

P.S
12.1

$\frac{1}{3}$ of all integers are divisible by 3 and

2. $\frac{1}{7}$ of integers are divisible by 7. What fraction of integers will be divisible by 3 or 7 or both?

Ans: $\frac{1}{3} + \frac{1}{7} - \frac{1}{3} \times \frac{1}{7} = \frac{1}{3} + \frac{1}{7} - \frac{1}{21} = \frac{9}{21} = \frac{3}{7}$

3. Suppose you sample from the numbers 1 to 1000 with equal probabilities $\frac{1}{1000}$. What are the probabilities P_0 to P_9 that the last digit of your sample is 0, ..., 9? What is the expected mean m of that last digit? What is its variance σ^2 ?

Ans: $P_i = 1000 \times \frac{1}{1000} = \frac{1}{10}$

Expected mean of that last digit x :

$$m = E[x] = \sum_i P_i x_i = \frac{1}{10} \sum_{i=0}^9 i = \frac{45}{10} = \underline{\underline{4.5}}$$

$$\begin{aligned} \sigma^2 &= E[x^2] - (E[x])^2 = \frac{1}{10} \sum P_i x_i^2 - (4.5)^2 \\ &= \frac{1}{10} \sum_{i=0}^9 i^2 - (4.5)^2 = \frac{285}{10} - (4.5)^2 = \underline{\underline{8.25}} \end{aligned}$$

5. Sample again from 1 to 1000 with equal probabilities and let x be the 1st digit ($x=1$ if the number is 15). What are the probabilities P_1 to P_9 (adding to 1) of $x=1, \dots, 9$? What are the mean & variance of x ?

Ans:

$$P_1 = \frac{112}{1000}$$

$$P_2 = P_3 = \dots = P_9 = \frac{111}{1000}$$

$$m = \sum_i P_i x_i = \frac{112}{1000} \times 1 + \frac{111}{1000} (2+3+\dots+9)$$

$$= \frac{112 + 111(44)}{1000} = \frac{4996}{1000} = 4.996 \approx 5$$

which is close to $\frac{1}{9} (1+2+\dots+9) = 5$

$$\sigma^2 = E[x^2] - m^2 = \frac{112}{1000} (1^2) + \frac{111}{1000} (2^2 + \dots + 9^2) - m^2$$

$$= \frac{112 + 111(284)}{1000} - m^2 \approx \frac{31635}{1000} - 5^2 = 6.635$$

6. Suppose you have $N=4$ samples: 157, 312, 696, 602 in problem 5. What are the 1st digits x_1 to x_4 of the squares? What is the sample mean μ ? What is the sample variance S^2 ?

Ans: The 1st digits of 157, 312, 696, 602 are 2, 9, 4, 3.

The sample mean is:

$$\mu = \frac{1}{4}(2+9+4+3) = \frac{18}{4} = \underline{\underline{4.5}}$$

The sample variance with $N-1 = 4-1 = 3$ is:

$$S^2 = \frac{1}{3} \left[(-2.5)^2 + (4.5)^2 + (-0.5)^2 + (-1.5)^2 \right]$$
$$= \frac{1}{3}(29)$$

$$\begin{aligned}
 7. \quad \sigma^2 &= \sum P_i (\sigma_i - m)^2 = \sum P_i (\sigma_i^2 - 2m\sigma_i + m^2) \\
 &= \sum P_i \sigma_i^2 - 2m \sum P_i \sigma_i + m^2 \sum P_i \\
 &= \sum P_i \sigma_i^2 - 2m^2 + m^2 = \sum P_i \sigma_i^2 - m^2 \\
 &= \underline{E[\sigma^2]} - m^2
 \end{aligned}$$

8. If all 24 samples from a population produce the same age $x=20$, what are the sample mean μ and sample variance S^2 ? What if $x=20$ or 21, 12 times each?

Ans. $\mu = \frac{1}{N} \sum x_i = \frac{20}{1} = 20$

$$S^2 = \frac{1}{N-1} \sum (x_i - \mu)^2 = 0$$

1.
 (b) The sum of N independent flips (0 or 1) is the count of heads after N tries.

The rule for the variance of a sum gives
 $\sigma^2 =$ _____

Ans: Independent flips \rightarrow $N \times N$ covariance matrix is diagonal.

The diagonal entries are the variances $\sigma^2 = pq = p - p^2$ for each flip.

