

Suppose that X_1, X_2, \dots, X_n is a random sample from the exponential distribution with rate $\lambda > 0$.

Derive a hypothesis test of size α for

$$H_0 : \lambda = \lambda_0 \quad \text{vs.} \quad H_1 : \lambda = \lambda_1$$

where $\lambda_1 > \lambda_0$.


What statistic should we use?

One test has rejection rule:

$$\bar{X} < \frac{\chi^2_{1-\alpha, 2n}}{2n\lambda_0}$$

“Denote” this by 

$$\alpha = P\left(\bar{X} < \frac{\chi^2_{1-\alpha, 2n}}{2n\lambda_0}; \lambda_0\right)$$


$$= P\left(\text{; \lambda_0\right)$$

One another has rejection rule:

$$\min(X_1, X_2, \dots, X_n) < \frac{-\ln(1 - \alpha)}{n\lambda_0}$$

“Denote” this by 

$$\alpha = P\left(\min(X_1, X_2, \dots, X_n) < \frac{-\ln(1 - \alpha)}{n\lambda_0}; \lambda_0\right)$$

$$= P\left(\text{; \lambda_0\right)$$

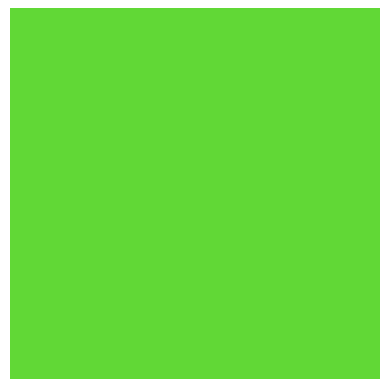
Consider “all” tests:



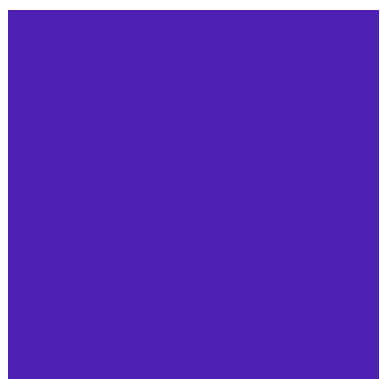
$$P(\text{ } \square \text{ } ; \lambda_0) = \alpha$$



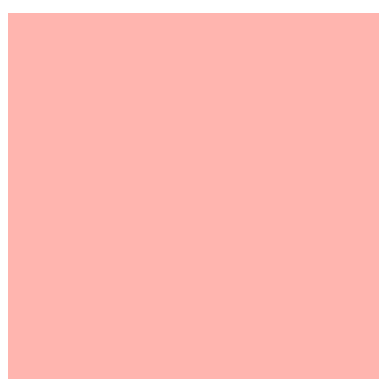
$$P(\text{ } \square \text{ } ; \lambda_0) = \alpha$$



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When H_1 is true:



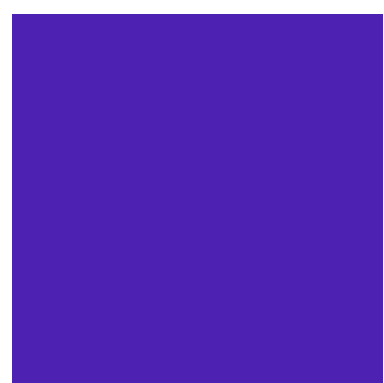
$$P(\text{blue square} ; \lambda_1) = ?$$



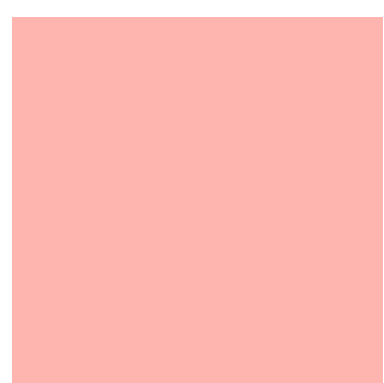
$$P(\text{orange square} ; \lambda_1) = ?$$



$$P(\text{green square} ; \lambda_1) = ?$$



$$P(\text{purple square} ; \lambda_1) = ?$$



$$P(\text{pink square} ; \lambda_1) = ?$$

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-
-

- Want these numbers
- to be **large!!!**
-

When H_1 is true:



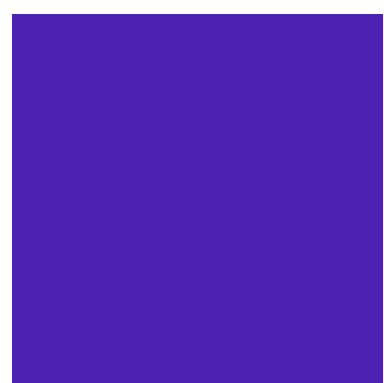
$$P(\text{blue square} ; \lambda_1) = ?$$



