Bayesian sequential hypothesis testing in discrete time

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Markovian Embedding

Concentration of the posterior distribution $_{\rm O}$

Is the value function monotone in time?

Outline



2 Markovian Embedding

3 Concentration of the posterior distribution

Is the value function monotone in time?



Motivation

Testing unknown parameter with a Bernoulli prior: (Shiryaev, 1978)

- Observe a sequence of i.i.d. random variables distributed with density p_θ(x)
- $\theta \in \{0,1\}$ (Bernoulli prior)
- Can formulate stopping problem in terms of Π, the posterior probability process (Markovian)

$$V(\pi) = \inf_{\tau} \mathbb{E}_{\pi}[\Pi_{\tau} \wedge (1 - \Pi_{\tau}) + c\tau]$$

- $\blacksquare \implies V(\pi)$ is concave
- There exists constant stopping boundaries

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Motivation

Testing the unknown drift of a Brownian motion: (Ekström and Vaicenavicius, 2015)

- $\blacksquare dX_t = Bdt + dW_t, B \text{ is a r.v.}$
- **B** has a general prior μ
- $V(0,\pi) = \inf_{\tau} \mathbb{E}_{\pi}[\Pi_{\tau} \wedge (1 \Pi_{\tau}) + c\tau]$
- $\blacksquare \implies V(\pi)$ is concave
- ⇒ Volatility of Π is non-increasing in time
- $\blacksquare \implies \text{There exists monotone stopping boundaries}$

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Motivation

Questions

- Can we test other distributions in discrete time? e.g. unknown variance of a Gaussian?
- Does the problem exhibit similar structural properties?



Problem Setting

- The tester observes *X*₁, *X*₂,... sequentially with cost *c* at each step
- X_k's are drawn from a one-parameter exponential family depending on r.v. ⊖
- Conditioning on $\Theta = u$, X_k 's are independent, and

$$\mathbb{P}(X_k \in A | \Theta = u) = \int_A p_u(x) v(dx)$$

where

$$p_u(x) := \exp\{ux - B(u)\},\$$

and v is a σ -finite measure on \mathbb{R} .

Bayesian set-up

- µ: prior of the unknown parameter ⊖, denote the support of µ by S
- Want to test:

 $\begin{array}{ll} H_0: & \Theta \leq \theta_0, \\ H_1: & \Theta > \theta_0, \end{array}$

Let *d* = *i* represents *H_i* is accepted,
Define the cost function

$$V := \inf_{\tau \in \mathscr{T}} \inf_{d \in \mathscr{D}^{\tau}} \left\{ \mathbb{P}(d = 1, \Theta \le \theta_0) + \mathbb{P}(d = 0, \Theta > \theta_0) + c\mathbb{E}[\tau] \right\}$$

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Reformulation in the π **coordinate**

Define the posterior probability process Π

$$\Pi_n := \mathbb{P}(\Theta > \theta_0 | \mathscr{F}_n^X),$$

with $\Pi_0 = \pi$, Given $\tau \in \mathscr{T}$,

$$d = \begin{cases} 0 & \text{if } \Pi_{\tau} \leq 1/2 \\ 1 & \text{if } \Pi_{\tau} > 1/2 \end{cases}$$

Consequently,

$$V = \inf_{\tau \in \mathscr{T}} \mathbb{E} \left[\Pi_{\tau} \wedge (1 - \Pi_{\tau}) + c\tau \right],$$

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Properties of the □ process

At time *n*, given $X_1 = x_1, \ldots, X_n = x_n$, by independence,

$$\mathbb{P}(\Theta > \theta_0 | X_1 = x_1, \dots, X_n = x_n) = \frac{\int_{\mathcal{S}^+} \prod_{i=1}^n p_u(x_i) \mu(du)}{\int_{\mathcal{S}} \prod_{i=1}^n p_u(x_i) \mu(du)}$$
$$= \frac{\int_{\mathcal{S}^+} \exp\{u\sum_{i=1}^n x_i - nB(u)\} \mu(du)}{\int_{\mathcal{S}} \exp\{u\sum_{i=1}^n x_i - nB(u)\} \mu(du)}$$

• Denoting $Y_n := \sum_{i=1}^n X_i$:

$$\Pi_n = q(n, Y_n).$$

where

$$q(n,y) := \frac{\int_{\mathcal{S}^+} e^{uy - nB(u)}\mu(du)}{\int_{\mathcal{S}} e^{uy - nB(u)}\mu(du)}$$

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Parameterization of the posterior distribution

Denote by

$$\mu_{n,y}(du) := \frac{e^{uy - nB(u)}\mu(du)}{\int_{\mathcal{S}} e^{uy - nB(u)}\mu(du)}$$

the posterior distribution of Θ at time *n* conditional on $Y_n = y$.

Lemma

The function $y \mapsto q(n, y) : \mathbb{R} \to (0, 1)$ is an increasing bijection for each fixed n.

