2) Let X and y be random variables. Let Z = X+y the a) sum of two multivariate random variables. We can then write $\Sigma_{zz} = E((z-\mu_z)(z-\mu_z)^T)$ where $\mu_z = E[z] = E[x+y]$ using the linearity of the expectation | uz= E[x] + E[y] = |x + py then we can rewrite the covariance as = E(((x+y)-(px+py))((x+y)-(px-py)))) rearranging we can get = E((x-px)+(y-py))(x-px)+(y-py))) now we can compute $= E((x-\mu_{x})(x-\mu_{x})^{T}+(x-\mu_{x})(y-\mu_{y})^{T}+(y-\mu_{y})(x-\mu_{x})^{T}+(y-\mu_{y})(y-\mu_{y})^{T})$ $\sum_{zz} = E[(x-\mu x)(x-\mu x)^{T}] + E[(x-\mu x)(y-\mu y)^{T}] + E[(y-\mu y)(x-\mu x)^{T}] + E[(y-\mu y)(y-\mu y)^{T}]$.. \Sz= \Six+ Kxy+ Kxy + Kxy + \Sixy \ b) Let X and y be two independent multivariate random variables using the linear independent properly E(AB)=E(A)E(B) we can then rewrite Kxy = E[(x-px)(y-py)) = E[x-px] E[(y-py)] Examining E[x-px]=E[x]-px-ond by definition Ux=E[x] E[x-px] = E[x]-E[x]=0 Which means () From the above results, we can deduce that the covariance of the sum of two independent multivariate random variables Z=X+y, X,y independent Zzz = Zxx + Kxy + Kxy + Zyy = Zxx + Zyy : Zz= 5x+ 5yy

3) 10 independent sensors for object detection,
$$p(\text{detected}) = 0.1$$

Our system fits the requirements at a binomial distribution where we have $n=10$ independent experiments on how many sensors, detected the object with proposition $p=0.1$

a) Let X be a random variable such that
$$X \sim B(n_1p) = B(10, 0.1)$$

$$P(X = X) = \binom{10}{x} \cdot (0.1)^{x} (1-0.1)^{10-x}$$

b)
$$P(X_{7/1}) = 1 - P(X = 0)$$

 $P(X = 0) = \binom{10}{0} \cdot (0.1)^{0} \cdot (0.9)^{0} = \frac{10!}{0! (10^{2}0)!} \times 1 \times 0.3487$

$$P(X71) = 1 - 0.3487 = 0.6513$$

$$65\% \text{ Chance at least one sensor detects the object}$$

4) Two dimensional normally distributed random variable, $\mu = \begin{bmatrix} 3.0 \\ 4.0 \end{bmatrix}$ Principal axis (eigenvector) forms a 30 degree angle with the x-axis. The variance of that axis is 1.0, other is 0.25

PDF is in the form
$$P(x) = \frac{1}{2\pi \sqrt{|\Sigma|}} exp\left(-\frac{1}{2}(x-y)^{T} \Sigma^{-1}(x-y)\right)$$

We can compute the covariance matrix using the information we have on the eigenvectors (principal axis) and eigenvalues (variance) of the uncertainty ellipse

$$\overline{Z} = U \Lambda U^{T}$$
 where $U = Rot_{X}(30^{\circ}) = \begin{bmatrix} \cos \theta - \sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$ $\Lambda = \begin{bmatrix} 1 & 0 \\ 0 & 0.25 \end{bmatrix}$

Funning the operations on Python we get $\Sigma = \begin{bmatrix} 0.8125 & 0.3248 \\ 0.3248 & 0.4375 \end{bmatrix}$ $|\Sigma| = 0.25 \quad \Sigma^{-1} = \begin{bmatrix} 1.75 & -1.259 \\ -1.299 & 3.25 \end{bmatrix}$

$$P(X) = \frac{1}{2\pi \sqrt{0.25}} \exp\left(-\frac{1}{2} \left[X_1 - 3.0, X_2 - 4.0\right] \begin{bmatrix} 1.75 - 1.299 \\ -1.299 & 3.25 \end{bmatrix} \begin{bmatrix} X_1 - 3.0 \\ X_2 - 4.0 \end{bmatrix}\right)$$

5) Let
$$X$$
 be the number of children a family has until they have a body, inclusive. Assume $p(body)=0.5=p(girl)$
 $\frac{1}{2} B - X = 1$

So $P(X=1)=\frac{1}{2}$
 $P(X=2)=\frac{1}{4}$
 $P(X=3)=\frac{1}{8}$

We see that the saries is conveying to a geometric distribution $P(X=K)=(1-p)^{K-1}p$ where $p=\frac{1}{2}$
 $P(X=K)=(1-p)^{K-1}p$ where $p=\frac{1}{2}$

The expected value of a geometrically distributed random variable defined over N is

$$E[X]=\frac{1}{p} + \frac{1}{2} = \frac{1}{2}$$
So the average expected children per family in this V illage is Z . The python script attached simulates N many samples and converges to also Z