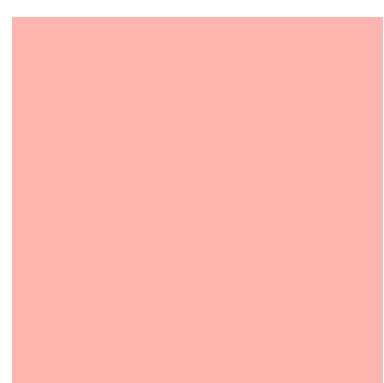
$$P(\text{orange square} ; \lambda_1) = ?$$



$$P(\text{green square} ; \lambda_1) = ?$$



$$P(\text{purple square} ; \lambda_1) = ?$$



$$P(\text{pink square} ; \lambda_1) = ?$$

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-
-

- The **best** test will
- be **largest!!!**
-

Tests are defined by rejection **regions**.

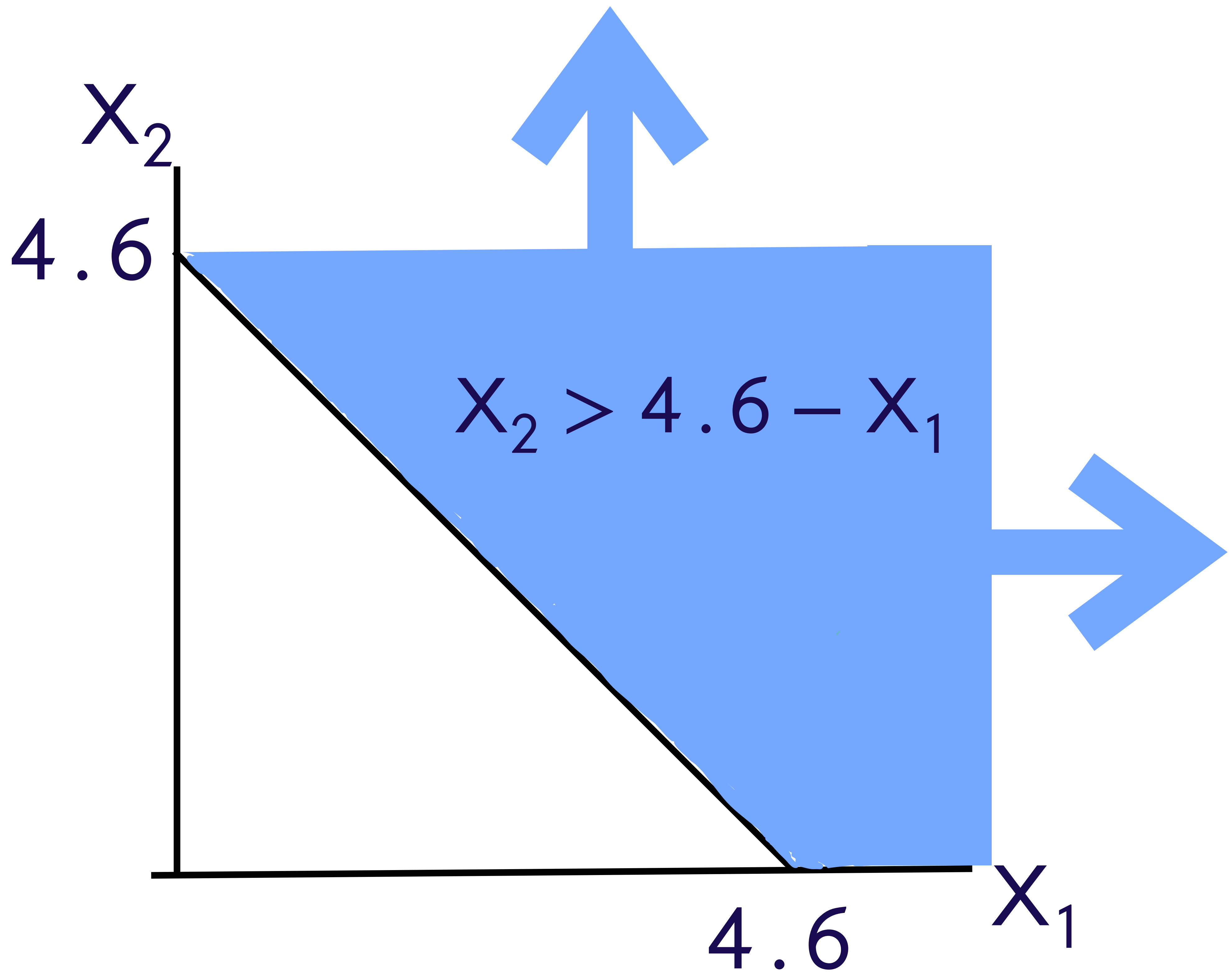
For example, when $n=2$:

