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UNIVERSITÀ  
CATTOLICA  
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# LOCAL NONPARAMETRIC INFERENCE ON FUNCTIONAL DATA WITH MANIFOLD DOMAIN

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**Statistical Methods for Data Analysis and Decision Sciences**

**Third Conference of the Statistics and Data Science Group  
of the Italian Statistical Society**



Niels Lundtorp Olsen  
Technical University of Denmark



Simone Vantini  
Politecnico di Milano



**POLITECNICO**  
MILANO 1863

# PROBLEM FORMULATION

Functional data on  $L^2(D) \cap \mathcal{C}^0(D)$ , where  $D \subset \mathbb{R}^p$ .

**Aim:** test **locally** a functional hypothesis  $H_0$  against  $H_1$ .

We assume that the domain  $D$  is a Riemannian manifold of  $\mathbb{R}^p$

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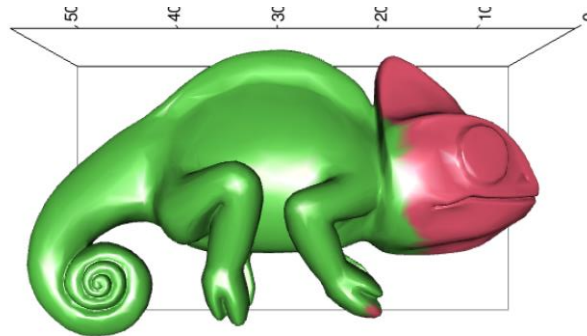
**Aim:** test **locally** a functional hypothesis  $H_0$  against  $H_1$ .

We assume that the domain  $D$  is a Riemannian manifold of  $\mathbb{R}^p$

**Example.** Testing differences between two groups of functional data defined on a complex chameleon-shaped manifold

$$y_i(x) = \mu_j(x) + \varepsilon_{ij}(x) \quad j = 1, 2; \quad i = 1, \dots, n_j$$

$$H_0 : \mu_1(x) = \mu_2(x) \quad \forall x \in D; \quad H_1 : \mu_1(x) \neq \mu_2(x) \text{ for some } x \in D$$

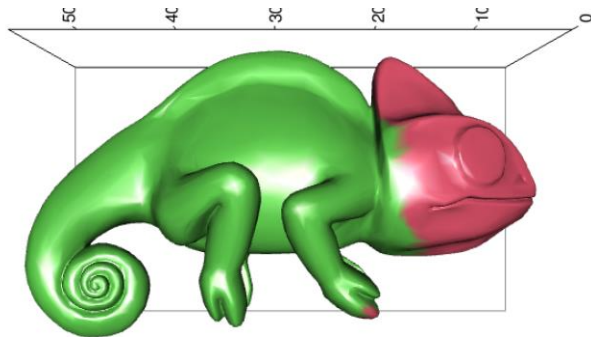


# PROBLEM FORMULATION

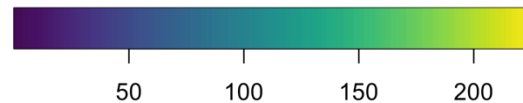
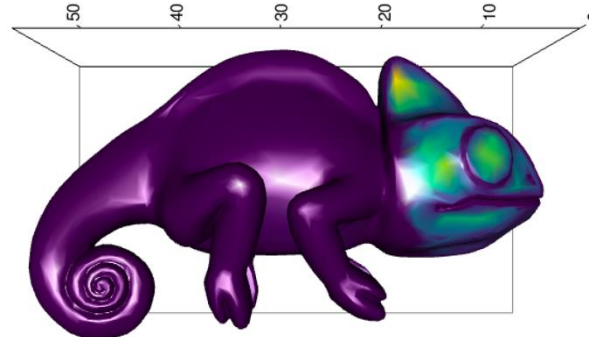
Functional data on  $L^2(D) \cap \mathcal{C}^0(D)$ , where  $D \subset \mathbb{R}^p$ .

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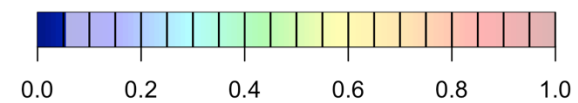
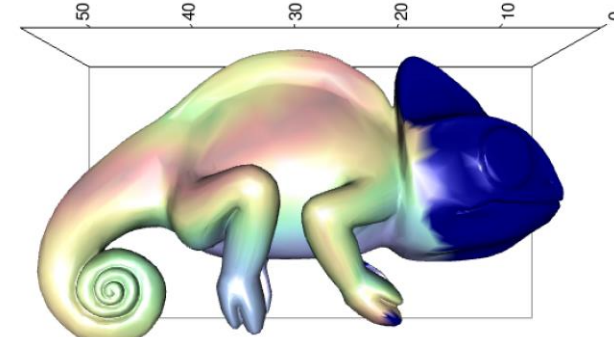
True mean difference



Pointwise t-test statistic



Pointwise p-value



# PROBLEM FORMULATION



functional data on  $L^2(D) \cap C^0(D)$ , where  $D \subset \mathbb{R}^p$ .

: test locally a functional hypothesis  $H_0$  against  $H_1$ .

**Multiplicity issue!**  
**no control of the amount of type I errors**  
**over the domain.**

True mean difference

Pointwise t-test statistic

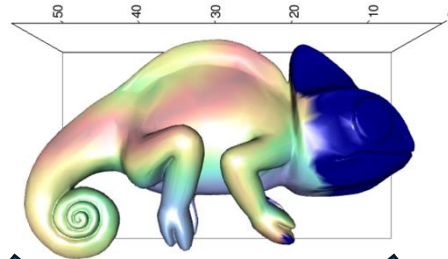
Pointwise p-value

**AIM**

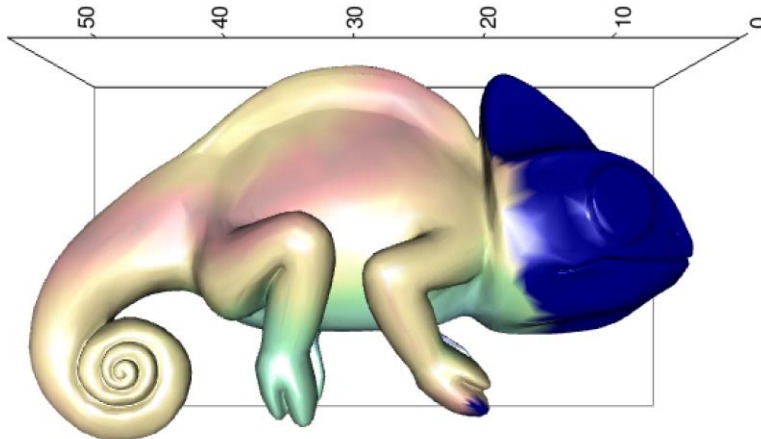
Computing an adjusted p-value function defined on  $D$  that controls an error rate defined on the whole domain.

