# Lecture 21: Neyman-Pearson lemma

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#### Neyman-Pearson test

Let  $X_1,...,X_n$  be a sample from some distribution with probability function f and parameter  $\theta$ . To test

$$H_0: \theta = \theta_0 \qquad H_A: \theta = \theta_1,$$

the **Neyman-Pearson** test rejects  $H_0$  when

$$\frac{L(\theta_1|X)}{L(\theta_0|X)} = \frac{f(X_1, ..., X_n|\theta_1)}{f(X_1, ..., X_n|\theta_0)} > k$$

where k is chosen so that  $\beta(\theta_0) = \alpha$ .

### Warm-up

Let  $X_1,...,X_n \stackrel{iid}{\sim} Poisson(\lambda)$ , with pmf  $f(x) = \frac{e^{-\lambda}\lambda^x}{x!}$ . We want to test  $H_0: \lambda = \lambda_0$  vs.  $H_A: \lambda = \lambda_1$ , where  $\lambda_1 > \lambda_0$ . The Neyman-Pearson test rejects when

$$\frac{L(\lambda_1|\mathbf{X})}{L(\lambda_0|\mathbf{X})} > k$$
.  $\omega$  went  $\mathcal{X}$  st  $\beta(\lambda_0) = \alpha$ 

- 1. Calculate  $\frac{L(\lambda_1|\mathbf{X})}{L(\lambda_0|\mathbf{X})}$
- 2. Rearrange the ratio to show that  $\frac{L(\lambda_1|\mathbf{X})}{L(\lambda_0|\mathbf{X})} > k$  if and only if  $\sum_i X_i > c$  for some c
- 3. Using the fact that  $\sum_i X_i \sim Poisson(n\lambda)$ , find c such that  $\beta(\lambda_0) = \alpha$

$$\frac{L(\lambda_{1}|X)}{L(\lambda_{0}|X)} = \frac{e^{-\lambda_{1}} \lambda_{1} \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} \lambda_{i}}{e^{-\lambda_{0}} \lambda_{0} \sum_{i=1}^{\infty} \lambda_{i}} = e^{-\lambda_{0}} \left(\frac{\lambda_{1}}{\lambda_{0}}\right)^{2ix_{i}}$$

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$$\frac{L(\lambda_{0}|X)}{L(\lambda_{0}|X)} = \frac{e^{-\lambda_{1}} \lambda_{0} \sum_{i=1}^{\infty} \lambda_{i}}{e^{-\lambda_{0}} \lambda_{0} \sum_{i=1}^{\infty} \lambda_{i}} + h(\lambda_{0}-\lambda_{i}) > \log H$$

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$$\frac{L(\lambda_{1}|X)}{L(\lambda_{1}|X)} = \frac{e^{-\lambda_{1}} \lambda_{0}}{e^{-\lambda_{1}} \lambda_{0}} + h(\lambda_{1}-\lambda_{0})$$

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e-n2 2 2:X:

$$\frac{\log \pi + n(\lambda_1 - \lambda_0)}{(\log \lambda_1 - \log \lambda_0)}$$

$$\sim Poisson(n\lambda)$$

 $C = (X_i)$ 

 $L(\lambda|\lambda) = \Pi \frac{e^{-\lambda} \lambda^{x_i}}{2}$ 

=> Eixi ~ Paissan (n20)  $\mathcal{H}_{o_j}$   $\lambda = \lambda_o$ Undes quantile of Paisson (n 20) C = upper &

### Uniformly most powerful tests

**Big idea:** can't do better than the Neyman-Pearson test for two simple hypotheses!

What does it mean for one test to be "better" than another?

**Definition:** Consider testing  $H_0: \theta \in \Theta_0$  vs.  $H_A: \theta \in \Theta_1$ . Let  $\mathcal{C}_{\alpha}$  be the set of level  $\alpha$  tests for these hypotheses. A test in  $\mathcal{C}_{\alpha}$  is the **uniformly most powerful** level  $\alpha$  test if:

It has power 
$$\beta(\theta) \geq \beta^*(\theta)$$
  $\forall \theta \in H$ ,

power function
for unp test

any other level a test

of these hypotheses

(i.e.  $\beta^*(\theta) \leq d \forall \theta \in H_0$ )

we your - Plance setting:  $H_0: G = \theta_0$   $H_A: G = \theta_0$ 

unp:  $\beta(\theta_0) \geq \beta^*(\theta_0)$ 

**Lemma:** The Neyman-Pearson test is a *uniformly most powerful* level  $\alpha$  test of  $H_0: \theta = \theta_0$  vs.  $H_A: \theta = \theta_1$ .

