

Principles of Digital Communication

March 10, 2021



Reading was.

- m-ary hypothesis testing
 - Q-function
 - Hypothesis testing with Additive Gaussian Noise
-

m-ary Hyp. Test:

$$H \in \{0, \dots, m-1\}$$

$$Pr_{\mathcal{H}} \quad P_H(0) \dots P_H(m-1).$$

observation γ specified by $P_{\gamma|H}(y|i)$

- we need to design $\hat{H}(\gamma)$ so as to maximize

$$Pr(H = \hat{H}(\gamma))$$

the "best" $\hat{H}$ is the "MAP" rule

$$\hat{H}(\gamma) = \underset{0 \leq \hat{i} < m}{\operatorname{argmax}} P_r(H = \hat{i} | \gamma = \gamma).$$

- Properties of the Gaussian distribution.

"Standard" Gaussian ($\equiv$ Standard Normal)

Z : Gaussian $\stackrel{0}{=}$ mean $\text{variance} = \stackrel{1}{=}$

$$\Pr(Z > x) \triangleq Q(x).$$

General scalar Gaussian

$$X \sim \mathcal{N}(\mu, \sigma^2)$$

mean variance

$\Rightarrow \frac{X - \mu}{\sigma}$ is a standard Gaussian

$$\begin{aligned} \underline{\Pr(X > a)} &= \Pr\left(\frac{X - \mu}{\sigma} > \frac{a - \mu}{\sigma}\right) \\ &= Q\left(\frac{a - \mu}{\sigma}\right). \end{aligned}$$

Hyp. testing with Gaussian noise.

• Binary, scalar.

$$H=0 \Rightarrow Y = C_0 + Z$$

$$H=1 \Rightarrow Y = C_1 + Z$$

By computing the MAP rule

$$y(c_1 - c_0) \underset{0}{\overset{1}{\gtrless}} \text{threshold} //$$

A prob. error expressed in terms of the Q funct.

Binary Hypotheses but $\gamma \in \mathbb{R}^n$.

$$H=0 \Rightarrow \gamma = c_0 + z$$

$$H=1 \Rightarrow \gamma = c_1 + z$$

$$c_0 \in \mathbb{R}^n, c_1 \in \mathbb{R}^n$$

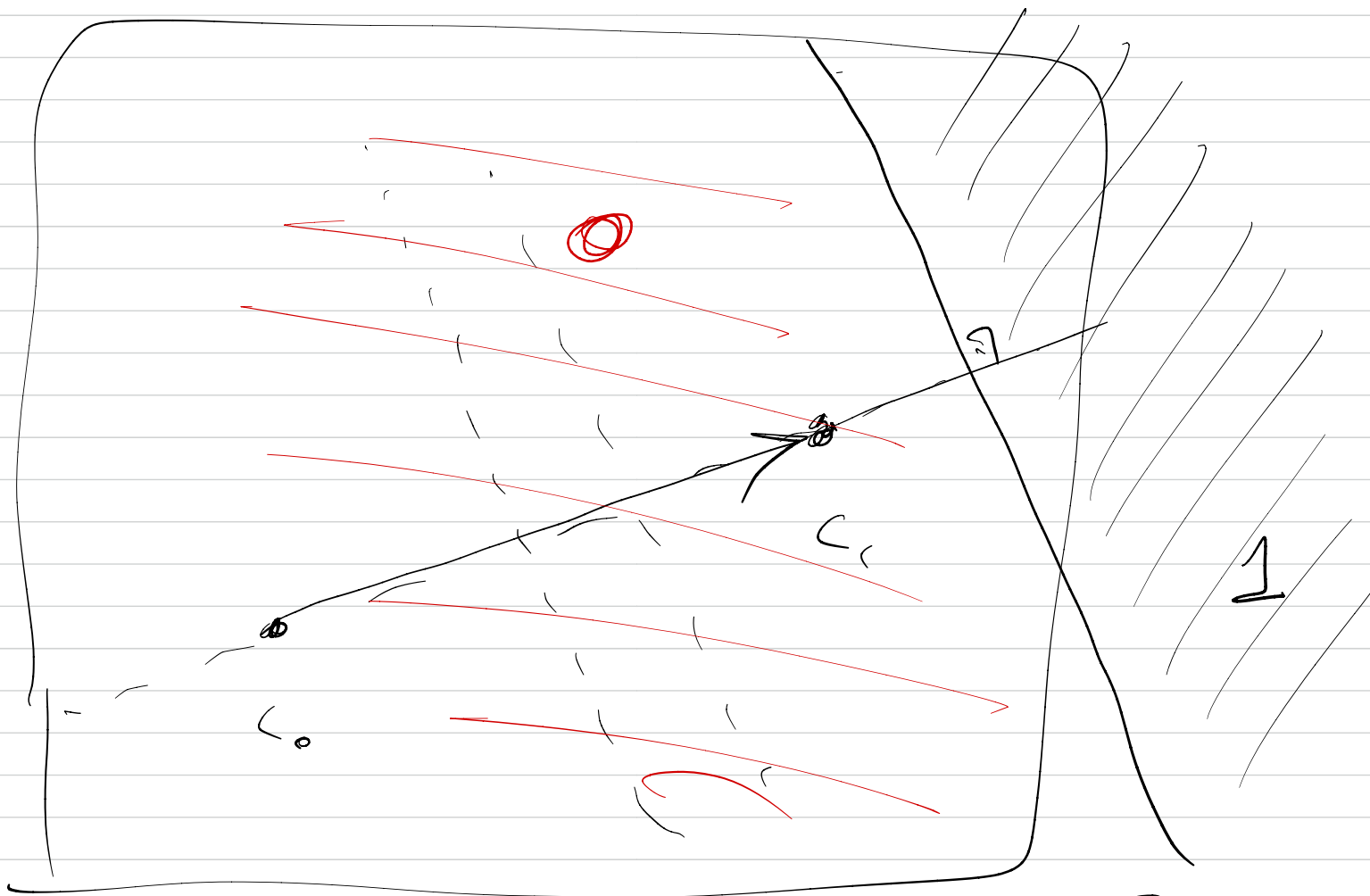
$$z \sim N\left(\begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}, \sigma^2 I\right)$$

