Collective & Point Anomaly Detection in R

useR! 2019. Toulouse, France.

Daniel Grose

July 10, 2019

What is an Anomaly ?

Simulated Data

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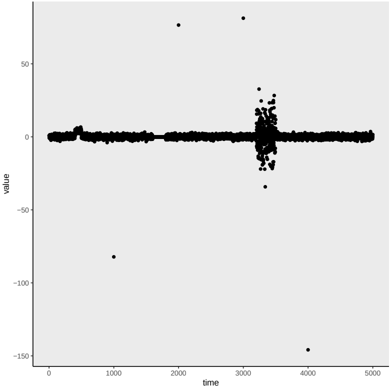

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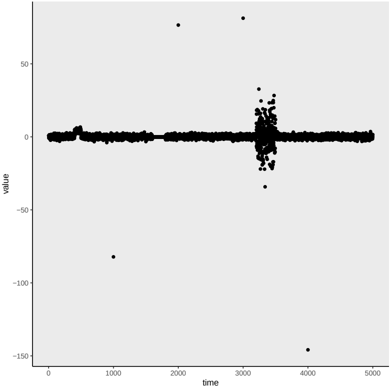

Anomalies

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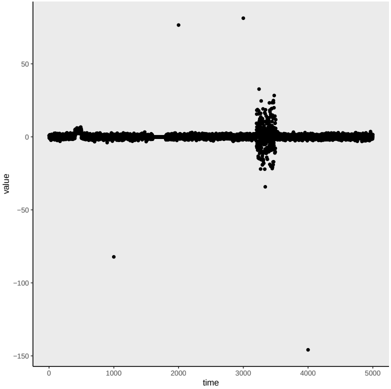

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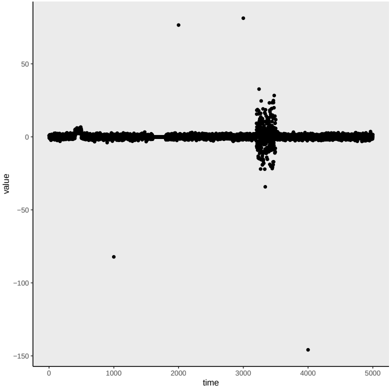

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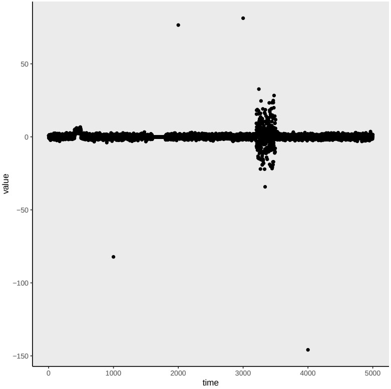

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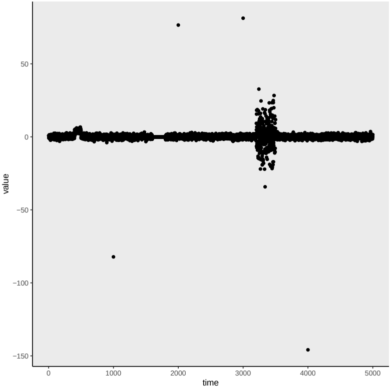

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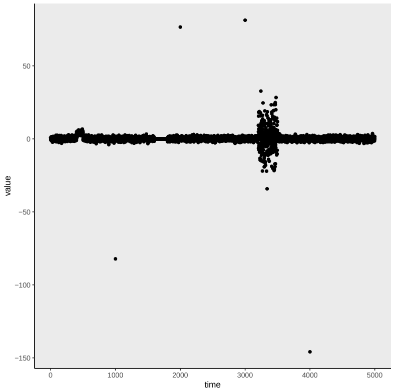

Anomalies - observations that do not conform with the pattern of the data.

- Point Anomaly - a *global* or *contextual* outlier.
- Collective Anomaly - observations that are credible in their context but unusual as a group.

