

**Mathematical Statistics**

*3 hours*

1. Give the Central Limit Theorem (assumptions and result).  
*Donner le théorème de la limite centrale (hypothèses et conclusions)*
2. Give the law of large numbers (assumptions and result)  
*Donner la loi des grands nombres (hypothèses et conclusion).*
3. Give Cochran's Theorem.  
*Donner le théorème de Cochran*

**Exercise 1** Let  $X_1, \dots, X_n$  be i.i.d. random variables with uniform distribution on  $[0, \theta]$  with  $\theta > 0$ .

*Soit  $X_1, \dots, X_n$  i.i.d. de loi uniforme sur  $[0, \theta]$  avec  $\theta > 0$ .*

4. What is the maximum likelihood estimator  $\hat{\theta}_n$  of  $\theta$ ?  
*Quel est l'estimateur du maximum de vraisemblance  $\hat{\theta}_n$  de  $\theta$ ?*
5. Compute the cumulative distribution function of  $\hat{\theta}_n$ .  
*Calculer la fonction de répartition de  $\hat{\theta}_n$*
6. Compute the density of  $\hat{\theta}_n$ .  
*Calculer la densité de  $\hat{\theta}_n$*
7. For which value of  $a \in \mathbb{R}$ ,  $a\hat{\theta}_n$  is unbiased.  
*Pour quelle valeur de  $a \in \mathbb{R}$ ,  $a\hat{\theta}_n$  est-il sans biais?*
8. For which value of  $b \in \mathbb{R}$ , the quadratic risk of  $b\hat{\theta}_n$  is minimum?  
*Pour quelle valeur de  $b \in \mathbb{R}$ , le risque quadratique de  $b\hat{\theta}_n$  est-il minimum?*

**Exercise 2** Let  $X_1, \dots, X_n$  be i.i.d. Gaussian random variables with mean  $\theta \in \mathbb{R} = \Theta$  and variance 1.

*soit  $X_1, \dots, X_n$  i.i.d. gaussienne de moyenne  $\theta \in \mathbb{R} = \Theta$  et de variance 1.*

9. Give an estimator  $\hat{\theta}_n$  of  $\theta$  based on the moment method.  
*Donner un estimateur  $\hat{\theta}_n$  de  $\theta$  basé sur la méthode des moments.*
10. Give the estimator  $\tilde{\theta}_n$  of  $\theta$  based on the median.  
*Donner un estimateur  $\tilde{\theta}_n$  de  $\theta$  basé sur la médiane.*

11. Show that  $\sqrt{n} (\tilde{\theta}_n - \theta)$  converges to some limit distribution and specify the limit.

*Montrer que  $\sqrt{n} (\tilde{\theta}_n - \theta)$  converge en loi et préciser la limite.*

We now use a Bayesian approach to estimate  $\theta$  and use the prior  $\nu_\tau$  on  $\Theta$  given by the Gaussian distribution with mean 0 and variance  $\tau^2 > 0$ .

*On utilise à présent une approche bayésienne pour estimer  $\theta$  basée sur la loi a priori  $\nu_\tau$  qui est gaussienne de moyenne 0 et de variance  $\tau^2 > 0$*

12. Show that the posterior distribution is Gaussian with mean  $\frac{n\tau^2}{n\tau^2+1}\bar{X}_n$  and variance  $\frac{\tau^2}{n\tau^2+1}$

*Montrer que la loi a posteriori est gaussienne de moyenne  $\frac{n\tau^2}{n\tau^2+1}\bar{X}_n$  et de variance  $\frac{\tau^2}{n\tau^2+1}$*

13. Compute the Bayes estimator  $\hat{\theta}_n^\tau$  associated to the prior  $\nu_\tau$ .

*Calculer l'estimateur bayésien  $\hat{\theta}_n^\tau$  associé à la loi a priori  $\nu_\tau$*

14. Compute the quadratic risk  $R(\theta, \bar{X}_n)$  of  $\bar{X}_n$  at  $\theta$ .

*Calculer le risque quadratique  $R(\theta, \bar{X}_n)$  de  $\bar{X}_n$  en  $\theta$*

15. Compute the quadratic risk  $R(\theta, \hat{\theta}_n^\tau)$  of  $\hat{\theta}_n^\tau$  at  $\theta$ .

*Calculer le risque quadratique  $R(\theta, \hat{\theta}_n^\tau)$  de  $\hat{\theta}_n^\tau$  en  $\theta$*

Given an estimator  $\bar{\theta}_n$  of  $\theta$ , we denote by  $R^\tau(\bar{\theta}_n)$ , the Bayes risk of  $\bar{\theta}_n$  with respect to the prior  $\nu_\tau$ .