Reject H_0 if $\bar{X} > 2.3$

$$\Leftrightarrow \frac{X_1 + X_2}{2} > 2.3$$

$$\Leftrightarrow X_2 > 4.6 - X_1$$

Reject H_0 if (X_1, X_2) is in this region



$$H_0 : \theta = \theta_0 \quad \text{vs.} \quad H_1 : \theta = \theta_1$$

$$P(\text{red} ; \lambda_0) = \alpha$$

$$P(\vec{X} \in R_1 ; \lambda_0) = \alpha$$

$$P(\text{blue} ; \lambda_0) = \alpha$$

$$P(\vec{X} \in R_2 ; \lambda_0) = \alpha$$

$$P(\text{green} ; \lambda_0) = \alpha$$

$$P(\vec{X} \in R_3 ; \lambda_0) = \alpha$$

$$P(\text{yellow} ; \lambda_0) = \alpha$$

$$P(\vec{X} \in R_4 ; \lambda_0) = \alpha$$

$$P(\text{purple} ; \lambda_0) = \alpha$$

$$P(\vec{X} \in R_5 ; \lambda_0) = \alpha$$

⋮

⋮

$$H_0 : \theta = \theta_0 \quad \text{vs.} \quad H_1 : \theta = \theta_1$$

Definition:

A test R^* is a best test of size/level α for the above hypotheses if

1. $P(\vec{X} \in R^*; \theta_0) = \alpha$ and

2. If R represents any other test with

$$P(\vec{X} \in R; \theta_0) = \alpha,$$

then

$$P(\vec{X} \in R^*; \theta_1) \geq P(\vec{X} \in R; \theta_1).$$

The Neyman-Pearson Lemma (setup)

Let X_1, X_2, \dots, X_n be a random sample from a distribution with pdf f which depends on an unknown parameter θ .

Write the joint pdf as

$$f(\vec{x}; \theta) \stackrel{\text{iid}}{=} \prod_{i=1}^n f(x_i; \theta)$$

The Neyman-Pearson Lemma

$$H_0 : \theta = \theta_0 \quad \text{vs.} \quad H_1 : \theta = \theta_1$$

The best test of size/level α is to reject H_0 , in favor of H_1 if $\vec{X} \in R^*$ where

$$R^* = \left\{ \vec{x} : \frac{f(\vec{x}; \theta_0)}{f(\vec{x}; \theta_1)} \leq c \right\}$$

For discrete X_1, X_2, \dots, X_n

$$f(\vec{x}; \theta) = P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n; \theta)$$

$$R^* = \left\{ \vec{x} : \frac{f(\vec{x}; \theta_0)}{f(\vec{x}; \theta_1)} \leq c \right\}$$

- If H_0 is true and H_1 is false, the ratio is large.
- If H_0 is false and H_1 is true, the ratio is small. **This is when we should reject H_0 !**

Example:

Suppose that X_1, X_2, \dots, X_n is a random sample from the exponential distribution with rate $\lambda > 0$.

Find the best test of size/level α for testing

$$H_0 : \lambda = \lambda_0 \quad \text{vs.} \quad H_1 : \lambda = \lambda_1$$

where $\lambda_1 > \lambda_0$.

pdf: $f(x; \lambda) = \lambda e^{-\lambda x}$

joint pdf: $f(\vec{x}; \lambda) \stackrel{\text{iid}}{=} \prod_{i=1}^n f(x_i; \lambda)$

$$= \prod_{i=1}^n \lambda e^{-\lambda x_i} = \lambda^n e^{-\lambda \sum_{i=1}^n x_i}$$

“likelihood ratio”: $\frac{f(\vec{x}; \lambda_0)}{f(\vec{x}; \lambda_1)}$

“likelihood ratio”:

$$\frac{f(\vec{x}; \lambda_0)}{f(\vec{x}; \lambda_1)} = \frac{\lambda_0^n e^{-\lambda_0 \sum_{i=1}^n x_i}}{\lambda_1^n e^{-\lambda_1 \sum_{i=1}^n x_i}}$$
$$= \left(\frac{\lambda_0}{\lambda_1} \right)^n e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i}$$

The Neyman-Pearson Lemma says:

“Reject H_0 , in favor of H_1 , if

$$\left(\frac{\lambda_0}{\lambda_1}\right)^n e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i} \leq c$$

where c is to be determined.”

