

# CHANGE DETECTION ALGORITHMS

FUNDAMENTALS

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# LECTURE SUMMARY

1. Introduction

2. Deterministic tests

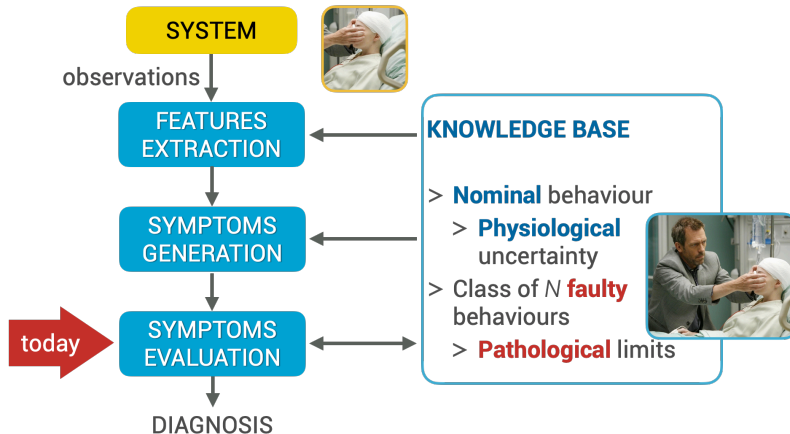
3. Basic Probabilistic Tests

4. Conclusions

# INTRODUCTION

# INTRODUCTION

## REMEMBER THE PARALLEL WITH MEDICAL DIAGNOSIS?



# INTRODUCTION

## DIAGNOSIS $\Rightarrow$ (MULTIPLE) HYPOTHESIS TESTING

### 1 DETECTION

Testing the **null hypothesis**:

$\mathcal{H}_0$ : “Is the system behaving in a **nominal** way?”

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### 2 ISOLATION

Testing the  $N$  **faulty hypotheses**:

$\mathcal{H}_i$ : “Is the system behaving as if the  **$i$ -th fault** is present?”

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$\mathcal{H}_i$ : “Is the system behaving as if the  **$i$ -th fault** is present?”

### 3 IDENTIFICATION AND ESTIMATION

If every but one  $\mathcal{H}_i$  is falsified  $\Rightarrow$  **estimate** parameters of  $i$ -th fault

If every  $\mathcal{H}_i$  is falsified  $\Rightarrow$  **identify** model of new fault

# INTRODUCTION

## THE BOY WHO CRIED WOLF

### Aesop's Fable: The Boy Who Cried Wolf

1. The shepherd boy cries wolf when there is no wolf. Villagers rush in and get mad to find out it was a joke.

*[Repeat 1. for other  $N - 1$  times]*

2. Finally the wolf comes, the boy cries wolf but the villagers do not come. The wolf eats the boy.



<https://developers.google.com/machine-learning/crash-course/classification/true-false-positive-negative>



# INTRODUCTION

## THE BOY AS A WOLF DETECTOR: CONFUSION MATRIX

Here we assume  $\mathcal{H}_0$  = “No wolf” = **healthy**.

		Reality	
		Wolf	No Wolf
Boy	Wolf	<b>True Positive (TP)</b> Boy is a hero!	<b>False positive (FP)</b> Villagers are mad!
	No Wolf	<b>False negative (FN)</b> Boy is eaten	<b>True negative (TN)</b> Everyone is fine

An FP is also called Type-I error, while a FN is also called Type-II error.