*Etant donné un estimateur  $\bar{\theta}_n$  de  $\theta$ , on note  $R^\tau(\bar{\theta}_n)$ , the risk de Bayes de  $\bar{\theta}_n$  associé à la loi a priori  $\nu_\tau$*

16. Compute  $R_n = R^\tau(\bar{X}_n)$  and show that this quantity is independent of  $\tau$ .

*Calculer  $R_n = R^\tau(\bar{X}_n)$  et montrer que cette quantité est indépendante de  $\tau$ .*

17. Compute  $R^\tau(\hat{\theta}_n^\tau)$

*Calculer  $R^\tau(\hat{\theta}_n^\tau)$*

18. Show that

*Montrer que*

$$\lim_{\tau \rightarrow +\infty} R^\tau(\hat{\theta}_n^\tau) = \sup_{\theta \in \Theta} R(\theta, \bar{X}_n)$$

19. Show that  $\bar{X}_n$  is minimax.

*Montrer que  $\bar{X}_n$  est minimax.*

**Exercise 3** Let  $X_1, \dots, X_n$  be i.i.d. random variables with density  
Soit  $X_1, \dots, X_n$  i.i.d. de densité

$$f_\theta(x) = \frac{\theta}{x^{\theta+1}} \mathbb{1}_{x \geq 1} \text{ with } \theta \in \Theta = (0, +\infty).$$

20. Compute the cumulative distribution function of  $X_1$ .  
*Calculer la fonction de répartition de  $X_1$*
21. Show that the statistical model is an exponential family.  
*Montrer que le modèle statistique est une famille exponentielle*
22. What is the maximum likelihood  $\hat{\theta}_n$  estimator of  $\theta$ ?  
*Quel est l'estimateur du maximum de vraisemblance?*
23. What is the limit in distribution of  $\sqrt{n} (\hat{\theta}_n - \theta)$ ?  
*Quelle est la limite en loi de  $\sqrt{n} (\hat{\theta}_n - \theta)$ ?*
24. Build an asymptotic two-sided confidence interval for  $\theta$ .  
*Construire un intervalle de confiance asymptotique bilatère pour  $\theta$*



Exercise 1  $X_1, \dots, X_n$  iid  $\text{U}[0, \theta]$

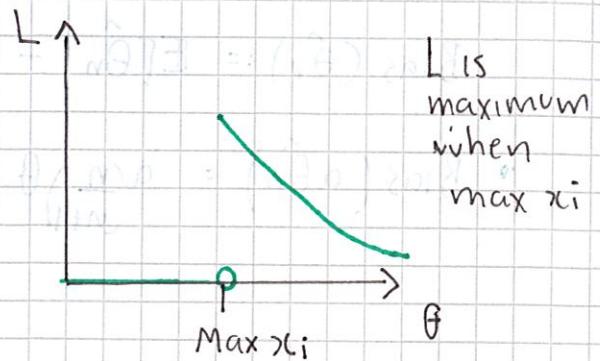
$$L = f(x_1) f(x_2) \dots f(x_n)$$

if  $\max x_i > \theta$

$$L = 0$$

if  $\max x_i \leq \theta$

$$L = \left(\frac{1}{\theta}\right)^n$$



L is maximum when  
 $\max x_i$

Max Likelihood Estimator  $\hat{\theta}_n = \max x_i$

Cumulative distribution function

$$\text{of } \hat{\theta}_n = \max x_i$$

$$F_{\hat{\theta}_n}(x) = \Pr(X_1 \leq x, X_2 \leq x, \dots, X_n \leq x)$$

$$\stackrel{\text{ind}}{=} \Pr(X_1 \leq x) \Pr(X_2 \leq x) \dots \Pr(X_n \leq x)$$