# ADJUSTED P-VALUE FUNCTIONS

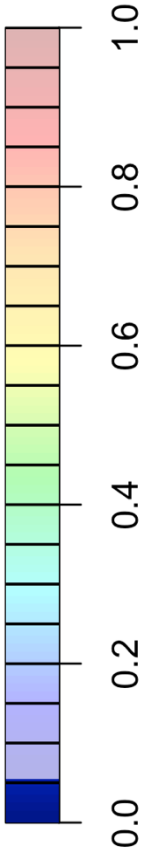
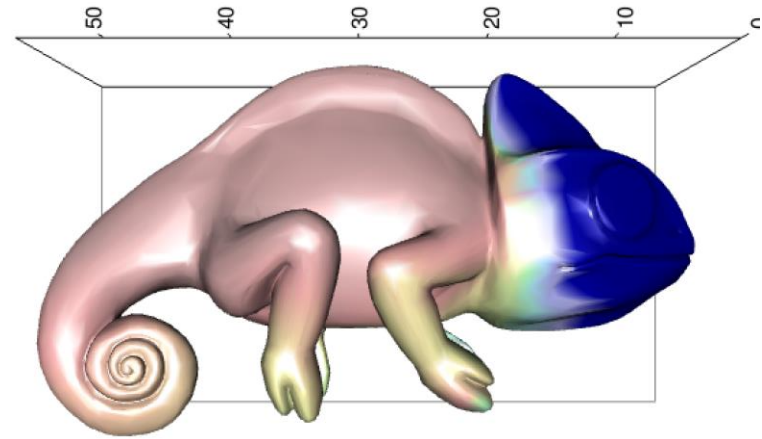
Pointwise p-value



FDR adjusted p-value



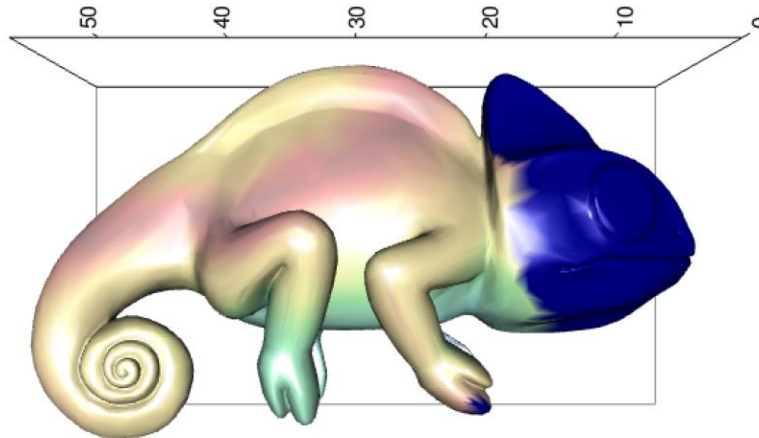
Ball-wise adjusted p-value



## FDR-adjusted p-value function

Olsen et al 2021 TEST

$$\tilde{p}(t) = \min_{s \geq p(t)} \left\{ 1, \frac{\mu(D) \cdot s}{\mu(\{r : p(r) \leq s\})} \right\}$$





# THE FUNCTIONAL FALSE DISCOVERY RATE

The FDR in multivariate statistics (Benjamini and Hochberg, 1995).

TABLE 1  
*Number of errors committed when testing  $m$  null hypotheses*

	<i>Declared non-significant</i>	<i>Declared significant</i>	<i>Total</i>
True null hypotheses	<b>U</b>	<b>V</b>	$m_0$
Non-true null hypotheses	<b>T</b>	<b>S</b>	$m - m_0$
	$m - \mathbf{R}$	<b>R</b>	$m$

$$\text{FDR} = \mathbb{E} \left[ \frac{V}{R} 1(R > 0) \right]$$

# THE FUNCTIONAL FALSE DISCOVERY RATE

The FDR in functional data analysis.

	Declared non significant	Declared significant	
True null Hypotheses	$U$ $\mu\{t \in D : H_{0t} \text{ true}, \tilde{p}(t) > \alpha\}$	$V$ $\mu\{t \in D : H_{0t} \text{ true}, \tilde{p}(t) \leq \alpha\}$	$m_o$
False null Hypotheses	$T$ $\mu\{t \in D : H_{0t} \text{ false}, \tilde{p}(t) > \alpha\}$	$S$ $\mu\{t \in D : H_{0t} \text{ false}, \tilde{p}(t) \leq \alpha\}$	$m_1$
	$m - R$	$R$	$m$

$$\text{FDR} = \mathbb{E} \left[ \frac{V}{R} 1(R > 0) \right]$$

# THE FUNCTIONAL BENJAMINI HOCHBERG PROCEDURE

1. Choose a suited functional test (either parametric or non-parametric).

$$H_0^{\mathcal{I}} : \mathcal{Y}_1^{\mathcal{I}} = \mathcal{Y}_2^{\mathcal{I}} \quad H_1^{\mathcal{I}} : \mathcal{Y}_1^{\mathcal{I}} \neq \mathcal{Y}_2^{\mathcal{I}}$$

2. Compute the unadjusted  $p$ -value function.

$$p(t) = \limsup_{\mathcal{I} \rightarrow t} p^{\mathcal{I}}$$

3. Perform functional FDR procedure:

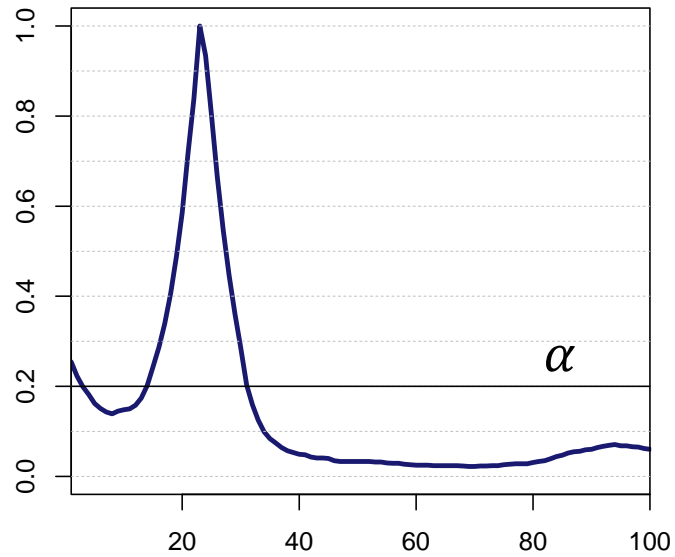
A. Adjust the threshold

$$p(t) < \alpha^*, \quad \text{with} \quad \alpha^* = \arg \max_{\bar{p}} \left\{ \frac{\alpha \mu\{r : p(r) \leq \bar{p}\}}{\mu(D)} \geq \bar{p} \right\}$$

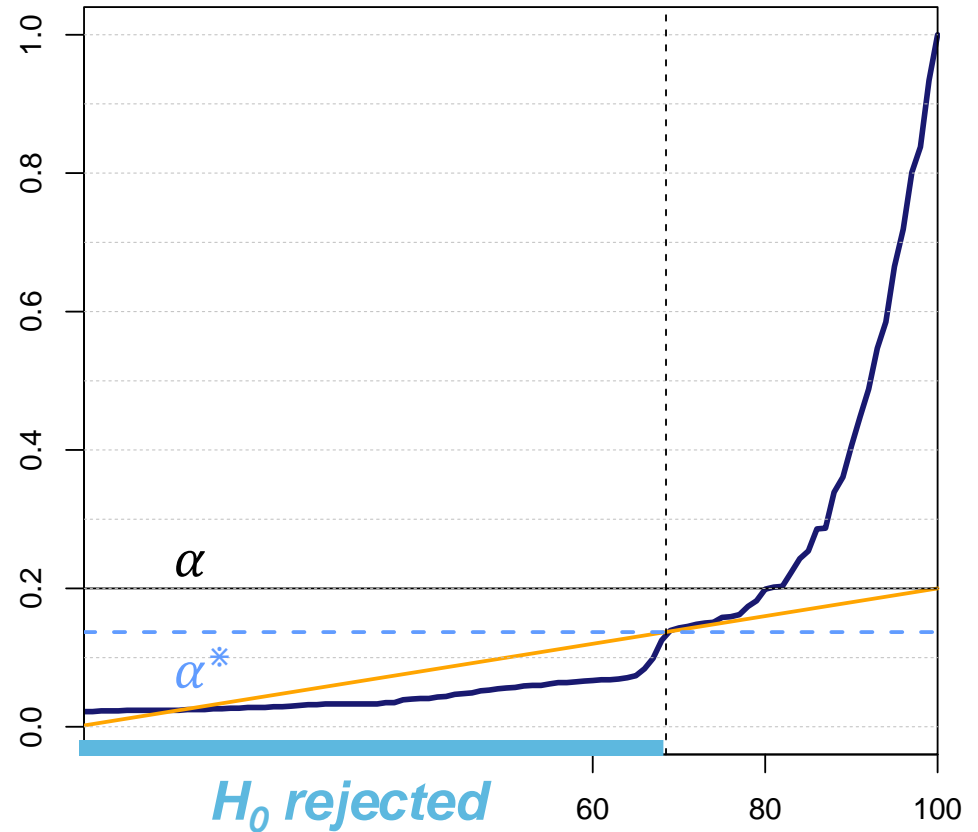
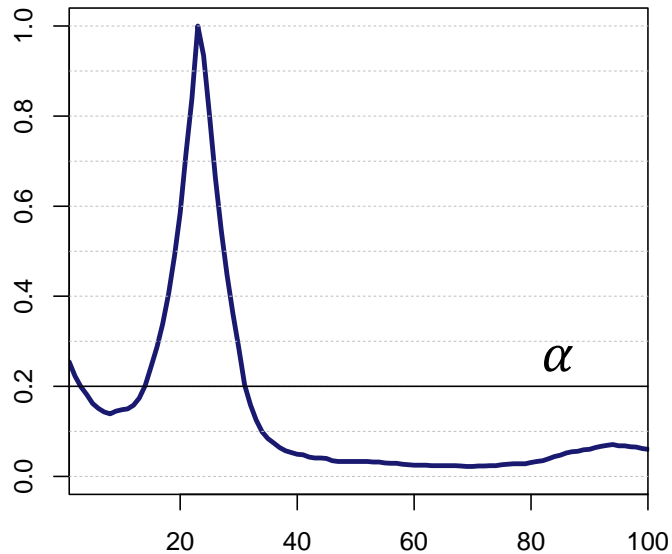
B. Adjust the  $p$ -value