Remark

- Π is a Markov process
- y can take any value in \mathbb{R}
- At time n, knowing y gives all the information of the posterior.
- Refer the set $\{(n, y(n, \pi)), n \ge 0\}$ as the π -level curve.

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Properties of the value function

The optimal stopping problem can be written as

$$V(n,\pi) = \inf_{\tau \in \mathscr{T}} \mathbb{E}_{n,\pi}[\Pi_{\tau+n} \wedge (1-\Pi_{\tau+n}) + c\tau].$$
(1)

Lemma

The value function $V(n,\pi)$ satisfies

$$V(n-1,\pi) = \min\{\pi \land (1-\pi), c + \mathbb{E}_{n-1,\pi}[V(n,\Pi_n)]\}$$

Lemma

Let $f : [0,1] \to [0,\infty)$ be a concave function. Then $\pi \mapsto \mathbb{E}_{n,\pi}[f(\Pi_{n+1})]$ is concave on (0,1).

Proof. By implicit differentiation.

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Concavity and its consequence

Main Theorem (1)

The function $\pi \mapsto V(n,\pi)$ is concave for each fixed $n \ge 0$.

Remark. *V* can be extended for every $\pi \in [0, 1]$ and the concavity is preserved.



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Concavity and its consequence

Introduce now

■ The continuation region *C*:

$$\mathscr{C} := \{(n,\pi) \in \mathbb{N}_0 \times [0,1] : V(n,\pi) < \pi \wedge (1-\pi)\},\$$

■ The stopping region *D* by

$$\mathscr{D} := \{(n,\pi) \in \mathbb{N}_0 \times [0,1] : V(n,\pi) = \pi \wedge (1-\pi)\}.$$

The stopping time

$$\tau^* := \inf\{k \ge 0 : (n+k, \Pi_{n+k}) \in \mathscr{D}\}$$

is an optimal strategy.

Remark

- The continuation region is of the form $(b_1(n), b_2(n))$
- The concavity result is connected with time-monotonicity of the value function

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The posterior distribution gradually squeezes in

Main Theorem (2)

If $a < \theta_0 < b$, then

$$n\mapsto \mathbb{P}_{n,\pi}(\Theta\leq a)$$
 & $n\mapsto \mathbb{P}_{n,\pi}(\Theta>b)$

are decreasing.

Remark

As a consequence, let $0 < \pi_1 < \pi_2 < 1$. Then

$$n\mapsto y(n,\pi_2)-y(n,\pi_1)$$

is non-decreasing.

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Conditions for monotonicity in time

Assumption

For any $\pi \in (0,1)$ and $n \ge m \ge 0$, the random variable $\Pi_{m+1} | \{\Pi_m = \pi\}$ dominates $\Pi_{n+1} | \{\Pi_n = \pi\}$ in convex order.

Theorem

Assume the above holds. Then $V(n,\pi)$ is non-decreasing in n, and the boundaries b_1 and b_2 are thus non-decreasing and non-increasing, respectively.

But is the assumption correct?

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One sufficient condition

If there exists a π_0 , such that Π_{n+1} is more concentrated around it than Π_{m+1} , then we are done.

Main Theorem (3)

- Observations are continuously distributed with density h(x)pu(x)
 s.t. I := {h > 0} is an interval.
- $h(x)p_u(x)$ is increasing in x on I, and S^+ is a singleton

then $V(n,\pi)$ is non-decreasing in n.

Remark. The following cases also go through

- The symmetric case when *h*(*x*)*p*_{*u*}(*x*) is decreasing in *x* on *l*, and *S*[−] is a singleton.
- When $I := \{h > 0\}$ is a union of disjoint intervals.

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Examples of Main theorem 3

Example 1. (Exponential observations)

$$h(x)p_u(x) = \begin{cases} \exp\{ux + \log u\} & x < 0\\ 0 & x \ge 0 \end{cases}$$

Example 2. (Gaussian observations with unknown variance)

$$h(x)p_u(x) = \begin{cases} \frac{2}{\sqrt{-\pi x}} \exp\left\{ux + \frac{1}{2}\log u\right\} & x < 0\\ 0 & x \ge 0 \end{cases}$$

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Does it hold for other distributions?

For arbitrary priors:

Example 3. (Gaussian observations with unknown mean)

$$h(x)\rho_u(x)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{x^2}{2}}\exp\{ux-B(u)\}.$$

Time-monotonicity follows from the continuous case.

Example 4. (Bernoulli observations)

 $h(x)p_{\hat{u}}(x) = \exp\{\hat{u}x - \log(1+\hat{u})\},\$

Convex order of Π_n can be shown.

Example 5. (Binomial observations) Can be regarded as modification of the Bernoulli case.

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Further discussion

Conjecture

The function $V(n, \pi)$ is non-decreasing in n.



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Questions and suggestions

Thank you!