$$\Pr(X \leq x) = \int_{-\infty}^x \frac{1}{\theta} \mathbb{1}_{[0, \theta]} d\tau$$

$$\text{if } x < 0 \quad F(x) = 0$$

$$\text{if } 0 \leq x \leq \theta \quad F(x) = \left(\frac{x}{\theta}\right)^n$$

$$\text{if } x > \theta \quad F(x) = 1$$

$$\text{if } x = \frac{x}{\theta}$$

$$0 \leq x \leq \theta$$

$$\text{if } x < 0 = 0$$

$$\text{if } x > \theta = 1$$

$$f(x) = \frac{dF(x)}{dx} =$$

$$\text{if } x < 0 \quad f(x) = 0$$

$$\text{if } 0 \leq x \leq \theta \quad f(x) = n \left(\frac{x}{\theta}\right)^{n-1}$$

$$\text{if } x > \theta \quad f(x) = 0$$

$$E[\hat{\theta}_n] = \int_{-\infty}^{\infty} x f(x) dx = \int_0^{\theta} x n \left(\frac{x}{\theta}\right)^{n-1} dx = \frac{n x^{n+1}}{(n+1) \theta^n} \Big|_0^{\theta}$$

$$= \frac{n \theta^{n+1}}{(n+1) \theta^n} = \frac{n}{n+1} \theta \Rightarrow E[a \hat{\theta}_n] = \frac{an}{(n+1)} \theta$$

$$\text{Bias}(\hat{\theta}_n) := \mathbb{E}[\hat{\theta}_n] - \theta$$

•  $\text{Bias}(a\hat{\theta}_n) = a \frac{n}{n+1}\theta - \theta \Rightarrow \text{unbiased if } a \frac{n}{n+1}\theta - \theta = 0$

$$a = \left( \frac{n+1}{n} \right)$$

•  $\text{RISK}(\hat{\theta}_n) = \text{Bias}^2(\hat{\theta}_n) + \text{var}(\hat{\theta}_n)$

$$\begin{aligned} &= \left( \frac{n}{n+1} \theta - \theta \right)^2 + \frac{n\theta^2}{n+2} \\ &= \left[ \left( \frac{n}{n+1} \right) G - G \right]^2 + \frac{n\theta^2}{n+2} - \left( \frac{n\theta^2}{n+1} \right) \end{aligned}$$

$$\text{RISK}(b\hat{\theta}_n) =$$

$$\left[ b \left( \frac{n}{n+1} \theta - \theta \right)^2 + \left( \frac{b^2 n \theta^2}{n+2} - \frac{b^2 n^2 \theta^2}{(n+1)^2} \right) \right]$$

$$\text{var}(\hat{\theta}_n) = \mathbb{E}[\hat{\theta}_n^2] - (\mathbb{E}[\hat{\theta}_n])^2$$

$$\begin{aligned} \mathbb{E}[\hat{\theta}_n^2] &= \int_{-\infty}^{\infty} x^2 f(x) dx \\ &= \int_0^G x^2 \frac{n x^{n-1}}{\theta^n} dx \end{aligned}$$

$$= n \frac{x^{n+2}}{(n+2)\theta^n} \Big|_0^G$$

$$= \frac{n\theta^2}{n+2}$$

$$\text{var}(\hat{\theta}_n) = \frac{n\theta^2}{n+2} - \left( \frac{n\theta}{n+1} \right)^2$$

$$\mathbb{E}[b\hat{\theta}_n]^2 = b^2 \left( \frac{n}{n+2} \theta \right)^2$$

$$\text{var}(b\hat{\theta}_n) = b^2 \left( \frac{n}{n+2} \theta \right)^2 - \left( \frac{bn\theta}{n+1} \right)^2$$

$$= b^2 \frac{n\theta^2}{(n+2)} - b^2 \frac{n^2\theta^2}{(n+1)^2}$$

## Exercise 2

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\theta)^2}{2}}$$

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx = \int_{-\infty}^{\infty} \frac{x}{\sqrt{2\pi}} e^{-\frac{(x-\theta)^2}{2}} dx$$