$$\tilde{p}(t) < \alpha, \quad \text{with} \quad \tilde{p}(t) = \min_{s \geq p(t)} \left\{ 1, \frac{\mu(D)s}{\mu\{r : p(r) \leq s\}} \right\}$$

# ADJUSTING THE THRESHOLD

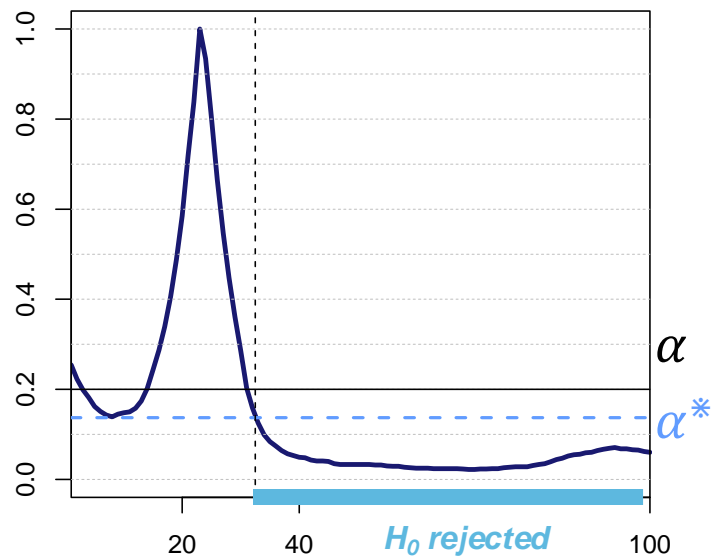
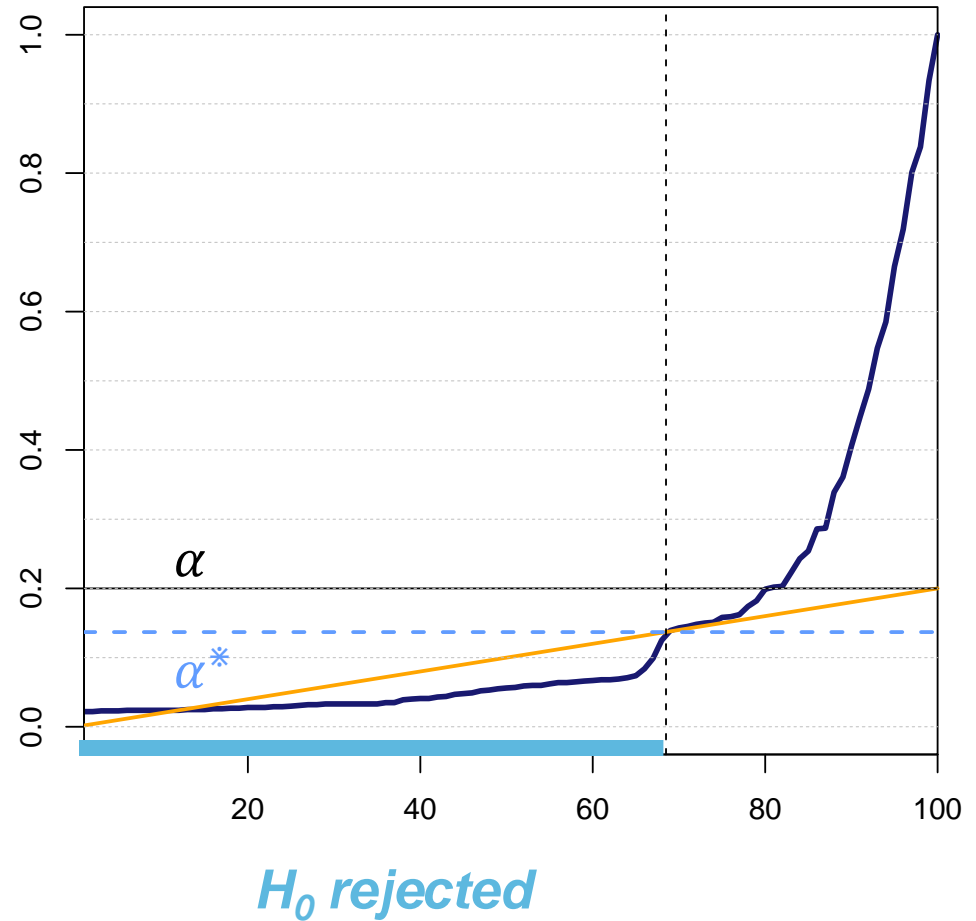
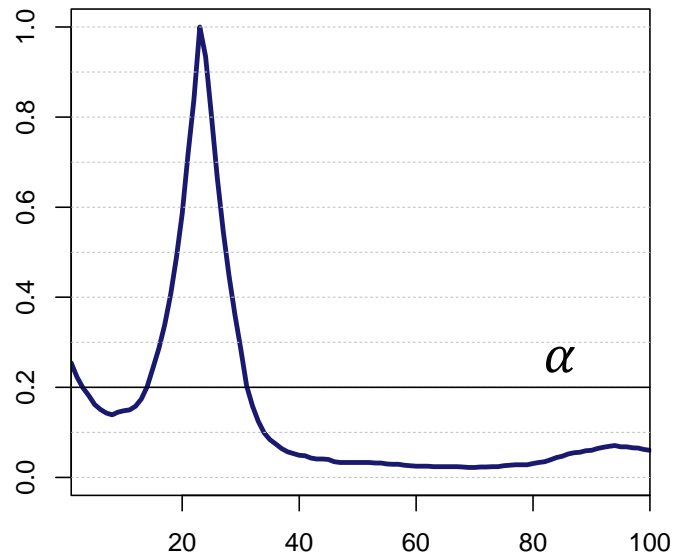