# INTRODUCTION

## DETECTION PERFORMANCE

### Definition (Detection errors)

**True Positive**  $TP \triangleq \#\neg\mathcal{H}_0(F)$

**True Negative**  $TN \triangleq \#\mathcal{H}_0(H)$

**False Positive**  $FP \triangleq \#\neg\mathcal{H}_0(H)$

**False Negative**  $FN \triangleq \#\mathcal{H}_0(F)$

### Definition (Detection performance)

**False Positive Rate**  $FPR \triangleq \frac{FP}{FP+TN}$

**True Negative Rate**  $TNR \triangleq 1 - FPR$

**True Positive Rate**  $TPR \triangleq \frac{TP}{TP+FN}$

**False Negative Rate**  $FNR \triangleq 1 - TPR$

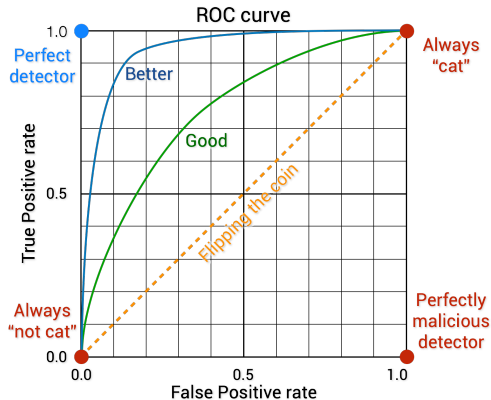
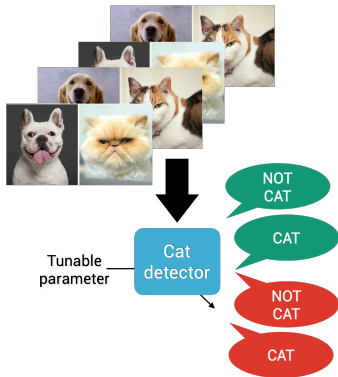
**Accuracy**  $ACC \triangleq \frac{TP+TN}{TP+FP+TN+FN}$

**Recall**  $RE \triangleq \frac{TP}{TP+FN} = TPR$

 Tom Fawcett. "An introduction to ROC analysis". In: *Pattern recognition letters* 27.8 (2006), pp. 861–874

# INTRODUCTION

## DETECTION PERFORMANCE

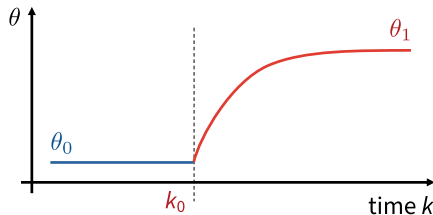


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# INTRODUCTION

## THE CHANGE DETECTION PROBLEM

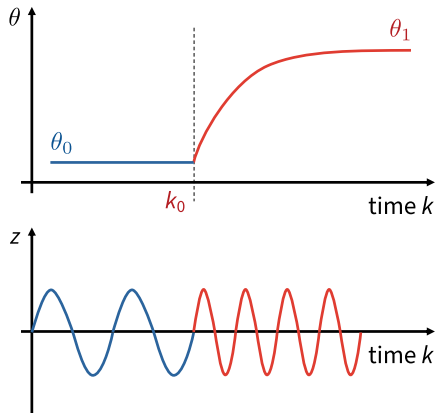
- ▶ Behaviour of system is described by a parameter  $\theta$
- ▶ It changes from a known **nominal** value  $\theta_0$  to a **faulty**  $\theta_1$  at some time instant  $k_0$



# INTRODUCTION

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- ▶ Behaviour of system is described by a parameter  $\theta$
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- ▶ You can only measure a **symptom**  $z(k)$



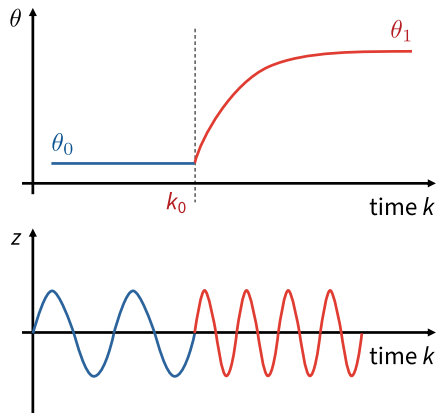
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### Change detection problem

Estimate  $k_0$  and  $\theta_1$  by looking at  $z(k)$



# DETERMINISTIC TESTS

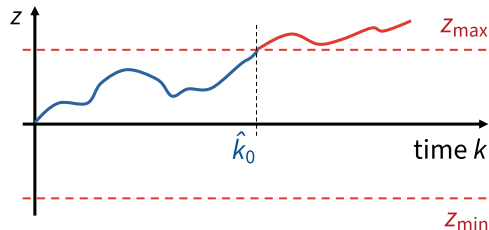
# DETERMINISTIC TESTS

## LIMIT CHECK: SCALAR VARIABLES

- ▶ In any process you know which are the **minimum** and **maximum allowed** values
  - ▶ E.g.: you heart rate at rest should be between 60 and 100 bpm

