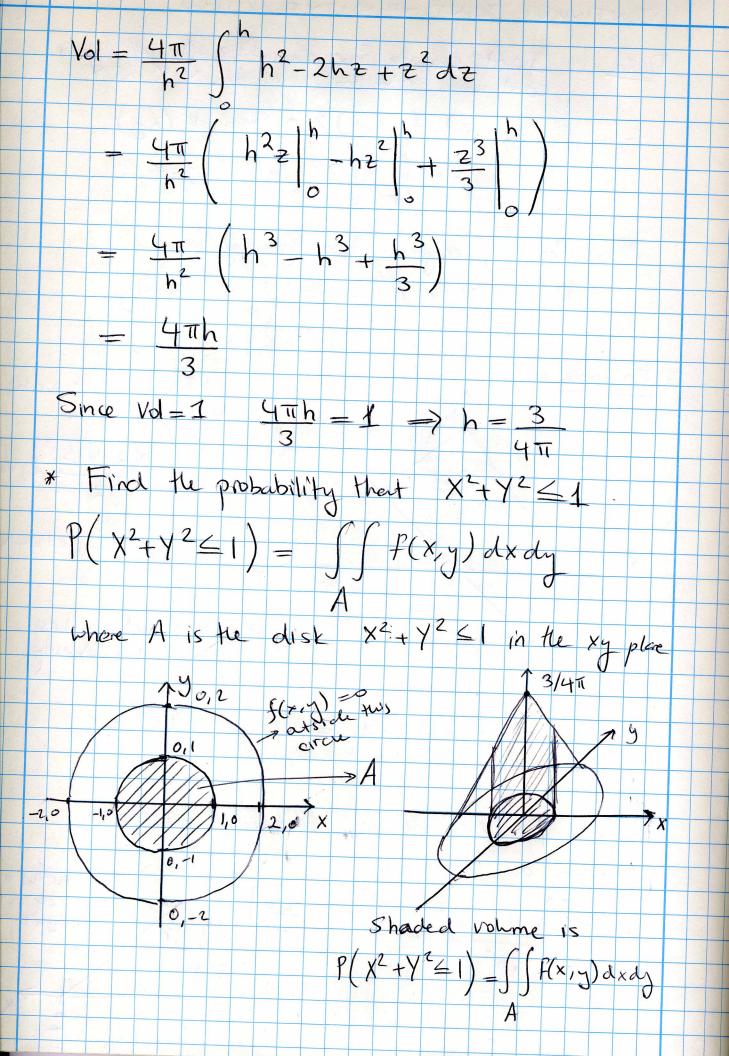
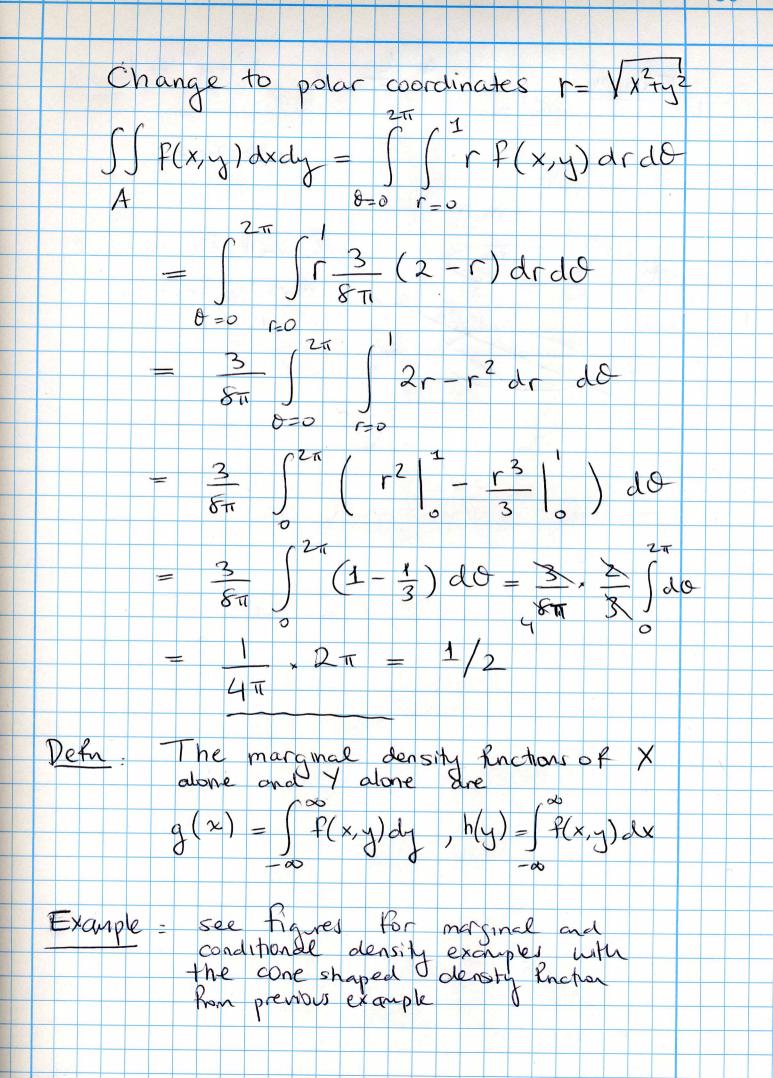
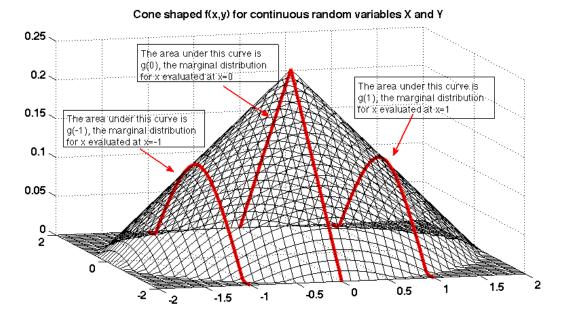
CONTINUOUS JOINT DENSITY FUNCTION

