

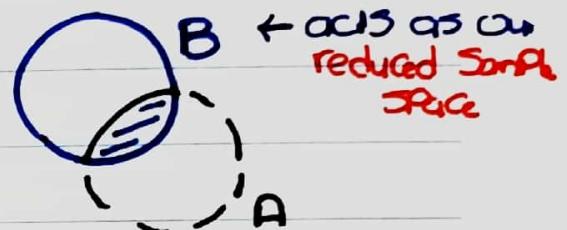
Probability Refresher

Conditional Probability

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{n(A \cap B)}{n(B)}$$

↓
Probability of
A given B

Joint Probability
of A, B (Probability
of both occurring simul.)



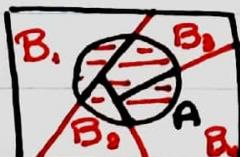
• If B is guaranteed to occur what's the Probability
of A?

• $n(A)$ is the no. of ways
in which A can occur.

Total Probability

→ Given a Set of events B_1, B_2, \dots, B_k that disjointly
Partition the Sample Space the Probability of any event
A of the Sample Probability Space is

$$P(A) = \sum_{i=1}^k P(A \cap B_i) = \sum_{i=1}^k P(A|B_i) P(B_i)$$



← A is constructed through its
intersections with B_i .

• Check Ps

Bayes Rule

$$P(B_i|A) = \frac{P(A|B_i)P(B_i)}{P(A)}$$

→ Prior Probability
(Before learning about A)

↓
Posterior Probability
(After learning about A)

↓ Marginal Probability

$$\sum_{j=1}^k P(A|B_j)P(B_j)$$

<bonus>

- In Bayesian inference, B can be a Parameter and we're often interested in finding its distribution given the observed data A.
- In this case $P(A|B)$ is a function in the Parameter B and is regarded as the likelihood of the Parameter B given the data A. (the data is known, the Parameter isn't).

</bonus>

Statistical Independence

- If $P(A \cap B) = P(A)P(B)$ then A and B are independent events

$$P(A|B) = P(A) \quad \text{and} \quad P(B|A) = P(B) \quad \text{implies}$$

→ Whether A has happened or not does not affect B and vice versa.

Marginal Distribution

$$P_x(x) = \int_{-\infty}^{\infty} P(x,y) dy$$

} helps find the probability of $x=x$ irrespective to any outcome of Y

• Sum for discrete (Σ)

Two random variables are independent if

$$P(x, y) = P_x(x) P_y(y) \quad (\text{For all } x, y \text{ in their range})$$

- Joint density
- Marginal densities

* Expected Value

$$\mu_x = E(x) = \int_{-\infty}^{\infty} x P_x(x) dx$$

- More generally

$$\mu_{g(x,y)} = E(g(x,y)) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) P(x,y) dy dx$$

* Variance

$$\begin{aligned} \text{Var}(g(x)) &= E((g(x) - E(g(x)))^2) = E((g(x))^2) - (E(g(x)))^2 \\ &= E[(g(x))^2] - (E[g(x)])^2 \end{aligned}$$

$$\text{So } \text{Var}(x) = E(x^2) - (E(x))^2$$

• also applies
for $g(x,y)$

* Covariance

$$\begin{aligned} \text{Cov}(x,y) &= E((x - E(x))(y - E(y))) \\ &= E(XY) - E(X)E(Y) \end{aligned}$$

* Correlation

$$\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{\sigma_x \sigma_y} \quad -1 \leq \text{Corr}(X,Y) \leq 1$$

• Perfectly anti-correlated ↘

• Perfectly correlated ↑

NN Sheet 1

Q1)

	Red Box	Blue Box	Green Box
Apples	3	5	3
Oranges	4	5	3
Limes	3	0	4

a) $P(Fruit = Orange | Box = Red) = \frac{n(F=Orange \cap B=Red)}{n(B=Red)}$

• n is the no. of fruits.

$$= \frac{4}{3+4+3} = 0.4$$

b) $P(F=Orange) = P(F=Orange | B=red) \cdot P(B=red)$

• By the law of total Probability.

