

Let X_1, X_2, \dots be a \mathcal{F}_t -adapted random sequence.

Consider hypothesis test, for known densities P_0, P_1 :

$$H_0: X_t \stackrel{iid}{\sim} P_0 \quad \forall t$$

$$H_1: X_t \stackrel{iid}{\sim} P_1 \quad \forall t$$

Goal: define a stopping time $\mathcal{T} \in \mathbb{N}$ such that at time \mathcal{T} declare hypothesis.

Define likelihood ratio @ time t , $L_t = \prod_{s=1}^t \frac{P_1(X_s)}{P_0(X_s)}$.

Let $\mathbb{E}_i[\cdot], P_i[\cdot]$ be expectation and probability laws under H_i .

Note L_t is an \mathcal{F}_t -adapted martingale under H_0 :

$$\begin{aligned} \mathbb{E}_0[L_{t+1} | \mathcal{F}_t] &= L_t \cdot \mathbb{E}_0 \left[\frac{P_1(X_{t+1})}{P_0(X_{t+1})} \mid \mathcal{F}_t \right] \\ &= L_t \cdot \int_{\mathcal{X}} \frac{P_1(x)}{P_0(x)} P_0(x) dx \\ &= L_t. \end{aligned}$$

We can apply maximal inequality for super-martingale

$$\Rightarrow P_0(\exists t \in \mathbb{N} : L_t > 1/\delta) \leq \delta$$

But also note L_t^{-1} is a martingale under H_1 .

$$\Rightarrow P_1(\exists t \in \mathbb{N} : L_t^{-1} > 1/\delta) \leq \delta$$

$$\Rightarrow P_1(\exists t \in \mathbb{N} : L_t < \delta) \leq \delta$$

$$\mathcal{T} = \min \{ t : L_t \notin [\delta, 1/\delta] \}$$

Example: Gaussian $P_0 = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \equiv \mathcal{N}(0,1)$ $P_1 = \frac{1}{\sqrt{2\pi}} e^{-(x-\Delta)^2/2} \equiv \mathcal{N}(\Delta,1)$

$$L_t = \prod_{s=1}^t \frac{P_1(X_s)}{P_0(X_s)} = \prod_{s=1}^t \exp\left(-\frac{(X_s - \Delta)^2}{2} + \frac{X_s^2}{2}\right)$$

$$= \prod_{s=1}^t \exp\left(X_s \Delta - \frac{\Delta^2}{2}\right)$$

$$= \exp\left(\Delta \left(\sum X_s\right) - t \frac{\Delta^2}{2}\right)$$

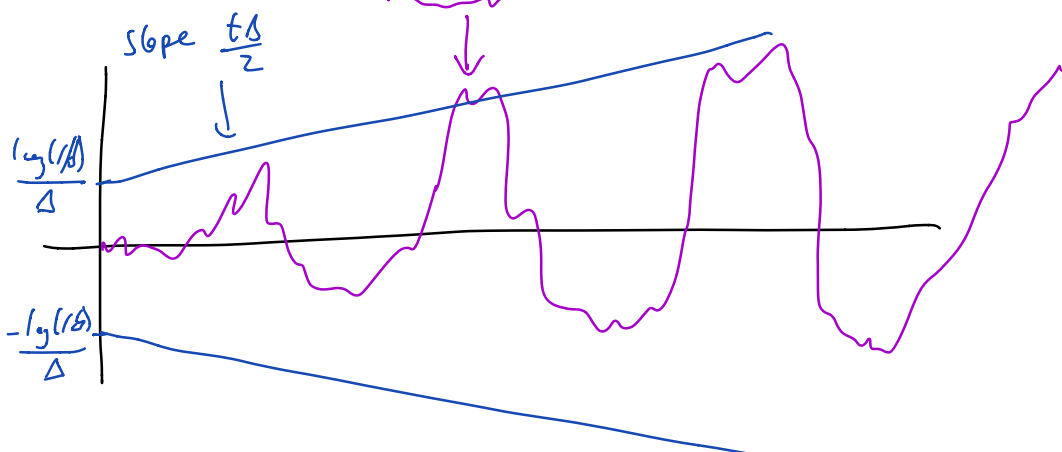
$$P_0\left(\exists t \in \mathbb{N} : \sum X_s \geq \frac{t\Delta}{2} + \frac{\log(1/\delta)}{\Delta}\right)$$

