

Probability & Statistics : A Brief Introduction

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Probability and Statistics?

- Probability
 - Formally defined using a set of axioms
 - Seeks to determine the likelihood that a given event or observation, or measurement will or has happened
 - What is the probability of throwing a 7 using two dice?
- Statistics
 - Used to analyze the frequency of past events
 - Uses a given sample of data to assess a probabilistic model's validity or determine values of its parameters
 - After observing several throws of two dice, can we determine whether they are loaded

Probability

- Probability can be defined in terms of Kolmogorov axioms
 - The probability is a real-valued function defined on subsets A, B, \dots in sample space S

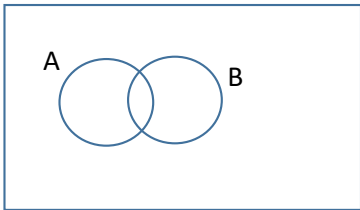
For every subset A in S , $P(A) \geq 0$

If $A \cap B = \emptyset$, $P(A \cup B) = P(A) + P(B)$

$P(S) = 1$

- This means the probability is a measure in which the measure of the entire sample space is 1

Intersection of A & B





Two fair dice are tossed.

of possible outcomes: 36

Let's define event A as all throws where the sum of two faces is 4

Event B occurs whenever d2 greater or equal then d1

$$P(A) = ? \quad 3/36$$

$$P(B) = ? \quad 21/36$$

$$P(A \wedge B) = ? \quad 2/36$$

$$P(B | A) = ? \quad 2/3$$

$$P(A | B) = ? \quad 2/21$$

Conditional probability formula

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

Bayes' Theorem

- Bayes' theorem

Using $P(A \cap B) = P(B \cap A)$

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

- For disjoint A_i

$$P(B) = \sum_i P(B | A_i)P(A_i)$$

then

$$P(A | B) = \frac{P(B | A)P(A)}{\sum_i P(B | A_i)P(A_i)}$$

The Reverend Thomas Bayes
1702-1761

♦ *Probability is that degree
of confidence dictated by
the evidence through
Bayes's theorem. -- E.T.
Jaynes*



Pacific Northwest National Laboratory

Bayes' Theorem

- Suppose in the general population
 - $P(\text{disease}) = 0.001$
 - $P(\text{no disease}) = 0.999$
- Suppose there is a test to check for the disease
 - $P(+, \text{disease}) = 0.98$
 - $P(-, \text{disease}) = 0.02$
- But also
 - $P(+, \text{no disease}) = 0.03$
 - $P(-, \text{no disease}) = 0.97$
- You are tested for the disease and it comes back +. Should you be worried?

Bayes' Theorem

- Apply Bayes' theorem

$$P(disease,+) = \frac{P(+,disease)P(disease)}{P(+,disease)P(disease) + P(+,no\ disease)P(no\ disease)}$$

$$P(disease,+) = \frac{0.98 \cdot 0.001}{0.98 \cdot 0.001 + 0.03 \cdot 0.999} = 0.032$$

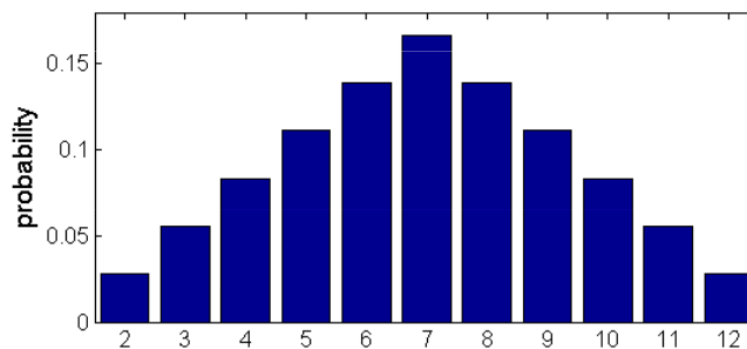
- 3.2% of people testing positive have the disease
- Your degree of belief about having the disease is 3.2%

Probability distributions

- Discrete:

probability mass function (pmf)

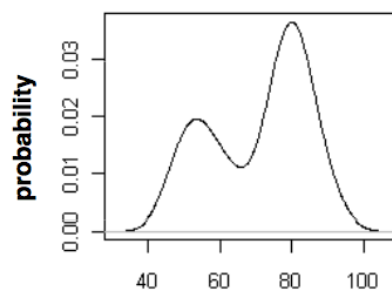
example:
sum of two
fair dice



- Continuous:

probability density function (pdf)

example:
waiting time between
eruptions of Old Faithful
(minutes)



Probability Density Function

- Let the sample space S be the space of all possible outcomes of an experiment
- Let x be a possible outcome
 - Then $P(x \text{ found in } [x, x+dx]) = f(x)dx$
 - $f(x)$ is called the **probability density function (pdf)**
 - It may be called $f(x;\theta)$ since the pdf could depend on one or more parameters θ
 - Often, we will want to determine θ from a set of measurements
- Of course x must be somewhere so

$$\int_{-\infty}^{\infty} f(x)dx = 1$$

Mean and Variance

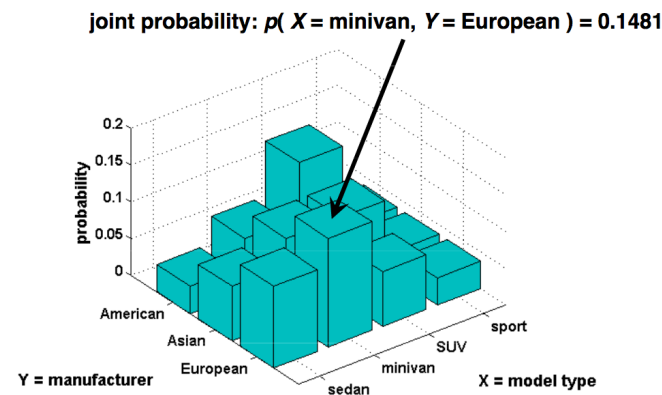
- Definitions of mean and variance are given in terms of expectation values