$$w = x - \theta$$

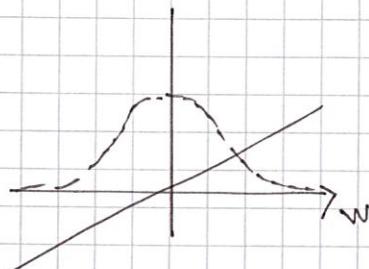
$$dw = dx$$

$$= \int_{-\infty}^{\infty} \frac{(w+\theta)}{\sqrt{2\pi}} e^{-\frac{(w+\theta)^2}{2}} dw$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} w e^{-\frac{w^2}{2}} dw + \frac{\theta}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{w^2}{2}} dw$$

$$= 0$$

$$= \theta$$



pair function  
times impair function

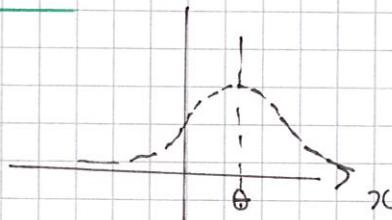
$$E[X] = \theta$$

by Moment  
Method

$$\Rightarrow \hat{\theta}_n = \bar{x}_n$$

$$\text{median } x \text{ s.t } F(x) = \frac{1}{2}$$

$$\hat{q}\left(\frac{1}{2}\right) = m = \theta$$



symmetric on  $\theta$

$$\hat{\theta}_n = \hat{q}\left(\frac{1}{2}\right)$$

$$\text{Thm } \sqrt{n} \left( \hat{q}_n(u) - q(u) \right) \xrightarrow{L} N\left(0, \frac{u(1-u)}{(F'(q(u)))^2}\right)$$

$$\sqrt{n} (\hat{\theta}_n - \theta) \xrightarrow{L} N\left(0, \frac{1}{\left(\frac{1}{\sqrt{2\pi}}\right)^2}\right)$$

$$\begin{aligned} F'(q(u)) &= f(q(u)) \\ &= \frac{1}{\sqrt{2\pi}} e^{-\frac{(q(u)-\theta)^2}{2}} \end{aligned}$$

$$q\left(\frac{1}{2}\right) = 0 \Rightarrow f\left(q\left(\frac{1}{2}\right)\right) = \frac{1}{\sqrt{2\pi}}$$

$$\xrightarrow{L} N\left(0, \frac{\pi}{2}\right)$$



Posterior Gaussian

$$f(x_i | \mu) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2}}$$

$$\Pi(\mu) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2\tau^2}}$$

$$\Pi(\mu) L_n f(x_i^n | \mu) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2\tau^2}} \frac{1}{(2\pi)^{n/2}} e^{\frac{-\sum (x_i - \mu)^2}{2}}$$

$$\propto e^{-\frac{\mu^2}{2\tau^2} - \frac{1}{2} \sum_{i=1}^n (x_i^2 + \mu^2 - 2x_i\mu)}$$

$$\bar{x} = \frac{1}{n} \sum x_i$$

$$\propto e^{-\frac{1}{2} \left[ \frac{\mu^2}{\tau^2} + n\mu^2 - 2\mu\bar{x} + \sum_i x_i^2 \right]}$$

$$\propto e^{-\frac{1}{2} \left( \frac{1}{\tau^2} + n \right) \left[ \frac{\mu^2 - 2\mu n \bar{x}}{\left( \frac{1}{\tau^2} + n \right)} + \frac{\sum x_i^2}{\left( \frac{1}{\tau^2} + n \right)} \right]}$$

$$\propto e^{-\frac{1}{2} \left( \frac{\tau^2}{1+n\tau^2} \right) \left[ \frac{\mu^2 + 2\mu n \bar{x} \left( \frac{\tau^2}{n\tau^2+1} \right) + \sum x_i^2 \left( \frac{\tau^2}{1+n\tau^2} \right)}{\frac{\tau^2}{n\tau^2+1}} \right]}$$

$$\text{Variance} = \left( \frac{\tau^2}{1+n\tau^2} \right)$$

$$\propto e^{-\frac{1}{2\sigma^2} \left[ -2\mu n \bar{x} \sigma^2 + \mu^2 + \sum x_i^2 \sigma^2 \right]}$$

