

M146 HW1 Melody Chen #705120273

a)	<table border="1"> <tr><td>4 red</td></tr> <tr><td>3 blue</td></tr> <tr><td>3 white</td></tr> </table>	4 red	3 blue	3 white	<table border="1"> <tr><td>2 red</td></tr> <tr><td>4 blue</td></tr> <tr><td>4 white</td></tr> </table>	2 red	4 blue	4 white
4 red								
3 blue								
3 white								
2 red								
4 blue								
4 white								
	#1	#2						

$P(\text{"picked two red"})$

$$= P(\text{"picked two red"}) \cap P(\text{"urn 1"}) + P(\text{"picked two red"}) \cap P(\text{"urn 2"}) \\ = P(\text{"picked two red"} | \text{"urn 1"}) P(\text{"urn 1"}) + P(\text{"picked two red"} | \text{"urn 2"}) P(\text{"urn 2"})$$

$$P(\text{"picked two red"} | \text{"urn 1"}) = \left(\frac{4}{10}\right)\left(\frac{3}{9}\right) = 0.1\bar{3}$$

$$P(\text{"picked two red"} | \text{"urn 2"}) = \left(\frac{2}{10}\right)\left(\frac{1}{9}\right) = 0.0\bar{2}$$

$$P(\text{"urn 1"}) = 0.4 \quad P(\text{"urn 2"}) = 0.6$$

$$\Rightarrow P(\text{"picked two red"}) = (0.1\bar{3})(0.4) + (0.0\bar{2})(0.6) \\ = 0.06\bar{6}$$

b) Let $2B$ = event where 2nd ball is blue, $1B$ = 1st ball blue, $1R$ = 1st ball red

$$P(2B) = P(2B \cap \text{"urn 1"}) + P(2B \cap \text{"urn 2"})$$

$$P(2B \cap \text{"urn 1"}) = P(2B \cap \text{"urn 1"} \cap 1B) + P(2B \cap \text{"urn 1"} \cap 1B^c) \\ = P(2B \cap 1B | \text{"urn 1"}) P(\text{"urn 1"}) + P(2B \cap 1B^c | \text{"urn 1"}) P(\text{"urn 1"})$$

$$P(2B \cap 1B | \text{"urn 1"}) = P((2B | \text{"urn 1"}) \cap (1B | \text{"urn 1"})) \\ = P((2B | \text{"urn 1"}) | (1B | \text{"urn 1"})) P(1B | \text{"urn 1"}) \\ = \left(\frac{2}{9}\right)\left(\frac{3}{10}\right) = 0.06\bar{6}$$

$$P(2B \cap 1B^c | \text{"urn 1"}) = P((2B | \text{"urn 1"}) | (1B^c | \text{"urn 1"})) P(1B^c | \text{"urn 1"}) \\ = \left(\frac{3}{9}\right)\left(\frac{7}{10}\right) = 0.2\bar{3}$$

$$P(2B \cap \text{"urn 1"}) = (0.06\bar{6})(0.4) + (0.2\bar{3})(0.4) = 0.12$$

$$P(2B \cap \text{"urn 2"}) = \text{use same logic as for urn 1} \dots \\ = \left(\frac{4}{10}\right)\left(\frac{3}{9}\right)(0.6) + \left(\frac{6}{10}\right)\left(\frac{4}{9}\right)(0.6) = 0.24$$

$$P(2B) = 0.12 + 0.24 = 0.36$$

$$C) P(2B | 1R) = \frac{P(2B \cap 1R)}{P(1R)}$$

$$P(2B \cap 1R) = P(2B \cap 1R \cap \text{"urn 1"}) \cap P(2B \cap 1R \cap \text{"urn 2"})$$

$$= P((2B \cap 1R) | \text{"urn 1"}) P(\text{"urn 1"}) + P(2B \cap 1R | \text{"urn 2"}) P(\text{"urn 2"}) \\ = \left(\frac{4}{10}\right)\left(\frac{3}{9}\right)(0.4) + \left(\frac{2}{10}\right)\left(\frac{4}{9}\right)(0.6) = 0.10\bar{6}$$

$$P(1R) = P(1R \cap \text{"urn 1"}) \cap P(1R \cap \text{"urn 2"}) = 0.4\left(\frac{4}{10}\right) + 0.6\left(\frac{2}{10}\right) \\ = 0.28$$

$$P(2B | 1R) = \frac{0.10\bar{6}}{0.28} = 0.38$$

2) Total # of combinations: 6^6

Combinations that can result in 3 numbers each appear twice:

