

1) A_1, A_2 - indep. A_2, B

$$p(A_1 \cap A_2 | B) = p(A_1 | B) \cdot p(A_2 | B)$$

$$p(A_1 \cap A_2) = p(A_1 | A_2) \cdot p(A_2) \quad \text{True}$$

product rule

2) A, B - ind. \bar{A}, \bar{B} - ind(?)

$$p(\bar{A} \cap \bar{B}) = p(\overline{A \cup B}) = 1 - p(A \cup B)$$

$$p(\bar{A} | \bar{B}) \cdot p(\bar{B})$$

$$p(\bar{A}) p(\bar{B})$$

3) R t - test, S - sick
"0, 1" "0, 1"

$$p(t | s) = 0.99$$

$$p(\bar{t} | \bar{s}) = 0.99$$

$$p(s) = 0.01$$

$$\sum_{s, \bar{s}} p(t, s)$$

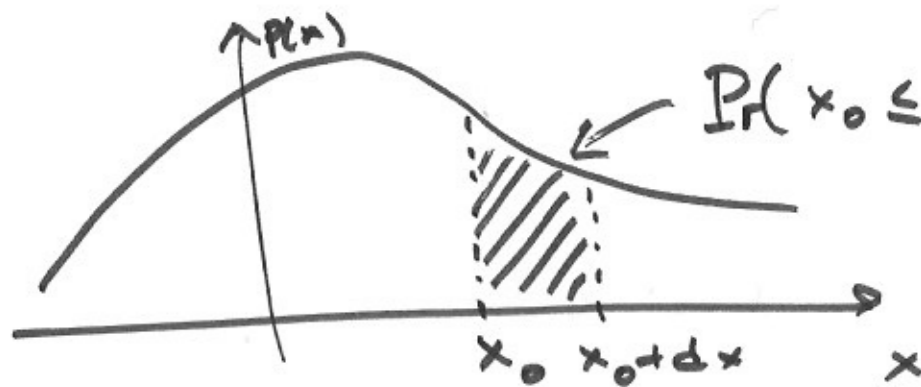
marginalising

$$p(s | t) = \frac{p(t | s) \cdot p(s)}{p(t)}$$

$$= \frac{0.99 \cdot 0.01}{0.99 \cdot 0.01 + 0.01} = \frac{1}{2}$$

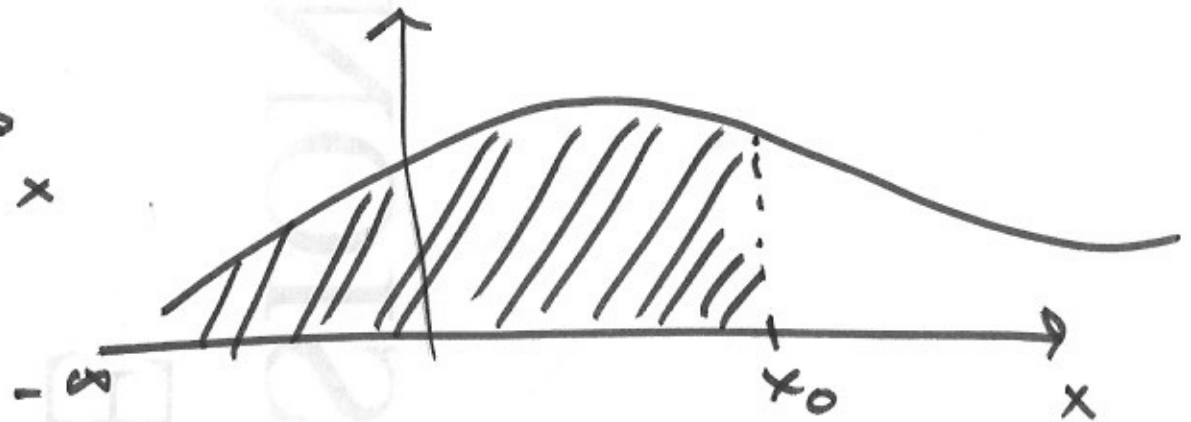
$$p(t) = p(t | s) \cdot p(s) + p(t | \bar{s}) \cdot p(\bar{s})$$

(1)



probability
density function
(pdf)