Modelling Anomalies

Overview

Assume a parametric model for x_t with PDF $f(x, \theta(t))$

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Example 1 - simulated data

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R> x[401:500] = rnorm(100,4,1)
R> x[1601:1800] = rnorm(200,0,0.01)
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R> res<-uvcapa(x)
R> plot(res)
R> res
Univariate CAPA detecting changes in mean and variance.
observations = 5000
minimum segment length = 10
maximum segment length = 5000
Point anomalies detected : 4
  location  strength
1     1000  67.19607
2     2000  41.68110
3     3000 136.37800
4     4000  45.35898
Collective anomalies detected : 3
  start  end  mean.change variance.change
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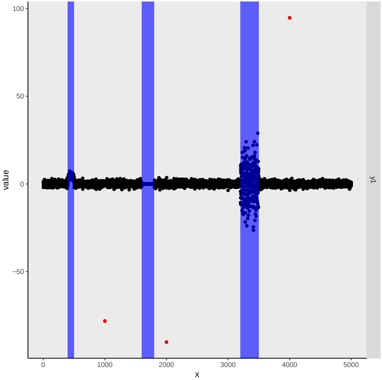

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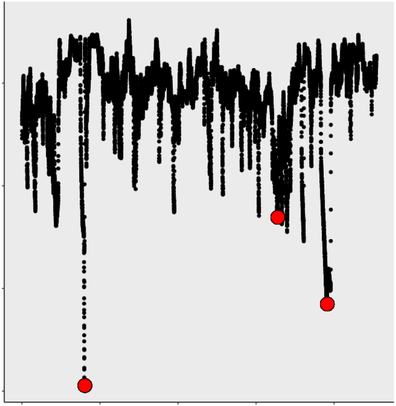

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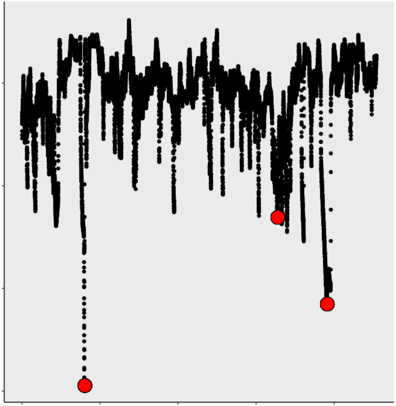

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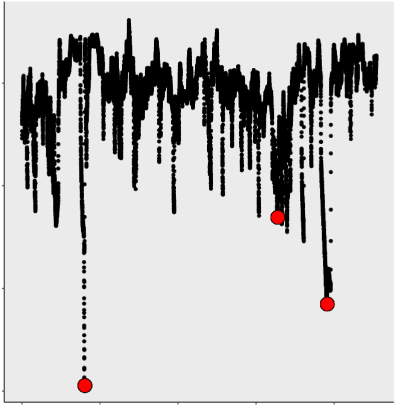

- Temperature sensor in a large industrial machine.

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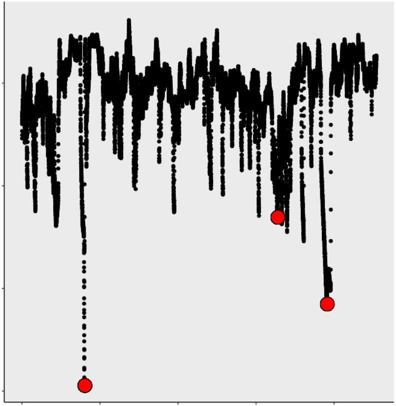

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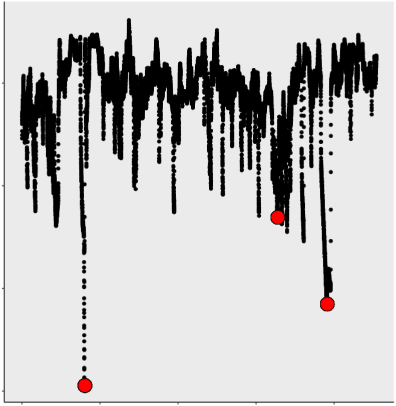

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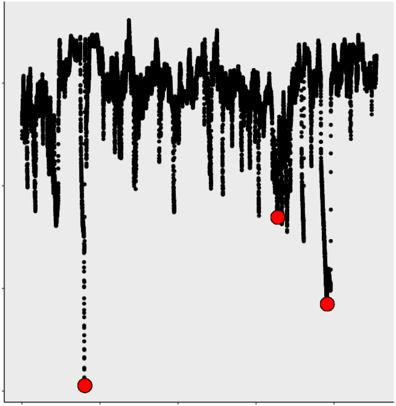

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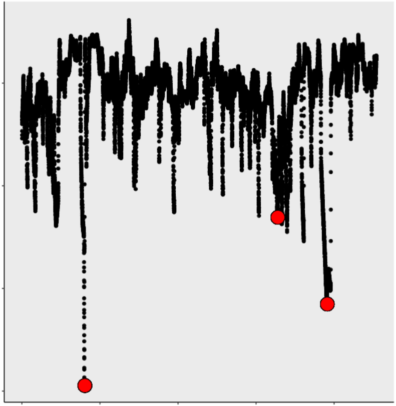

- Temperature sensor in a large industrial machine.
- Taken from the Numenta Anomaly Benchmark (NAB).
- 22695 observations at 5 minute intervals.
- Three known anomalies as identified by an engineer.
- Data is highly autocorrelated.