$$+ P(F=Orange | B=blue) \cdot P(B=blue)$$

$$+ P(F=Orange | B=green) \cdot P(B=green)$$

$$= \frac{4}{3+4+3} \cdot \frac{1}{5} + \frac{5}{3+4+3} \cdot \frac{1}{5} + \frac{3}{3+4+3} \cdot \frac{3}{5}$$

$$= 0.36$$

$$c) P(B=\text{Red} | F=\text{Orange}) = \frac{P(F=\text{Orange} | B=\text{red}) \cdot P(B=\text{red})}{P(F=\text{Orange})}$$

• By Bayes Rule

$$= \frac{0.4 \times 0.2}{0.36} = 0.\dot{2}\dot{4}$$

» Alternatively,

$$P(B=\text{Red} | F=\text{Orange}) = \frac{n(B=\text{Red} \cap F=\text{Orange})}{n(F=\text{Orange})}$$

• By Conditional Probability.

$$= \frac{4}{4+5+3 \times 3} = 0.\dot{2}$$

$$d) P(B=\text{green} | F=\text{Apple}) = \frac{n(B=\text{green} \cap F=\text{Apple})}{n(\text{Apple})}$$

$$= \frac{3 \times 3}{3+5+3 \times 3} = \frac{9}{17}$$

» Alternatively,

$$\begin{aligned} P(F=\text{Apple}) &= P(F=\text{Apple} | B=\text{Red}) \cdot P(B=\text{Red}) \\ &\quad + P(F=\text{Apple} | B=\text{blue}) \cdot P(B=\text{blue}) \\ &\quad + P(F=\text{Apple} | B=\text{green}) \cdot P(B=\text{green}) \end{aligned}$$

$$= \frac{3}{3+4+3} \cdot \frac{1}{5} + \frac{5}{5+5+0} \cdot \frac{1}{5} + \frac{3}{3+3+4} \cdot \frac{3}{5} = \frac{17}{50}$$

$$P(B=\text{green} | F=\text{Apple}) = \left(\frac{3}{3+3+4} \cdot \frac{3}{5} \right) / \left(\frac{17}{50} \right) = \frac{9}{17}$$

Q2) Let x_1 be the result from the 1st PnP and let x_2 be the result from the 2nd PnP.

$$a) P(x_1=h \wedge x_2=h | x_1=h) = \frac{P(x_1=h \wedge x_2=h)}{P(x_1=h)}$$

$$= \frac{1/4}{2/4} = \frac{1}{2}$$

$\nwarrow (h,h)$ only
 $\swarrow (h,t), (t,h)$

Can also do $\frac{n(x_1=h \wedge x_2=h)}{n(x_1=h)} = \frac{1}{2}$

b) $P(x_1=h \wedge x_2=h | x_1=h \vee x_2=h)$

$$\frac{P(x_1=h \wedge x_2=h)}{P(x_1=h \vee x_2=h)} = \frac{1/4}{3/4} = \frac{1}{3}$$

$\nwarrow (h,h)$
 $\swarrow (h,h), (h,T), (T,h)$

Note:
 $(A \vee B) \neq A \vee B$
 $A \wedge B$

• Normally, the Sample Space Shouldn't be given.

Q3)

- The two events E, F are independent iff

$$P(E \cap F) = P(E)P(F)$$

→ The Sample Space is $\{(h,h), (h,t), (t,h), (t,t)\}$

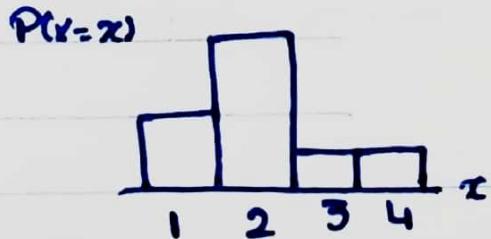
$$P(E) = \frac{2}{4} \quad \begin{matrix} \leftarrow (h,h), (h,t) \\ \text{1st Coin lands} \\ \text{on head} \end{matrix}$$

$$P(F) = \frac{2}{4} \quad \begin{matrix} \leftarrow (h,t), (t,t) \\ \text{2nd Coin lands} \\ \text{on tail} \end{matrix}$$

$$P(E \cap F) = \frac{1}{4} \quad \begin{matrix} \leftarrow (h,t) \\ \text{ } \end{matrix}$$

- Clearly, $P(E \cap F) = P(E)P(F)$ and the two events are thereby independent.