**Intuition: is  $z(k)$  inside a known range?**

Limit check:  $z(k) \notin [z_{\min} z_{\max}] \Rightarrow \text{ALARM}$



**PROS**

**CONS**



# DETERMINISTIC TESTS

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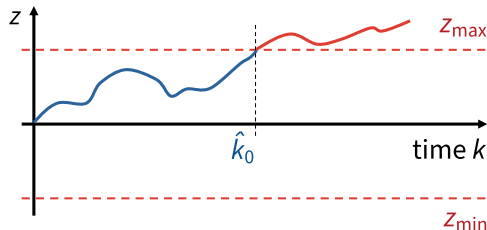
Limit check:  $z(k) \notin [z_{\min} z_{\max}] \Rightarrow \text{ALARM}$

### PROS

- + It holds for sure!
- + Simple to define and check

### CONS

- Over conservative
- Works in steady state only



# DETERMINISTIC TESTS

## LIMIT CHECK: VECTOR VARIABLES

► Assume  $z(k) \in \mathbb{R}^n$

### Intuition: evaluation function

**Define** a scalar valued **evaluation function** and reduce the problem to scalar limit-checking.

$$Z \triangleq f_{\text{ev}}(z(k)), \quad f_{\text{ev}} : \mathbb{R}^n \mapsto \mathbb{R}$$

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Most of the times you want  $f_{\text{ev}} : \mathbb{R}^n \mapsto \mathbb{R}^+$

# DETERMINISTIC TESTS

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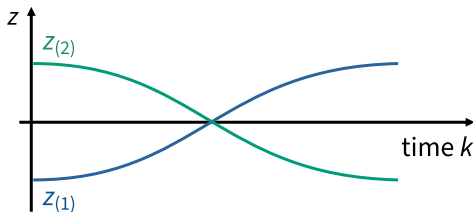
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Example:  $z \in \mathbb{R}^2$ ,  $f_{\text{ev}}(z(k)) = \|z(k)\|_2$



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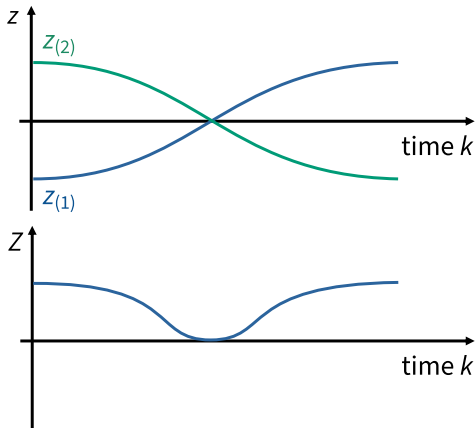
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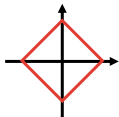
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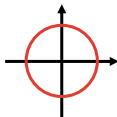
# DETERMINISTIC TESTS

## LIMIT CHECK: VECTOR VARIABLES – EXAMPLES

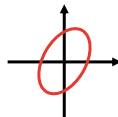
$$\|z\|_1 = c$$



$$\|z\|_2 = c$$

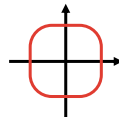


$$z^T A z = c$$



$$A \succeq 0$$

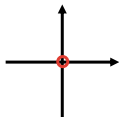
$$\|z\|_p = c$$



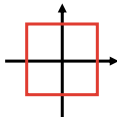
$$p > 2$$

$$c \in \mathbb{R}^+$$

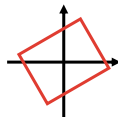
$$\|z\|_0 = c = 0$$



$$\|z\|_\infty = c$$

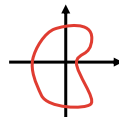


$$\|Az\|_\infty = c$$



$$A \in \mathbb{R}^{2 \times 2}$$

$$\text{poly}(z) = c$$



# DETERMINISTIC TESTS

## LIMIT CHECK: SEQUENCES OVER TIME

- ▶ In previous examples we applied limit checks only to instantaneous value  $z(k)$
- ▶ How to check a vector-valued sequence  $\{z(k)\}_{k_1}^{k_2}$  over time?