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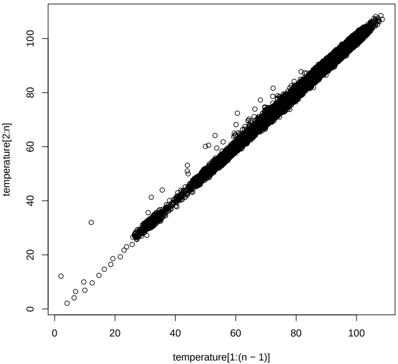
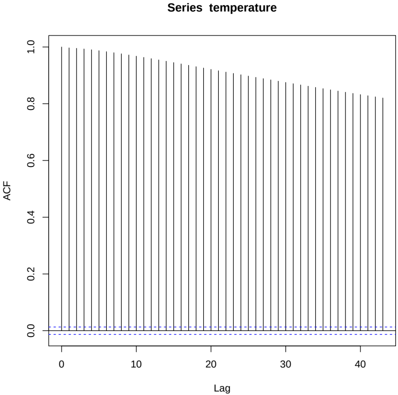
Example 2 - real data - accounting for autocorrelation





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R> library(robust)
R> rcov<-covRob(matrix(c(temperature[2:n],temperature[1:(n-1)]),
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R> inflated_penalty<-3*(1+psi)/(1-psi)*log(n)
R> res<-uvcapa(temperature,type="mean",beta=inflated_penalty,
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R> res # summary of results
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For details see

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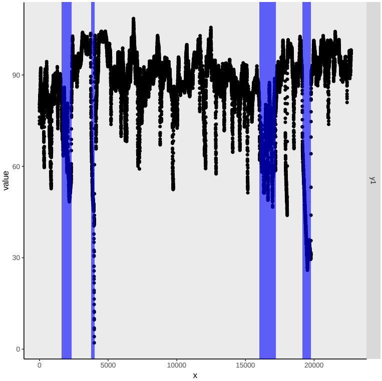

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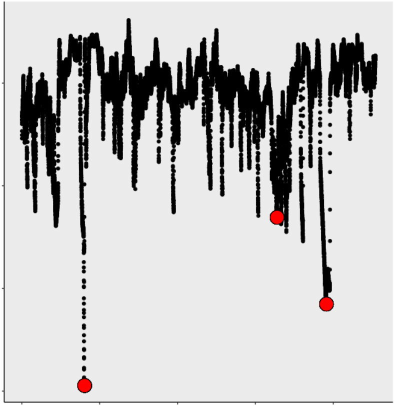

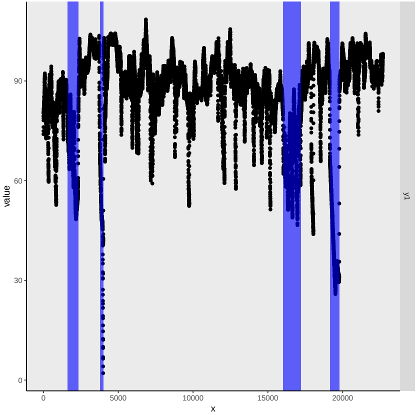

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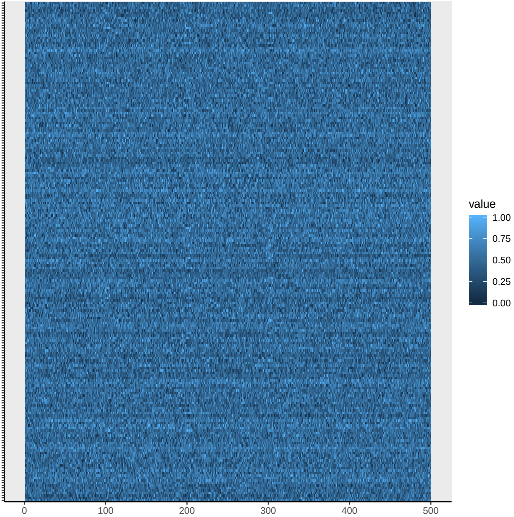