Q4)



a) $\sum_{x \in \mathcal{X}} P(X=x) = 0.25 + 0.5 + 0.125 + 0.125 = 1$

$$P(X=x) > 0 \quad \forall x$$

$$b) E(X) = \sum_x x P(X=x) = 1 \times 0.25 + 2 \times 0.5 \\ + 3 \times 0.125 + 4 \times 0.125 \\ = 2.125$$

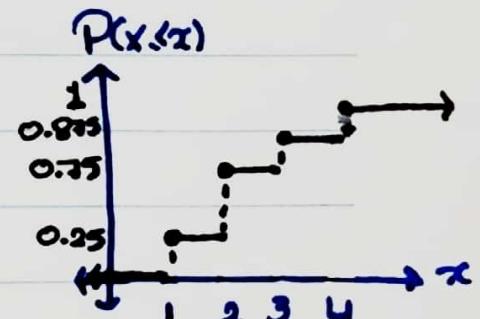
$$c) E(X^2) = \sum_x x^2 P(X=x) \\ = 1^2 \times 0.25 + 2^2 \times 0.5 + 3^2 \times 0.125 + 4^2 \times 0.125 \\ = 5.375$$

$$\text{Var}(X) = E(X^2) - (E(X))^2 \quad (\sigma^2) \\ = 5.375 - 2.125^2 = 0.859375$$

$$\text{STD}(X) = \sqrt{\text{Var}(X)} = 0.927 \quad (\sigma)$$

$$d) P(X \leq x) = \sum_{t \leq x} P(t)$$

x	1	2	3	4
$P(X=x)$	0.25	0.5	0.125	0.125
$P(X \leq x)$	0.25	0.75	0.875	1



e)

x	1	2	3	4
$y = \ln(x)$	0	0.693	1.0986	1.386
$P(Y=y)$	0.25	0.5	0.125	0.125

Under the Same Steps

$$E(Y) = 0.657 \\ \text{Var}(Y) = 0.1994 \\ \text{STD}(Y) = 0.4465$$

Q5) $E(x) = 1$ and $\text{Var}(x) = 5$

• $\text{Var}(x) = 5 \rightarrow E(x^2) = \text{Var}(x) + (E(x))^2 = 6$

a) $E((x+2)^2) = E(x^2 + 4x + 4)$

$$= E(x^2) + \underbrace{4E(x)}_{E(4x)} + \underbrace{4}_{E(4)}$$

$$= 6 + 4 \times 1 + 4 = 14$$

b) $\text{Var}(4 - 3x) = (-3)^2 \text{Var}(x) = 9 \times 5 = 45$

Q6)

- Box Contains 5 green and 5 blue balls.
- Two balls are drawn at random

The no. of ways to

Draw two balls

$${}^{10}C_2$$

Draw two different balls

$${}^5C_1 \times {}^5C_1$$

• For every chosen red there are 5 choices of green

Draw two similar balls

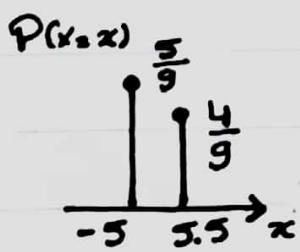
$${}^5C_2 + {}^5C_1$$

• Can choose 2 of the red or 2 of the green

- Note that the no. of ways to draw two similar balls is also the no. of ways to not draw two different balls. ($2 \times {}^5C_1 = {}^{10}C_2 - ({}^5C_1)^2$)
- Let X be a random variable representing the no. of points earned.
 $\rightarrow X \in \{-5, +5.5\}$ depending on whether the two balls are similar or not.