# ADJUSTING THE THRESHOLD

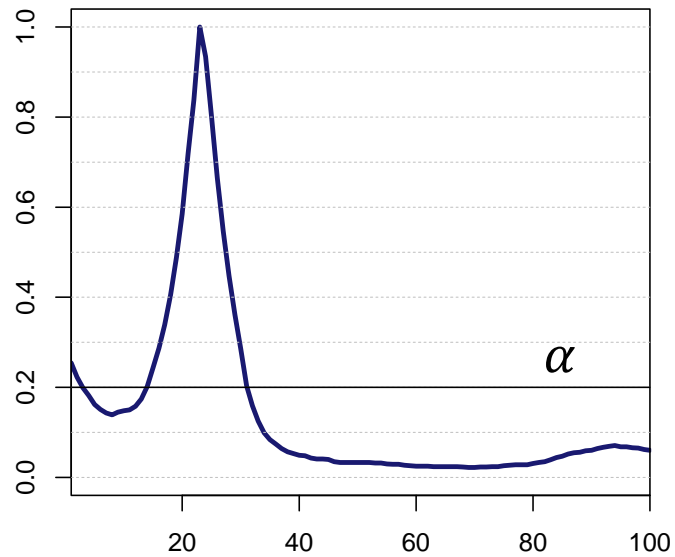


$$\alpha^* = \arg \max_{\bar{p}} \left\{ \frac{\alpha \mu\{r : p(r) \leq \bar{p}\}}{\mu(D)} \geq \bar{p} \right\}$$

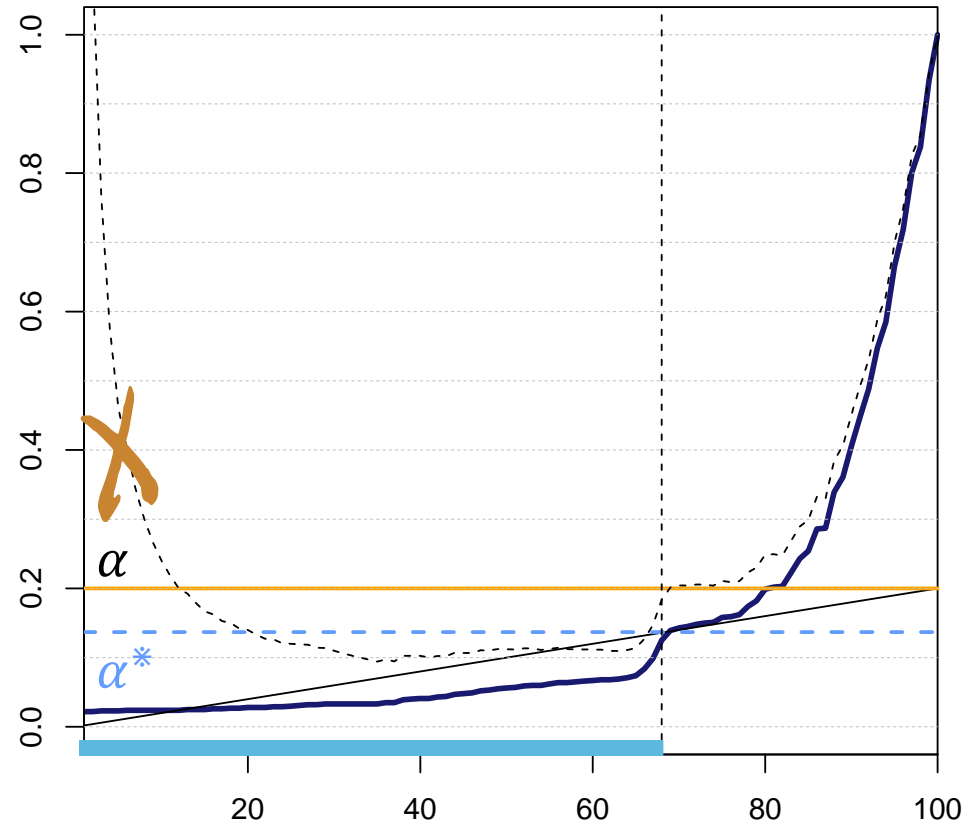
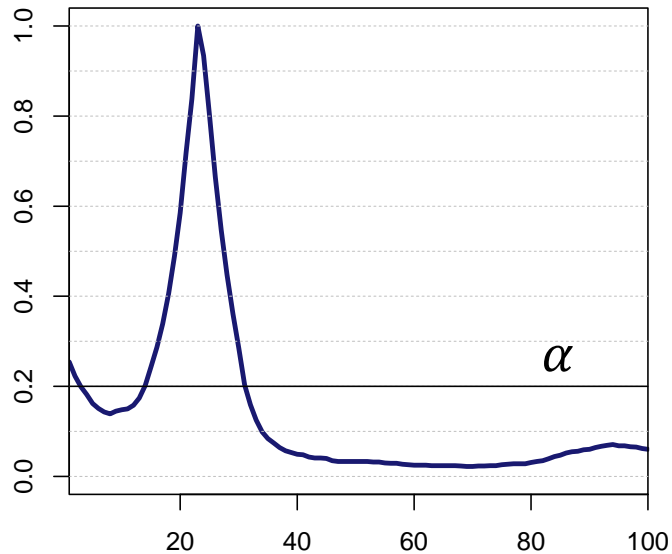
# ADJUSTING THE THRESHOLD



# ADJUSTING THE P-VALUE FUNCTION



# ADJUSTING THE P-VALUE FUNCTION

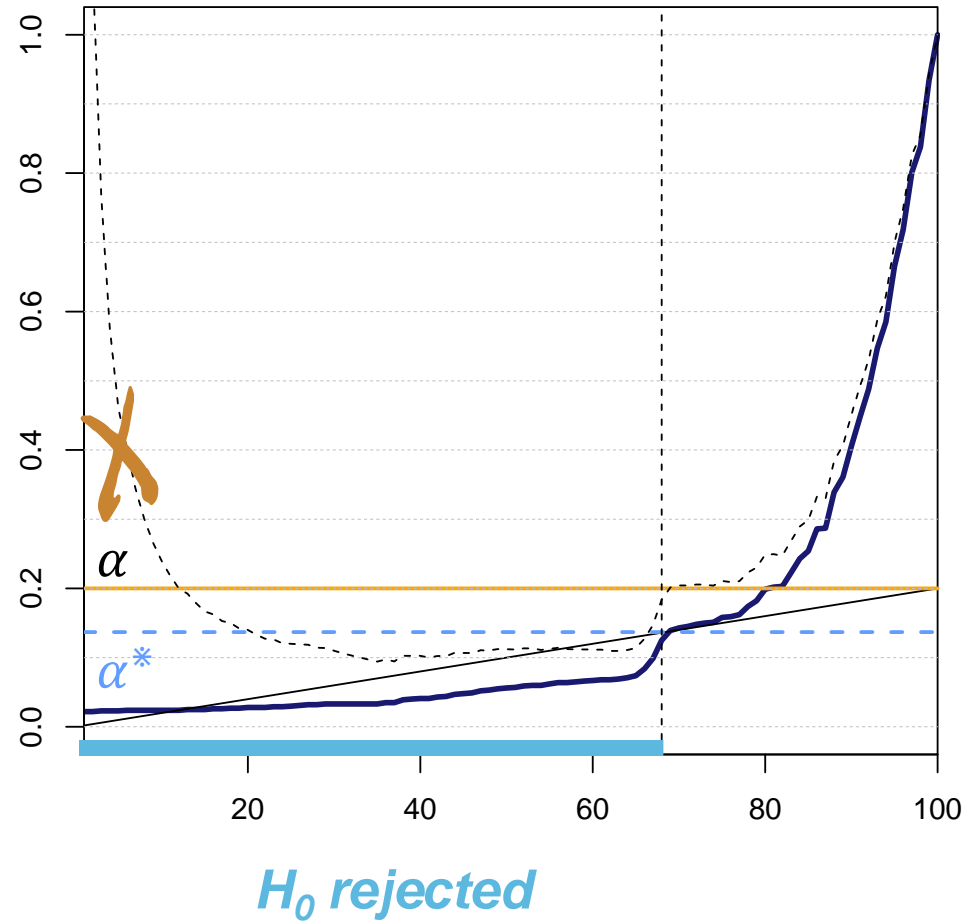
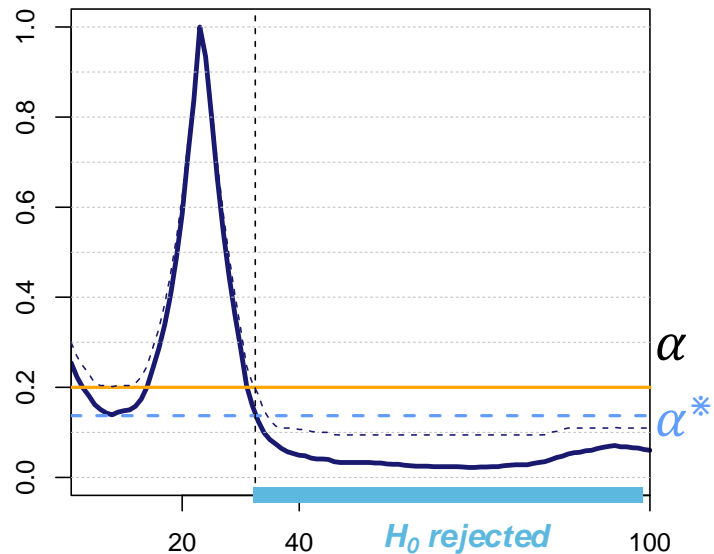
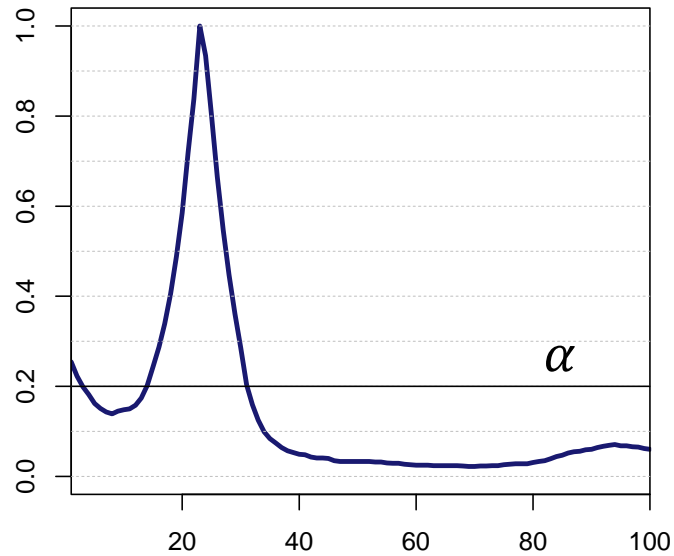