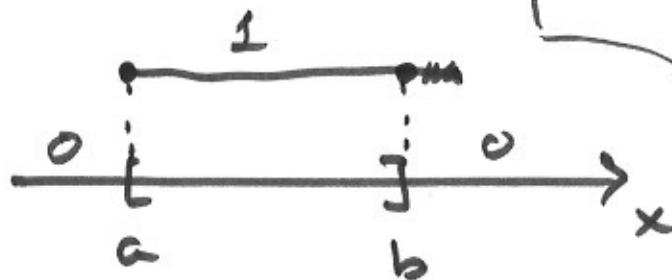
$$Pr(x_0 \leq x \leq x_0 + dx) = p(x) \cdot dx$$



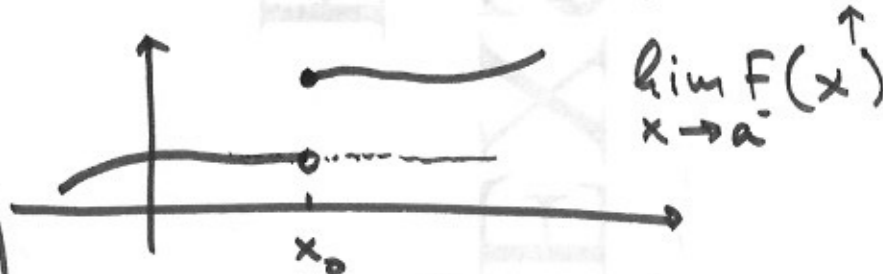
distribution function
= cumulative probability
density $P(x_0) = \int_{-\infty}^{x_0} p(x) dx$
 $Pr(x \leq x_0)$