$$\underbrace{6C3}_{\substack{\text{ways to choose} \\ \text{3 numbers}}} \cdot \frac{6!}{\underbrace{z!z!z!}_{\substack{\text{ways to} \\ \text{arrange the} \\ \text{six dies}}}} = 1800$$

$$P(\text{"3 diff. number each appearing twice"}) = \frac{1800}{6^6} = 0.0386$$

3) $P(A) = 0.25 \quad P(B) = 0.35 \quad P(C) = 0.4$

Let D = event of defective

$$P(D|A) = 0.05 \quad P(D|B) = 0.04 \quad P(D|C) = 0.02$$

$$\begin{aligned} P(D) &= P(D \cap A) + P(D \cap B) + P(D \cap C) \\ &= P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C) \\ &= 0.05(0.25) + 0.04(0.35) + 0.02(0.4) = 0.0345 \end{aligned}$$

$$P(\text{"defective bolt manufactured by A"}) = P(A|D) = \frac{P(A \cap D)}{P(D)} = \frac{P(D|A)P(A)}{P(D)} = \frac{(0.05)(0.25)}{0.0345} = 0.3623$$

$$P(\text{"defective bolt manufactured by B"}) = P(B|D) = \frac{P(B \cap D)}{P(D)} = \frac{P(D|B)P(B)}{P(D)} = \frac{(0.04)(0.35)}{0.0345} = 0.4058$$

$$P(\text{"defective bolt manufactured by C"}) = P(C|D) = \frac{P(C \cap D)}{P(D)} = \frac{P(D|C)P(C)}{P(D)} = \frac{(0.02)(0.4)}{0.0345} = 0.2319$$

4) a) Show that $E(X+Y) = E(X) + E(Y)$

$$\begin{aligned} E(X+Y) &= \sum_x \sum_y (X+y) P(Y=y, X=x) \\ &= \sum_x \sum_y x P(Y=y, X=x) + \sum_x \sum_y y P(Y=y, X=x) \\ &= \sum_x x \sum_y P(Y=y, X=x) + \sum_y y \sum_x P(Y=y, X=x) \\ &= \sum_x x P(X=x) + \sum_y y P(Y=y) = E(X) + E(Y) \end{aligned}$$

b) If X and Y are independent, show that $\text{Var}[X+Y] = \text{Var}(X) + \text{Var}(Y)$

$$\begin{aligned} \text{Var}(X+Y) &= E[((X+Y) - E(X+Y))^2] = E[(X - \mu_X + Y - \mu_Y)^2] \\ &= \sum_x \sum_y ((X - \mu_X)^2 + 2(X - \mu_X)(Y - \mu_Y) + (Y - \mu_Y)^2) p(x,y) \\ &= \sum_x \sum_y (X - \mu_X)^2 p(x,y) + 2 \sum_x \sum_y (X - \mu_X)(Y - \mu_Y) p(x,y) + \sum_x \sum_y (Y - \mu_Y)^2 p(x,y) \\ &= \sum_x (X - \mu_X)^2 p(x) + 2 \sum_x \sum_y xy p(x,y) - 2 \sum_x \sum_y x \mu_Y p(x,y) \\ &\quad - 2 \sum_x \sum_y \mu_X y p(x,y) + 2 \mu_X \mu_Y \sum_x \sum_y p(x,y) + \sum_y (Y - \mu_Y)^2 p(y) \end{aligned}$$

$$\begin{aligned}
 &= \text{Var}(x) + 2E(xy) - 2My \sum_x x p(x) - 2Mx \sum_y y p(y) + 2MxMy \\
 &\quad + \text{Var}(y) \\
 &= \text{Var}(x) + 2E(x)E(y) - 2My Mx - 2MxMy + 2MxMy \\
 &\quad + \text{Var}(y) \\
 &= \text{Var}(x) + \text{Var}(y)
 \end{aligned}$$

5) $T \sim \text{Exponential}(\lambda)$

a) $P(T \geq d | T \geq r) = P(T \geq d)$ because of memoryless property of exponentials

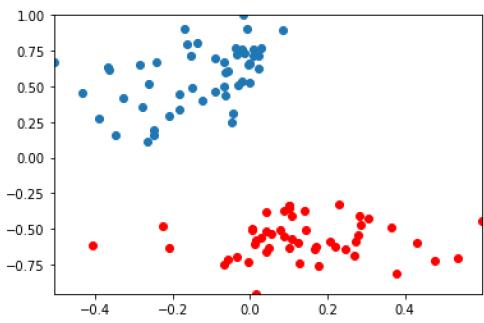
$$= 1 - P(T < d) = 1 - (1 - e^{-\lambda d}) = e^{-\lambda d}$$

