, trend stationary (**TS**)
– bugs open bi-weekly



$$X_t = 0.03811 * t + 1.60740 + Z_t$$

$$Z_t : AR(2)$$

Let m1 be the errors of ARIMA(0,1,0) model and m2 the errors from our model

H0 : m1=m2

H1: m1>m2

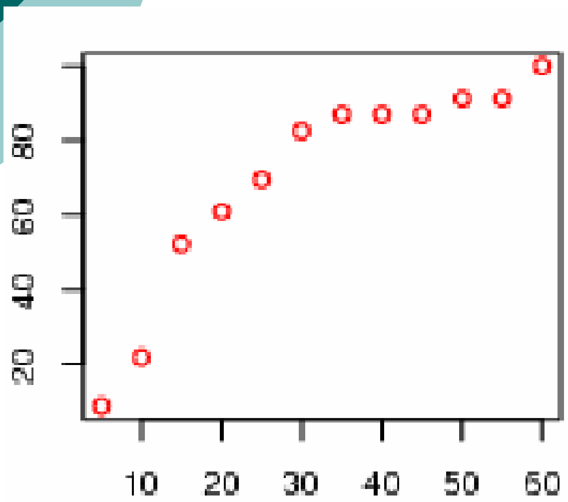
Jboss : models comparison

	h=1	h=2	h=3
S=20	T=0.047	T=0.093	T=0.008
S=70	T=0.040	T=0.015	T=0.053
S=80	T=0.053	T=0.002	T=0.052
S=90	T=0.078	T=0.010	T=0.129

With a threshold of 90%, m1>m2 in 11 cases/12

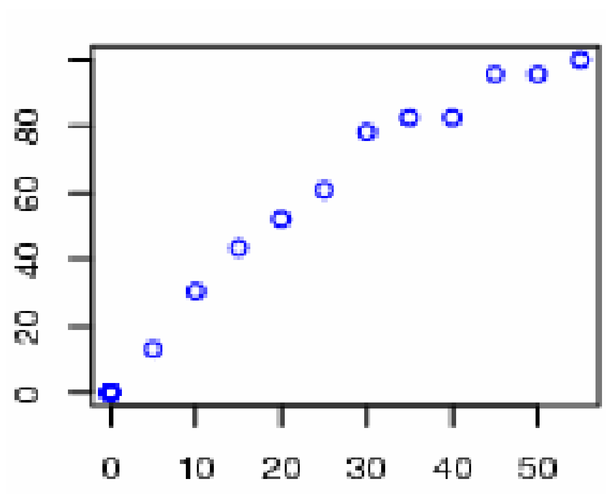
Jboss : prediction performance

learning size : 90



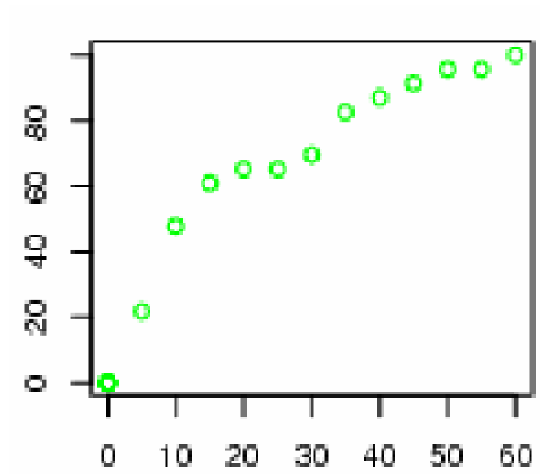
H=1

80%<30%



H=2

80%<30%

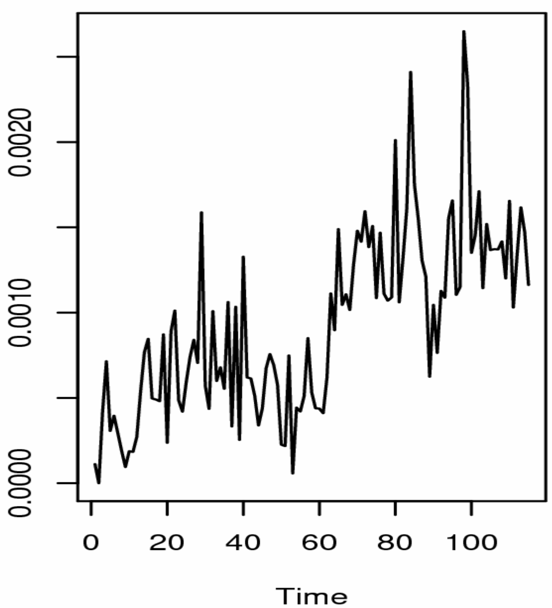


H=3

70%<30%

Jboss : normalised series

115 observations, trend stationary (**TS**) bi-weekly bug open normalized over size



