

# PROBABILISTIC MODELING AND BAYESIAN NETWORKs

## *Probability Distributions*





There are many distributions available; for each application we have to select the most appropriate

## DOMAIN

- Categorical, Ordinal or Continuous
- Bounded or Unbounded

## SHAPE

- Parameter-dependant
- Represented by the **moments**
- Best known: mean and variance

## MOMENTS AROUND 0

$$\mu'_k = E[X^k] = \int_{-\infty}^{\infty} x^k f(x) dx$$

## MOMENTS AROUND MEAN

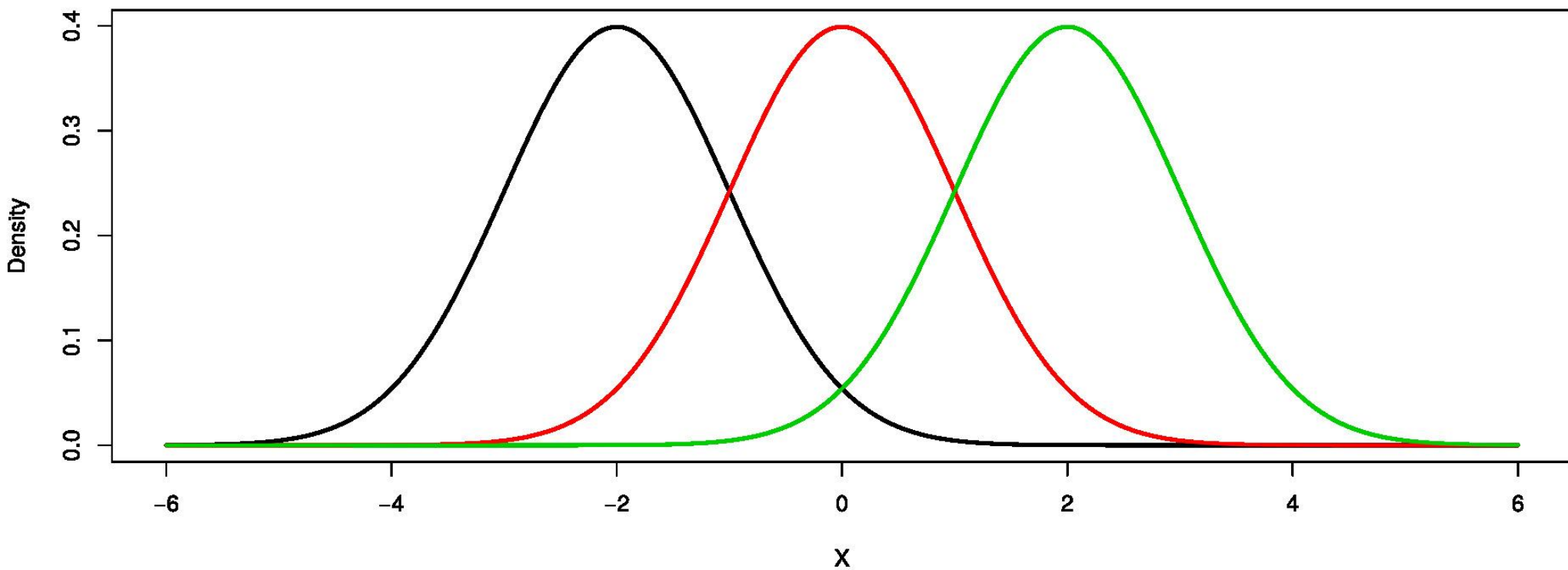
$$\mu_k = E[(X - \mu'_1)^k] = \int_{-\infty}^{\infty} (x - \mu'_1)^k f(x) dx$$

## SAMPLE MOMENTS

$$m'_k = \frac{1}{n} \sum_{i=1}^n x_i^k \qquad m_k = \frac{1}{n} \sum_{i=1}^n (x_i - m'_1)^k$$