$$\equiv \begin{pmatrix} E[z_i] = 0 & \forall i \\ E[z_i z_j] = 0 & i \neq j \\ E[z_i^2] = \sigma^2 \end{pmatrix}$$

$$\equiv z_1, \dots, z_n \text{ i.i.d } N(0, \sigma^2)$$

$\Rightarrow$ MAP rule:

$$\langle \gamma, c_1 - c_0 \rangle \underset{0}{\overset{1}{\gtrless}} \text{threshold}$$



$$\langle y, c_1 - c_0 \rangle = \text{threshold}$$

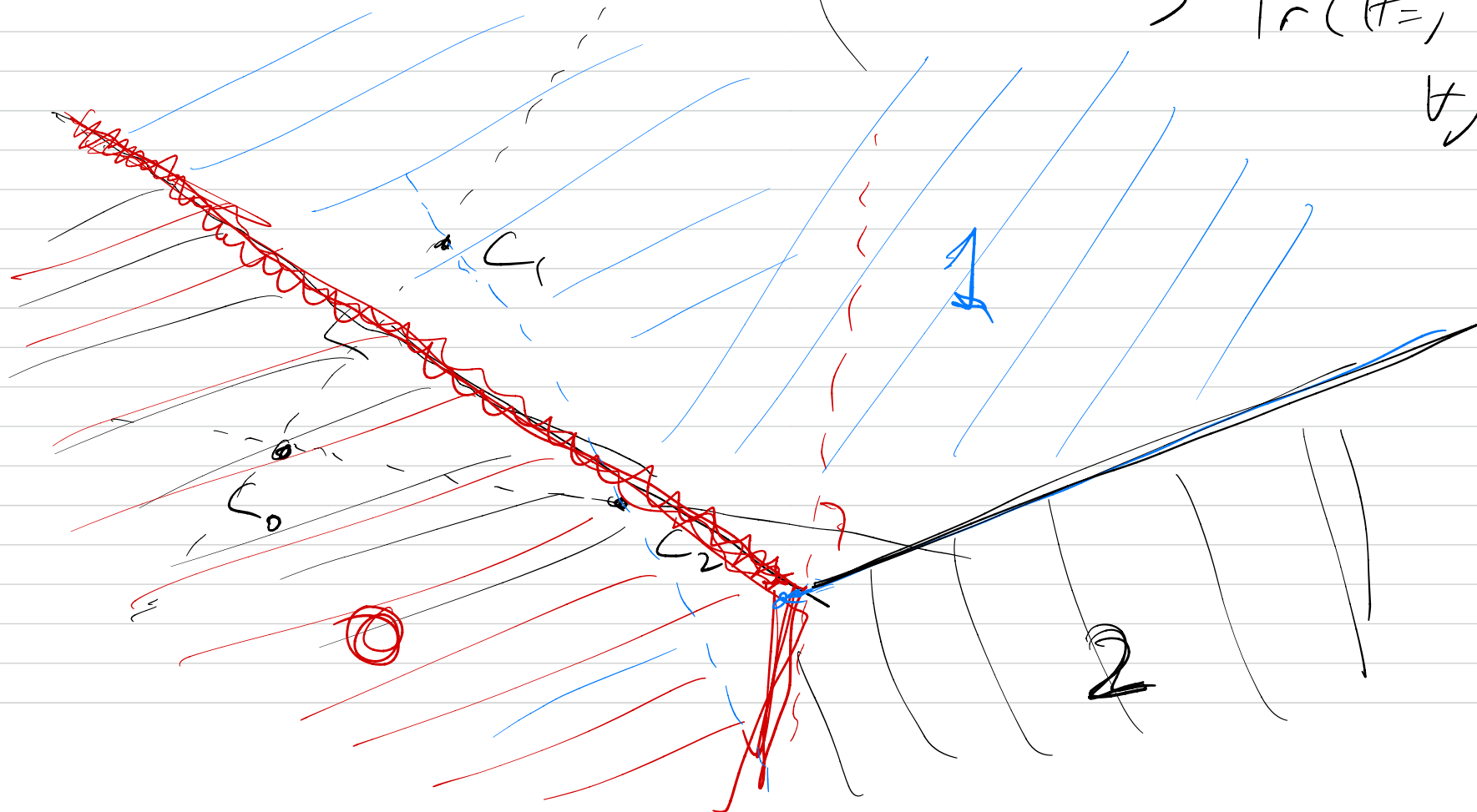
For m -ary Hyp. test, n -dim Gaussian observation

