

# Methodology for statistical detection of climate change

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# Detection

## Definition, according to the IPCC AR3 :

“Detection is the process of demonstrating that an observed change is significantly different (in a statistical sense) than can be explained by natural internal variability”

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## Detection of the anthropogenic climate change :

- Investigation of the presence of a particular signal, given by climate model simulation
- Double objectives :
  - Show the existence of a significant change of the observations
  - Validate the climate models

# Statistical modelisation

## Notations :

- $\psi$  : random climate vector, of dimension  $p$ , taking one value per year
- $C$  : the covariance matrix of  $\psi$
- $g$  : the climate change vector, of dimension  $p$ , given by a model

- 1 **Introduction**
- 2 **Presenting the problem**
  - Framework
  - Result when  $C$  is known
  - The problem when  $C$  is not known
- 3 **Proposed solution**
  - Regularisation
  - Bootstrap
- 4 **Some applications**
  - Climate scenario
  - Observations

# Framework

## Assumptions

- $(\psi_i)_{i \in \llbracket 1, n \rrbracket} \in \mathbb{R}^p$  rv iid having a  $N(0, C)$  distribution
- $\psi_{n+1} \in \mathbb{R}^p$ , independent of the  $(\psi_i)_{i \in \llbracket 1, n \rrbracket}$ , having a  $N(\mu g, C)$  distribution

With  $\mu \in \mathbb{R}$ ,  $g \in \mathbb{S}^{p-1} \subset \mathbb{R}^p$ , and  $C \in \mathcal{M}_p(\mathbb{R})$

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## Test

One wants to test :

$$H_0 : \mu = 0 \text{ vs } H_1 : \mu > 0$$

in large dimension, that is to say  $n \sim p$ .

# Investigated test family

One considers the following tests  $(T_f)_{f \in \mathbb{R}^p}$  :

## Test variable $d_f$

$$d_f = \langle \psi_{n+1}, f \rangle \sim_{H_0} N(0, f' C f)$$

## Rejection region

$$W_f = \left\{ \psi_{n+1} \in \mathbb{R}^p, d_f = \langle \psi_{n+1}, f \rangle \geq d_f^{(\alpha)} \right\}$$

with

$$d_f^{(\alpha)} = \Phi^{-1}(1 - \alpha) \sqrt{f' C f}$$



# Optimal $T_f$

## Question

Knowing  $C$  and  $g$ , is there an optimal  $T_f$  ?

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## Answer : yes

$T_{C^{-1}g}$  is optimal, among the  $(T_f)$ , within the following meaning

- $d_{C^{-1}g}$  maximise the signal-to-noise
- $T_{C^{-1}g}$  is the most powerful test
- $T_{C^{-1}g}$  is the likelihood ratio test

# Notations

In the case “ $C$  unknown”, one wants to approximate  $T_{C^{-1}g}$ .  
Two new test families are considered.

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## $\mathcal{T}_f$ tests

- $f$  is “estimated” : depending on  $(\psi_i)_{i \in \llbracket 1, n \rrbracket}$ , that are random, and on  $g$
- The level, conditionally to  $(\psi_i)_{i \in \llbracket 1, n \rrbracket}$ , is nominal;  
 $C$  is known, only for computing  $d_f^{(\alpha)} = \Phi^{-1}(1 - \alpha) \sqrt{f' C f}$

# Notations

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## $\mathcal{T}_f$ tests

## $\mathbb{T}_f$ tests

- $f$  is estimated
- The threshold  $d_f^{(\alpha)}$  is estimated depending on  $g$  and  $(\psi_i)_{i \in \llbracket 1, n \rrbracket}$ ; in the same way for the p-value
- The level is not necessarily nominal

# Notations

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Two new test families are considered.

$\mathcal{T}_f$  tests

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Naive test :  $T_g$

# Problem when $C$ is not known

## Objectives

One wants to construct a  $\mathbb{T}_f$  test having “good” properties :

- Nominal level
- A power greater than the one of the naive test  $T_g$

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## Remark

It is possible to firstly study  $\mathcal{I}_f$ , noticing that “ $\mathcal{I}_f > \mathbb{T}_f$ ”



# Using the empirical covariance matrix

$$\hat{C} = \frac{1}{n} \sum_{i=1}^n \psi_i \psi_i'$$

Does  $\mathcal{I}_{\hat{C}^{-1}g}$  have good properties ?

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Does  $\mathcal{I}_{\hat{C}^{-1}g}$  have good properties ?

**No !** ( $\hat{C}$  is quasi-singular)

The use of a pseudo-inverted truncation of  $\hat{C}$  doesn't give an efficient test either

# Regularisation in our case : shrinkage

## Main idea

One uses  $\gamma\hat{C} + \rho I_p$  instead of  $\hat{C}$ .