*$H_0$  rejected*

$$\tilde{p}(t) = \min_{s \geq p(t)} \left\{ 1, \frac{\mu(D)s}{\mu\{r : p(r) \leq s\}} \right\}$$



# ADJUSTING THE P-VALUE FUNCTION



# THE CONTROL OF THE FUNCTIONAL FALSE DISCOVERY RATE

$$\tilde{p}(t) < \alpha, \quad \text{with} \quad \tilde{p}(t) = \min_{s \geq p(t)} \left\{ 1, \frac{\mu(D)s}{\mu\{r : p(r) \leq s\}} \right\}$$

$$p(t) < \alpha^*, \quad \text{with} \quad \alpha^* = \arg \max_{\bar{p}} \left\{ \frac{\alpha \mu\{r : p(r) \leq \bar{p}\}}{\mu(D)} \geq \bar{p} \right\}$$

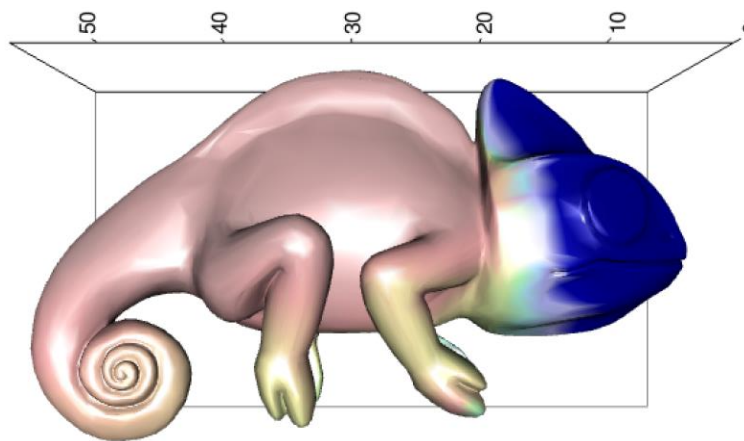
Control of the functional FDR:

$$FDR = \mathbb{E} \left[ \frac{V}{R} 1(R > 0) \right] \leq \alpha \frac{\mu(D_0)}{\mu(D)} \leq \alpha$$

## Ball-wise adjusted p-value function

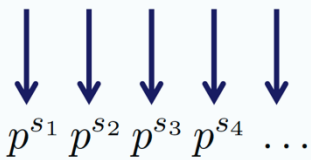
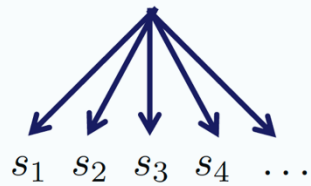
Olsen et al 2025+

$$\tilde{p}(t) = \sup_{\mathcal{I} \ni t} p^{\mathcal{I}}$$



# UNIFIED FRAMEWORK FOR LOCAL TESTING

Functional data



$$\tilde{p}(t) = \sup_{s \in \mathcal{S}: t \in s} p^s$$



$$t \in D : \tilde{p}(t) \leq \alpha$$

Family  $\mathcal{S}$  of subsets of  
the domain:  $s_j \in \mathcal{S}$

$p$ -values of test  $H_0^{s_j}$  vs  $H_1^{s_j}$   
with statistic  $T^{s_j} = \int_{s_j} T(t)dt$

Adjusted  $p$ -value  
function  $\forall t \in D$

Domain selection

# UNIFIED FRAMEWORK FOR LOCAL TESTING

Functional data

$s_1 \ s_2 \ s_3 \ s_4 \ \dots$

$p^{s_1} \ p^{s_2} \ p^{s_3} \ p^{s_4} \ \dots$

$$\tilde{p}(t) = \sup_{s \in \mathcal{S}: t \in s} p^s$$

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Family  $\mathcal{S}$  of subsets of  
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Adjusted  $p$ -value  
function  $\forall t \in D$

Domain selection

## Local adjustment

adjustment subsets should  
take into account proximity

One dimensional domain:  
adjustment sets are  
intervals.

How to choose suitable  
adjustment subsets when  
the domain is a manifold?

# ADJUSTMENT SUBSETS

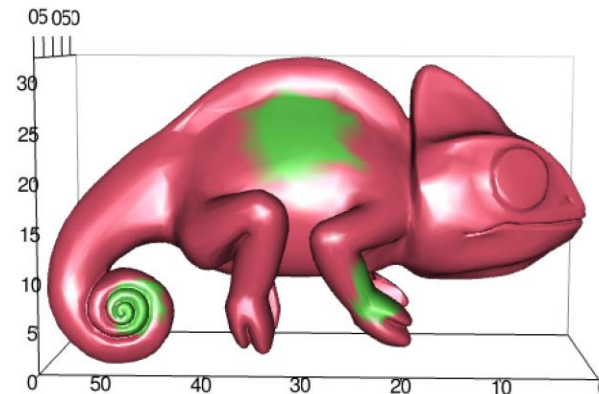
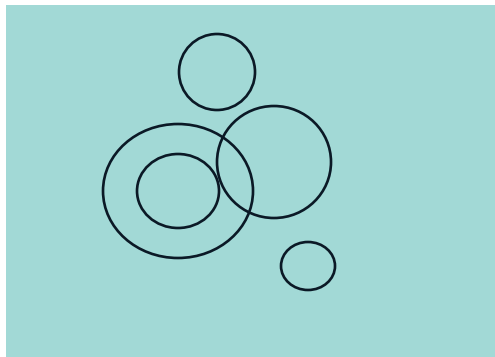
**Idea:** use balls as adjustment sets.

