

## Abstract

We propose a Bayesian procedure for testing monotonicity of a regression function. Our test is proved to be consistent and to achieve the optimal separation rate (up to a  $\log(n)$  factor). We propose a choice for the prior distribution and study the behaviour of our test for finite samples.

## Context and Aim

We consider the model

$$Y_i = f(i/n) + \epsilon_i, \quad \epsilon_i \stackrel{iid}{\sim} \mathcal{N}(0; \sigma^2), \quad (1)$$

with  $\sigma^2$  fixed or unknown. We want to test

$$H_0 : f \searrow \text{ vs } H_1 : f \text{ not } \searrow$$

We thus test a non parametric null, versus a non parametric alternative

## Bayesian approach to monotonicity testing

We build a prior on  $f$  by considering a piecewise constant approximation

$$f_{\omega, k}(\cdot) = \sum_{i=1}^k \omega_i \mathbb{1}_{I_i}(\cdot) \quad (2)$$

and then consider the prior

$$\pi : \begin{cases} k & \sim \pi_k \\ \omega_i & \stackrel{iid}{\sim} g \\ \sigma & \sim h \end{cases}$$

The Bayes Factor approach fails under  $H_0$  when  $f$  has flat parts (see [McVinish and Rousseau, 2011]). We thus consider a modified version of the BF. For a given  $M_n^k$

$$\delta_n^\pi = \mathbb{1} \left\{ \pi(H(\omega, k) > M_n^k | Y_n) > 1/2 \right\}$$

where

$$H(\omega, k) = \max_{j>i} (\omega_j - \omega_i)$$

it is thus **straightforward to implement**.

We want our test to be consistent against  $\alpha$ -Hölderian alternatives

$$\begin{aligned} \sup_{f \searrow} E_0^n(\delta_n^\pi) &= o(1) \\ \sup_{d(f, \searrow) > \rho, f \in H_\alpha(L)} E_0^n(1 - \delta_n^\pi) &= o(1) \end{aligned} \quad (3)$$

and to achieve an optimal separation rate  $\rho_n$  obtained in [Akakpo et al., 2012]

$$\begin{aligned} \sup_{f \in \searrow} E_0^n(\delta_n^\pi) &= o(1) \\ \sup_{d(f, \searrow) > \rho_n, f \in H_\alpha(L)} E_0^n(1 - \delta_n^\pi) &= o(1) \end{aligned} \quad (4)$$

## Theorem

Let  $M_n^k = M_0 \sqrt{k \log(n)/n}$  and let  $\pi$  be a prior on  $f_{\omega, k}$  such that  $\omega_i \stackrel{iid}{\sim} g$  and  $k \sim \pi_k$ ,  $\sigma \sim h$ . Assume that  $g$  and  $h$  put mass on  $\mathbb{R}$  and  $\mathbb{R}^{+*}$  respectively and that  $\pi_k$  is such that there exist positive constants  $C_d$  and  $C_u$  such that

$$e^{C_d k L(k)} \leq \pi_k(k) \leq e^{C_u k L(k)}$$

Where  $L(k)$  is either  $\log(k)$  or 1. Consider the test

$$H_0 : f \searrow \text{ versus } H_1 : f \text{ not } \searrow, f \in H_\alpha(L)$$

let  $\rho_n = M(n/\log(n))^{-\alpha/(2\alpha+1)}$ , then the test  $\delta_n^\pi$  is consistent and achieve the separation rate  $\rho_n$ .

## Examples

- Simulated data with  $\sigma$  known
- Regression functions adapted from the frequentist literature
- We choose for the prior

$$\begin{aligned} \pi_k &:= \mathcal{P}(\lambda) \\ g &:= \mathcal{N}(m; s^2) \end{aligned}$$

- explicit posterior  $\rightarrow$  easy to sample from
- The hyperparameter  $\lambda$  has a great influence on the results