### 1. First over all the components, then over time

Examples:  $Z = \|z(k)\|_{p,[k_1,k_2]} = \sum_{k=k_1}^{k_2} \|z(k)\|_p$  (sum of  $L^p$  norms)

$$Z = \| \{ \|z(k)\|_p \}_{k_1}^{k_2} \|_{\ell^q} \quad (\ell^q \text{ norm of } L^p \text{ norms})$$

# DETERMINISTIC TESTS

## LIMIT CHECK: SEQUENCES OVER TIME

- ▶ In previous examples we applied limit checks only to instantaneous value  $z(k)$
- ▶ How to check a vector-valued sequence  $\{z(k)\}_{k_1}^{k_2}$  over time?

### 2. First over time, then over all the components

Examples:  $Z = \left\| \sum_{k=k_1}^{k_2} z(k) / (k_2 - k_1 + 1) \right\|_p$  ( $L^p$  norm of averages)

$$Z = \left\| \text{FFT}(\{z(k)\}_{k_1}^{k_2}) \right\|_p$$
 ( $L^p$  norm of FFT components)

# DETERMINISTIC TESTS

## LIMIT CHECK: IMPROVEMENTS

- ▶ Time-varying limits
  - ▶ Dependent on operating conditions
  - ▶ Based on models  $\Rightarrow$  valid also in non-steady-state conditions
  - 👉 Lectures L4.x and L5.x
- ▶ Probabilistic checks
  - 👉 next section and next lecture

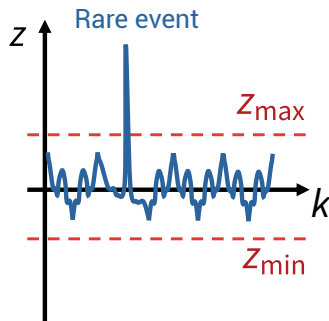


# BASIC PROBABILISTIC TESTS

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## MOTIVATIONS

- ✚ Deterministic checks leads to zero-FPR by construction
- ✚ They can have very poor TPR (no-free-lunch principle)
  - 👉 see slide on ▶ ROC
- ▶ Evident when  $z$  can have large but rare values
- ▶ When data is generated by a random process (i.e. always) with infinite support, you cannot define  $[z_{\min} z_{\max}]$

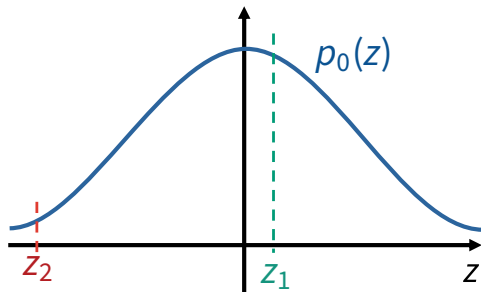


# BASIC PROBABILISTIC TESTS

## STATISTICAL HYPOTHESIS TESTING

### Intuition: check if the PDF changed

1. **Assume** that under  $\mathcal{H}_0$  data is generated by a random process with given PDF  $p_0(z)$
2. **Collect** actual data
3. **Answer** the question: is the data **likely** to have been drawn from  $p_0(z)$  or from another PDF ?



 Rolf Isermann. *Fault-diagnosis systems: an introduction from fault detection to fault tolerance*. Springer Science & Business Media, 2006, Ch. 7

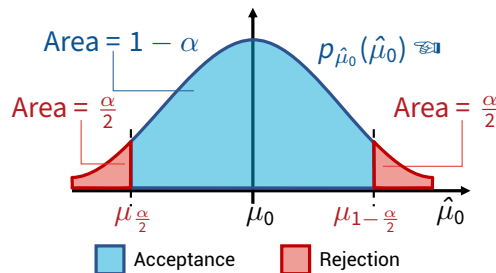
# BASIC PROBABILISTIC TESTS

## STATISTICAL HYPOTHESIS TESTING À-LA FISHER – EXAMPLE

### Intuition: check p-value of parameters

1. **Assume** that you know one parameter of  $p_0(z)$ , e.g. the **true mean**  $\mu_0$
2. **Compute** the **empirical mean**  $\hat{\mu}_0$  from data (its PDF is  $p_{\hat{\mu}_0}$ )
3. **Check** if its **p-value**  $< \alpha$ , where  $0 \leq \alpha \ll 1$  is the **significance**<sup>a</sup>

<sup>a</sup>The confidence level of this test is  $1 - \alpha$



? What is the FPR of this test?