Overall variance of the sum from N flips is:

$$Y = \begin{bmatrix} | & | & | & | \\ \hline 1 & 1 & 1 & 1 \\ \hline \end{bmatrix} \quad Y = \begin{bmatrix} 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_N \end{bmatrix} = \begin{bmatrix} \sigma_1 + \dots + \sigma_N \end{bmatrix}$$

$$\sigma^2 = AYA^T = \begin{bmatrix} 1 & \dots & 1 \end{bmatrix} N \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = N\sigma^2 = N(p - p^2)$$

2. What is the covariance σ_{kl} b/w the results x_1, \dots, x_n of exp. 3 and the results y_1, \dots, y_n of exp 5?

Ans:
$$\sigma_{35} = \sum_{\text{all } i,j} P_{ij} (x_i - m_3)(y_j - m_5)$$

3. For $M=3$ experiments, the variance-covariance matrix V will be 3×3 . There will be a probability P_{ijk} that the 3 outputs are x_i and y_j and z_k . Write down a formula for the matrix V .

Ans:
$$V = \sum_{\text{all } i,j,k} P_{ijk} U U^T$$

where
$$U = \begin{bmatrix} x_i - \bar{x} \\ y_j - \bar{y} \\ z_k - \bar{z} \end{bmatrix}$$

4. What is the covariance matrix V for $M=3$ independent expt with means m_1, m_2, m_3 and variances $\sigma_1^2, \sigma_2^2, \sigma_3^2$?

Ans:
$$V = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix}$$

6. The $n \times n$ matrix P contains joint probabilities $P_{ij} = \text{Prob}(X = x_i \text{ and } Y = y_j)$

$$\text{Conditional Probability}(Y = y_j | X = x_i) = \frac{P_{ij}}{P_{i1} + \dots + P_{in}} = \frac{P_{ij}}{P_i}$$

4. What is the covariance matrix V for $M=3$ independent expts with means m_1, m_2, m_3 and variances $\sigma_1^2, \sigma_2^2, \sigma_3^2$?

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12.3

1. Two measurements of the same variable x give 2 equations $x=b_1$ and $x=b_2$. Suppose the means are zero and the variances are σ_1^2 and σ_2^2 , with independent errors: V is diagonal with entries σ_1^2 and σ_2^2 . Write the 2 equations as $Ax=b$ (A is 2×1).

find this best estimate \hat{x} based on b_1 and b_2 :

$$\hat{x} = \frac{b_1/\sigma_1^2 + b_2/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} ; E[\hat{x}\hat{x}^T] = \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \right)^{-1}$$

Ans: $\left. \begin{matrix} x=b_1 \\ x=b_2 \end{matrix} \right\} \begin{bmatrix} 1 \\ 1 \end{bmatrix} [x] = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \iff Ax=b$

The covariance matrix V is diagonal since the measurements are independent:

$$V = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

$$[A] \text{ cov} = [b] \text{ cov} = [\dots]$$

$$(A^T V^{-1} A)^{-1} A^T V^{-1} b = \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \right)^{-1} \left(\frac{b_1}{\sigma_1^2} + \frac{b_2}{\sigma_2^2} \right)$$

The weighted least square solution is given

by:

$$A^T V^{-1} A \hat{x} = A^T V^{-1} b$$

$$A^T V^{-1} A = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_1^2} & 0 \\ 0 & \frac{1}{\sigma_2^2} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

$$A^T V^{-1} b = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_1^2} & 0 \\ 0 & \frac{1}{\sigma_2^2} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \frac{b_1}{\sigma_1^2} + \frac{b_2}{\sigma_2^2}$$

$$\Rightarrow \hat{x} = \frac{\frac{b_1}{\sigma_1^2} + \frac{b_2}{\sigma_2^2}}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}}$$

The variance of that estimate $V_{\hat{x}}$ should be written as

$$E[(\hat{x} - x)(\hat{x} - x)^T] = \text{Cov}[\hat{x}] = \text{Cov}[Lb]$$

$$= L \text{Cov}[b] L^T = (A^T V^{-1} A)^{-1} A^T V^{-1} V V^{-1} A (A^T V^{-1} A)^{-1}$$

$$= (A^T V^{-1} A)^{-1} = \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \right)^{-1}$$

2. (a) In problem 1, suppose the 2nd measurement b_2 becomes super-precise and its variance $\sigma_2 \rightarrow 0$.
 • What is the best estimate \hat{x} when σ_2 reaches zero?

Ans:
$$\hat{x} = \frac{b_1/\sigma_1^2 + b_2/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2}$$

$\sigma_2 \rightarrow 0$:

$$\hat{x} = \frac{b_1/\sigma_1^2 + b_2/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} \Rightarrow \frac{b_1\sigma_2^2 + b_2\sigma_1^2}{\sigma_2^2 + \sigma_1^2}$$

Multiplying by $\sigma_1^2\sigma_2^2$

$$\rightarrow \frac{b_2\sigma_1^2}{\sigma_1^2} = b_2$$

(b) The opposite case has $\sigma_2 \rightarrow \infty$ and no information is b_2 . What is now the best estimate \hat{x} based on b_1 and b_2 ?