Problem 2

$I_{[a,b]}(t)$
indicator
function

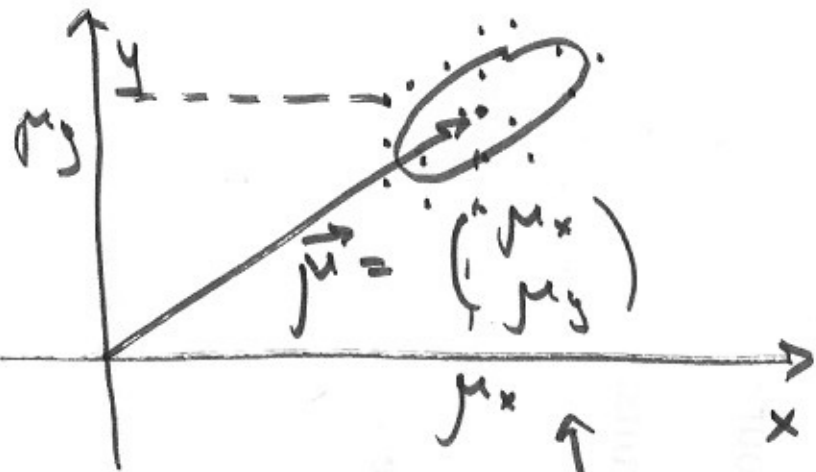


$$1) Pr([a, b]) = F(b) - F(a-) \quad \text{True}$$

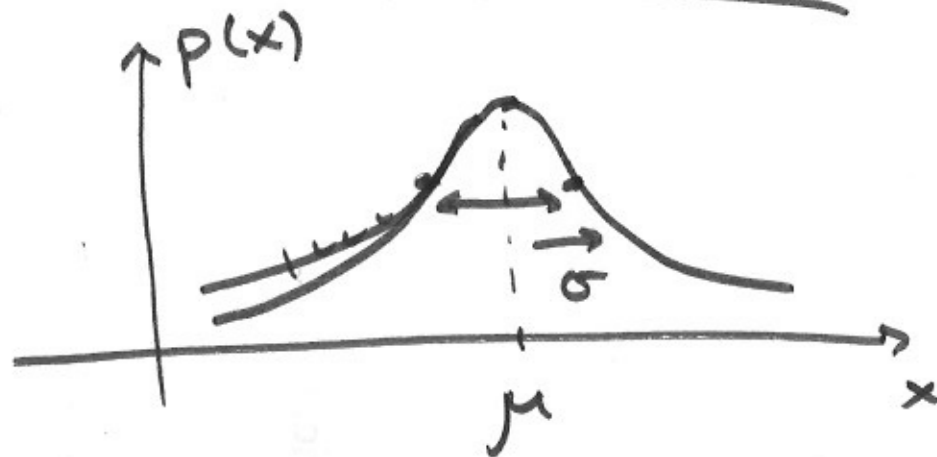


$$4) Pr(\{x\}) = F(x) - F(x-) \quad \text{True} \quad (2)$$

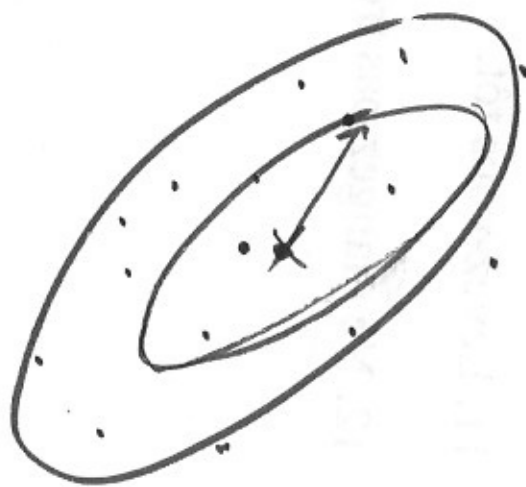
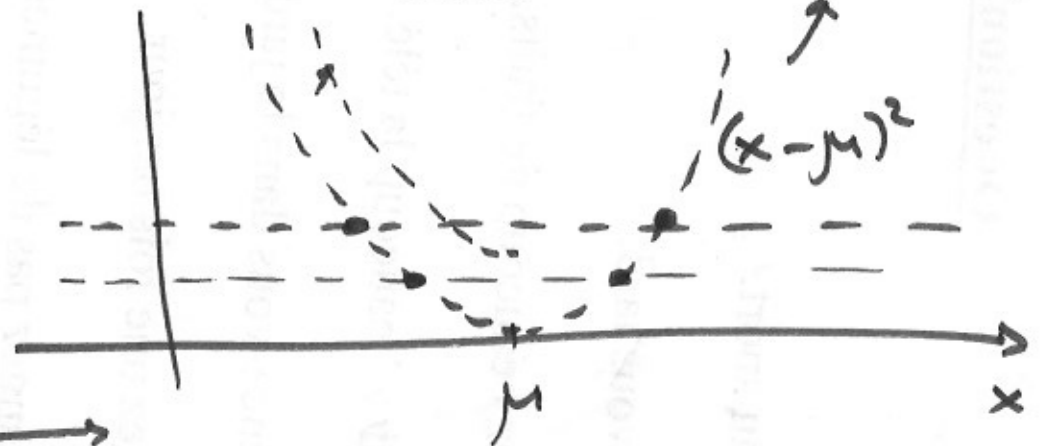
2-dimensional Normal distribution