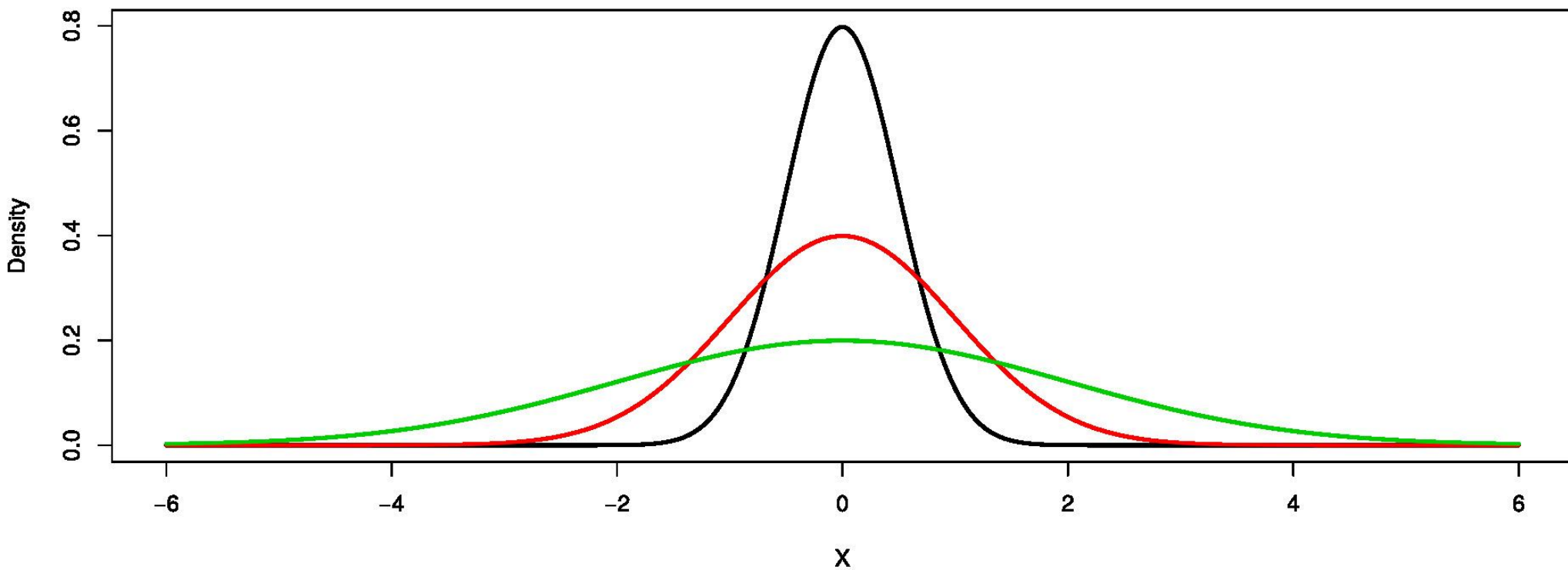
1<sup>ST</sup> MOMENT: MEAN

Information about the **LOCATION**



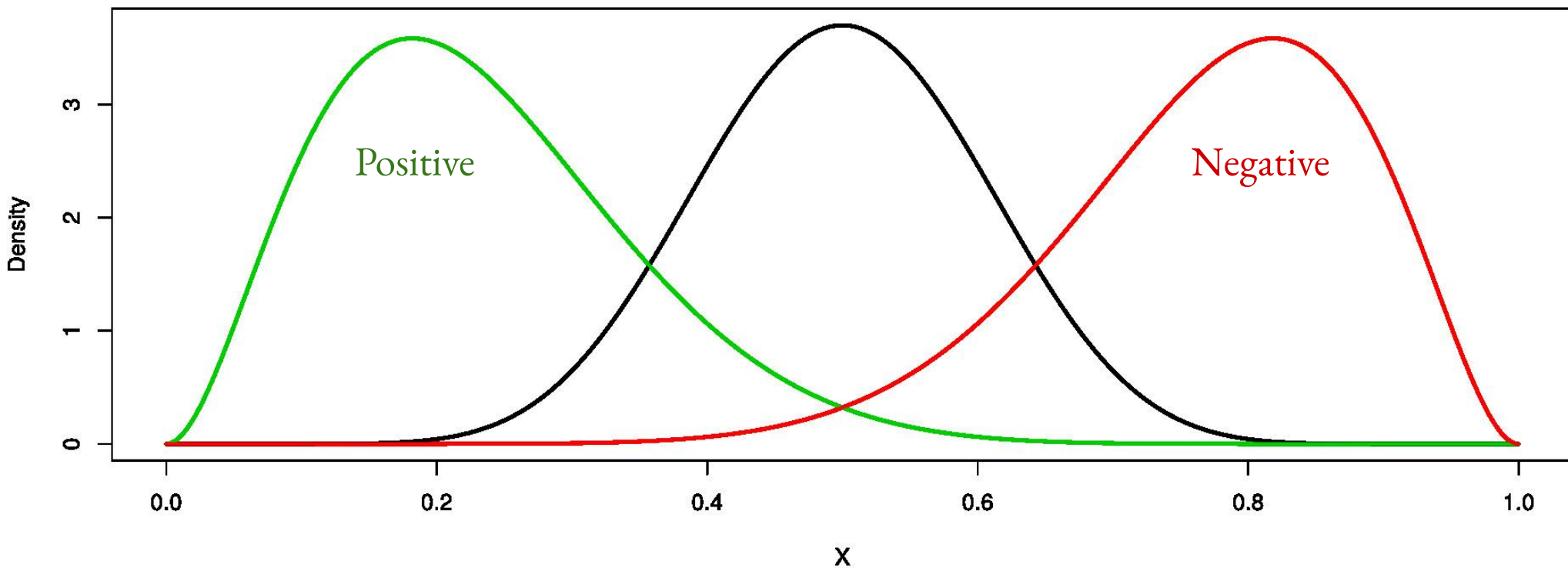
2<sup>ND</sup> MOMENT: VARIANCE

Information about the **SPREADNESS**



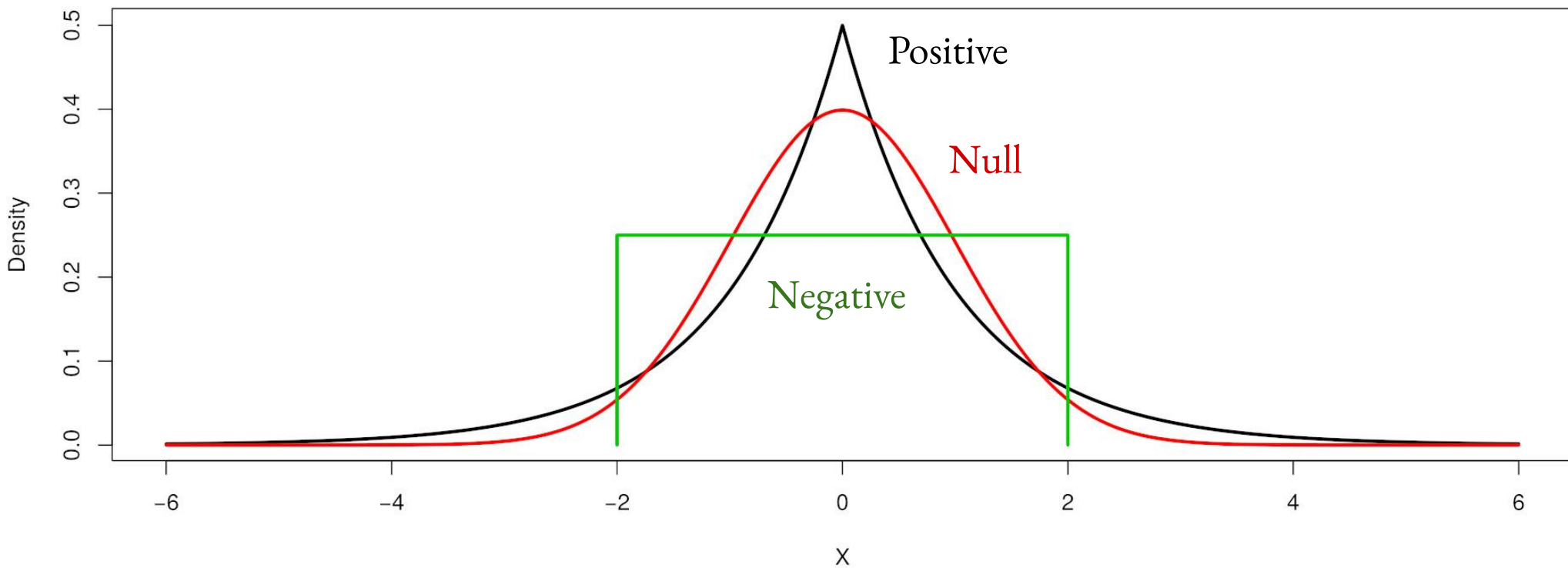
# 3<sup>RD</sup> MOMENT: SKEWNESS

Information about the **SYMMETRY**



# 4<sup>TH</sup> MOMENT: KURTOSIS

Information about the tendency to produce  
**OUTLIERS**



# SOME USEFUL PROPERTIES

## EXPECTATION

$$E[aX + bY + c] = aE[X] + bE[Y] + c$$

## VARIANCE

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

$$VAR(c) = 0$$



# PROBABILITY DISTRIBUTIONS

*Discrete Variables*



# MULTINOMIAL DISTRIBUTION

Probability distribution associated to categorical variables (discrete values with no particular order)