Ans:
$$\hat{x} = \frac{b_1/\sigma_1^2 + b_2/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} \rightarrow \frac{b_1/\sigma_1^2}{1/\sigma_1^2} = b_1$$

i.e., we are getting no information from the totally unreliable measurement $x = b_2$.

3. If x and y are independent with probabilities $P_1(x)$ and $P_2(y)$, then $P(x,y) = P_1(x) P_2(y)$.

By separating double integrals into products of single integrals $(-\infty$ to $+\infty)$ show that

$$\iint P(x,y) dx dy = 1 \quad \text{and} \quad \iint (x+y) P(x,y) dx dy = m_1 + m_2$$

Ans:

$$P(x,y) = P_1(x) P_2(y)$$

$$\begin{aligned} \iint P(x,y) dx dy &= \iint P_1(x) P_2(y) dx dy = \int P_1(x) dx \int P_2(y) dy \\ &= 1 \cdot 1 = 1 \end{aligned}$$

$$\begin{aligned} \iint (x+y) P(x,y) dx dy &= \iint x P_1(x) P_2(y) dx dy + \iint y P_1(x) P_2(y) dx dy \\ &= \int x P_1(x) dx \int P_2(y) dy + \int P_1(x) dx \int y P_2(y) dy \\ &= m_x \cdot 1 + 1 \cdot m_y = m_x + m_y \end{aligned}$$

4. Continue problem 3 for independent x, y to show that $P(x, y) = P_1(x)P_2(y)$ has

$$\iint (x - m_1)^2 P(x, y) dx dy = \sigma_1^2$$

$$\iint (x - m_1)(y - m_2) P(x, y) dx dy = 0$$

So the 2×2 covariance matrix V is diagonal and its entries are

Ans:
$$\iint (x - m_1)^2 P(x, y) dx dy = \int (x - m_1)^2 p(x) dx \int p(y) dy = \sigma_1^2$$

$$\iint (x - m_1)(y - m_2) P(x, y) dx dy = \int (x - m_1) p(x) dx \int (y - m_2) p(y) dy = (0)(0) = 0$$

5. Show that the inverse of a 2×2 covariance matrix V is

$$V^{-1} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}^{-1} = \frac{1}{1 - \rho^2} \begin{bmatrix} \frac{1}{\sigma_1^2} & -\rho/\sigma_2 \\ -\rho/\sigma_1 & \frac{1}{\sigma_2^2} \end{bmatrix}$$

with correlation $\rho = \frac{\sigma_{12}}{\sigma_1 \sigma_2}$

This produces the exponent $-(x - m)^T V^{-1} (x - m)$ in a 2-variable Gaussian.

Kalman filter

Qns:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

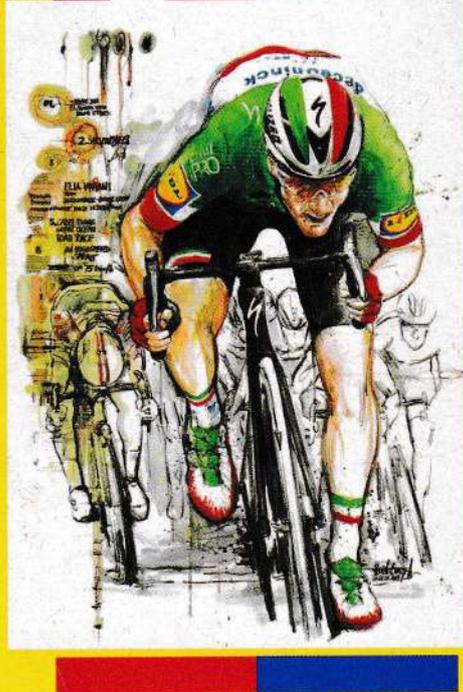
$$V^{-1} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}^{-1} = \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \begin{bmatrix} \sigma_2^2 & -\sigma_{12} \\ -\sigma_{12} & \sigma_1^2 \end{bmatrix}$$

$$= \frac{1}{\sigma_1^2 \sigma_2^2 (1-\rho^2)} \begin{bmatrix} \sigma_2^2 & -\sigma_{12} \\ -\sigma_{12} & \sigma_1^2 \end{bmatrix} \quad \rho = \frac{\sigma_{12}}{\sigma_1 \sigma_2}$$

$$= \frac{1}{1-\rho^2} \begin{bmatrix} \frac{1}{\sigma_1^2} & -\rho/\sigma_1\sigma_2 \\ -\rho/\sigma_1\sigma_2 & \frac{1}{\sigma_2^2} \end{bmatrix}$$

$$\begin{bmatrix} \frac{1}{\sigma_1^2} & -\rho/\sigma_1\sigma_2 \\ -\rho/\sigma_1\sigma_2 & \frac{1}{\sigma_2^2} \end{bmatrix}^{-1} = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} = V$$

Success



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