For a given manifold  $D$  with metric  $d$ , define  $B(x; \epsilon)$  (the ball of center  $x$  and radius  $\epsilon$ ) as

$$B(x; \epsilon) = \{y \in D \mid d(x; y) < \epsilon\}; \quad x \in D; \epsilon > 0$$

The adjustment family  $\mathcal{S}$  consists of the collection of all balls of  $D$  of radius smaller than a constant  $r$ :

$$\mathcal{S} = \{B(x; \epsilon)\}_{x \in D, \epsilon \leq r}$$



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$$\mathcal{S} = \{B(x; \epsilon)\}_{x \in D, \epsilon \leq r}$$

**Theorem 1.**  $\tilde{p}(x)$  controls the ball-wise error rate:

$$\forall \alpha \in (0, 1), \quad \forall B(x, \epsilon) \subseteq D : H_0^I \text{ is true}, \quad \mathbb{P}(\exists s \in I : \tilde{p}(s) \leq \alpha) \leq \alpha$$



**Example.** Yearly measurements (1987-2015) of ice cover on the northern hemisphere, as measured by the satellites of Copernicus Programme. The aim is to test for significant change in ice cover during the period.

$$y_i(x) = a(x) + b(x)t_i + \varepsilon_i(x)$$

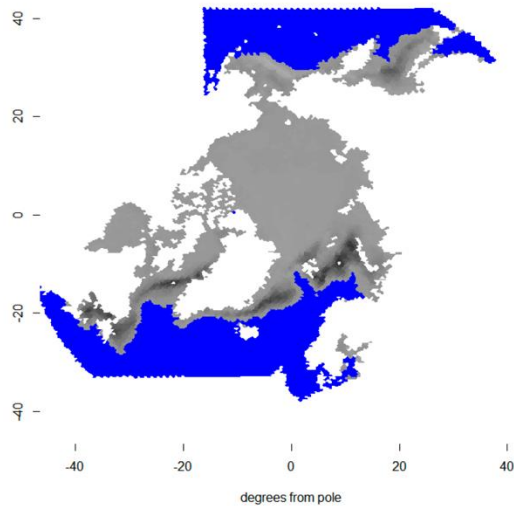
$$H_0 : b(x) = 0 \quad \forall x \in D; \quad H_1 : b(x) \neq 0 \text{ for some } x \in D$$



# PROBLEM FORMULATION

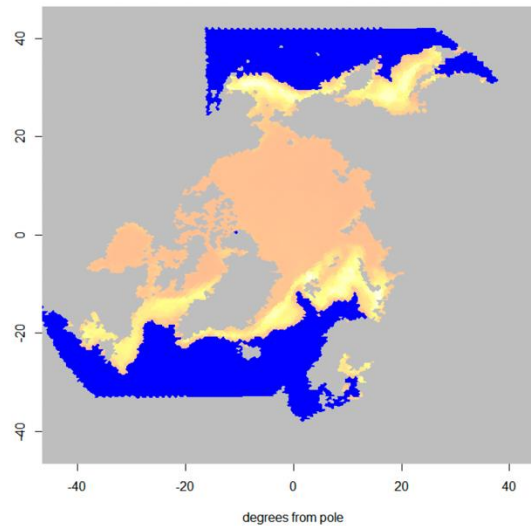
**Example.** Yearly measurements (1987-2015) of ice cover on the northern hemisphere, as measured by the satellites of Copernicus Programme. The aim is to test for significant change in ice cover during the period.

Trend



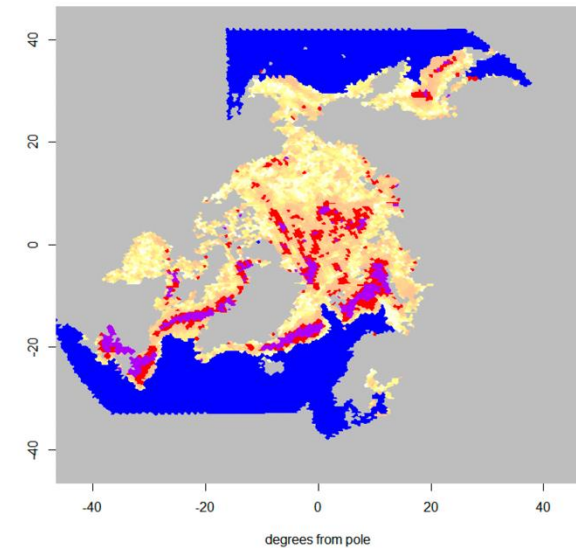
**Constant zero ice cover**  
**Negative trend**  
Zero trend

sddev



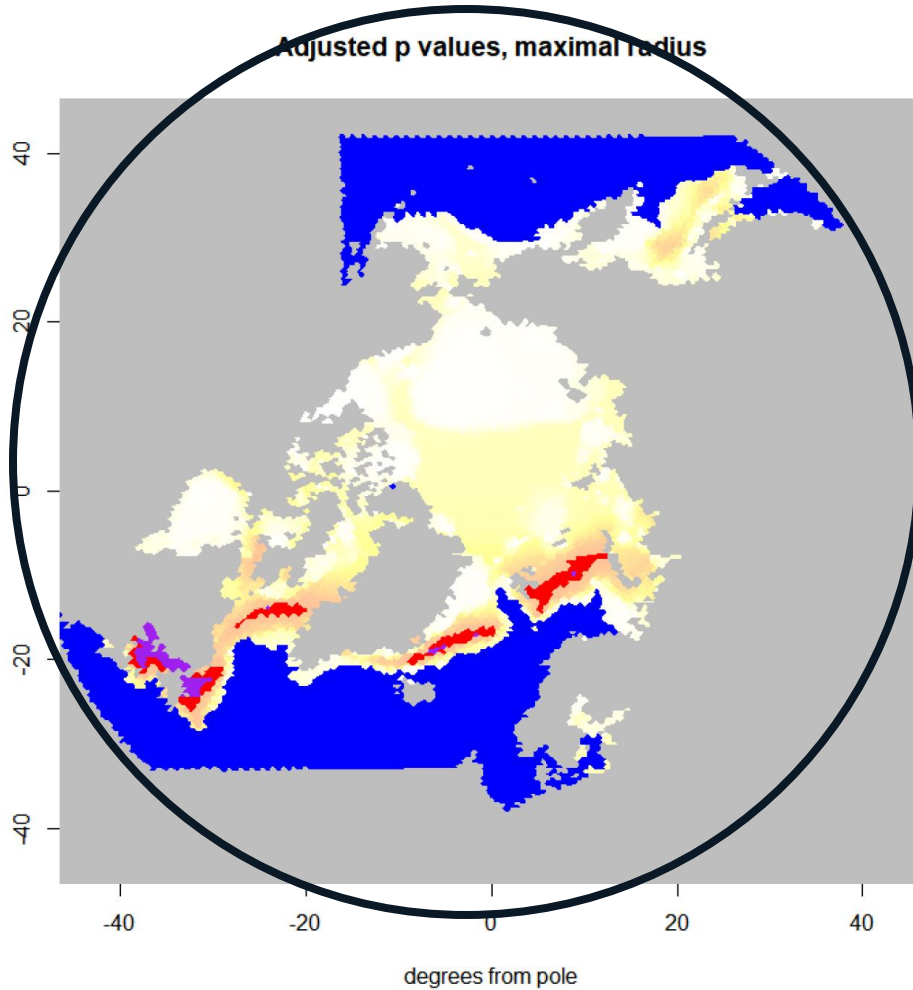
**Constant zero ice cover**  
Small sd  
Large sd

Unadjusted p values



**Constant zero ice cover**  
**p-value smaller than 5%**  
p-value smaller than 1%

# ICE COVER DATA ANALYSIS



**Constant zero ice cover**

**Adjusted p-value smaller  
than 5%**

**Adjusted p-value smaller  
than 1%**

# DISCUSSION

- A method for local inference of functional data with manifold domains.
- A novel way to adjust for multiplicity when the domain is complex.
- The adjustment methods can be plugged-in with every available testing procedure.



## Future works

- Are balls the only available type of adjustment sets for local adjustment?
- Is it possible to tune  $r$  with a data driven approach?
- Is it possible to develop a local adjustment for the false discovery rate?

