

# ACM 157 PS5

(2)  $H_0: \theta = \frac{1}{2}$   $H_1: \theta > \frac{1}{2} \Rightarrow R = \{X: X_{(n)} > c\}$

(a)  $P(\text{Type I error}) = P(X_{(n)} > c | \theta \in \Theta_0) = P(X_{(n)} > c | \theta = \frac{1}{2})$

$P(\text{Type II error}) = 1 - P(X_{(n)} > c | \theta \in \Theta_2) = \begin{cases} 1 - (2c)^n & c \leq \frac{1}{2} \\ 0 & c > \frac{1}{2} \end{cases}$

$\hookrightarrow 1 - P(X_{(n)} > c | \theta > \frac{1}{2})$

$\Rightarrow$  In general  $\beta(\theta) = P(X \in R | \theta) = P(X_{(n)} > c | \theta)$

given  $X \sim U[0, \theta] \Rightarrow P(X_{(n)} > c | \theta) = 1 - \left(\frac{c}{\theta}\right)^n$

$\Rightarrow \beta(\theta) = \begin{cases} 1 - \left(\frac{c}{\theta}\right)^n & \theta > c \\ 1 & c \leq \theta \\ 0 & c > \theta \end{cases}$

(b)  $\alpha = \sup_{\theta \in \Theta_0} \beta(\theta) = \sup_{\theta = \frac{1}{2}} \left(1 - \left(\frac{c}{\theta}\right)^n\right) = 1 - (2c)^n = \alpha$   
 $\Rightarrow c = \frac{(1-\alpha)^{1/n}}{2}$

(c)  $n = 20$   $X_{(n)} = .48$

$p(x) = \inf_{\alpha \in (0,1)} \{ \alpha : X \in R_\alpha \} = \inf_{\alpha \in (0,1)} \{ \alpha : X_{(n)} > \frac{(1-\alpha)^{1/n}}{2} \}$

$\Rightarrow \inf_{\alpha \in (0,1)} \left\{ \alpha : X_{(n)} = .48 > \frac{(1-\alpha)^{1/n}}{2} \right\} \Rightarrow \text{limit at } \alpha = 1 - (2 \cdot .48)^{20}$   
 $\hookrightarrow \approx .5579$

$p\text{-value}(\alpha^*) \approx .5579$

(2)

$$X_1, \dots, X_n \sim N(\mu, \sigma^2), \sigma^2 = 2, H_0: \mu = 0 \quad H_1: \mu = 1$$

$$\text{Test } R = \{X: \bar{X}_n > c\} \Rightarrow \beta(\mu) = P(X \in R | \mu)$$

$$\beta(\mu) = P(\bar{X}_n > c | \mu)$$

$$\Rightarrow \text{given } X \sim N(\mu, \sigma^2) = N(\mu, 2) \Rightarrow \bar{X}_n \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

thus  $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \sim N(0, 1)$  the standard normal distribution

given  $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma}$  applies only linear transformations

$$\Rightarrow \beta(\mu) = P(\bar{X}_n > c | \mu) = P\left(\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} > \frac{\sqrt{n}(c - \mu)}{\sigma} | \mu\right)$$

$$= 1 - \Phi\left(\frac{\sqrt{n}(c - \mu)}{\sigma}\right) \text{ where } \Phi \text{ is the standard normal CDF}$$

$$\alpha = \sup_{\mu \in H_0 \rightarrow \mu=0} \beta(\mu) \Rightarrow \beta(0) = 1 - \Phi\left(\frac{\sqrt{n}(c)}{\sigma}\right) = \alpha \Rightarrow c = \frac{\sigma \cdot \Phi^{-1}(1 - \alpha)}{\sqrt{n}}$$

$$\Rightarrow \text{test of size } \alpha \text{ has } c = \frac{\Phi^{-1}(1 - \alpha)}{\sqrt{n}}$$

,  $\sigma = 2$

$$(b) \text{ Power under } H_1: \mu = 1 = \beta(1) = 1 - \Phi\left(\frac{\sqrt{n}(c - 1)}{\sigma}\right) = 1 - \Phi\left(\frac{\Phi^{-1}(1 - \alpha) - \sqrt{n}}{\sqrt{n}}\right)$$

$$\Rightarrow \text{Power under } H_1 = 1 - \Phi\left(\Phi^{-1}(1 - \alpha) - \sqrt{n}\right)$$

(c)