$$X_t = 0.001178 * t - 1.896278 + Z_t$$

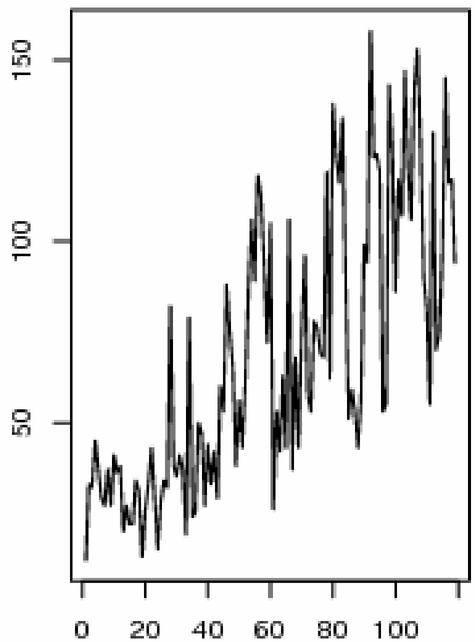
$$Z_t : ARMA(4,3)$$

70% of prediction errors <25%

With a threshold of 95%, m1>m2 in 10 cases/12

Eclipse

119 observations, trend stationary (**TS**)
– bug open bi-weekly non normalized



$$X_t = 0.03419 * t + 4.75902 + Z_t$$

$$Z_t : ARMA(5,4)$$

Let m1 be the errors of ARIMA(0,1,0) model and m2 the errors from our model

H0 : m1=m2

H1: m1>m2

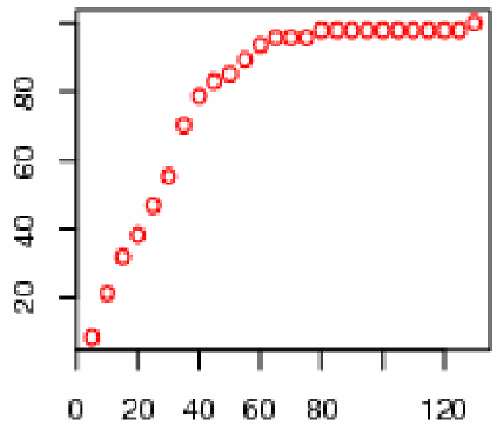
Eclipse : models comparison

	h=1	h=2	h=3
S=60	T=0.083	T=0.015	T=0.000
S=70	T=0.574	T=0.021	T=0.003
S=80	T=0.540	T=0.034	T=0.007
S=90	T=0.481	T=0.005	T=0.013

With a threshold of 95%, m1>m2 when h=2,3

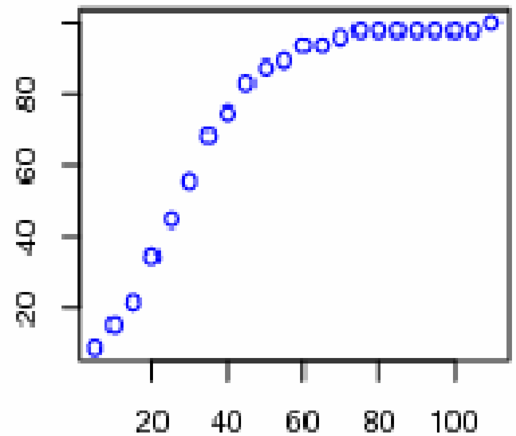
Eclipse : prediction performance

learning size : 70



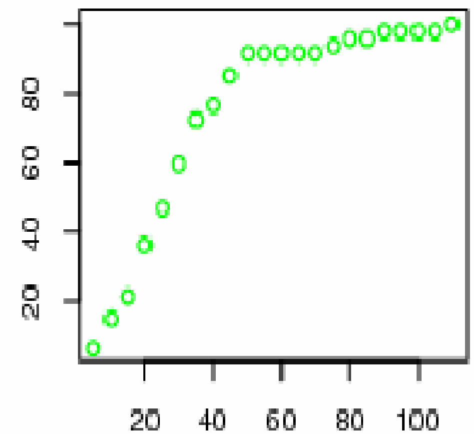
H=1

70%<35%



H=2

70%<35%



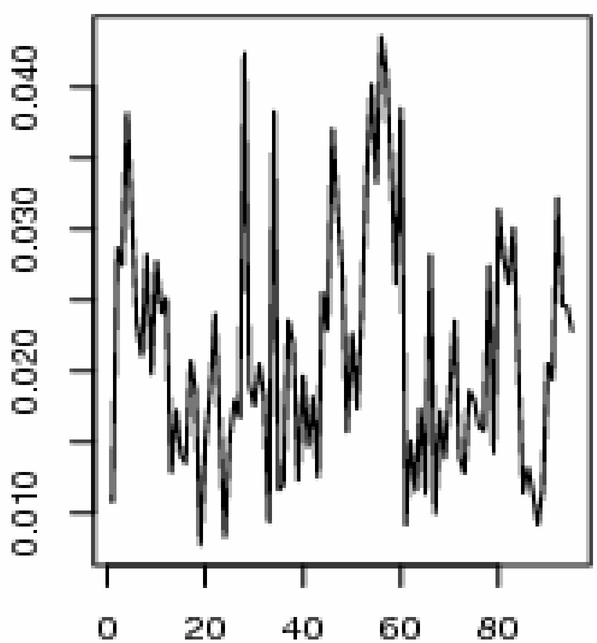
H=3

75%<35%

Eclipse : normalised series

119 observations, stationary, bug open

rmalized time series



$$X_t : ARIMA(5,0,5)$$

80% of prediction errors <40%

With a threshold of 95%, m1>m2 when h=2,3

Conclusion

Difficulties

- The non automatic steps of the analysis
- Dynamic prediction with a single model

On going work

- Extraction of temporal features at the system level
- Perform a multivariate analysis
- Prospect non linear methods