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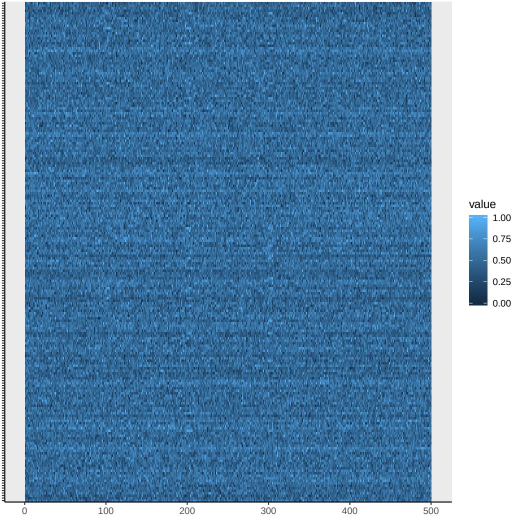

```
R> data(simulated)
# randomly shuffle the columns
R> set.seed(0)
R> m<-ncol(sim.data)
R> res<-capa(sim.data[,sample(1:m)],
           type="mean",max_lag=5)
R> plot(res)
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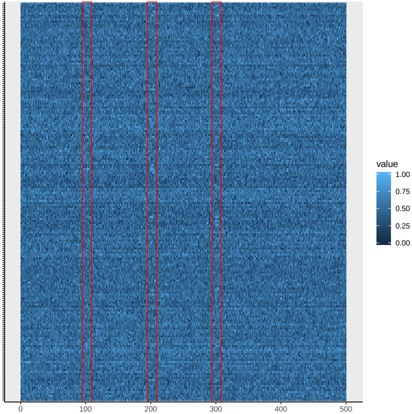

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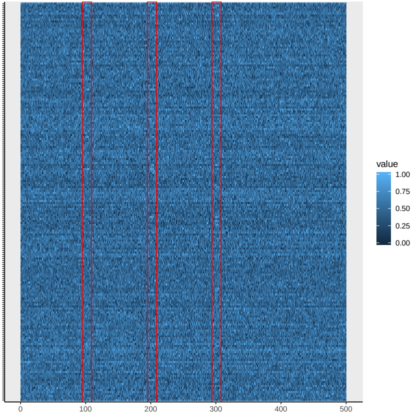

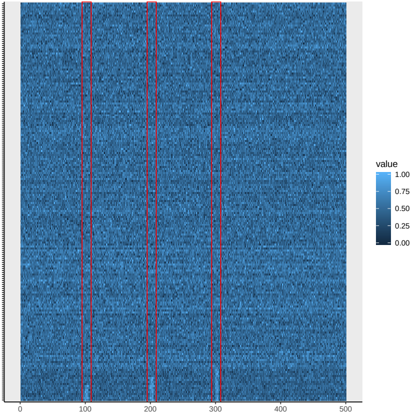

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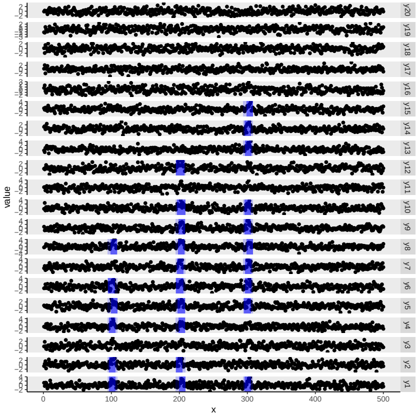

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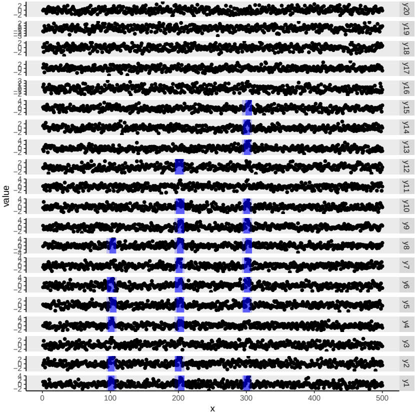

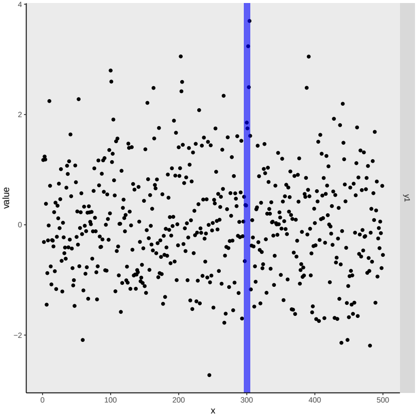

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References

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