$\beta(\mu)$  has 2 inputs in input space  $\mu = 0, 1$

$$\Rightarrow \lim_{n \rightarrow \infty} \beta(0) = 1 - \Phi\left(\sqrt{n} \left( \frac{\Phi^{-1}(1-\alpha)}{\sqrt{n}} \right)\right) = 1 - (1-\alpha) = \alpha$$

$$\Rightarrow \lim_{n \rightarrow \infty} \beta(1) = \lim_{n \rightarrow \infty} 1 - \Phi\left(\Phi^{-1}(1-\alpha) - \sqrt{n}\right), \text{ assuming } \Phi^{-1}(1-\alpha)$$

is finite this yields  ~~$\lim_{n \rightarrow \infty} \Phi(k - \sqrt{n})$~~   $\lim_{n \rightarrow \infty} \Phi(k - \sqrt{n})$ ,  $k$  is finite  
 $\hookrightarrow \alpha \neq 0$

$$\Rightarrow \lim_{n \rightarrow \infty} \Phi(-\sqrt{n}) = \Phi(-\infty) = 0 \Rightarrow$$

$$\lim_{n \rightarrow \infty} \beta(1) = \lim_{n \rightarrow \infty} 1 - \Phi(\Phi^{-1}(1-\alpha) - \sqrt{n}) = 1 - 0 = 1$$

$$\Rightarrow \left. \lim_{n \rightarrow \infty} \beta(0) = \alpha, \lim_{n \rightarrow \infty} \beta(1) = 1 \right\}$$



$$(3) \quad W = \left| \frac{\hat{\lambda} - \lambda_0}{\hat{se}_{\hat{\lambda}}} \right| > c \Rightarrow \alpha = \sup_{\lambda \in \Theta, \lambda = \lambda_0} P(\hat{\theta}) = P(\lambda_0)$$

$$P(\lambda_0) = P(W > c | \lambda = \lambda_0) = P\left(\left| \frac{\hat{\lambda} - \lambda_0}{\hat{se}} \right| > c\right)$$

$$= P\left(\frac{\hat{\lambda} - \lambda_0}{\hat{se}} > c\right) + P\left(\frac{\hat{\lambda} - \lambda_0}{\hat{se}} < -c\right) \quad \frac{\hat{\lambda} - \lambda_0}{\hat{se}} \sim N(0, 1)$$

$$= P\left(\frac{\hat{\lambda} - \lambda_0}{\hat{se}} > c\right) + P\left(\frac{\hat{\lambda} - \lambda_0}{\hat{se}} < -c\right) \Rightarrow P\left(\left| \frac{\hat{\lambda} - \lambda_0}{\hat{se}} \right| > c\right) = 2 \Phi(-c)$$

$$2 \Phi(-c) = \alpha \Rightarrow c = -\Phi^{-1}\left(\frac{\alpha}{2}\right) = -z_{\frac{\alpha}{2}}$$

$$\text{Wald test } \left| \frac{\hat{\lambda} - \lambda_0}{\hat{se}} \right| > -z_{\frac{\alpha}{2}} = z_{1-\frac{\alpha}{2}} \Rightarrow \left| \frac{\hat{\lambda} - \lambda_0}{\hat{se}} \right| > z_{1-\frac{\alpha}{2}}$$

$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmax}} (L(x_1, x_n | \lambda)) = \underset{\lambda}{\operatorname{argmax}} \left( \prod_{i=1}^n \frac{\lambda^{x_i}}{x_i!} e^{-\lambda} \right) = \underset{\lambda}{\operatorname{argmax}} \left( \ln \left( \prod_{i=1}^n \frac{\lambda^{x_i}}{x_i!} e^{-\lambda} \right) \right)$$

$$\Rightarrow \hat{\lambda}_{MLE} = \underset{\lambda}{\operatorname{argmax}} (\ln(L(x_1, x_n | \lambda))) = \underset{\lambda}{\operatorname{argmax}} \left( \sum_{i=1}^n \ln \left( \frac{\lambda^{x_i}}{x_i!} e^{-\lambda} \right) \right) =$$

$$= \underset{\lambda}{\operatorname{argmax}} \left( \sum_{i=1}^n \ln \left( \frac{\lambda^{x_i}}{x_i!} e^{-\lambda} \right) \right) = \sum_{i=1}^n \ln(e^{-\lambda}) + \ln(\lambda^{x_i}) - \ln(x_i!)$$

$$\frac{d}{d\lambda} \left( \sum_{i=1}^n -\lambda + \ln(\lambda^{x_i}) - \ln(x_i!) \right) = \sum_{i=1}^n -1 + \frac{x_i}{\lambda} = -n + \frac{1}{\lambda} \sum_{i=1}^n x_i = 0 \quad \text{second deriv. test satisfied}$$

$$\Rightarrow \frac{d}{d\lambda} (\ln(L(x | \lambda))) = 0 = -n + \frac{1}{\lambda} \sum x_i \Rightarrow \lambda = \frac{\sum x_i}{n} = \underset{\lambda}{\operatorname{argmax}} \frac{d^2}{d\lambda^2} = -\frac{1}{\lambda^2} \sum x_i < 0$$