$$H=i \Rightarrow Y = c_i + Z \quad c_i \in \mathbb{R}^n$$

$$Z \sim N(0, \sigma^2 I)$$

MAP rule:

$$\text{decide } i \text{ iff } \left(\begin{aligned} &Pr(H=i | Y=y) \\ &> Pr(H=j | Y=y) \end{aligned} \right)_{\forall j}$$



How do we find the threshold.

$$\text{when } P(H=i | Y=y) > P(H=j | Y=y)$$

$$\equiv \underbrace{f_{Y|H}(y|i)} \underbrace{P_H(i)} > \underbrace{f_{Y|H}(y|j)} \underbrace{P_H(j)}$$

$$f_{Y|H}(y|i) = ?$$

$$\hookrightarrow \text{given } H=i, Y = \begin{bmatrix} c_{i1} + z_1 \\ c_{i2} + z_2 \\ \vdots \\ c_{in} + z_n \end{bmatrix} \begin{matrix} \leftarrow \\ \leftarrow \\ \\ \leftarrow \end{matrix}$$

So given $H=i$, $Y_1, \dots, Y_n$ are independent,

$$Y_k \sim N(c_{ik}, \sigma^2)$$

$$f_{Y_k|H}(y_k|i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2} (y_k - c_{ik})^2\right)$$

$$f_{Y|H}(y|i) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2} \underbrace{\sum_{k=1}^n (y_k - c_{ik})^2}_{\|y - c_i\|^2}\right)$$

S_e i is better than j

$$\equiv \frac{p_H(i)}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2} \|y - c_i\|^2\right)$$

$$> \frac{p_H(j)}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2} \|y - c_j\|^2\right)$$

$$\equiv \exp\left(+\frac{1}{2\sigma^2} \|y - c_j\|^2 - \frac{1}{2\sigma^2} \|y - c_i\|^2\right) > \frac{p_H(j)}{p_H(i)}$$

$$\equiv \frac{1}{2\sigma^2} \left[\|y - c_j\|^2 - \|y - c_i\|^2 \right] > \ln \frac{p_H(j)}{p_H(i)}$$

Recall: $\|a - b\|^2 = \|a\|^2 - 2\langle a, b \rangle + \|b\|^2$

$$\equiv \frac{1}{2\sigma^2} \left[2\langle y, c_i - c_j \rangle + \|c_j\|^2 - \|c_i\|^2 \right] > \ln \frac{p_H(j)}{p_H(i)}$$

$$\equiv \langle y, c_i - c_j \rangle > \underbrace{\sigma^2 \ln \frac{p_H(j)}{p_H(i)} + \frac{1}{2} [\|c_i\|^2 - \|c_j\|^2]}$$