Pf: N-P ks+ rejects when 
$$\frac{f(x \mid \theta_i)}{f(x \mid \theta_0)} > H$$

where we choose  $H$  st  $\beta NP(\theta_0) = \alpha$ 
 $\Rightarrow N \cdot P + est \Rightarrow \alpha \text{ level } \alpha + est$ 

Let  $\beta^*$  be power of where level  $\alpha + est$ 

of these hypotheses

 $\Rightarrow \beta^*(\theta_0) \perp \alpha \Rightarrow \beta NP(\theta_0) - \beta^*(\theta_0) \geq \alpha$ 

WTS:  $\beta NP(\theta_i) \geq \beta^*(\theta_i) \Rightarrow \beta NP(\theta_i) - \beta^*(\theta_i) \geq \alpha$ 

In fact, we will show that

 $\beta NP(\theta_i) - \beta^*(\theta_i) \geq H(\beta NP(\theta_0) - \beta^*(\theta_0)) \geq \alpha$ 

**Lemma:** The Neyman-Pearson test is a *uniformly most powerful* level  $\alpha$  test of  $H_0$ :  $\theta = \theta_0$  vs.  $H_A$ :  $\theta = \theta_1$ . Bur (6) - B\*(0) = H(Bur(00) -B\*(00) >0 475 Let ONP denote N-P rejection function Likewise, &\* rejection function for other test BNP (0) = Po (reject Ho) = Po (BNP (x) = 1)  $= \int_{a}^{b} \emptyset_{\mu\rho}(x) f(x|\theta) dx$ 13 \* (0) - ) = 0 \* (x) f(x(6) dx

**Lemma:** The Neyman-Pearson test is a *uniformly most powerful* 

level 
$$\alpha$$
 test of  $H_0: \theta = \theta_0$  vs.  $H_A: \theta = \theta_1$ .  

$$\beta_{NP}(\theta_n) - \beta^*(\theta_n) = \int_{\mathcal{R}} (\omega_{NP}(x) - \omega^*(x)) f(x(\theta_n)) dx$$

$$\begin{bmatrix}
\beta_{NP}(\Theta_{i}) - \beta^{*}(\Theta_{i})
\end{bmatrix} - W(\beta_{NP}(\Theta_{0}) - \beta^{*}(\Theta_{0}))$$

$$= \int (\Theta_{NP}(x) - \Theta^{*}(x)) (f(x|\Theta_{i}) - Wf(x|\Theta_{0})) dx$$

**Lemma:** The Neyman-Pearson test is a *uniformly most powerful* level  $\alpha$  test of  $H_0: \theta = \theta_0$  vs.  $H_A: \theta = \theta_1$ .

level 
$$\alpha$$
 test of  $H_0: \theta = \theta_0$  vs.  $H_A: \theta = \theta_1$ .

$$\begin{bmatrix} \beta_{NP}(\Theta_1) - \beta^*(\Theta_1) \end{bmatrix} - W(\beta_{NP}(\Theta_0) - \beta^*(\Theta_0) \\
= \int_{\mathcal{X}} (\Theta_{NP}(x) - \Theta^*(x)) (f(x|\Theta_1) - Wf(x|\Theta_0)) dx$$
Show: integrand is always  $\geq 0$ 

$$\int_{\mathcal{X}} (\Theta_{NP}(x) - \Theta^*(x)) (f(x|\Theta_1) - Wf(x|\Theta_0)) dx$$

$$= 0 \text{ if tests agree}$$

**Lemma:** The Neyman-Pearson test is a *uniformly most powerful* level  $\alpha$  test of  $H_0: \theta = \theta_0$  vs.  $H_A: \theta = \theta_1$ .

integrand 
$$20$$

=> [Bnp(G)] - B\*(O)] - H (Bnp(GO)] - B\*(O))  $\geq 0$ 

=> Bnp(G)] - B\*(O)  $\geq H$  (Bnp(GO) - B\*(O))

 $\geq 0$ 

=> Bnp(O)  $\geq B*(O)$