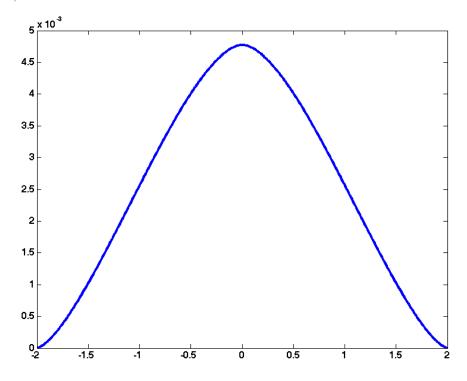
Joint density Rinction f(2, y) of the continuous random variables X and Y Detn = a) f(x,y) >0 for all (x,y) b)  $\int \int f(x, y) dx dy = 1$ For any region A in the xy plane  $P[(X,Y) \in A] = \int F(x,y) dxdy$ A150 A Example : f(xy) shaped like a cone h  $f(x,y) = \begin{cases} h(2 - \sqrt{x^2 + y^2}), \sqrt{x^2 + y^2} \le 2 \end{cases}$ ZE (-2, 3) X ( 0, elseuhere Area at (0, -2) Find h that makes f(x, y) a valid density  $\int \infty \int \infty F(x,y) dx dy = Volume under cone$  $= \int (Area of circle at height z) dz$  $= \int \frac{4\pi(h-2)^2}{h^2} dz = \int \frac{\pi}{2} \frac{h-2}{h-2} \frac{h}{h-2} \frac{\pi}{n}$   $= \int \frac{4\pi(h-2)^2}{h^2} dz = \int \frac{\pi}{2} \frac{h-2}{h-2} \frac{h}{n}$   $= \int \frac{4\pi(h-2)^2}{h^2} dz = \int \frac{\pi}{2} \frac{h}{n} \frac{h}{n}$ > Rachis of circle at height Z 2 \* 7 ×