$$\propto e^{-\frac{1}{2\sigma^2} \left[ \mu^2 + 2\mu n \bar{x} \sigma^2 \pm (n \bar{x} \sigma^2)^2 \right] - \frac{1}{2} \sum x_i^2}$$

$$\propto e^{-\frac{1}{2\sigma^2} \left[ \mu - n \bar{x} \sigma^2 \right]^2 + \frac{1}{2} n^2 \bar{x}^2 \sigma^2 - \frac{1}{2} \sum x_i^2}$$

$$\text{Mean} = n \bar{x} \sigma^2$$

$$= \bar{x} \frac{n\tau^2}{1+n\tau^2} \Rightarrow f(\mu | x^n) \stackrel{d}{\sim} N(M_p, \sigma^2)$$

under  $\ell$  (square loss function)

Bayes Estimator  $\hat{\mu}$  is equal to the posteriori mean  
because minimizing Bayes risk is equivalent  
to minimize the posteriori mean

$$\begin{aligned} \frac{dR}{d\hat{\theta}} &= \frac{d}{d\hat{\theta}} \int (\theta - \hat{\theta})^2 f(\theta|\mu) d\theta = 2 \int (\theta - \hat{\theta}) f(\theta|\mu) d\theta \\ &= 2 \int \theta f(\theta|\mu) d\theta - 2 \hat{\theta} \underbrace{\int f(\theta|\mu) d\theta}_1 = 0 \\ \Rightarrow \hat{\theta} &= \int \theta f(\theta|\mu) d\theta = \underset{P}{E}[\theta] \end{aligned}$$

$$\text{Bayes EST. } \hat{\mu}_p = \left( \frac{n\tau^2}{n\tau^2 + 1} \right) \bar{x}$$

$$\text{Quadratic Risk } \bar{x}_n \quad \text{Bias } \bar{x}_n = E\bar{x}_n - \mu = 0$$

$$\text{Quadratic Risk } \hat{\mu}_p \quad \text{var } \bar{x}_n = \frac{1}{n^2} n \text{ var}(X) = \frac{1}{n} \quad \left. \begin{array}{l} R(\bar{x}_n, \mu) = \frac{1}{n} \end{array} \right\}$$

$$\begin{aligned} \text{Bias } \hat{\mu}_p &= E[\hat{\mu}_p] - \mu = \frac{n\tau^2}{n\tau^2 + 1} E\bar{x}_n - \mu = \frac{n\tau^2 \mu - \mu(n\tau^2 + 1)}{n\tau^2 + 1} \\ &= -\frac{\mu}{n\tau^2 + 1} \end{aligned}$$

$$\text{var } (\hat{\mu}_p) = \left( \frac{n\tau^2}{n\tau^2 + 1} \right)^2 \text{var } \bar{x}_n = \left( \frac{n\tau^2}{n\tau^2 + 1} \right)^2 \frac{1}{n} = \frac{n\tau^4}{(n\tau^2 + 1)^2}$$

$$\text{Quadratic Risk } \hat{\mu}_p = \frac{\mu}{(n\tau^2 + 1)^2} + \frac{n\tau^4}{(n\tau^2 + 1)^2} = \frac{\mu + n\tau^4}{(n\tau^2 + 1)^2}$$

Bayes risk r

$$r(\Pi(\theta), \hat{\epsilon}) = \int R(\theta, \hat{\epsilon}) \Pi(\theta) d\theta$$

$$r(\Pi(\mu), \bar{X}_n) = \int \frac{1}{n} \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2T^2}} d\mu = \frac{1}{n}$$

$$\underline{r(\Pi(\mu), \bar{X}_n) = \frac{1}{n}}$$

$$r(\hat{\mu}_p, \Pi(\mu)) = \int \frac{\mu + nT^4}{(nT^2 + 1)^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2T^2}} d\mu$$

$$\underline{r(\Pi(\mu), \hat{\mu}_p) = \frac{nT^4}{(nT^2 + 1)^2}}$$

$$\sup_{\theta} R(\theta, \bar{X}_n) = \frac{1}{n}$$

$$\inf_{\hat{\mu}} \sup_{\theta} R(\theta, \bar{X}_n) = \frac{1}{n}$$

$$\lim_{T \rightarrow \infty} R(\hat{\mu}_p) = \lim_{T \rightarrow \infty} \frac{nT^4}{(nT^2 + 1)^2}$$