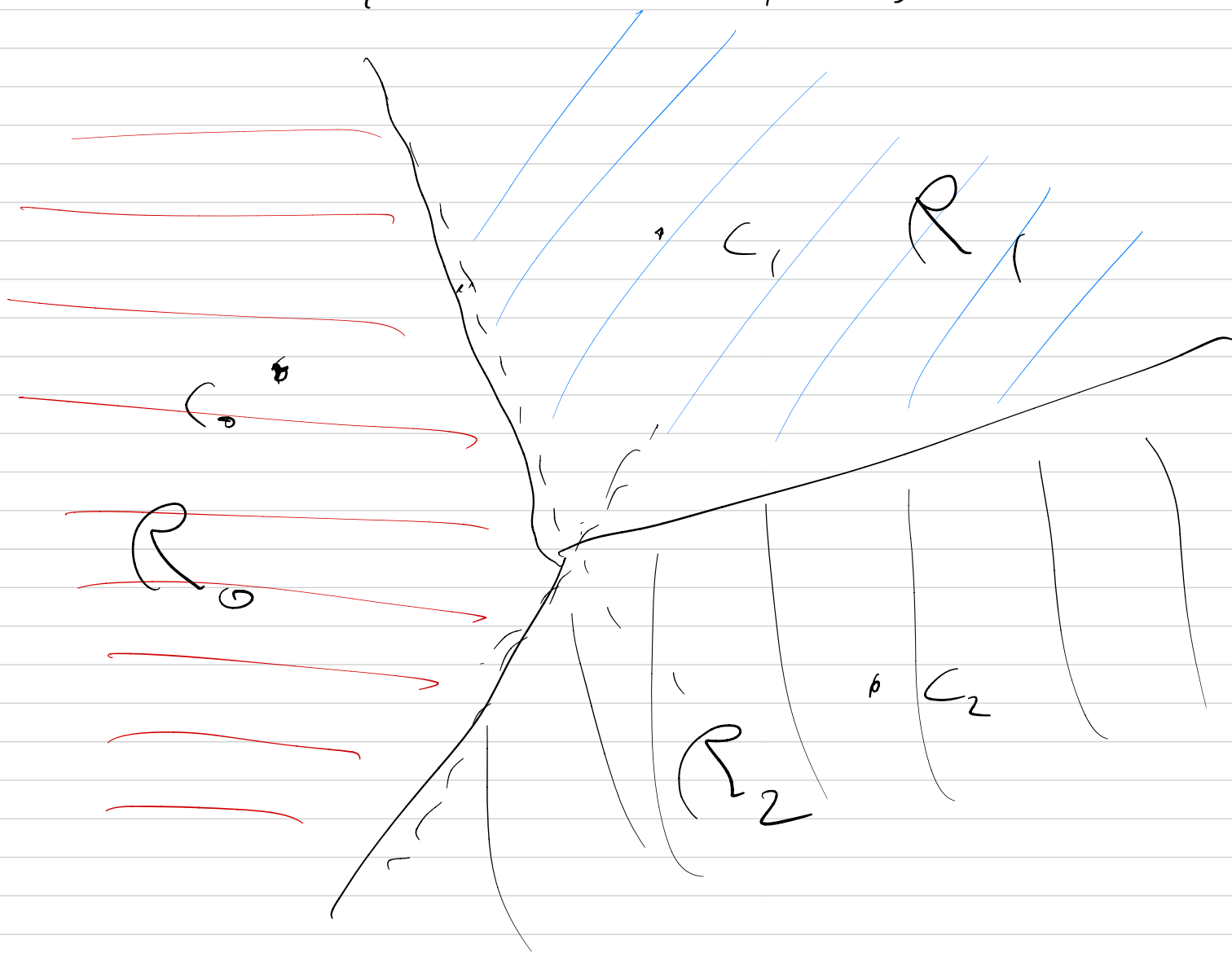
Question: can the point $c_{\bar{i}}$ fall
in to the decision region of j ?

Answer: yes it is possible, but
(not when the hypotheses are a-priori
equally likely.)

when $P_H(\bar{i}) = \frac{1}{m}$ for $\bar{i} \in \{0, \dots, m-1\}$,

then " $c_{\bar{i}}$ is better than j "