# BASIC PROBABILISTIC TESTS

## STATISTICAL HYPOTHESIS TESTING À-LA FISHER – EXAMPLE

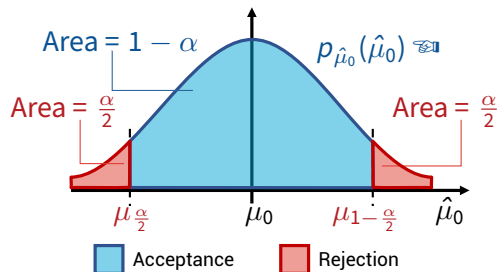
$\mu_0$  True mean of data (known)

$\hat{\mu}_0$  Empirical mean of data

$p_{\hat{\mu}_0}$  PDF of  $\hat{\mu}_0$  (not of data!)

$$\mu_{\frac{\alpha}{2}} : \int_{-\infty}^{\mu_{\frac{\alpha}{2}}} p_{\hat{\mu}_0}(\mu) d\mu = \frac{\alpha}{2}$$

$$\mu_{1-\frac{\alpha}{2}} : \int_{\mu_{1-\frac{\alpha}{2}}}^{\infty} p_{\hat{\mu}_0}(\mu) d\mu = \frac{\alpha}{2}$$



► Did you know?  $\mathbb{E}[\hat{\mu}_0] = \mu_0$ , because  $\hat{\mu}_0$  is an unbiased estimator

# BASIC PROBABILISTIC TESTS

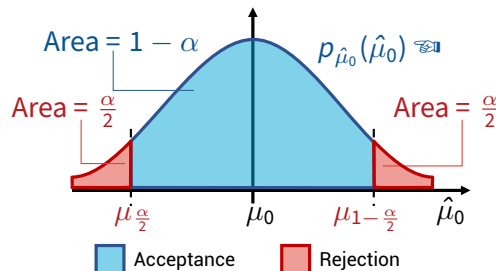
## STATISTICAL HYPOTHESIS TESTING À-LA FISHER – EXAMPLE

### Definition (p-value)

The **p-value** of a given realization  $x^*$  of a random process  $X$  is the **probability** that  $X$  can take values more **extreme** than  $x^*$ .



Do you know how many tails has your distribution?

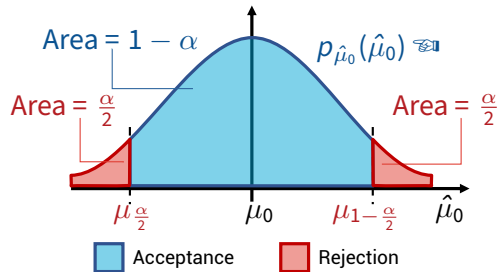


# BASIC PROBABILISTIC TESTS

## STATISTICAL HYPOTHESIS TESTING À-LA FISHER – EXAMPLE

### The Perils of the P-value

- ▶ One of most-abused concept in science
- ▶ It tells you how likely is the data given  $\mathcal{H}_0$ , not the other way around!
- ▶ Completely nonsense if your hypothesis on PDF of data is wrong



<https://www.scientificamerican.com/article/the-significant-problem-of-p-values/>

# BASIC PROBABILISTIC TESTS

## EMPIRICAL MOMENTS

- In the following we will make use of empirical mean and variance computed over a moving window

**Mean**

$$\hat{\mu}_{[k-N+1,k]} \triangleq \frac{1}{N} \sum_{j=k-N+1}^k z(j)$$

**Variance**

$$\hat{\sigma}_{[k-N+1,k]}^2 \triangleq \frac{1}{N-1} \sum_{j=k-N+1}^k (z(j) - \mu_0)^2$$

- We may use a shortened notation such as  $\hat{\mu}(k) \equiv \hat{\mu}_{[k-N+1,k]}$
- In case  $\mu_0$  is not known, we may replace it with  $\hat{\mu}$  in the computation of  $\hat{\sigma}^2$



# BASIC PROBABILISTIC TESTS

## TESTING THE MEAN – T-STUDENT

### PROBLEM

- 🎯 Determine if the mean of a normal random variable changed
- ▶ Nominal mean  $\mu_0$  is known
- ▶ Nominal variance is not known, but constant
- ▶ Empirical moments  $\hat{\mu}(k)$  and  $\hat{\sigma}^2(k)$  are estimated from last  $N$  samples