b) $E(T) = \int_0^\infty t (\lambda e^{-\lambda t}) dt$

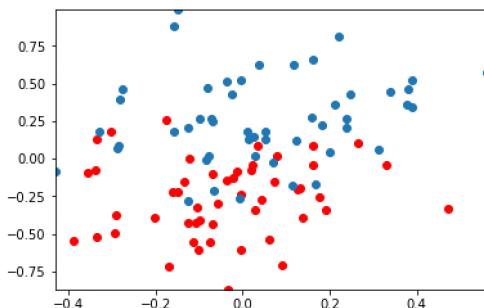
$$\begin{aligned}
 &= \lambda \left[-\frac{t}{\lambda} e^{-\lambda t} + \frac{1}{\lambda} \int_0^\infty e^{-\lambda t} dt \right]_0^\infty = \lambda \left[-\frac{t}{\lambda} e^{-\lambda t} - \frac{1}{\lambda^2} e^{-\lambda t} \right]_0^\infty \\
 &= \lambda \left(\frac{1}{\lambda^2} \right) = \frac{1}{\lambda}
 \end{aligned}$$

$u=t \quad dv=e^{-\lambda t}dt$
 $du=dt \quad v=-\frac{1}{\lambda}e^{-\lambda t}$

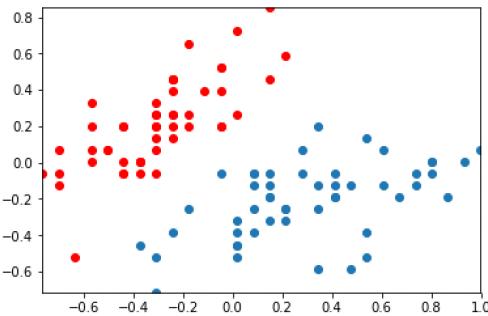
6) a) Data Set #1



Data Set #3



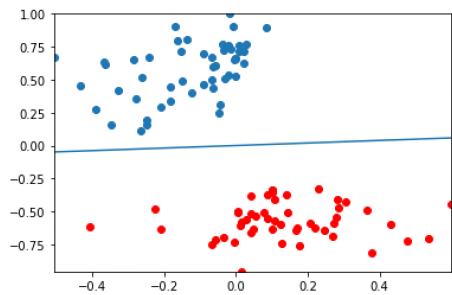
Data Set #2



Data set #1 and #2
are separable.

b) Data Set #1

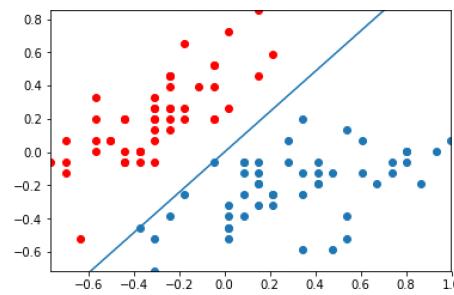
w vector: [0, 0.1421720000000002, -1.47323]
 w1: 0.1421720000000002 w2: -1.47323
 b bias: 0
 # of updates: 2



Data Set #1 converges.

Data Set #2

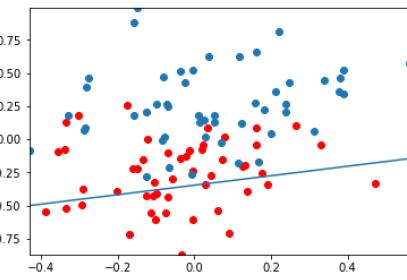
w vector: [0, -1.10918, 0.91344]
 w1: -1.10918 w2: 0.91344
 b bias: 0
 # of updates: 4



Data Set #2 converges.

Data Set #3

w vector: [-1, 1.0291400000000066, -2.8796620000003377]
 w1: 1.0291400000000066 w2: -2.8796620000003377
 b bias: -1
 # of updates: 4501



Data Set #3 does not converge as data is not linearly separable, which is a criteria for using the perceptron algorithm. In addition, the # of updates is significantly large, unlike data set #1 and #2, showing that perceptron algorithm does not converge.

c) Data Set #1

$$\gamma_{w,b} = 0.13687$$

$$\frac{1}{\gamma_{w,b}^2} = 53.3819$$

Data Set #2

$$\gamma_{w,b} = 0.000265$$

$$\frac{1}{\gamma_{w,b}^2} = 14251382.48$$

Data Set #3 does not converge.

Compare to the upper bound $\frac{1}{\gamma_{w,b}^2}$, our algorithm converged in 2 updates, which is significantly smaller.

Compare to the upper bound $\frac{1}{\gamma_{w,b}^2}$, our algorithm converged in 4 updates, which is significantly smaller.