## Problem 1

a.) What is the probability that x = 1?

We find the marginal from the joint.

$$p(x) = \sum_{y} p(x, y)$$
$$\frac{1}{4} + \frac{1}{6}; x = 0$$

$$\frac{1}{4} + \frac{1}{3}$$
;  $x = 1$ 

And we can see,

$$Pr(x=1) = \frac{7}{12}$$

b.) What is the probability that x = 1, given y = 1?

From the definition,

$$Pr(x=1|y=1) = \frac{Pr(x=1|y=1)}{Pr(y=1)}$$

From the given table, we can see,

$$\dot{c} \frac{\frac{1}{3}}{\frac{1}{6} + \frac{1}{3}} = \frac{2}{3}$$

And so 
$$Pr(x=1|y=1) = \frac{2}{3}$$

c.) What is the variance of the random variable X?

From the definition,

$$var(X) = E[X^2] - E[X]^2$$

And so we calculate the expectation of X from its definition,

$$E[X] = \sum_{x \neq f(x)} x * f(x)$$

$$\frac{0*5}{12} + \frac{1*7}{12}$$

$$E[X] = \frac{7}{12}$$

Using an alternate definition to calculate variance:

$$var(X) = \sum_{x} (x - \mu)^{2} * p(x)$$

$$\frac{\left(0 - \frac{7}{12}\right)^{2} * 5}{12} + \frac{\left(1 - \frac{7}{12}\right)^{2} * 7}{12}$$

$$\frac{35}{144} = 0.243$$

So then, var(X)=0.243

d.) What is the variance of X, given that y = 1?

We find the conditional expectation of X given that Y = y = 1.

$$E[X|Y=y=1] = \frac{0*1}{3} + \frac{1*2}{3} = \frac{2}{3}$$

Then,

$$var(X|Y=y=1) = \frac{\left(0 - \frac{2}{3}\right)^{2} * 1}{3} + \frac{\left(1 - \frac{2}{3}\right)^{2} * 2}{3}$$

$$\frac{2}{3}$$

e.) What is 
$$E[X^3+X^2+3Y^7|Y=1]$$
 ?

From the linearity of expectation, we have,

$$E[X^3|y=1]+E[X^2|y=1]+3*E[Y^7|y=1]$$

Where the last term is equal to 3. Then we can calculate the moment generating function of the random variable W=g(X) where

$$g(X)=X\vee i$$
 ).

$$M_{w}(s) = E[e^{sW}] = \sum_{w} e^{sW} * f_{w}(w) = e^{s0} * f_{w}(0) + e^{s1} * f_{w}(1)$$

$$M_w(s) = \frac{1}{3} + \frac{2}{3}e^s$$

We can find the second and third moments by taking successive derivatives of the m.g.f., and evaluating them at s=0.

$$\frac{dM}{ds} = \frac{2}{3} * e^{s} \to \frac{2}{3} e^{s}|_{s=0} = \frac{2}{3} = \mu_{1} = E[W^{1}]$$

$$\frac{d^2M}{ds^2} = \frac{d}{ds} \left( \frac{dM}{ds} \right) = \frac{2}{3} * e^s \to \frac{2}{3} e^s |_{s=0} = \frac{2}{3} = \mu_2 = E[W^2]$$

$$\frac{d^{3}M}{ds^{3}} = \frac{d}{ds} \left( \frac{d^{2}M}{ds^{2}} \right) = \frac{2}{3} * e^{s} \to \frac{2}{3} e^{s}|_{s=0} = \frac{2}{3} = \mu_{3} = E[W^{3}]$$

Rewriting our original expression,

$$E[W^3] + E[W^2] + 3*E[Y^7|y=1] = \frac{2}{3} + \frac{2}{3} + 1$$
  
 $\frac{7}{3}$ 

## Problem 2

We have a subspace  $W \subseteq \mathbb{R}^3$  defined by the span of  $v_1$  and  $v_2$ , where

$$v_1 = \langle 1, 1, 1 \rangle$$

$$v_2 = \langle 1, 0, 0 \rangle$$

We wish to find the projection of 3 points (vectors) onto this subspace. Our points are:

$$p_1 = \langle 3,3,3 \rangle$$
  
 $p_2 = \langle 1,2,3 \rangle$   
 $p_3 = \langle 0,0,1 \rangle$ 

We can call the projections of these points  $\widehat{p}_1$ ,  $\widehat{p}_2 \wedge \widehat{p}_3$ . If we have an orthogonal basis for W such as  $\{u_1,u_2\}$ , then we can find these projections by the following formula,