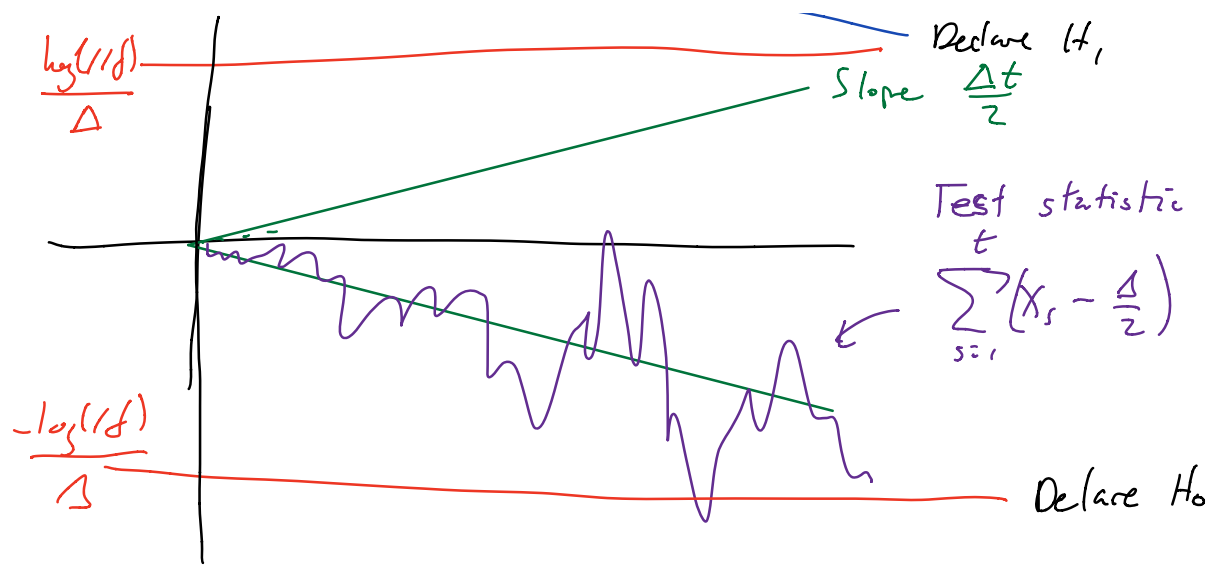
$$= P_0\left(\exists t \in \mathbb{N} : L_t \geq 1/\delta\right) \leq \delta$$

$$P_1\left(\exists t \in \mathbb{N} : \sum X_s \leq \frac{t\Delta}{2} - \frac{\log(1/\delta)}{\Delta}\right) \leq \delta$$

$$\mathcal{T} = \min \left\{ t : L_t \notin [\delta, 1/\delta] \right\}$$

$$= \min \left\{ t : \sum_{s=1}^t X_s - \frac{t\Delta}{2} \notin \left[\frac{-\log(1/\delta)}{\Delta}, \frac{\log(1/\delta)}{\Delta} \right] \right\}$$





Conclude that test is correct in the sense that it will not output incorrect hypothesis w.p $\geq 1-\delta$.

When will test stop? That is, $\mathbb{E}_i[S]$?

Lemma (Wald's identity). Let X_t be iid w/ mean μ . Let $S \in \mathbb{N}$ be a stopping time with $\mathbb{E}[S] < \infty$. Then $\mathbb{E}\left[\sum_{t=1}^S X_t\right] = \mu \cdot \mathbb{E}[S]$.

Proof (sketch): if $\mu \in (-\infty, \infty)$ statement trivial so assume otherwise. Then we can conclude $\mathbb{E}[|X_t|] < c$ for some $c < \infty$. w/ $\mathbb{E}[S] < \infty$ we can apply Doob's optional stopping to martingale

$$M_t = \sum_{s=1}^t X_s - t\mu. \quad \mathbb{E}[M_S] = \mathbb{E}[M_0] = 0 \quad \square$$

To apply Wald's inequality consider

$$\mathbb{E}_0 [L_{\mathcal{S}'}] = \textcircled{\star}$$

where $\mathcal{S}' = \min\{t \in \mathbb{N} : L_t < \delta\}$

$$\textcircled{\star} = \mathbb{E}_0 \left[\sum_{t=1}^{\mathcal{S}'} \log \left(\frac{P_1(X_t)}{P_0(X_t)} \right) \right]$$

$$= \mathbb{E}_0[\mathcal{S}'] \mathbb{E}_0 \left[\log \left(\frac{P_1(X_t)}{P_0(X_t)} \right) \right] = \textcircled{A}$$

But at \mathcal{S}' , we have that

$$L_{\mathcal{S}'} \approx \delta \quad (\text{ignoring the overshoot})$$

$$\Rightarrow \textcircled{\star} = \mathbb{E}_0 [L_{\mathcal{S}'}] \approx \log(\delta) = \textcircled{B}$$

$$\mathbb{E}_0[\mathcal{S}'] = \frac{\log(\delta)}{\mathbb{E}_0 \left[\log \left(\frac{P_1(X_1)}{P_0(X_1)} \right) \right]}$$

$$= \frac{\log(1/d)}{KL(P_0 | P_1)}.$$

Recall $KL(p|q) = \int p(x) \log\left(\frac{p(x)}{q(x)}\right) dx$.

Similar calculation leads to

$$E_1[\tau] = \frac{\log(1/\delta)}{KL(p_1|p_0)}$$

Recall: on HW1 you showed that any procedure that decides between $N(0,1)$ and $N(\Delta,1)$

requires at least $\frac{\log(1/\delta)}{KL(p_1|p_0)}$ samples.

$$= \frac{2\log(1/\delta)}{\Delta^2}$$

Conclude: This test of H_0 vs H_1 ,

is optimal in the sense that

the expected stopping time cannot be

improved. Sequential probability ratio test (SPRT).