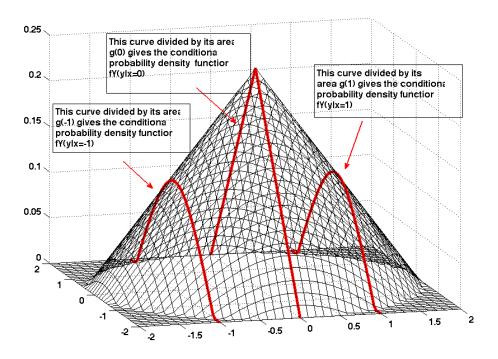




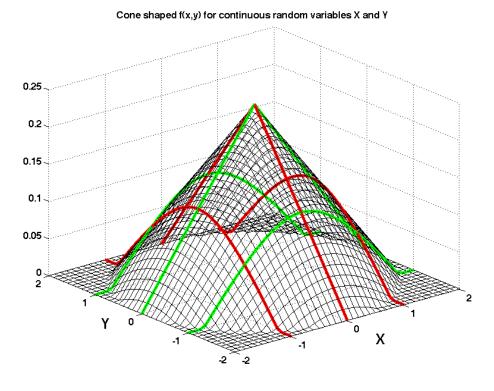
The areas under the red curves are the values for the marginal distribution g(x) evaluated at x=-1, x=0 and x=1



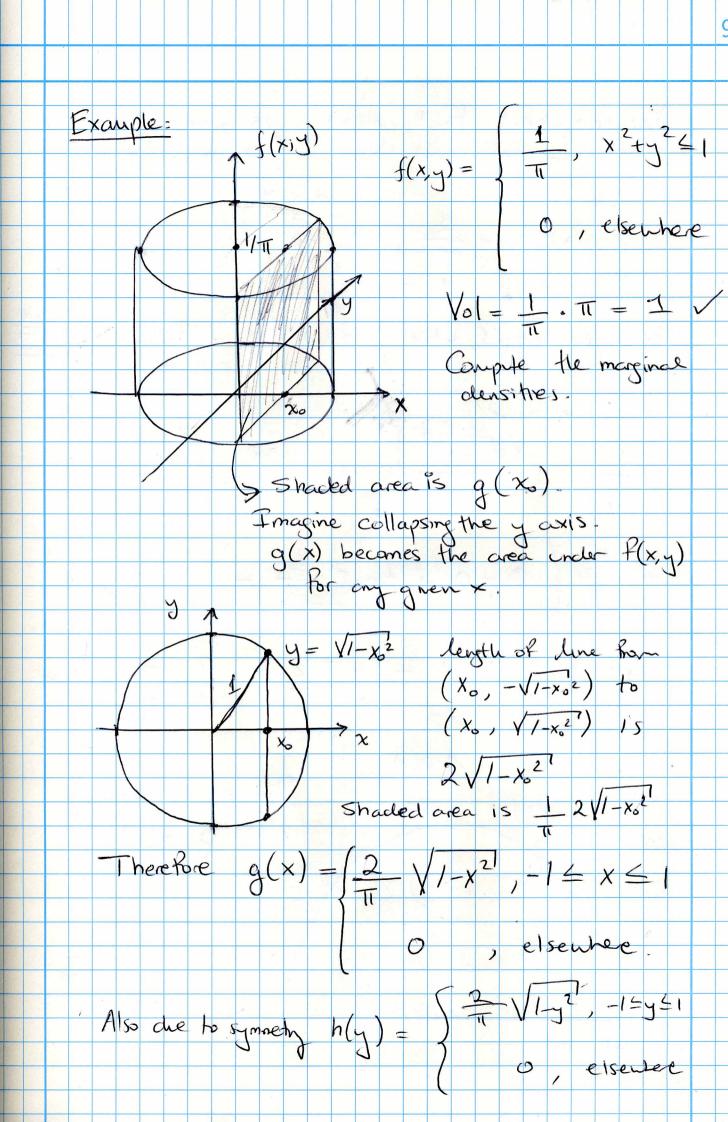
If we draw the red curves at each value of x, and for each compute the area underneath, we get the marginal distribution g(x) which we can then plot as a graph.