$$= \lim_{T \rightarrow \infty} \frac{4nT^3}{4n^2T^3 + 4nT} =$$

$$= \lim_{T \rightarrow \infty} \frac{1}{n} = \frac{1}{n}$$



### Exercise 3

$$f(x) = \frac{\theta}{x^{\theta+1}} \mathbb{1}_{x>1} \quad \theta \in (0, \infty)$$

Cumulative

$$\begin{aligned} F(x) &= \int_{-\infty}^x f(x_1) dx_1 = \int_1^x \frac{\theta}{x^{\theta+1}} dx_1 = \int_1^x \theta x^{-(\theta+1)} dx \\ &= \left[ \frac{\theta x^{1-(\theta+1)}}{1-(\theta+1)} \right]_1^x = \left[ -\frac{\theta}{\theta+1} x^{-\theta} \right]_1^x = -\frac{1}{\theta+1} \left| x^{-\theta} \right|_1^x = 1 \end{aligned}$$

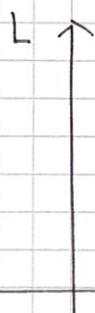
Exponential family

$$\begin{aligned} \frac{\theta}{x^{\theta+1}} &= \exp \left[ \log \left( \frac{\theta}{x^{\theta+1}} \right) \right] = \exp \left[ \log \theta - \log x^{\theta+1} \right] \\ &= \exp \left[ \log \theta - (\theta+1) \log x \right] \\ &= \theta e^{-\theta \log x} e^{-\log x} = \theta e^{-\theta \log x} \frac{1}{x} \\ &= \lambda(\theta) e^{\beta(\theta) T(x)} h(x) \end{aligned}$$

### Maximum Likelihood

$$L = f(x_1) f(x_2) \cdots f(x_n) = \text{if } \min x_i > 1$$

$$\text{if } \min x_i < 1 \quad L = \frac{\theta^n}{(x^{\theta+1})^n}$$



$$\text{if } \min x_i < 1 \quad L = 0$$

$$\log L = n \log \theta - n(\theta+1) \log x$$

$$\begin{aligned} \frac{d \log L}{d \theta} &= n \frac{1}{\theta} - n \log x = 0 \\ \Rightarrow \hat{\theta}_n &= (\log x)^{-1} \end{aligned}$$

2.37.000000

$$(\text{m} \cdot \text{g}) \cdot \frac{\text{f}}{\text{g}} = \text{m} \cdot \frac{\text{f}}{1000}$$

$$\text{m} \cdot \frac{\text{f}}{1000} = \text{m} \cdot \frac{\text{f}}{1000} + \text{m} \cdot \frac{\text{f}}{1000}$$

$$\begin{matrix} \text{m} & \text{f} \\ \text{m} & \text{f} \\ \text{m} & \text{f} \end{matrix} = \begin{matrix} \text{m} & \text{f} \\ \text{m} & \text{f} \\ \text{m} & \text{f} \end{matrix} + \begin{matrix} \text{m} & \text{f} \\ \text{m} & \text{f} \\ \text{m} & \text{f} \end{matrix}$$

$$\text{m} \cdot \frac{\text{f}}{1000} = \text{m} \cdot \frac{\text{f}}{1000} + \text{m} \cdot \frac{\text{f}}{1000}$$

$$\text{m} \cdot \frac{\text{f}}{1000} = \text{m} \cdot \frac{\text{f}}{1000}$$

$$\text{m} \cdot \frac{\text{f}}{1000} = \text{m} \cdot \frac{\text{f}}{1000}$$

$$(0.3) \cdot (0.7) = (0.21)$$

$$0.21 = \text{m} \cdot \frac{\text{f}}{1000}$$

$$0.21 = \text{m} \cdot \frac{\text{f}}{1000}$$

$$0 = 0 \quad \text{Es ist kein } \Delta$$

$$0.21 \cdot 1000 = 210 \text{ g}$$

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