(1) 
$$p_i = \frac{p_i \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{p_i \cdot u_2}{u_2 \cdot u_2} u_2$$

We apply Gram-Schmidt to find the orthogonal basis for W. First, we let  $u_1=v_1$ . Then to find  $u_2$ , we use,

$$u_2 = v_2 - pro j_{v_1} v_2 = v_2 - \frac{v_2 \cdot v_1}{v_1 \cdot v_1} v_1$$

We find that

$$u_2 = \left\langle \frac{2}{3}, \frac{-1}{3}, \frac{-1}{3} \right\rangle$$

With our orthogonal basis in hand, we simply apply formula 1 to each p vector. Doing the calculations in python gives the following results:

$$\widehat{p}_1 = \langle 3, 3, 3 \rangle$$
  
 $\widehat{p}_2 = \langle 2.22, 1.5, 1.5 \rangle$   
 $\widehat{p}_2 = \langle 5.55, 5, 5 \rangle$ 

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In [25]: import numpy as np

p1 = np.ones(3, dtype=np.float)*3
    p2 = np.arange(3, dtype=np.float)
    p3 = np.zeros(3, dtype=np.float) + [0, 0, 1]
    u1 = np.ones(3, dtype=np.float)
    u2 = np.zeros(3, dtype=np.float)
    u2 = np.zeros(3, dtype=np.float) + [2/3, -1/3, -1/3]

p1hat = np.dot(np.dot(p1,u1)/np.dot(u1, u1), u1) + np.dot(np.dot(p1,u2)/np.dot(u2, u2), u2)
    p2hat = np.dot(np.dot(p2,u1)/np.dot(u1, u1), u1) + np.dot(np.dot(p2,u2)/np.dot(u2, u2), u2)
    p3hat = np.dot(np.dot(p3,u1)/np.dot(u1, u1), u1) + np.dot(np.dot(p3,u2)/np.dot(u2, u2), u2)
    print(p1hat, p2hat, p3hat)

[3. 3. 3.] [2.22044605e-16 1.500000000e+00 1.50000000e+00] [5.55111512e-17 5.00000000e-01 5.00000000e-01]
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## Problem 3

We know that  $Pr(Heads) = \frac{2}{3}$  and therefore  $Pr(Tails) = \frac{1}{3}$ . We wish to know the probability of getting 50 heads or fewer in 100 tosses.

This can be represented in a binomial distribution, as the probability of 50 or fewer successes in 100 trials.

Then we know that the expected value of the distribution is:

$$n*p = 66.67$$
.

From this, the standard deviation is given by:

$$\sqrt{np(1-p)} = \sqrt{\frac{\frac{100*2}{3}*1}{3}} = 4.714$$

Using a normal approximation and applying the central limit theorem:

$$Pr(heads < 50) = Pr\left(z < \frac{50 - 66.67}{4.714}\right) = Pr(z \leftarrow 3.53)$$

$$\vdots 0.0001$$

To check our answer, you can also sum the binomial distributions evaluated at 1 through 50:

$$Pr(heads \le 50) = \sum_{i=1}^{50} {100 \choose i} \left(\frac{2}{3}\right)^i \left(1 - \frac{2}{3}\right)^{100-i}$$

This calculation was done in python and resulted in the same answer.

```
In [8]: import numpy as np
    from scipy import special as sp

p = 2/3
    n = 100
    probability_array = np.zeros(50)

for i in range (50):
        probability_array[i] = sp.comb(n, i)*(p**i)*((1-p)**(n-i))
        #print(probability_array[i])

print("The sum of all these probabilities is: {}".format(np.sum(probability_array)))

The sum of all these probabilities is: 0.0001989326425396602
```