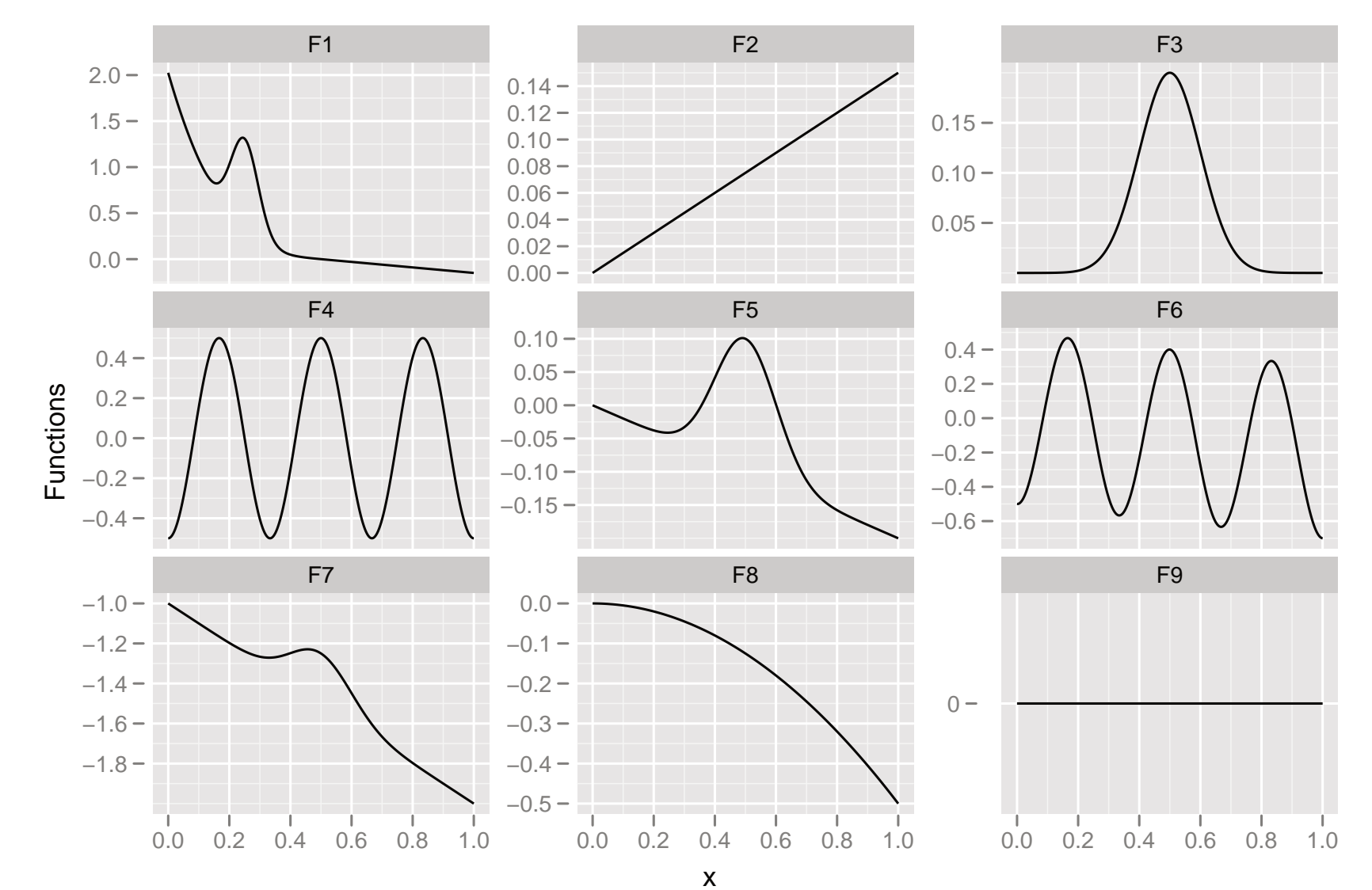


FIGURE: Plot of the regression function

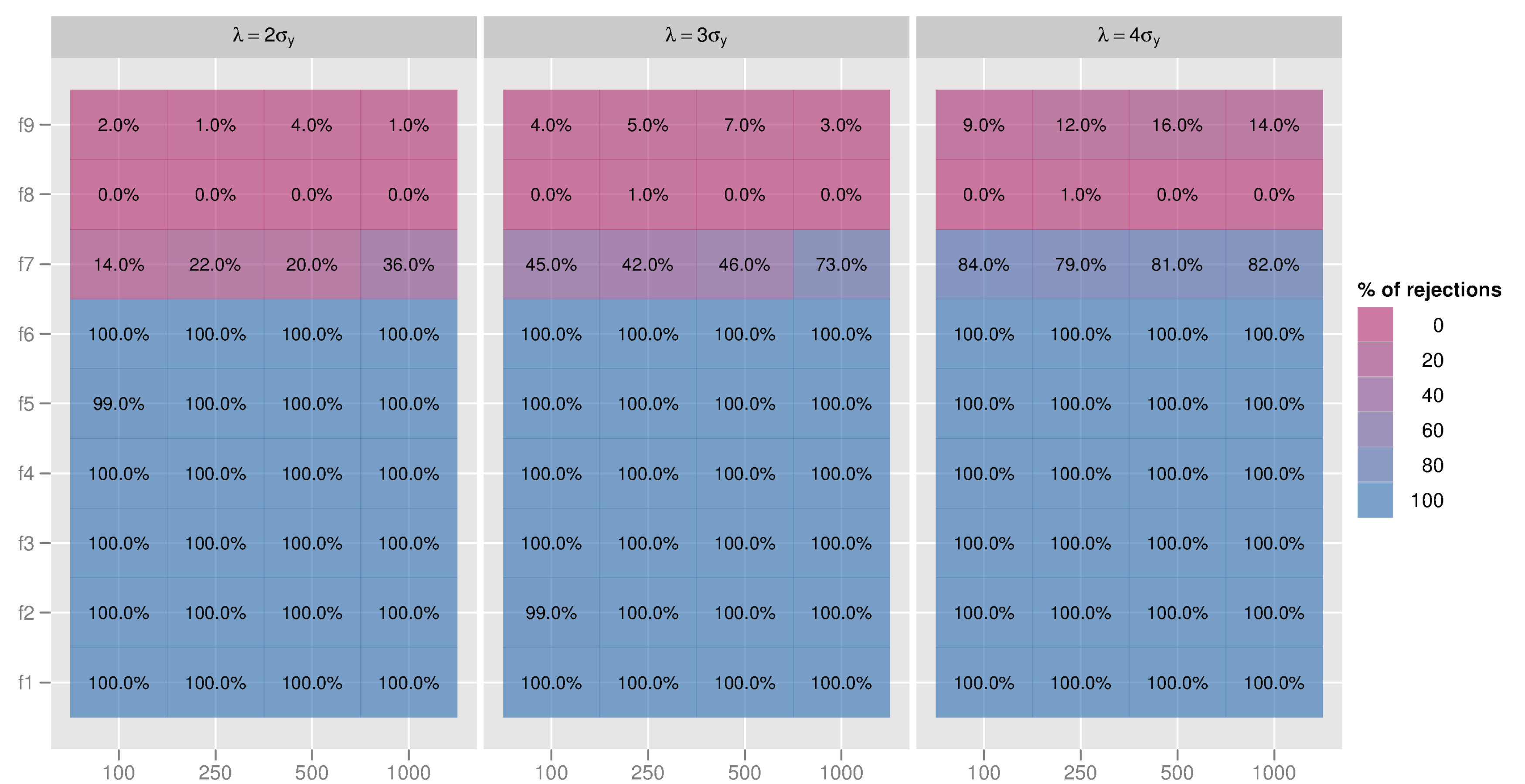


FIGURE: Result of the simulation study

## Comparison with frequentist methods

- Frequentist methods  $\rightarrow$  computationally difficult
- We obtain similar results for  $\{f_1, \dots, f_6\}$
- Loss of power for  $f_7$
- Similar Type I error for  $\lambda = 3\sigma_y$

## References

## Extensions

Our method could easily be adapted to test for other qualitative assumptions

- $H_0 : f$  is positive
- $H_0 : f$  is convex
- $H_0 : f$  is unimodal
- ...