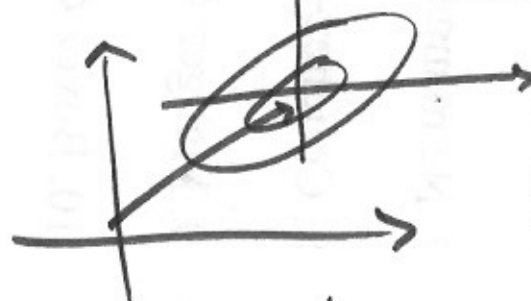
$x, y \rightarrow x_1, x_2,$



$$p(x | \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$



level sets

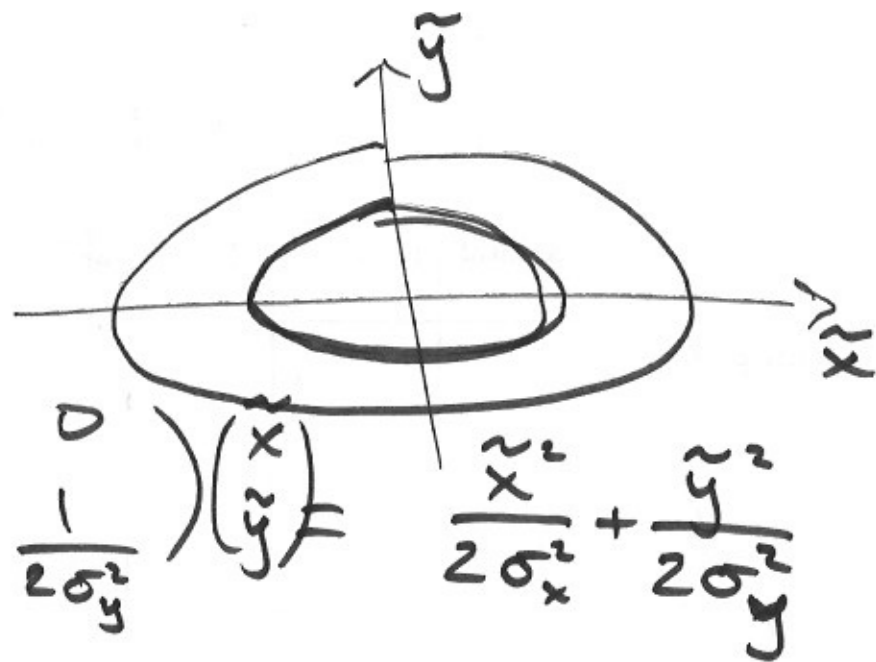


$$x, y \rightarrow \begin{aligned} \tilde{x} &= x - \mu_x \\ \tilde{y} &= y - \mu_y \end{aligned}$$

$$\mu_x = \frac{1}{n} \sum_i x_i, \quad \mu_y = \frac{1}{n} \sum_i y_i$$

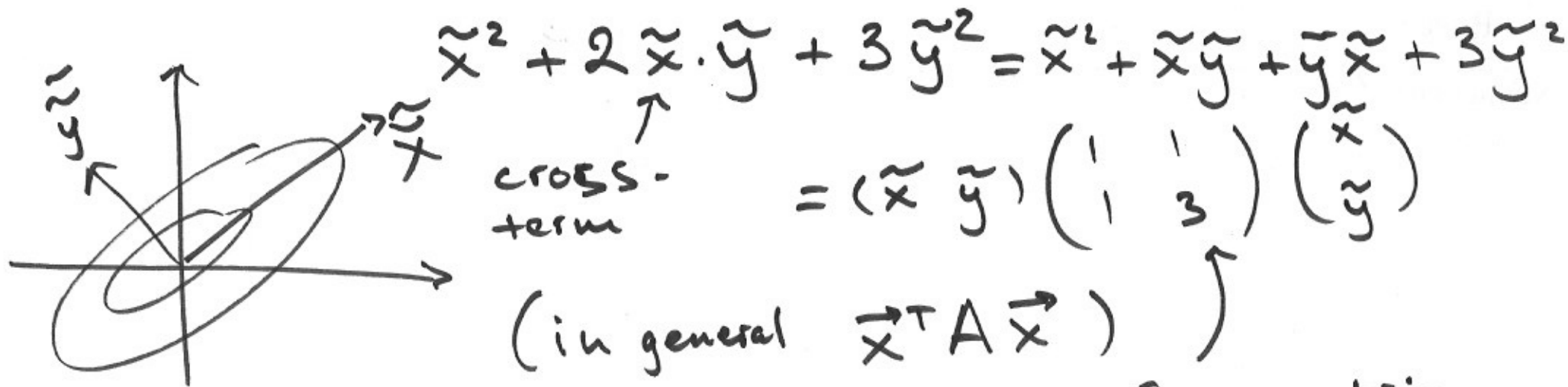
$$- \left(\frac{(x - \mu_x)^2}{2\sigma_x^2} + \frac{(y - \mu_y)^2}{2\sigma_y^2} \right)$$

$f(x, y)$



$$\begin{pmatrix} \tilde{x} & \tilde{y} \end{pmatrix} \begin{pmatrix} \frac{1}{2\sigma_x^2} & 0 \\ 0 & \frac{1}{2\sigma_y^2} \end{pmatrix} \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$$

Quadratic form



$$= \begin{pmatrix} \tilde{x} & \tilde{y} \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$$

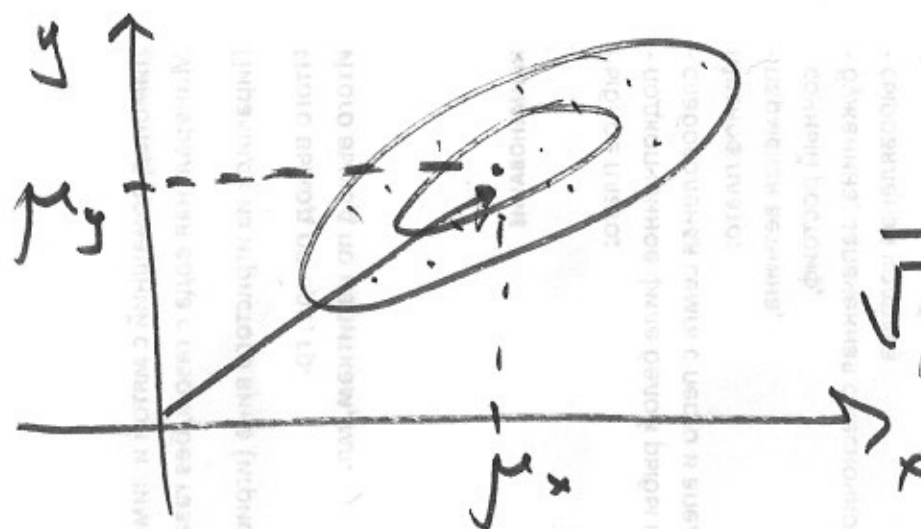
(in general $\vec{x}^T A \vec{x}$)