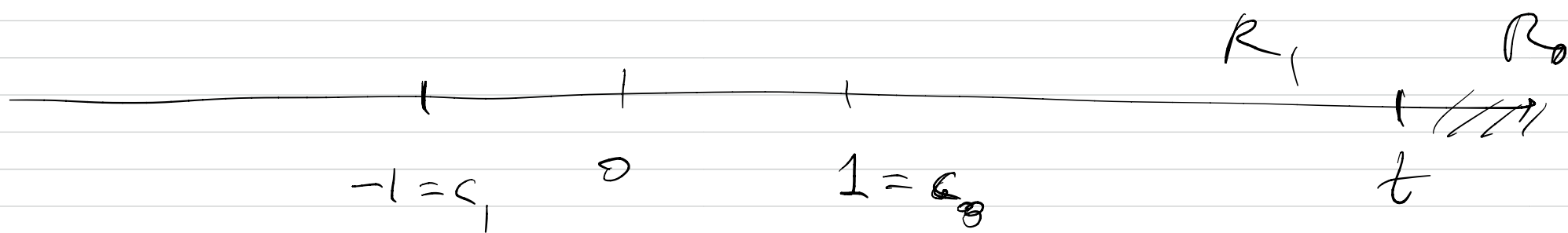
$$\equiv \|y - c_{\bar{i}}\| < \|y - c_j\|$$



To give an example when $c_i \in \mathbb{R}$, $j \neq i$

let $n=1$ (all scalars)

$$c_0 = 1, \quad c_1 = -1 \quad \sigma^2 = 1.$$



the boundary that separates R_1 & R_0 is

$$p_H(0) e^{-\frac{1}{2}(t-1)^2} = p_H(1) e^{-\frac{1}{2}(t+1)^2}$$

$$\begin{aligned} \frac{p_H(0)}{p_H(1)} &= \exp\left(\frac{1}{2}(t-1)^2 - \frac{1}{2}(t+1)^2\right) \\ &= \exp(-2t) \end{aligned}$$

$$t = -\frac{1}{2} \ln \left(\frac{p_H(0)}{p_H(1)} \right)$$

t can take on any value in $\mathbb{R}$ if we choose $p_H(0)$, $p_H(1)$ appropriately.