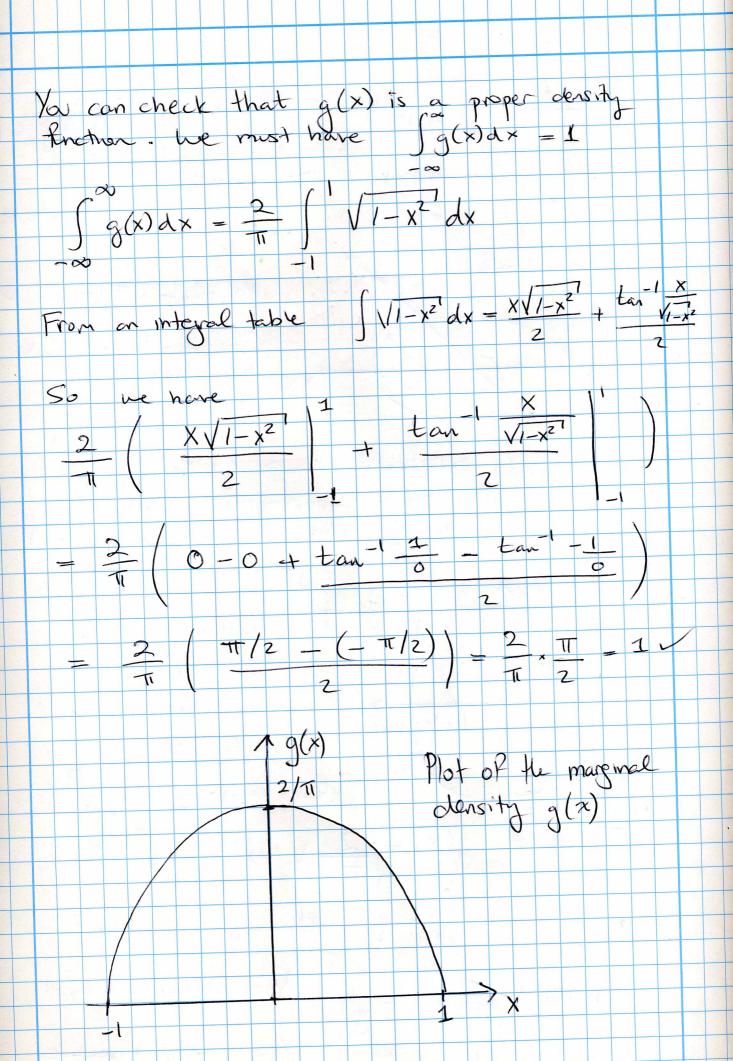


Once normalized by dividing with the appropriate value of g(x), the red curves are the conditional densities  $f_Y(y|x=-1)$ ,  $f_Y(y|x=0)$  and  $f_Y(y|x=1)$ .



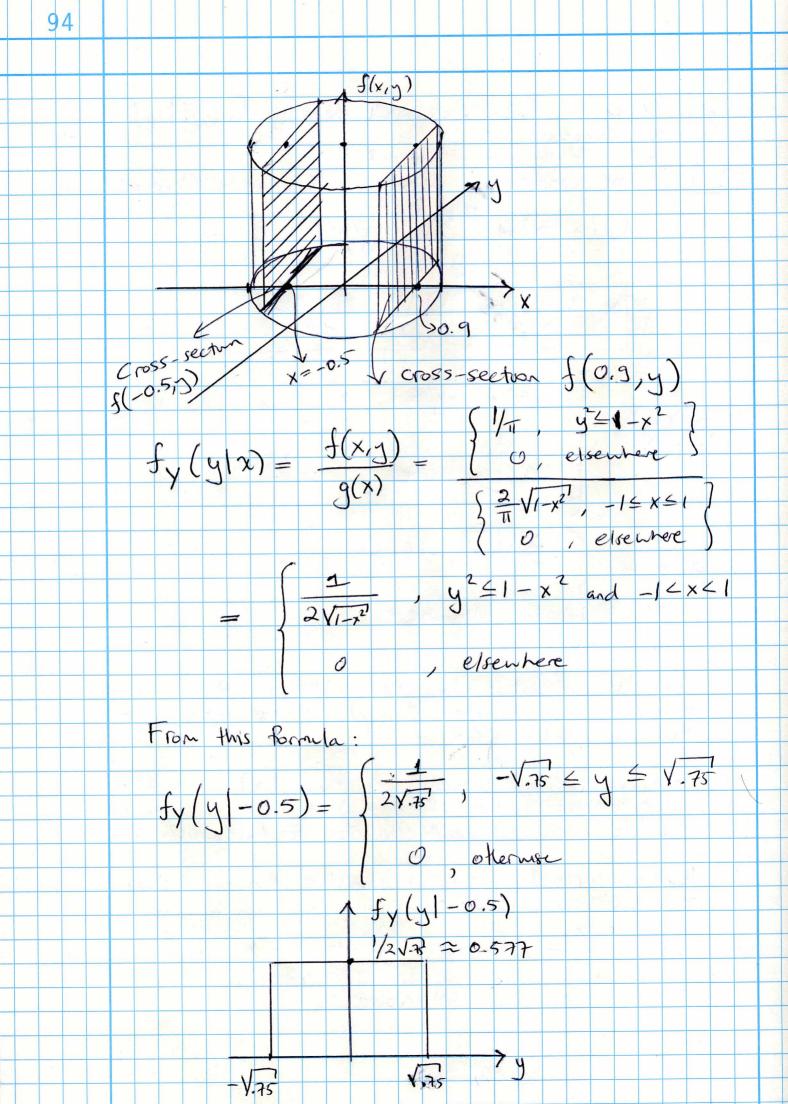
The areas under the green curves are the values for the marginal distribution h(y) evaluated at y=-1, y=0 and y=1. Again if we normalize these curves by dividing with the appropriate value of h(y), the green curves become the conditional densities  $f_X(x|y=-1)$ ,  $f_X(x|y=0)$ and  $f_X(x|y=1)$ .