$$\hat{se} = \sqrt{V(\hat{\lambda})} = \sqrt{V\left(\frac{\sum x_i}{n}\right)} = \sqrt{\frac{1}{n^2} V(\sum x_i)} = \sqrt{\frac{n}{n^2} V(x_1)} = \sqrt{\frac{\hat{\lambda}}{n}} \approx \sqrt{\frac{\hat{\lambda}}{n}}$$

$$\hat{se} = \sqrt{\frac{\hat{\lambda}}{n}} \Rightarrow W = \left| \frac{\frac{1}{n} \sum_{i=1}^n x_i - \lambda_0}{\sqrt{\frac{1}{n^2} \sum_{i=1}^n x_i}} \right| > z_{1-\frac{\alpha}{2}}$$

```
clc; clear; close all;
```

## Question 3

### Part B

The results of the average wald\_test below show a type 1 error rate of  $\sim .054$ .

```
type1_error = 0;

lambda = 1;
n = 20;

alpha = .05;

for i = 1:10000
    sample = poissrnd(lambda, [n, 1]);
    wald_score = abs(((sum(sample)/ n) - 1) / sqrt(sum(sample) / (n^2)));
    if wald_score > norminv(1 - alpha / 2)
        type1_error = type1_error + 1;
    end
end

disp(type1_error / 10000)
```

0.0549

## Question 4

Using permutation test since the number of samples are small and the normality assumption for the estimated parameter does not hold. The result of the permutation test yield a p-value on average of  $\sim .03 < .05$  which concludes that there is statistically significant evidence that the two distributions are different and the pH levels of the soil differ between the two locations.

```
error = 0;

sample1 = [7.58, 8.52, 8.01, 7.99, 7.93, 7.89, 7.85, 7.82, 7.80];
sample2 = [7.85, 7.73, 8.53, 7.40, 7.35, 7.30, 7.27, 7.27, 7.23];

initial_diff = abs(mean(sample1) - mean(sample2));

n = 10000;

Z = cat(2, sample1, sample2);

for i = 1:n
    Z_pi = Z(randperm(length(Z)));
    sample1_perm = Z_pi(1:length(sample1));
    sample2_perm = Z_pi(length(sample1) + 1:end);
    perm_diff = abs(mean(sample1_perm) - mean(sample2_perm));
```

```

    if perm_diff > initial_diff
        error = error + 1;
    end
end

disp('p-value from permutation test:');

```

p-value from permutation test:

```
disp(error / n);
```

0.0349

## Question 5

### Wald T-test

We notice that the p-value for the wald test is significantly lower than the threshold for significance of .05, which concludes that there is a statistically significant difference between the distribution of Twain and Snodgrass, suggesting that Twain did not write the Snodgrass essays

```

sample_t = [0.225, 0.262, 0.217, 0.240, 0.230, 0.229, 0.235, 0.217];
sample_s = [0.209, 0.205, 0.196, 0.210, 0.202, 0.207, 0.224, 0.223, 0.220, 0.201];

standard_err = sqrt(var(sample_t) / length(sample_t) + var(sample_s) /
length(sample_s));

wald_score = abs((mean(sample_t) - mean(sample_s)) / standard_err);

p_value = 2 * normcdf(-1 * wald_score);

alpha = .05;

if wald_score > norminv(1 - alpha / 2)
    disp('H_0 rejected with p-value:');
    disp(p_value);
else
    disp('H_0 accepted with p-value:');
    disp(p_value);
end

```

H\_0 rejected with p-value:  
2.1260e-04

### Permutation test

We notice that the p-value for the wald test is significantly lower than the threshold for significance of .05, which concludes that there is a statistically significant difference between the distribution of Twain and Snodgrass, suggesting that Twain did not write the Snodgrass essays. Additionally, we also notice that the permutation test yields a p-value different from the Wald T-test which also makes sense given that the normality assumption might not hold for the Wald T-test and thus the test produces results different from the permutation test, likely a

result of the small quantity of data and the difference in method - both methods still conclude the same result though.

```
error = 0;

initial_diff = abs(mean(sample_t) - mean(sample_s));

n = 10000;

Z = cat(2, sample_t, sample_s);

for i = 1:n
    Z_pi = Z(randperm(length(Z)));
    sample1_perm = Z_pi(1:length(sample_t));
    sample2_perm = Z_pi(length(sample_t) + 1:end);
    perm_diff = abs(mean(sample1_perm) - mean(sample2_perm));
    if perm_diff > initial_diff
        error = error + 1;
    end
end

disp('p-value from permutation test:');
```

p-value from permutation test:

```
disp(error / n);
```

7.0000e-04