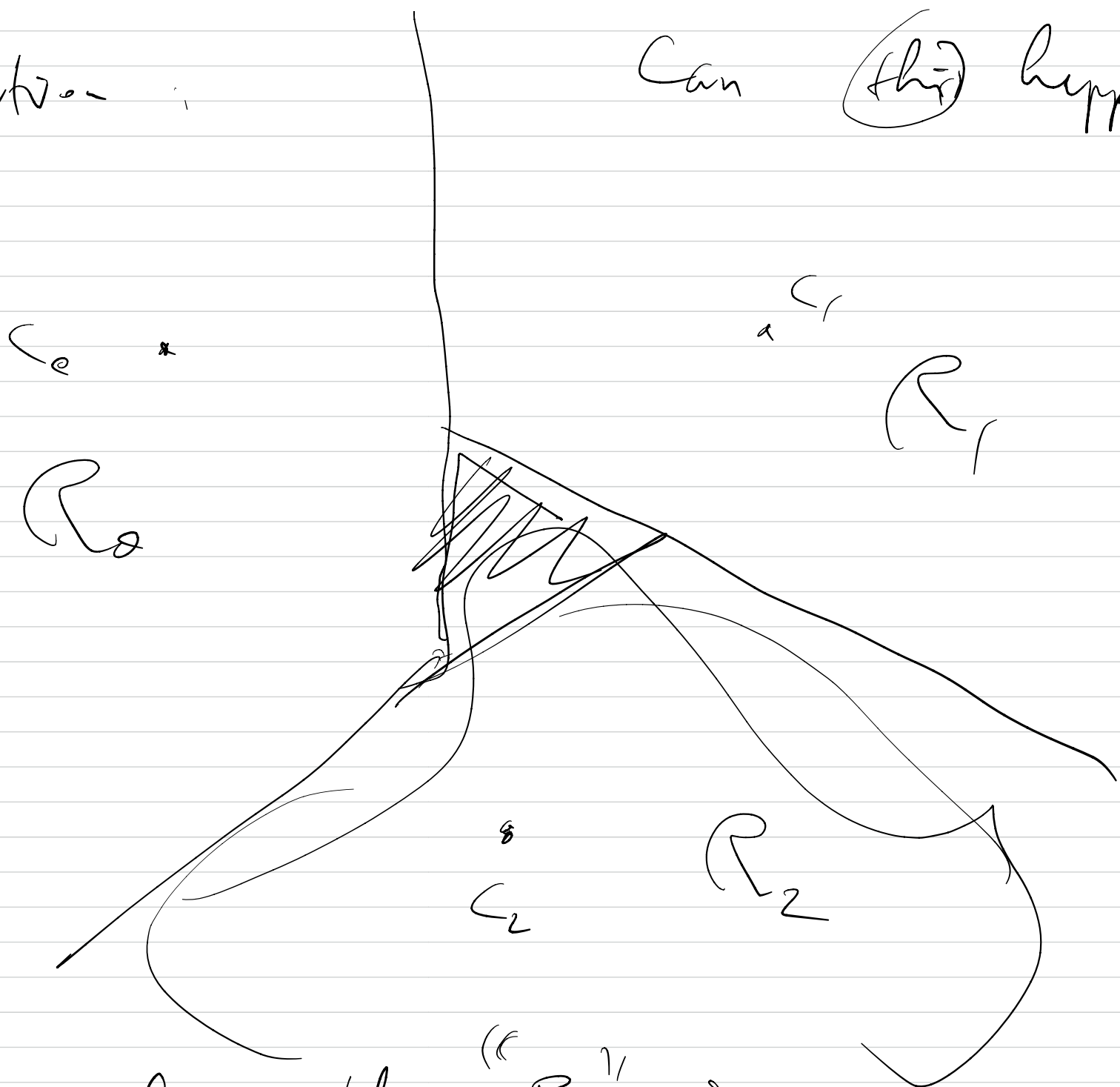
eg. to make $t=0$ we need to choose

$$\frac{p_H(1)}{p_H(0)} = e^{20} \Rightarrow p_H(1) = \frac{e^{20}}{e^{20} + 1}$$