Niels Lundtorp Olsen, Alessia Pini, and Simone Vantini. False discovery rate for functional data. *Test*, 2021.

Niels Lundtorp Olsen, Alessia Pini, and Simone Vantini. Local inference for functional data on manifold domains using permutation tests <https://arxiv.org/abs/2306.07738>

# SELECTED REFERENCES

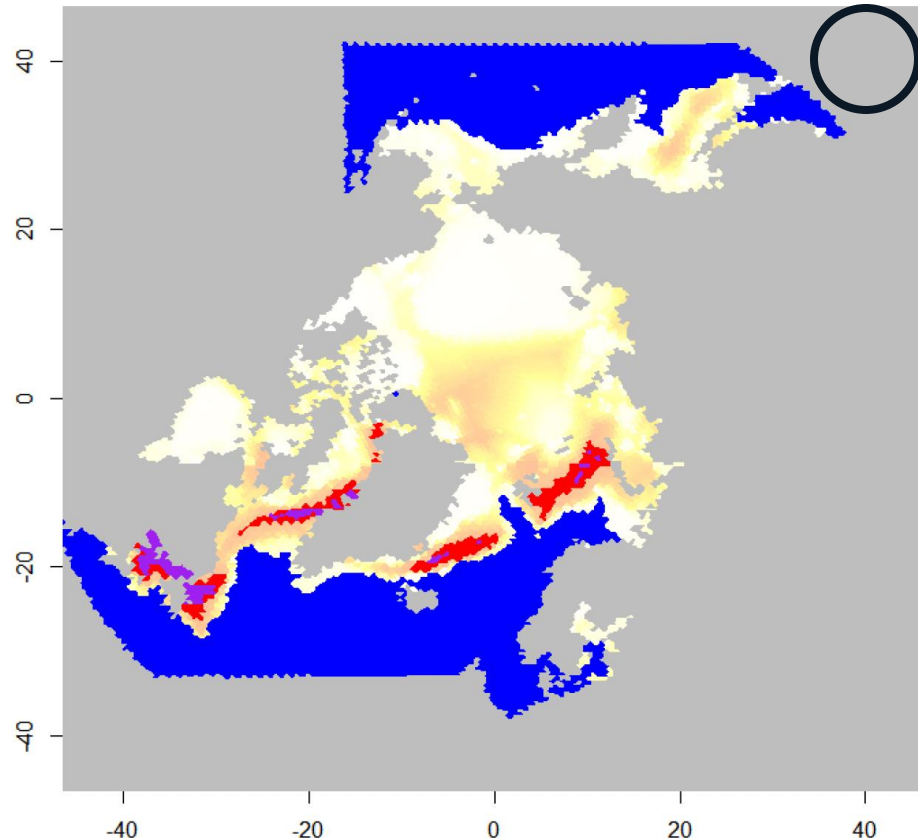
- Konrad Abramowicz, Alessia Pini, Lina Schelin, Sara Sjöstedt de Luna, Aymeric Stamm, and Simone Vantini. Domain selection and familywise error rate for functional data: A unified framework. *Biometrics*, 2022.
- Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the royal statistical society Series B*, 1995.
- David Freedman and David Lane. A nonstochastic interpretation of reported significance levels. *Journal of Business & Economic Statistics*, 1(4) (1983).
- Sture Holm: A simple sequentially rejective multiple test procedure *Scandinavian Journal of Statistics*, 6(2) (1979)
- Dominik Liebl and Matthew Reimherr. Fast and fair simultaneous confidence bands for functional parameters. *Journal of the royal statistical society Series B*, 2023.
- Niels Lundtorp Olsen, Alessia Pini, and Simone Vantini. False discovery rate for functional data. *Test*, 2021.
- Ruth Marcus, Eric Peritz, and K. R. Gabriel. On closed testing procedures with special reference to ordered analysis of variance. *Biometrika*, 63(3) (1976).
- Alessia Pini and Simone Vantini. Interval-wise testing for functional data. *Journal of Nonparametric Statistics*, 29(2), 2017.
- Olga Vsevolozhskaya, Marc Greenwood, and Dmitri Holodov. Pairwise comparison of treatment levels in functional analysis of variance with application to erythrocyte hemolysis. *The Annals of Applied Statistics*, 8 (2014).