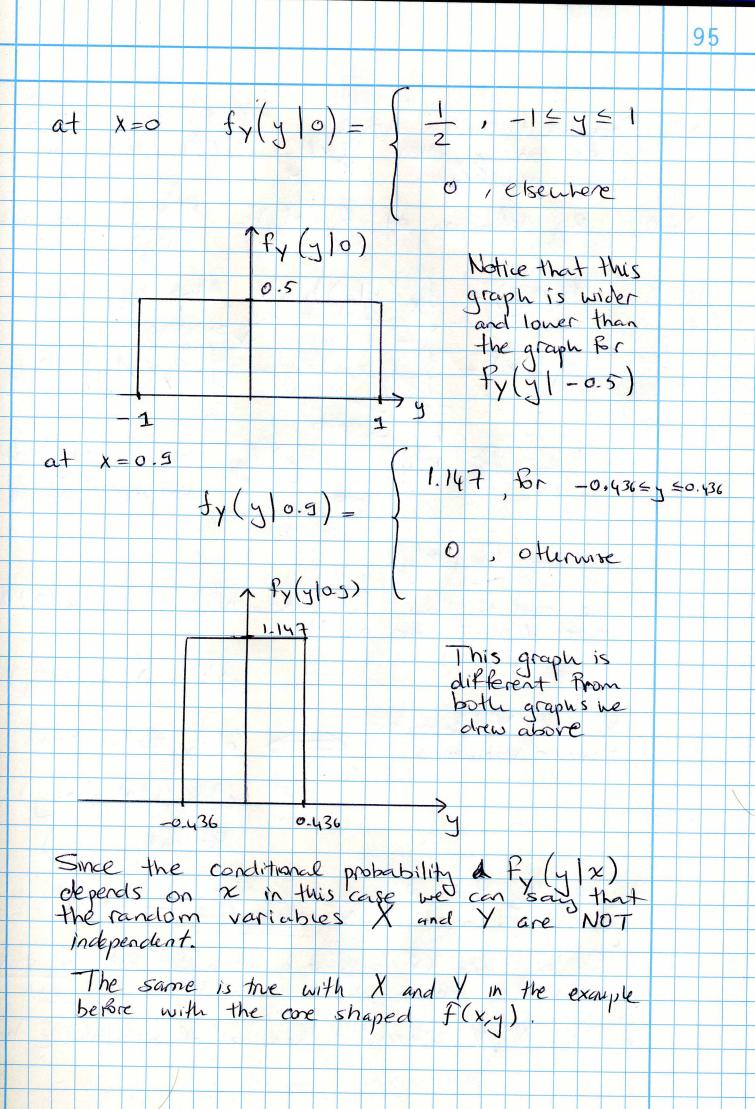




Lets compte the conditional density fy (y/x) for our example. Defu = The conditional density Ructions are defined as  $f_{y}(y|x) = \frac{P(x,y)}{g(x)}, g(x) > 0$  $f_{\mathbf{X}}(\mathbf{x}|\mathbf{y}) = \frac{\tilde{\mathbf{P}}(\mathbf{x},\mathbf{y})}{h(\mathbf{y})}, h(\mathbf{y}) > 0$  $F(x,y) = \begin{cases} \frac{1}{\pi}, x^2 + y^2 \leq 1\\ \frac{1}{\pi}, x^2 + y^2 \leq 1\\ 0, elsewhere \end{cases}$  $g(x) = \begin{cases} \frac{2}{\pi} \sqrt{1-x^2}, -1 \le x \le 1 \\ 0, \text{ elsewhere} \end{cases}$ a) From the definition  $f_{Y}(y|x)$  is defined only for those values of x for which g(x) > 0. For an example this is  $-1 \le x \le 1$ . b) Once we fix a particular x, Fy(y|x) at that x is the cross-section of f(x,y) at that x pormalized by the area inderneath the cross-section which is g(x)With & Fixed we can have the formula Br the Cross-section  $\frac{1}{\pi} \quad \text{for } y^2 \leq 1 - x^2$ o otherwise.