### SOLUTION

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### SOLUTION

- ▶ The following random variable

$$t(k) = \frac{\hat{\mu}(k) - \mu_0}{\hat{\sigma}(k)/\sqrt{N}}$$

is **t-Student** with  $N - 1$  degrees of freedom

- ➡ test if  $|t| > t_{\alpha, N-1}$

# BASIC PROBABILISTIC TESTS

## TESTING THE MEAN – MORE T-STUDENT

### PROBLEM

- ◎ Same as before, but ... nominal mean  $\mu_0$  is **unknown**

### SOLUTION

# BASIC PROBABILISTIC TESTS

## TESTING THE MEAN – MORE T-STUDENT

### PROBLEM

- Same as before, but ... nominal mean  $\mu_0$  is **unknown**

### SOLUTION

- Estimate true mean before and after change as  $\hat{\mu}_0(k) = \hat{\mu}_{[k-N_0+1,k]}$  and, respectively,  $\hat{\mu}_1(k) = \hat{\mu}_{[k,k+N_1-1]}$
- Similarly estimate  $\hat{\sigma}_0^2$  and  $\hat{\sigma}_1^2$
- ➔ The following random variable is **t-Student** with  $N_0 + N_1 - 2$  degrees of freedom

$$t(k) = \frac{\hat{\mu}_0(k) - \hat{\mu}_1(k)}{\sqrt{(N_0 - 1)\hat{\sigma}_0^2(k) + (N_1 - 1)\hat{\sigma}_1^2(k)}} \sqrt{\frac{N_0 N_1 (N_0 + N_1 - 2)}{N_0 + N_1}}$$

# BASIC PROBABILISTIC TESTS

## TESTING THE VARIANCE – $\chi^2$

### PROBLEM

- ⊙ Determine if variance of a normal random variables changed from a known value  $\sigma_0^2$

### SOLUTION

# BASIC PROBABILISTIC TESTS

## TESTING THE VARIANCE – $\chi^2$

### PROBLEM

- ⊙ Determine if variance of a normal random variables changed from a known value  $\sigma_0^2$

### SOLUTION

- ▶ Compute the empirical variance  $\hat{\sigma}^2(k)$  from previous  $N$  samples
- ▶ The following random variable is  $\chi^2$  with  $N - 1$  degrees of freedom

$$\chi^2(k) = \frac{(N - 1)\hat{\sigma}^2}{\sigma_0^2}$$

- ➡ if  $\chi^2(k) > \chi_{N-1, 1-\alpha}^2$  then reject  $\mathcal{H}_0$  with significance  $\alpha$



how many tails has  $\chi^2$  ?

# BASIC PROBABILISTIC TESTS

## TESTING THE VARIANCE – F-TEST

### PROBLEM

- ◎ Same as before, but true  $\sigma_0$  is unknown

### SOLUTION

# BASIC PROBABILISTIC TESTS

## TESTING THE VARIANCE – F-TEST

### PROBLEM

- 🎯 Same as before, but true  $\sigma_0$  is unknown

### SOLUTION

- ▶ Compute the empirical variance  $\hat{\sigma}_0^2(k)$  from previous  $N_0$  samples, and  $\hat{\sigma}_1^2(k)$  from next  $N_1$  samples
- ▶ The following random variable is  $F$  with  $(N_0 - 1, N_1 - 1)$  degrees of freedom

$$F(k) = \frac{\hat{\sigma}_0^2}{\hat{\sigma}_1^2}$$

- ➡ if  $F > F_{N_0-1, N_1-1, 1-\alpha}$  then reject  $\mathcal{H}_0$  with significance  $\alpha$



how many tails has  $F$  ?



# BASIC PROBABILISTIC TESTS

## LIMITATIONS

- ▶ To **falsify** the null hypothesis with **good significance** you need a **high number of samples** before and after the (hypothetical) change
- ▶ this **delays detection**
- 👉 **likelihood based algorithms** (such as CUSUM), next lecture

# CONCLUSIONS

# CONCLUSIONS

## IN THIS LECTURE WE COVERED

- ▶ Fundamentals of change detection
- ▶ Deterministic tests
- ▶ Basic probabilistic tests

Next lecture: **Advanced probabilistic tests**

# CONCLUSIONS

THANK YOU FOR YOUR ATTENTION!

For further information:  
Course page on **Brightspace**  
or  
our **MS Team**