**THANK YOU FOR YOUR ATTENTION!**



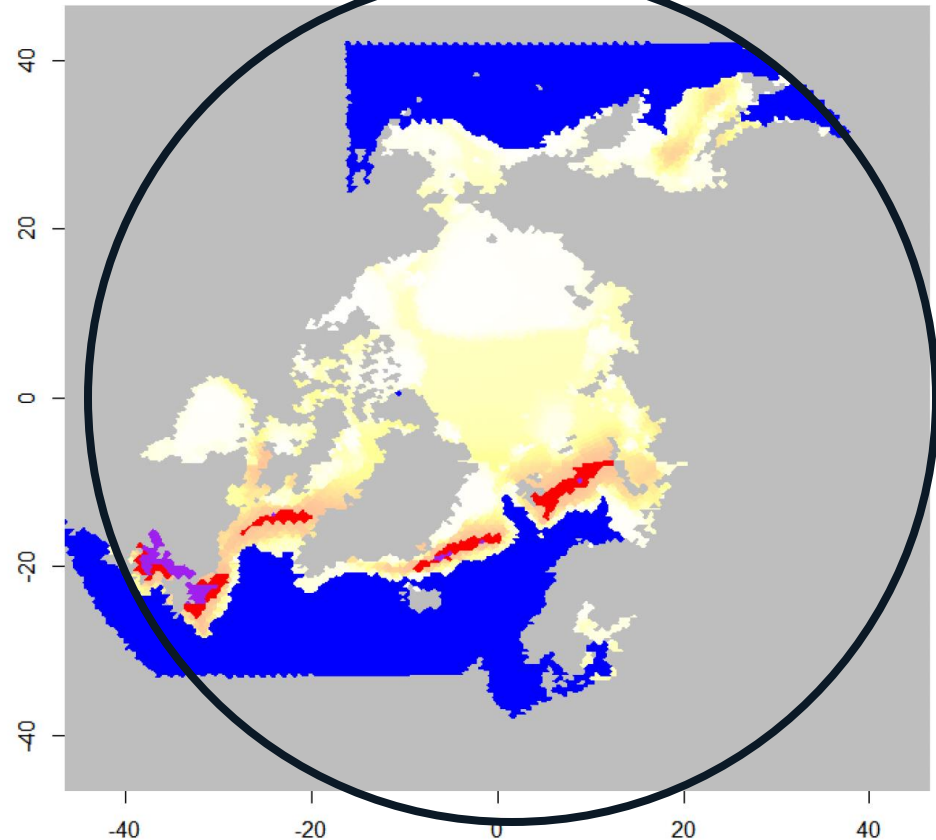
# ICE COVER DATA ANALYSIS

Adjusted p values with  $r_{\max} = 1275\text{km}$



degrees from pole

Adjusted p values, maximal radius



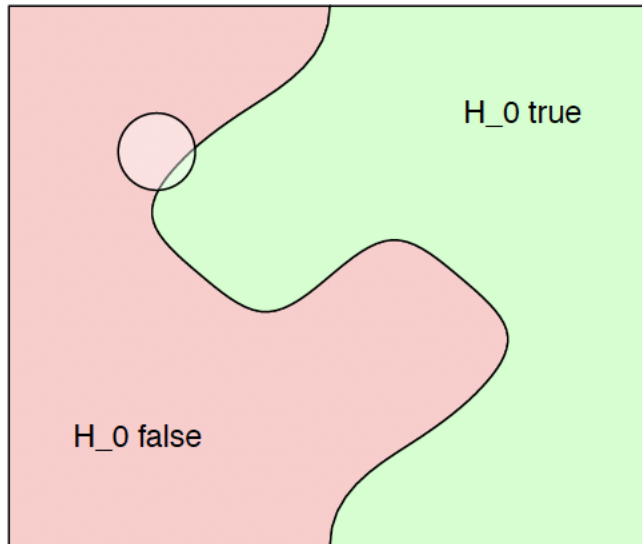
degrees from pole

**Constant zero ice cover**  
**Adjusted p-value smaller than 5%**  
**Adjusted p-value smaller than 1%**

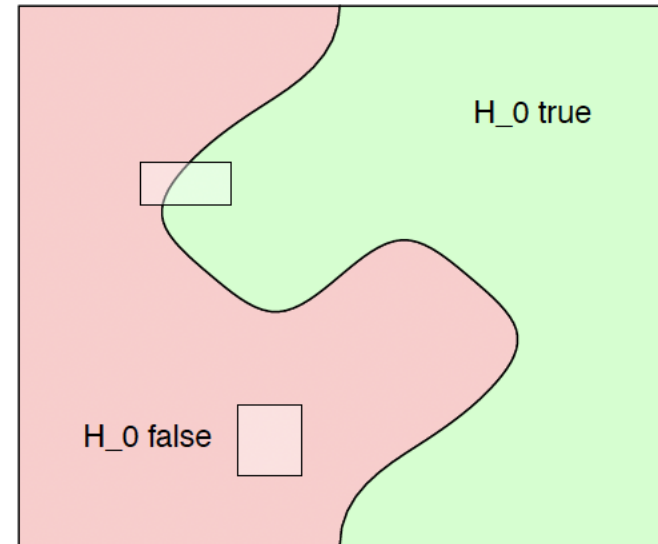
# EFFECT OF THE METRIC

- The control that is obtained is strictly related to the type of adjustment sets that are used, which depends on the metric.
- By changing it, one can define different adjustment sets:

## Spatial domain



## Spatiotemporal domain



# EFFECT OF THE RADIUS

- The radius  $r$  also influences the adjustment family and hence the control.
- Two extreme cases:

$$r \rightarrow 0$$

Adjustment subsets collapse to points. No adjustment is performed and:

$$\tilde{p}(x) = p(x).$$

The power is maximized, but the error control is minimal.

$$r \rightarrow \infty$$

Adjustment subsets include all possible balls. The procedure is very conservative since the adjustment family is very large. The power is minimized, but the error control is maximal.



# CURRENT LITERATURE OF LOCAL INFERENCE

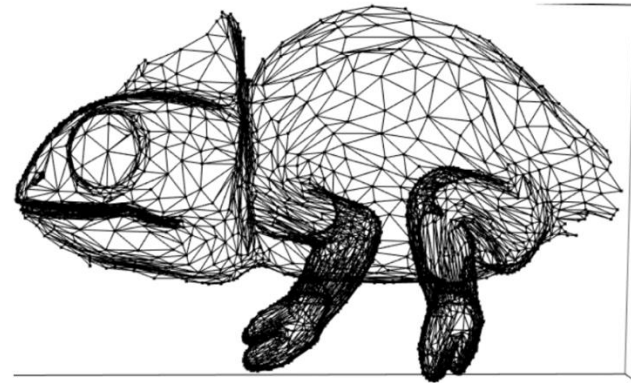
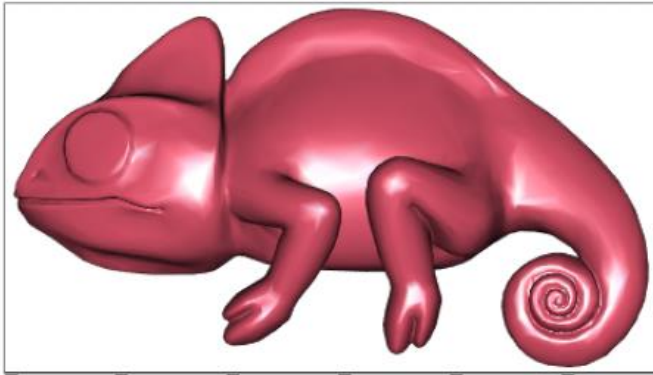
➤ One dimensional domains

➤ Manifold domains

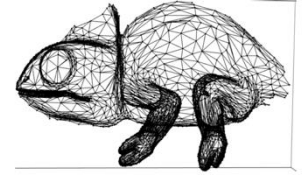
- ❖ **Global adjustment**: the adjustment is based on the pointwise p-values only
- ❖ **Local adjustment**: the adjustment is based on the topological structure of the domain

	One dimensional D	Manifold D
Global adjustment	Multivariate approaches (Holm, Bonferroni, Benjamini Hochberg) Functional FDR (Olsen etal 2021)	<b>Functional FDR (Olsen etal 2021)</b> Threshold Wise Testing (Abramowicz etal 2022)
Local adjustment	Interval Wise Testing (Pini Vantini 2017) Functional confidence bands (Liebl Rheimerr 2023) Partition closed testing (Vsevolozhskaya etal 2014)	<b>Ball Wise Testing</b>

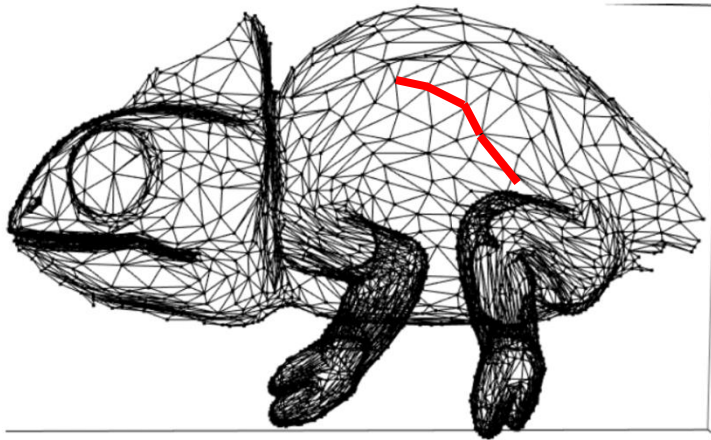
- Triangulation to approximate the points of the manifold.



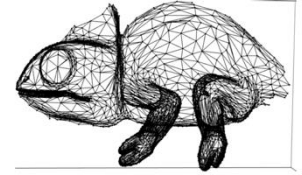
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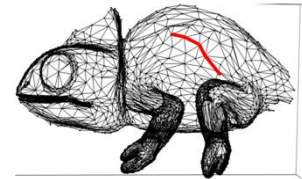
- Dijkstra's algorithm to compute geodesic distance on the manifold.



- Triangulation to approximate the points of the manifold.



- Dijkstra's algorithm to compute geodesic distance on the manifold.

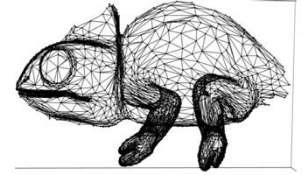


- Integral approximation for computing the test statistic on balls.

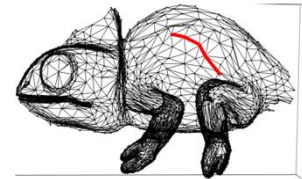
$$\int_{B(x,r)} f(u) \, du = \sum_{\{v \in E: d(x,e) < r\}} W(e) f(e)$$

$$W(e) = \frac{1}{3} \sum_{S: e \text{ is a vertex of } S} A(S), \quad e \in E$$

- Triangulation to approximate the points of the manifold.



- Dijkstra's algorithm to compute geodesic distance on the manifold.



- Integral approximation for computing the test statistic on balls.

$$\int_{B(x,r)} f(u) \, du = \sum_{\{v \in E: d(x,e) < r\}} W(e) f(e)$$

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- Permutation tests to evaluate the p-value of tests on balls.

$$y_i(x) = a(x) + b(x)t_i + \varepsilon_i(x)$$

$$\text{Under } H_0 : y_i(x) = a(x) + \varepsilon_i(x)$$

$$\hat{\varepsilon}_i(x) = y_i(x) - \hat{a}(x)$$

Freedman and Lane method:  
Permutation of the  
estimated residuals under  
the null hypothesis