$$P(X = -5) = \frac{{}^5C_1 \times {}^5C_1}{{}^{10}C_2} = \frac{5}{9}$$

$$P(X = 5.5) = \frac{{}^5C_2 + {}^5C_2}{{}^{10}C_2} = \frac{4}{9}$$



$$a) E(X) = -5 \times \frac{5}{9} + 5.5 \times \frac{4}{9} = -\frac{1}{3}$$

$$b) E(X^2) = 25 \times \frac{5}{9} + 5.5^2 \times \frac{4}{9} = \frac{82}{3}$$

$$\text{Var}(X) = \frac{82}{3} - \left(\frac{1}{3}\right)^2 = \frac{245}{9}$$

- Can also compute the two Probabilities using a Probability tree



Q7) Let X be a continuous random variable representing the amount of time that a computer runs before breaking down.

→ The Probability density function is

$$f(x) = \begin{cases} \lambda e^{-x/100} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$\int_{-\infty}^{\infty} f(x) dx = 1 \rightarrow \int_0^{\infty} \lambda e^{-x/100} (-100) = 1$$

$$\therefore -\lambda (e^0(-100)) = 1 \quad (\lambda = \frac{1}{100})$$

$$a) P(50 < X < 150) = \int_{50}^{150} \frac{1}{100} e^{-x/100} dx = 0.3834$$

$$b) P(X < 100) = \int_{-\infty}^{100} f(x) dx = \int_0^{100} \frac{1}{100} e^{-x/100} dx = 0.632$$

Q8) Since it's a PDF

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^1 (a+bx^2) dx = \left[ax + \frac{bx^3}{3} \right]_0^1 = \left(a + \frac{b}{3} \right) = 1$$

. Since $E(x) = 35$

$$\int_{-\infty}^{\infty} x P(x) dx = \int_0^1 (ax + bx^3) dx = \left[\frac{ax^2}{2} + \frac{bx^4}{4} \right]_0^1 = \frac{a}{2} + \frac{b}{4} = 35$$

Solving the System

$$a + \frac{1}{3}b = 1$$

$$\frac{1}{2}a + \frac{1}{4}b = 35$$

yields

$$a = -137 \quad b = 414$$

$$P(x) = \begin{cases} 414x^2 - 137 & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Q9)

a) $E(ax+b) = \int_{-\infty}^{\infty} (ax+b)P(x)dx$

$$= a \int_{-\infty}^{\infty} xP(x)dx + b \int_{-\infty}^{\infty} P(x)dx$$
$$= a \cdot E(x) + b \cdot 1$$
$$= aE(x) + b$$

*Also holds for
I if x was
discrete*

b) $\text{Var}(ax+b) = E((ax+b)^2) - (E(ax+b))^2$

$$= E(a^2x^2 + 2abx + b^2) - (\overline{aE(x)+b})^2$$
$$= a^2 E(x^2) + 2ab E(x) + b^2$$
$$- a^2(E(x))^2 - 2abE(x) - b^2$$
$$= a^2(E(x^2) - (E(x))^2) = a^2 \text{Var}(x)$$

$$\begin{aligned}
 c) \quad \text{Var}(X+Y) &= E((X+Y)^2) - (E(X+Y))^2 \\
 &= E(X^2 + 2XY + Y^2) - (E(X) + E(Y))^2 \\
 &= E(X^2) + 2E(XY) + E(Y^2) \\
 &\quad - (E(X))^2 - 2E(X)E(Y) - (E(Y))^2 \\
 &= (E(X^2) - (E(X))^2) + (E(Y^2) - (E(Y))^2) \\
 &\quad + 2(E(XY) - E(X)E(Y)) \\
 &= \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)
 \end{aligned}$$

$$\begin{aligned}
 d) \quad \text{Cov}(X, Y) &= E((X - M_x)(Y - M_y)) \\
 &= E(XY - XM_y - YM_x + M_xM_y) \\
 &= E(XY) - M_y E(X) - M_x E(Y) + M_x M_y \\
 &= E(XY) - M_x M_y - M_x M_y + M_x M_y \\
 &= E(XY) - M_x M_y = E(XY) - E(X)E(Y)
 \end{aligned}$$

• Writing M_x, M_y
 For $E(X), E(Y)$ for
 easier notation.