## Justification

- Interpolation with the naive test  $T_g$
- Ridge regression point of view
- Power of the tests  $\mathcal{T}_{(\gamma\hat{C} + \rho I_p)^{-1}g}$

# Estimation of the parameters $(\gamma, \rho)$

Optimal shrinkage method (O. Ledoit, *A Well-Conditioned Estimator for Large Dimensional Covariance Matrices*)

## Framework :

- One reasons on  $\mathcal{M}_p(\mathbb{R})$  with the norm

$$\|A\|_{\mathcal{M}_p}^2 = \frac{\text{Tr}(AA')}{p}$$

- A “general asymptotics” framework is used :  $n, p_n, \frac{p_n}{n} \leq K$
- Estimators of the following family are investigated  
 $C^* = \gamma \hat{C} + \rho I_p$ . One researches the  $C^*$  minimising :

$$E \left( \|C^* - C\|_{\mathcal{M}_p}^2 \right)$$

# Estimation of the parameters $(\gamma, \rho)$

Optimal shrinkage method (O. Ledoit, *A Well-Conditioned Estimator for Large Dimensional Covariance Matrices*)

$n$  fixed : optimal  $\gamma_n^0$  and  $\rho_n^0$  depending on  $C$

$$\gamma_n^0 = \frac{\alpha^2}{\delta^2}, \quad \text{and} \quad \rho_n^0 = \frac{\beta^2 \nu}{\delta^2}$$

where

$$\nu = \langle C, I_p \rangle_{\mathcal{M}_p} = \frac{\text{Tr}(C)}{p}, \quad \alpha^2 = \|C - \nu I_p\|_{\mathcal{M}_p}^2,$$

$$\beta^2 = \mathbb{E} \left( \|\hat{C} - C\|_{\mathcal{M}_p}^2 \right), \quad \delta^2 = \mathbb{E} \left( \|\hat{C} - \nu I_p\|_{\mathcal{M}_p}^2 \right),$$

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Under “general asymptotics” : convergent estimators  $\hat{\gamma}_n^0$  and  $\hat{\rho}_n^0$  of  $\gamma_n^0$  and  $\rho_n^0$

$$\hat{\gamma} = \frac{\hat{\alpha}^2}{\hat{\delta}^2}, \quad \text{and} \quad \hat{\rho} = \frac{\hat{\beta}^2 \hat{\nu}}{\hat{\delta}^2}$$

With

$$\hat{\nu} = \langle \hat{C}, I_p \rangle_{\mathcal{M}_p} = \frac{\text{Tr}(\hat{C})}{p}, \quad \hat{\beta}^2 = \min \left( \hat{\delta}^2, \frac{1}{n^2} \sum_{i=1}^n \|\psi_i \psi_i' - \hat{C}\|_{\mathcal{M}_p}^2 \right),$$

$$\hat{\delta}^2 = \|\hat{C} - \hat{\nu} I_p\|_{\mathcal{M}_p}^2, \quad \hat{\alpha}^2 = \hat{\delta}^2 - \hat{\beta}^2.$$

## Estimation of the parameters $(\gamma, \rho)$

Optimal shrinkage method (O. Ledoit, *A Well-Conditioned Estimator for Large Dimensional Covariance Matrices*)

**$n$  fixed : optimal  $\gamma_n^0$  and  $\rho_n^0$  depending on  $C$**

**Under “general asymptotics” : convergent estimators  $\hat{\gamma}_n^0$  and  $\hat{\rho}_n^0$  of  $\gamma_n^0$  and  $\rho_n^0$**

A new estimator of  $C$  is defined :

$$\hat{C}_I = \hat{\gamma}_n^0 \hat{C} + \hat{\rho}_n^0 I_p$$

# Bootstrap's motivations

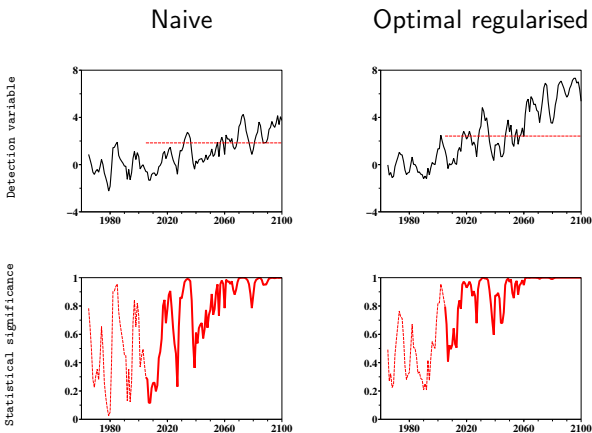
One has to achieve the construction of  $\mathbb{T}_{\hat{C}_I^{-1}g}$ , by :

- computing the test threshold (and more generally the  $p$ -value),
- verifying that this computation is correct, or that the level is close to the nominal value,
- computing the power.

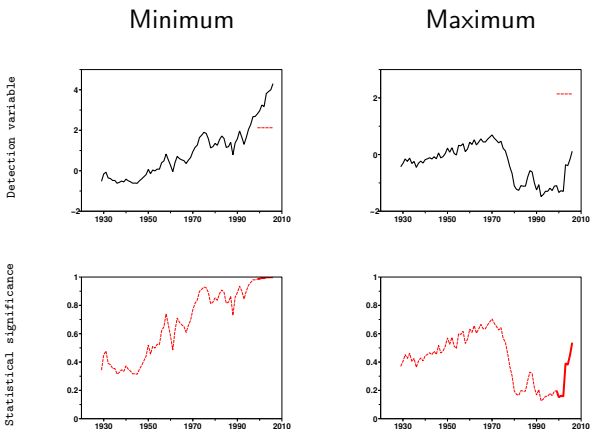


# Additional treatment

- Choice of a learning sample,
- Temporal treatment (mobile average),
- Spatial centering.



**Figure: Summer minimum temperatures in the model :** Comparison between the naive test  $T_g$  and the optimal regularised  $\mathbb{T}_{\hat{C}_I^{-1}g}$  for summer minimum temperatures taken from a climate scenario.



**Figure: Summer temperatures in observations :** Results for minimum and maximum temperatures

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## Questions