Symmetric

\tilde{x}, \tilde{y}

I need a positive-definite quadratic form

(4)



$$\frac{1}{\sqrt{(2\pi)^2}}$$

$$\Sigma = \begin{pmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{pmatrix}$$

covariance matrix

$$p(x, y) = \frac{1}{\sqrt{(2\pi)^2} |\Sigma|} \exp\left(-\frac{1}{2} \begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix} \right)^T \Sigma^{-1} \left(\begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix} \right)$$

precision matrix

$$= \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\right)$$

$$\left[\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2} - \frac{2\rho(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y} \right]$$

(5)

$$p(\vec{x} | \vec{\mu}, \Sigma) =$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T \Sigma^{-1} (\vec{x} - \vec{\mu})\right)$$

$$\det \Sigma = \prod \sigma_i^2$$

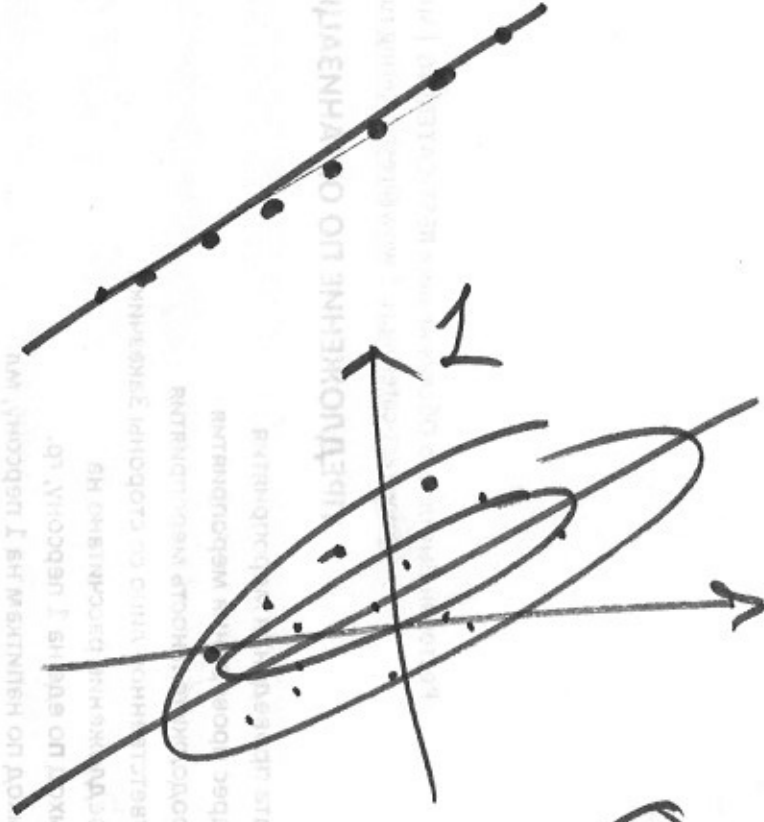
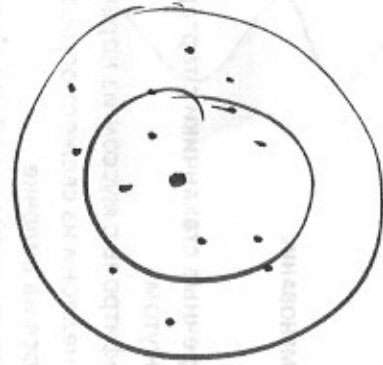
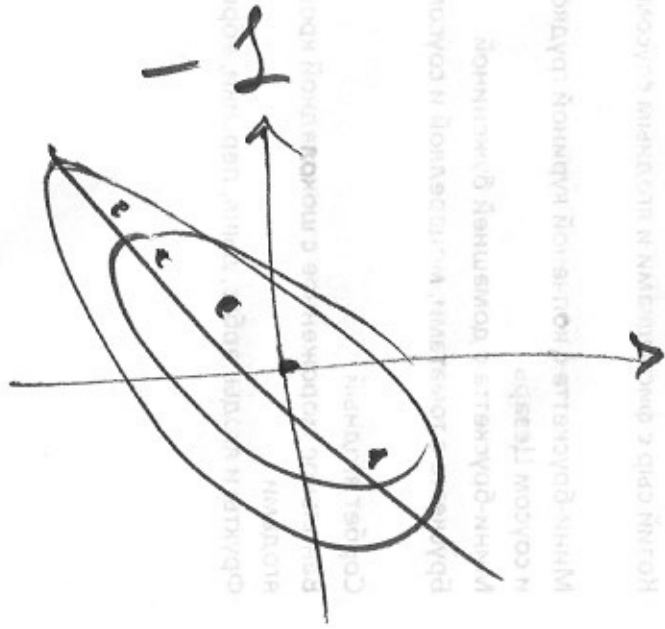
$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