• Notice $\underbrace{E(E(x))}_{\text{Treated as a const.}} = E(x)$ } as $\int_{-\infty}^{\infty} (\underbrace{\int_{-\infty}^{\infty} x P(x) dx}_{\text{not a function in } x}) P(x) dx$

Q10)

a) $E(XY) = \iint_{-\infty}^{\infty} xy P(x,y) dx dy$

• Due to independence

$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy P_x(x) P_y(y) dx dy$

$= \int_{-\infty}^{\infty} P_x(x) dx \int_{-\infty}^{\infty} P_y(y) dy = E(X) E(Y) \neq 0$

→ Won't be equal to zero unless either $E(X)$ or $E(Y)$ is zero

c) $\text{Cov}(X,Y) = E(XY) - E(X)E(Y) = 0$

d) $\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = 0$ • They are uncorrelated

b) $\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X,Y)$
 $= \text{Var}(X) + \text{Var}(Y)$

→ Only zero if both $\text{Var}(X)$, $\text{Var}(Y)$ are zero

e) $E(XY) - E(X+E(Y)) = E(X)E(Y) - (E(X)+E(Y))$
→ Not zero unless $E(X)E(Y) = E(X)+E(Y)$

F) . check c

$$g) \text{Var}(XY) = E(X^2Y^2) - (E(XY))^2$$

$$\begin{aligned} E(X^2Y^2) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^2 y^2 P(x,y) dx dy \\ &= \int_{-\infty}^{\infty} x^2 P_x(x) dx \int y^2 P_y(y) dy \\ &= E(X^2) E(Y^2) \end{aligned}$$

$$\text{Var}(XY) = E(X^2)E(Y^2) - (E(X))^2(E(Y))^2$$

• which isn't necessarily zero

$$h) \underbrace{\text{Var}(X+Y)}_{\substack{\text{Var}(X)+\text{Var}(Y) \\ (\text{as in b})}} - (\text{Var}(X) + \text{Var}(Y)) = 0$$

Q11)

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$a) E(X) = E(X-\mu) + \mu$$

$$\cdot E(X-\mu) = \int_{-\infty}^{\infty} (x-\mu) \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$\rightarrow \text{let } Z = \frac{x-\mu}{\sigma}, dz = \frac{dx}{\sigma}, x \rightarrow -\infty \rightarrow z \rightarrow -\infty \\ x \rightarrow \infty \rightarrow z \rightarrow \infty$$

$$E(X-\mu) = \frac{\sigma}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z e^{-z^2/2} dz$$

$$= \frac{\sigma}{\sqrt{2\pi}} \lim_{a \rightarrow \infty} \underbrace{\int_{-a}^a z e^{-z^2/2} dz}_{\text{zero}} \quad \bullet \text{Q.S}$$

$P(z) = z e^{-z^2/2}$ is odd
($P(-z) = -P(z)$)

b)

$$\text{Var}(X) = E((X-\mu)^2) = \int_{-\infty}^{\infty} (x-\mu)^2 \cdot \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

- let $Z = \frac{x-\mu}{\sigma}$, $dx = \sigma dz$, $\begin{matrix} x \rightarrow \infty \\ x \rightarrow -\infty \end{matrix} \rightarrow \begin{matrix} z \rightarrow \infty \\ z \rightarrow -\infty \end{matrix}$

$$= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 e^{-z^2/2} dz$$

• Integrating by Parts:

$$\begin{array}{ccc} u & & dv \\ z & \xrightarrow{-} & -e^{-z^2/2} \\ 1 & \swarrow & ze^{-z^2/2} \end{array}$$

$$= \frac{\sigma^2}{\sqrt{2\pi}} \left(\underset{①}{\int_{-\infty}^{\infty} 1 \cdot -ze^{-z^2/2} dz} + \underset{②}{\int_{-\infty}^{\infty} e^{-z^2/2} dz} \right)$$