DOMAIN  $X \in \{1, \dots, r\}$

PARAMETERS  $0 \leq p_1, \dots, p_r \leq 1; \sum_{i=1}^r p_i = 1$

FUNCTION  $P(X = x_i) = p_i$

SPECIAL CASES Bernoulli distribution (r=2)  
Uniform distribution

# BINOMIAL DISTRIBUTION

In a sample of size  $n$  drawn from a Bernoulli distribution, the binomial counts the number of outcomes of a certain type

DOMAIN  $X \in \{0, 1, \dots, n\}$

PARAMETERS  $n \geq 0; 0 \leq p \leq 1$

FUNCTION  $P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$

MOMENTS  $\mu'_1 = np; \mu_2 = np(1 - p)$

# HYPERGEOMETRIC DISTRIBUTION

In a set of  $N$  elements there are  $M$  of a special type. If we draw  $n$  elements without replacement, this variable counts the number of elements of the special type

DOMAIN

$$\max\{0, M - N + n\} \leq X \leq \min\{n, N\}$$

PARAMETERS

$$N \geq 0; 0 \leq M \leq N; 0 \leq n \leq N$$

FUNCTION

$$P(X = k) = \frac{\binom{M}{k} \binom{N-M}{n-k}}{\binom{N}{n}}$$

MOMENTS

$$\mu'_1 = \frac{nM}{N}; \mu_2 = \frac{nM}{N} \left(1 - \frac{M}{N}\right) \frac{N-n}{N-1}$$

# POISSON DISTRIBUTION

This distribution counts the number of events that happen in a certain period of time as long as the event rate is constant and events are independent

DOMAIN  $X \in \{0, 1, 2, \dots\}$

PARAMETERS  $\lambda > 0$

FUNCTION  $P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}$

MOMENTS  $\mu'_1 = \lambda; \mu_2 = \lambda$

# PROBABILITY DISTRIBUTIONS

*Continuous Variables*



# NORMAL DISTRIBUTION

This distributions represents many natural situations. In particular, it represents the distribution of the sum of random iid samples.