$$\begin{pmatrix} \sigma_1^2 \\ \sigma_2^2 \\ \vdots \\ \sigma_n^2 \end{pmatrix}$$

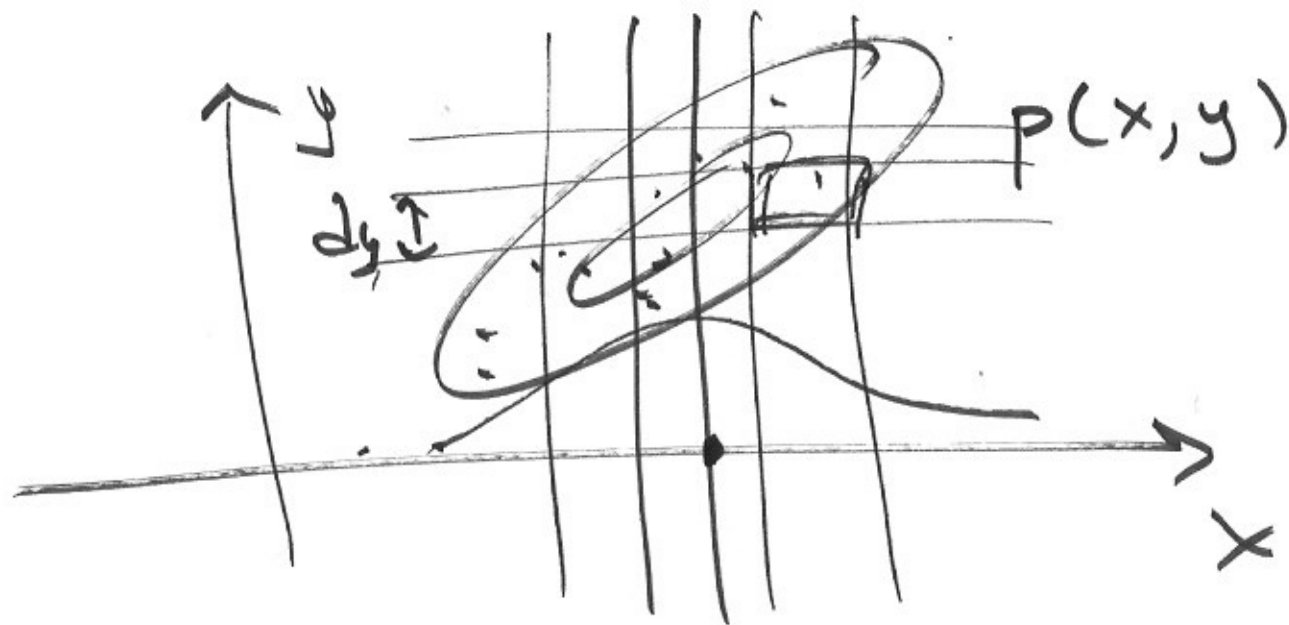
ρ - Pearson correlation coefficient

$$\rho = \frac{\sum_i (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{(\sum_i (x_i - \bar{x})^2) \cdot (\sum_i (y_i - \bar{y})^2)}}$$

$$-1 \leq \rho \leq 1$$



(6)



1) Marginalise over y

$$\int_{-\infty}^{+\infty} dy \cdot p(x, y) = p(x) \quad \begin{matrix} \uparrow \\ \text{also normal} \end{matrix} \quad (1D)$$

2) Take conditional

$$p(x|y) = \frac{p(x, y)}{\int dx p(x, y)} \quad \text{also normal} \quad (1D)$$