$$\begin{aligned} ① \lim_{z \rightarrow \pm\infty} \frac{z}{e^{-z^2/2}} \\ = \lim_{z \rightarrow \pm\infty} \frac{1}{ze^{z^2/2}} = \frac{1/z}{e^{z^2/2}} = 0 \end{aligned}$$

$$\begin{aligned} ② \text{ we know } \int_{-\infty}^{\infty} \frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi}\sigma} dx = 1 \\ \bullet \text{ let } Z = \frac{(x-\mu)}{\sigma} \end{aligned}$$

$$\int_{-\infty}^{\infty} \frac{e^{-z^2/2}}{\sqrt{2\pi}} dz = 1 \quad \bullet \text{ Thus, } ② = \sqrt{2\pi}$$

$$\text{Thus, we're left with } \text{Var}(X) = \frac{\sigma^2}{\sqrt{2\pi}} (0 + \sqrt{2\pi}) \\ = \sigma^2$$

• let $X \sim N(\mu, \sigma^2)$

$$\rightarrow E(X) = \mu \text{ and } \text{Var}(X) = \sigma^2$$

» For $Z = \frac{X-\mu}{\sigma}$ (using the results given in Q9)

$$\cdot E(Z) = \frac{E(X)-\mu}{\sigma} = \frac{\mu-\mu}{\sigma} = 0$$

$$\cdot \text{Var}(Z) = \text{Var}\left(\frac{X}{\sigma} - \frac{\mu}{\sigma}\right) = \frac{\text{Var}(X)}{\sigma^2} = 1$$

Q12)

$$E(e^{-\alpha x}) = \int_{-\infty}^{\infty} e^{-\alpha x} \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \cdot e^{-(\frac{x^2}{2} + \alpha x)} dx$$

• Not easy to integrate.

Observe

$$\begin{aligned} -\left(\frac{x^2}{2} + \alpha x\right) &= -\frac{1}{2}(x^2 + 2\alpha x) \\ &= -\frac{1}{2}((x+\alpha)^2 - \alpha^2) \quad \cdot \text{Complete the square} \\ &= \frac{-1}{2}(x+\alpha)^2 + \frac{\alpha^2}{2} \end{aligned}$$

$$\begin{aligned} E(e^{-\alpha x}) &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{1}{2}(x-(-\alpha))^2} \cdot e^{\alpha^2/2} dx \\ &= e^{\alpha^2/2} \int_{-\infty}^{\infty} \frac{e^{-\frac{1}{2}(x-(-\alpha))^2}}{\sqrt{2\pi}} dx \\ &= e^{\alpha^2/2} \quad \hookrightarrow \text{A Normal distribution} \\ &\quad \text{with } \mu = -\alpha \text{ and } \sigma = 1 \\ &\quad (\text{must integrate to 1}) \end{aligned}$$

Q13)

$$\begin{aligned} E(e^{-x} + e^{-2x} + x^2) &= E(e^{-x}) + E(e^{-2x}) + E(x^2) \\ &\quad \alpha=1 \qquad \qquad \alpha=2 \\ &= e^{0.5} + e^2 + 1 \end{aligned}$$

$$X \sim N(\mu=0, \sigma^2=1)$$

$$\cdot \sigma^2 = E(x^2) - \mu^2$$

$$\rightarrow \text{So } E(x^2) = 1$$

Q14)

Consider the numbers

X

-2

3

0.5

0.3

4.2

9

-3.4

1. Compute the mean

2. Compute the variance

3. Compute the standard deviation

4. What happens to the standard deviation (without computing it)
if we add the point 10,000.

$$1. \bar{X} = \frac{\sum x_i}{n} = 1.6571$$

$$2. S^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2 = \frac{1}{n-1} \left(\sum x_i^2 - n\bar{x}^2 \right)$$
$$= \frac{1}{7-1} (123.54 - 7 \times 1.657^2)$$
$$= 17.3867$$

$$3. S = 4.16967$$

4. It will greatly increase

squared distances to \bar{x} are
much larger