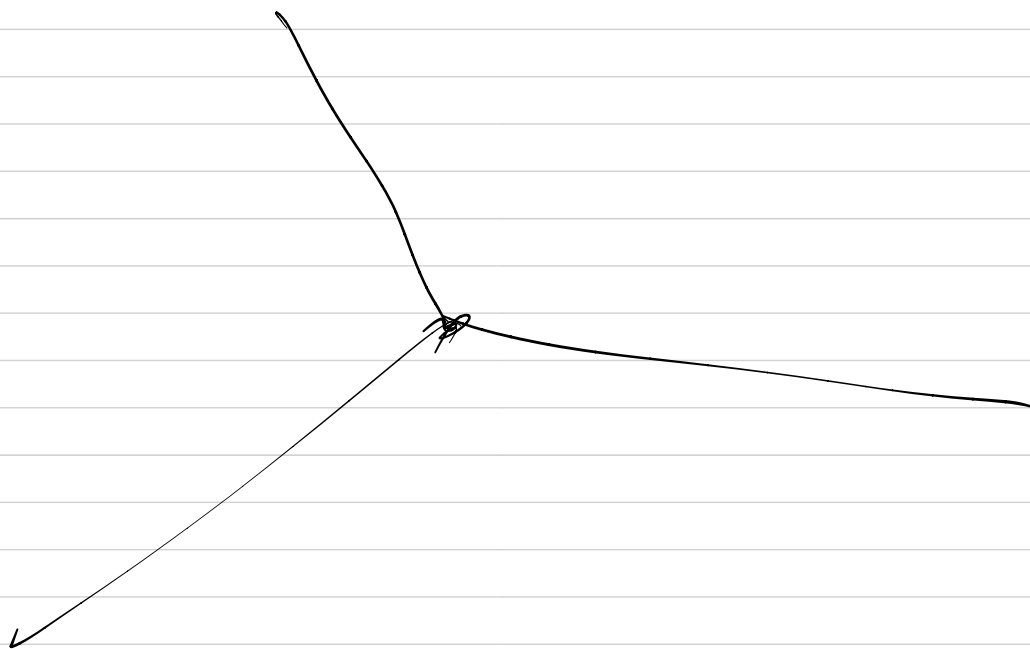
$$p_H(0) = \frac{1}{e^{20} + 1}$$

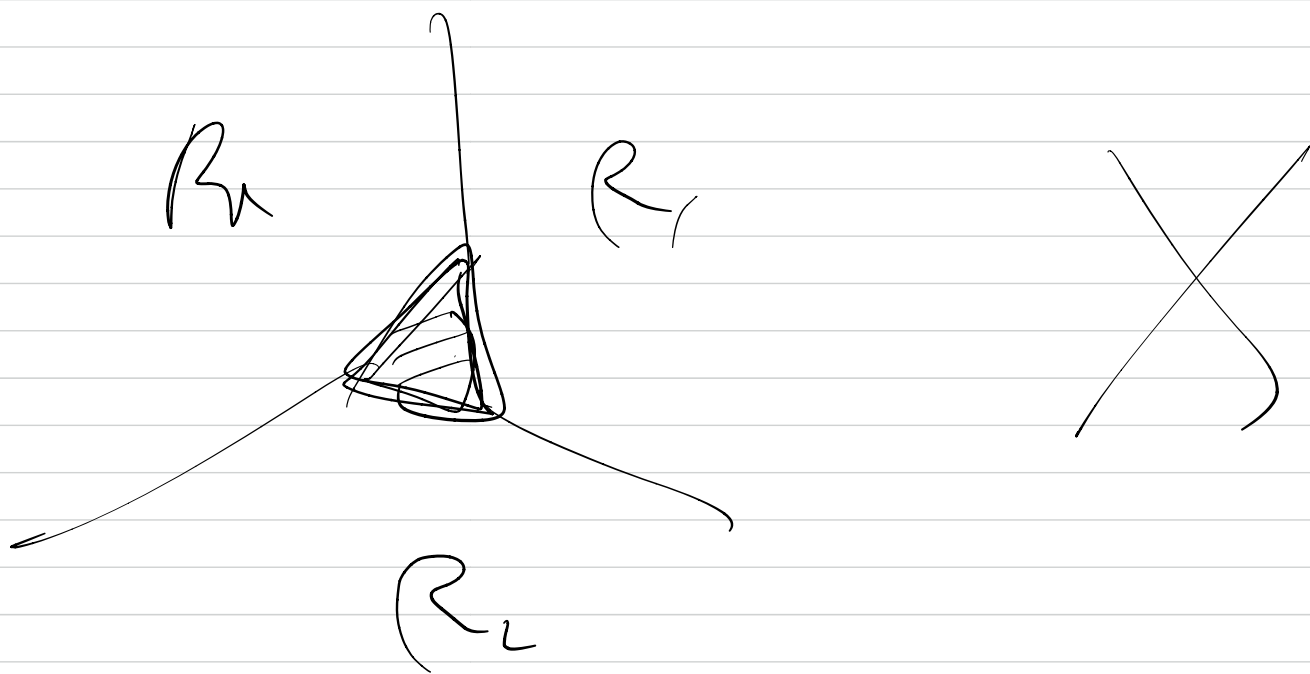
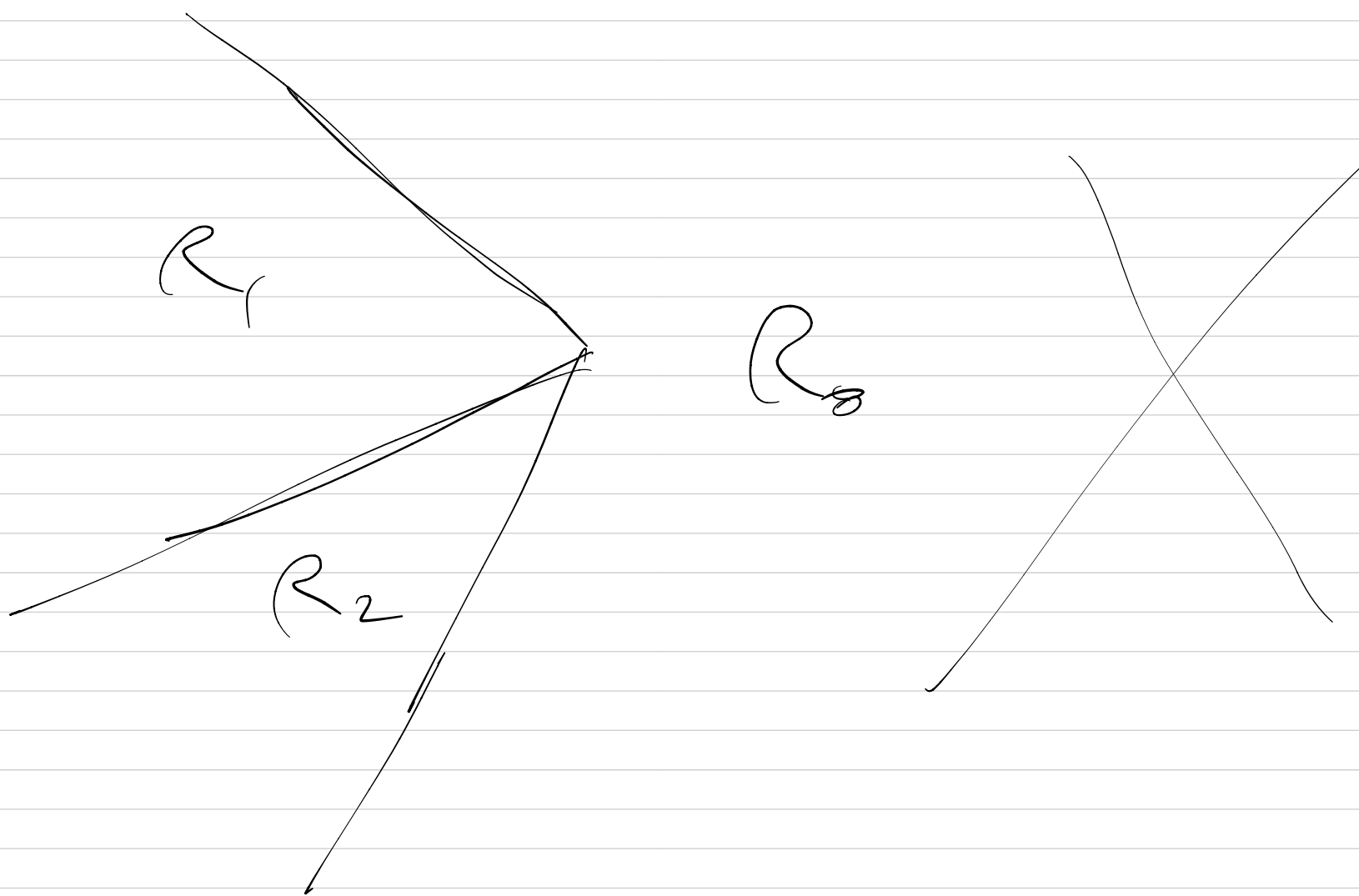
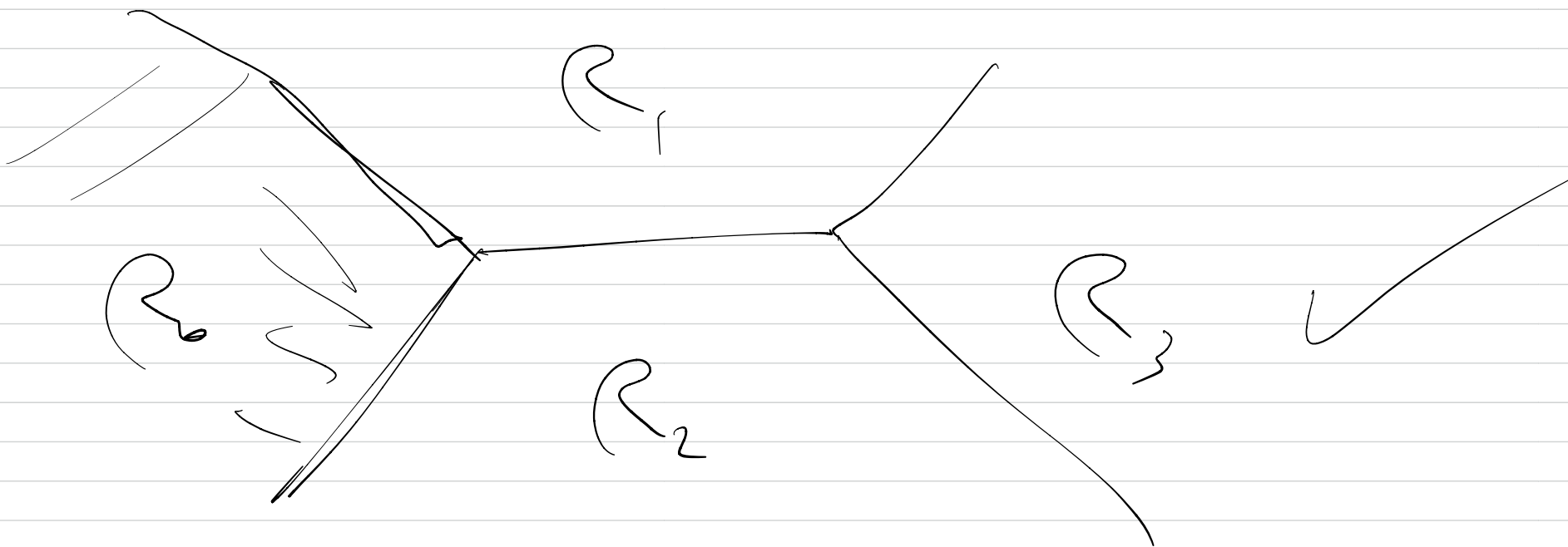
Question:

Can (this) happen?



We saw that the " R_i " is an intersection of Half-spaces.





Modify our Hypothesis test problem:

$H \in \{0, 1\}$, but we allow

$\hat{H} \in \{0, 1, ?\}$

$P_r(\hat{H} = 1 | H = 0)$, $P_r(\hat{H} = ? | H = 0)$

$P_r(\hat{H} = 0 | H = 1)$, $P_r(\hat{H} = ? | H = 1)$.