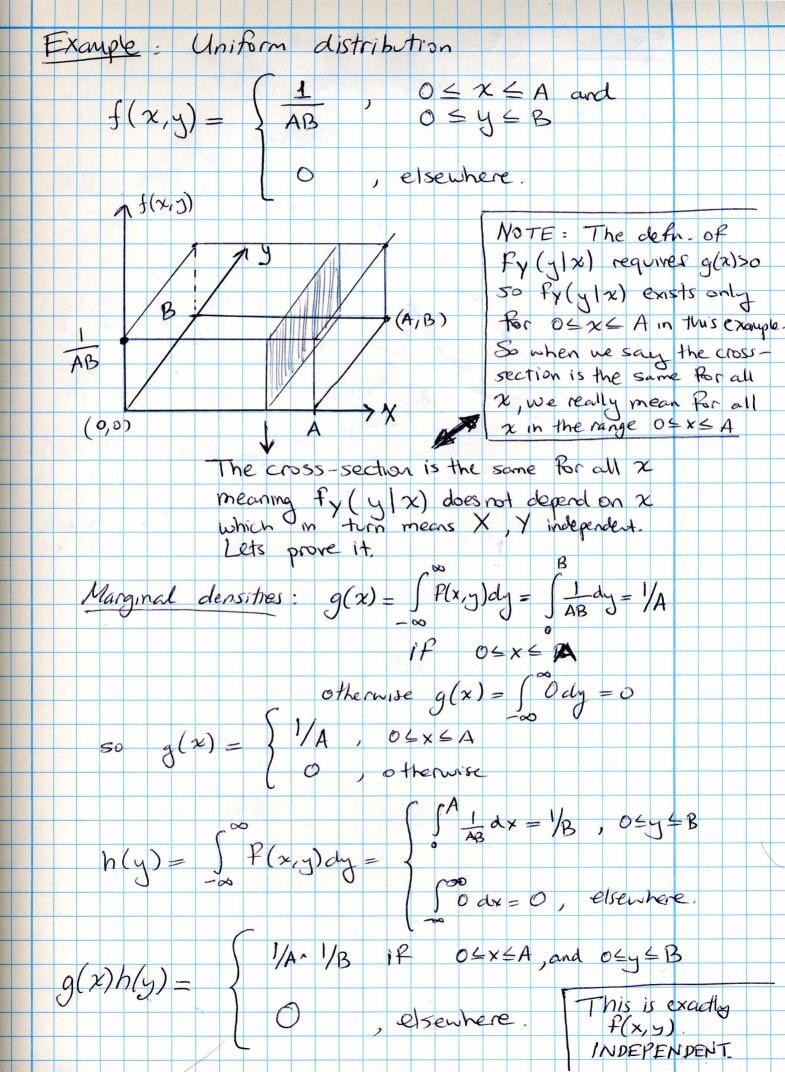
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Pehn Independent random variables. If  $f_x(x|y)$  does not depend on y, then f(x|y) = g(x) and also f(x,y) = g(x)h(y). <u>Proof</u> By definition of  $f_X(x|y) = \frac{F(x,y)}{h(y)}$  we get  $f(x,y) = f_x(x|y)h(y)$ . Also by defn.  $\int y = \int x(x|y)h(y) dx$  $g(x) = \int f(x,y) dy = \int f(x|y) h(y) dy$  $= f_{X}(x|y) \int h(y) dy \quad \text{since } f_{X}(x|y) dses$   $= f_{X}(x|y) \int h(y) dy \quad \text{since } f_{X}(x|y) dses$   $= f_{X}(x|y) \quad 1$ Same proof to show  $f_{Y}(y|x) = h(y)$  if  $f_{Y}(y|x)$  does Not depend on x. a) f'(x,y) = g(x)h(y)X and Y independent (x, y) = g(x)random variables (x, y) = g(x)c)  $f_{Y}(y|x) = h(y)$ for all (x,y)\* Showing one of a, b or c holds for all (x,y) is enagh to prove X, Y independent \* Showing one of a b or c does Not hold for some (x,y) Jis meno enough to show X, Y dependent \* If X, Y independent then all of a, b and c hold