Method of mixture

Consider hypothesis test w/ $E[X_e] = \mu$

$$H_0: \mu = 0$$

$$H_1: \mu \neq 0$$

Recall before, we had binary hypothesis

test of $L_t = \prod_{s=1}^t \frac{P(X_s; \Delta)}{P(X_s; 0)}$. Now we

don't know Δ . So we define prior

belief over Δ . Let $h(\mu)$ be a density.

Then
$$\bar{L}_t = \int_{\mu} h(\mu) \prod_{s=1}^t \frac{P(X_s; \mu)}{P(X_s; 0)} d\mu$$

is a martingale.

Previously we mixed w/ $h \equiv$ Gaussian

but this is arbitrary. In practice h

can be prior knowledge on effectsize μ .

Fix $x_1, \dots, x_n \in \mathbb{R}^d$ and then observe

$$y_i = \langle \theta^*, x_i \rangle + z_i \quad \text{where } z_i \sim \mathcal{N}(0, 1).$$

Then $\hat{\theta} = (X^T X)^{-1} X^T y$. W.p. $\geq 1 - \delta$, $z \in \mathcal{R}^d$

$$\frac{\langle \hat{\theta} - \theta^*, z \rangle}{\|z\|_{(X^T X)^{-1}}} \leq \sqrt{2 \log(1/\delta)}$$

Using Martingale bound (which allowed for $x_t \in \mathcal{F}_{t-1}$, $y_t \in \mathcal{Z}_t$)

$$\langle \hat{\theta} - \theta^*, z \rangle \leq \|z\|_{(X^T X)^{-1}} \cdot \|\hat{\theta} - \theta^*\|_{(X^T X)}$$

$$\leq \|z\|_{(X^T X)^{-1}} \cdot c \sqrt{d + \log(1/\delta)}$$

$$\frac{\langle \hat{\theta} - \theta^*, z \rangle}{\|z\|_{(X^T X)^{-1}}} \leq c \sqrt{d + \log(1/\delta)}$$

Fix $z = \mathbb{1}$ and then construct seq $(x_1, x_2, \dots$

where $x_t \in \mathcal{F}_t$ and $y_t = \langle \theta^*, x_t \rangle + z_t$

$$\mathbb{E} \left[\frac{|\langle \hat{\theta} - \theta^*, z \rangle|}{\|z\|_{(X^T X)^{-1}}} \right] \geq \sqrt{d}$$

$$\hat{\theta} = (X^T X)^{-1} X^T z = \left(\sum_{i=1}^n T_i e_i e_i^T \right)^{-1} \left(\sum_{t=1}^T e_{I_t} z_t \right)$$

$$y_t = \langle \theta^*, x_t \rangle + z_t$$

$\varepsilon_i \in \{-1, 1\}$ w.p. $1/2$. For N

$$\mathcal{T} = \min \left\{ N+1, \min \left\{ t : \sum_{i=1}^t \varepsilon_i \geq 1 \right\} \right\}$$

$$\mathbb{E} \left[\frac{1}{\mathcal{T}} \sum_{i=1}^{\mathcal{T}} \varepsilon_i \right] > 0 \quad \text{For a fixed } n \in \mathbb{N}$$

$$\mathbb{E} \left[\frac{1}{n} \sum_{i=1}^n \varepsilon_i \right] = 0$$

$$= \mathbb{E} \left[\sum_{t=1}^N \mathbb{1}_{\{\mathcal{T} = t\}} \frac{1}{t} \sum_{i=1}^t \varepsilon_i \right] + \mathbb{E} \left[\mathbb{1}_{\{\mathcal{T} = N+1\}} \frac{1}{N+1} \sum_{i=1}^N \varepsilon_i \right]$$

$$\geq \mathbb{E} \left[\sum_{t=1}^N \mathbb{1}_{\{\mathcal{T} = t\}} \cdot \frac{1}{t} \right] - \mathbb{E} \left[\frac{1}{N+1} \sum_{i=1}^{N+1} \varepsilon_i \right]$$

$$\geq \mathbb{E} \left[\mathbb{1}_{\{\mathcal{T} = 1\}} \cdot \frac{1}{1} \right] - \sqrt{\frac{2}{\pi(N+1)}}$$

$$\geq 0.1 -$$

$$\geq c > 0$$

$$\phi = \mathbb{E}_{z \sim \mathcal{N}(0,1)} [|z|] \quad (\text{I think it's } \sqrt{\frac{2}{\pi}})$$

$$2 \int_{x=0}^{\infty} \frac{1}{\sqrt{2\pi}} x e^{-x^2/2} dx \quad \begin{array}{l} u = x^2/2 \\ du = x \end{array}$$

$$= 2 \int_{u=0}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-u} du = \sqrt{\frac{2}{\pi}}$$