DOMAIN  $X \in \mathbb{R}$

PARAMETERS  $\mu \in \mathbb{R}; \sigma > 0$

FUNCTION  $f(X = x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

MOMENTS  $\mu'_1 = \mu; \mu_2 = \sigma^2$

# GAMMA DISTRIBUTION

Given a Poisson distribution, the time until the  $a$ -th event happens is represented by this type of distribution

DOMAIN  $X > 0$

PARAMETERS  $a > 0; b > 0$

FUNCTION  $f(X = x) = \frac{1}{\Gamma(a)b^a} e^{-\frac{x}{b}} x^{(a-1)}$

MOMENTS  $\mu'_1 = ab; \mu_2 = ab^2$



# BETA DISTRIBUTION

This distribution represents the ratio between two Gamma variables. Its main interest is that it is bounded between 0 and 1

DOMAIN  $0 \leq X \leq 1$

PARAMETERS  $a > 0; b > 0$

FUNCTION  $f(X = x) = \frac{1}{Beta(\alpha, \beta)} x^{\alpha-1} (1 - x)^{\beta-1}$

MOMENTS  $\mu'_1 = \frac{\alpha}{\alpha + \beta}; \mu_2 = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}$

# CHI SQUARE DISTRIBUTION

This distribution represents the sum of  $n$  Gaussian distributed variables with mean 0 and variance 1. It is used to model variance. It is also used in some statistical tests

DOMAIN  $X > 0$

PARAMETERS  $n > 0$

FUNCTION 
$$f(X = x) = \frac{1}{2^{n/2} \Gamma(n/2)} e^{-x/2} x^{n/2-1}$$

MOMENTS 
$$\mu'_1 = n; \mu_2 = 2n$$

# PROBABILITY DISTRIBUTIONS

*Random vectors*



# BIVARIATE NORMAL DISTRIBUTION

Extension of the Gaussian distribution to two dimensions

DOMAIN  $(X, Y) \in \mathbb{R}^2$

PARAMETERS  $\mu = \begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix} \quad \Sigma = \begin{pmatrix} \sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_X\sigma_Y & \sigma_Y^2 \end{pmatrix}$

FUNCTION 
$$f(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} e^{-a}$$
$$a = -\frac{1}{2(1-\rho^2)} \left[ \left( \frac{x-\mu_X}{\sigma_X} \right)^2 - 2\rho \left( \frac{x-\mu_X}{\sigma_X} \right) \left( \frac{y-\mu_Y}{\sigma_Y} \right) + \left( \frac{y-\mu_Y}{\sigma_Y} \right)^2 \right]$$

The marginals of the bivariate distribution are Gaussian distributions

# JOINT MOMENTS, BIVARIATE CASE

## FIRST ORDER

$$E[X] = \int_{\Omega_X} \int_{\Omega_Y} x f(x, y) dx dy \quad E[Y] = \int_{\Omega_X} \int_{\Omega_Y} y f(x, y) dx dy$$

## SECOND ORDER

$$E[X^2] = \int_{\Omega_X} \int_{\Omega_Y} x^2 f(x, y) dx dy \quad E[Y^2] = \int_{\Omega_X} \int_{\Omega_Y} y^2 f(x, y) dx dy$$

$$E[XY] = \int_{\Omega_X} \int_{\Omega_Y} xy f(x, y) dx dy$$

## SECOND ORDER AROUND THE MEAN: COVARIANCE

$$E[(X - E[X])(Y - E[Y])] = \int_{\Omega_X} \int_{\Omega_Y} (x - E[X])(y - E[Y]) f(x, y) dx dy$$

# USEFUL PROPERTIES

## VARIANCE OF SUM

$$VAR(aX + bY + c) = a^2 VAR(X) + b^2 VAR(Y) + 2ab COV(X, Y)$$

## CORRELATION

$$\rho_{XY} = \frac{COV(X, Y)}{\sqrt{VAR(X)VAR(Y)}}$$

## INDEPENDENT VARIABLES

$$COV(X, Y) = 0 \rightarrow \rho_{XY} = 0$$

# DIRICHLET DISTRIBUTION

Extension of the Beta distribution to two or more dimensions

DOMAIN  $(X_1, \dots, X_n) \in [0, 1]^n; \sum_i x_i = 1$

PARAMETERS  $(\alpha_1, \dots, \alpha_n); \alpha_i > 0$

FUNCTION  $f(x_1, \dots, x_n) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \prod_i x_i^{\alpha_i - 1}$

The marginals of the Dirichlet distribution are Beta distributions