**Example:** Let X and Y denote the position of an electron in the 2 dimensional Cartesian plane. Due to the uncertainty principle X and Y can't be measured exactly and are random variables. You are told that the measurement along the X-axis is independent from the measurement along the Y-axis. Furthermore, let X have a normal marginal density function with  $\mu_X$ ,  $\sigma_X$  and let Y have a normal marginal density function with  $\mu_Y$ ,  $\sigma_Y$ . What is the joint density function for X, Y? **Solution:** The marginal density function for X is

$$g(x) = \frac{1}{\sqrt{2\pi\sigma_X}} e^{-\frac{(x-\mu_X)^2}{2\sigma_X^2}}$$

The marginal density function for Y is

$$h(y) = \frac{1}{\sqrt{2\pi\sigma_Y}} e^{-\frac{(y-\mu_Y)^2}{2\sigma_Y^2}}$$

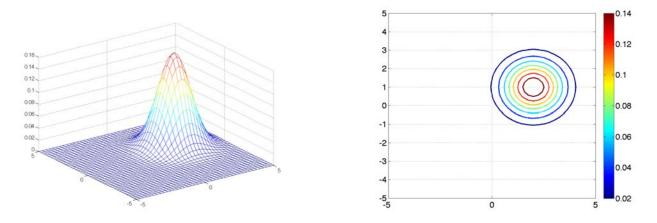
Using independence, we have f(x, y) = g(x)h(y), so:

$$f(x,y) = \frac{1}{\sqrt{2\pi\sigma_X}} e^{-\frac{(x-\mu_X)^2}{2\sigma_X^2}} \frac{1}{\sqrt{2\pi\sigma_Y}} e^{-\frac{(y-\mu_Y)^2}{2\sigma_Y^2}} = \frac{1}{2\pi\sigma_X\sigma_Y} e^{-\frac{(x-\mu_X)^2}{2\sigma_X^2} - \frac{(y-\mu_Y)^2}{2\sigma_Y^2}}$$

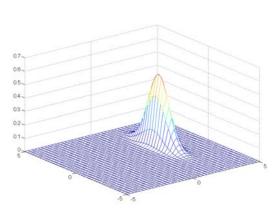
If we have  $\sigma_X = \sigma = \sigma$ , the joint density simplifies to

$$f(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-\mu_X)^2 + (y-\mu_Y)^2}{2\sigma^2}}$$

Here is what the joint density function f(x, y) looks like for  $\mu_X = 1$ ,  $\mu_Y = 2$  and  $\sigma_X = \sigma_Y = 1$ .



f(x, y) Contours of constant probability. Here is what the joint density function f(x, y) looks like for  $\mu_X = 1$ ,  $\mu_Y = 2$  and  $\sigma_X = 0.3$ ,  $\sigma_Y = 1$ .



f(x,y)

Contours of constant probability.

In this case there is more uncertainty in the Y position than the X position.