The rejection rule

$$\left(\frac{\lambda_0}{\lambda_1}\right)^n e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i} \leq c$$

is equivalent to the rule

“Reject H_0 , in favor of H_1 , if

$$e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i} \leq \left(\frac{\lambda_1}{\lambda_0}\right)^n c$$

**This is a new
constant.**

The Neyman-Pearson Lemma says:

“Reject H_0 , in favor of H_1 , if

$$\mathbf{e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n X_i} \leq c_1}$$

where c_1 is to be determined.”

$$e^{-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i} \leq c_1$$

Taking the log of both sides, this is equivalent to

$$-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i \leq c_2$$

(Neyman-Pearson says to reject H_0 if this happens.)

$$-(\lambda_0 - \lambda_1) \sum_{i=1}^n x_i \leq c_2$$

Divide both sides by $-(\lambda_0 - \lambda_1)$.

Note that $\lambda_1 > \lambda_0$, so $-(\lambda_0 - \lambda_1) > 0$.

This means that the inequality won't flip.

$$\sum_{i=1}^n x_i \leq c_3$$

The Neyman-Pearson Lemma says:

“Reject H_0 , in favor of H_1 , if

$$\sum_{i=1}^n X_i \leq c_3$$

where c_3 is to be determined.”

Let's find c_3 .

$$\alpha = P(\text{Type I Error})$$

$$= P(\text{Reject } H_0 | \lambda_0)$$

$$= P\left(\sum_{i=1}^n X_i < c_3; \lambda_0\right)$$

Wait a minute... this is equivalent to

$$= P(\bar{X} < c_4; \lambda_0)$$

where $c_4 = c_3/n$.

$$\alpha = P(\bar{X} < c_4; \lambda_0)$$

We already did this in the previous video!

$$c_4 = \frac{\chi^2_{1-\alpha, 2n}}{2n\lambda_0}$$

Conclusion:

The best test of size α for

$$H_0 : \lambda = \lambda_0 \quad \text{vs.} \quad H_1 : \lambda = \lambda_1$$

where $\lambda_1 > \lambda_0$,

is to reject H_0 , in favor of H_1 if

$$\bar{X} < \frac{\chi^2_{1-\alpha, 2n}}{2n\lambda_0}$$

Remember, R^* is the best test of size α if

$$P(\vec{X} \in R^*; \theta_0) = \alpha$$

and $P(\vec{X} \in R^*; \theta_1) \geq P(\vec{X} \in R; \theta_1)$

for any other test of size α .

$$P(\vec{X} \in R^*; \theta_1) \geq P(\vec{X} \in R; \theta_1)$$

Each of these tests has its own power function.

$$\begin{aligned}\gamma_R(\theta) &= P(\text{Reject } H_0; \theta) \\ &= P(\vec{X} \in R; \theta)\end{aligned}$$

$$P(\vec{X} \in R^*; \theta_1) \geq P(\vec{X} \in R; \theta_1)$$

becomes

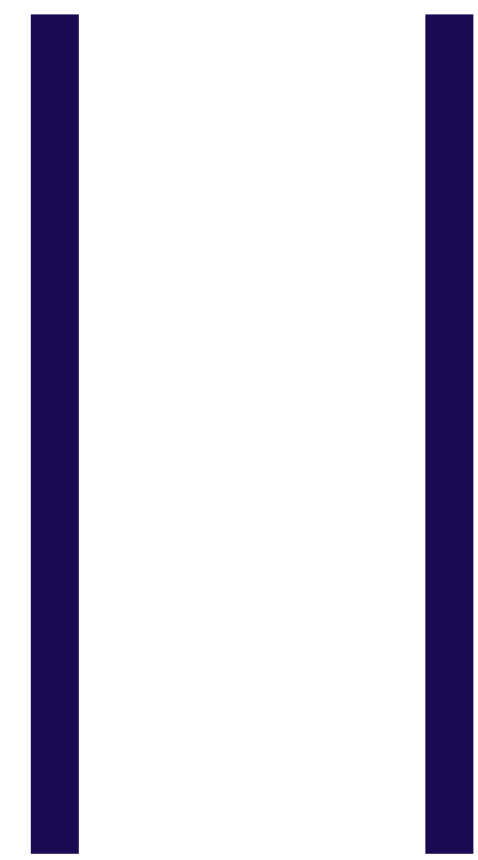
$$\gamma_{R^*}(\theta_1) \geq \gamma_R(\theta_1)$$

for any test described by R with

$$P(\vec{X} \in R; \theta_0) = \alpha$$

The best test of has highest power when H_1 is true.

“Best Test”



**“Most Powerful
Test”**