$$E[x] = \int x f(x) dx \equiv \mu$$

$$V[x] = E[(x - E[x])^2] = E[x^2] - \mu^2 \equiv \sigma^2$$

Multivariate probability distributions

- Scenario
 - Several random processes occur together
 - Want to know probabilities for each possible combination of outcomes
- Can describe as *joint probability* of several random variables
- Example: two processes whose outcomes are represented by random variables X and Y . Probability that process X has outcome x and process Y has outcome y is denoted as: $p(X = x, Y = y)$



Multivariate probability distributions

- *Marginal probability*

- Probability distribution of a single variable in a joint distribution

- Example: two random variables X and Y :

$$p(X = x) = \sum_{b=\text{all values of } Y} p(X = x, Y = b)$$

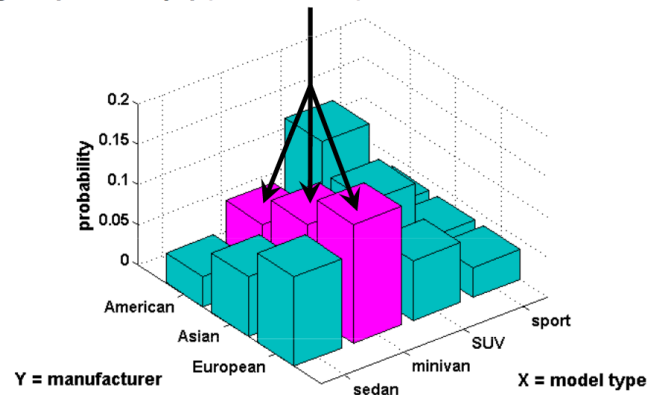
- *Conditional probability*

- Probability distribution of one variable *given* that another variable takes a certain value

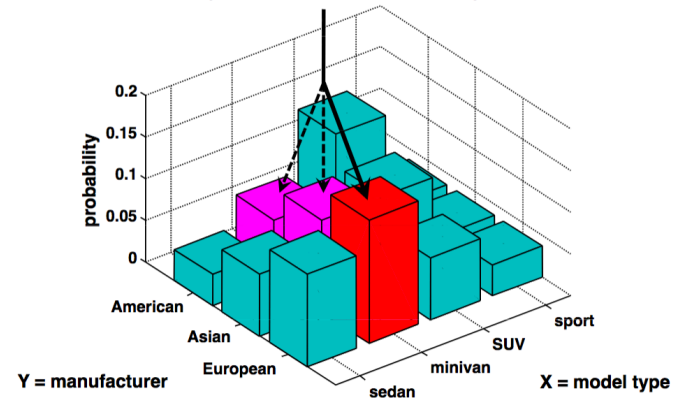
- Example: two random variables X and Y :

$$p(X = x | Y = y) = p(X = x, Y = y) / p(Y = y)$$

marginal probability: $p(X = \text{minivan}) = 0.0741 + 0.1111 + 0.1481 = 0.3333$



conditional probability: $p(Y = \text{European} | X = \text{minivan}) = 0.1481 / (0.0741 + 0.1111 + 0.1481) = 0.4433$



Covariance & Correlation

- Definitions of covariance and correlation coefficient

$$V_{xy} = \text{cov}[x, y] = E[(x - \mu_x)(y - \mu_y)] = E[xy] - \mu_x \mu_y$$

$$\rho_{xy} = \frac{\text{cov}[x, y]}{\sigma_x \sigma_y}$$

if x, y independent then $f(x, y) = f_x(x)f_y(y)$

and then $E[xy] = \iint xyf(x, y)dxdy = \mu_x \mu_y$

and so $\text{cov}[x, y] = 0$

Binomial Distribution

- Consider N independent experiments (Bernoulli trials)
- Let the outcome of each be pass or fail
- Let the probability of pass = p

Probability of n successes = $p^n (1 - p)^{N-n}$

But there are $\frac{N!}{n!(N-n)!}$ permutations for

N distinguishable objects, grouping them n at a time

$$f(n; N, p) = \frac{N!}{n!(N-n)!} p^n (1 - p)^{N-n}$$

An Example

100 examples from two classes are present in a training set. C1 is represented by 95% of the examples and class C2 by 5%. A random sample of 10 examples is selected. What is the probability that the selected sample of 10 examples has no example from class C2.

- First calculate the number of possible samples (ways in which 10 items out of 100 can be selected)
- This is given by $100!/10!90!$
- The number of possible ways in which no C2 example is selected = $(5!/0!5!)(95!/10!85!)$
- Thus the probability that a randomly selected set of 10 examples has representation from class C2:
- $= (5!/0!5!)(95!/10!85!)/(100!/10!90!) = 0.58375$

Binomial Distribution

- For the mean and variance we obtain (using small tricks)

$$E[n] = \sum_{n=0}^N n f(n; N, p) = Np$$

$$V[n] = E[n^2] - (E[n])^2 = Np(1-p)$$

- And note with the binomial theorem that

$$\sum_{n=0}^N f(n; N, p) = \sum_{n=0}^N \binom{N}{n} p^n (1-p)^{N-n} = (p + 1 - p)^N = 1$$

Binomial Distribution

- It's baseball season! What is the probability of a 0.300 hitter getting 4 hits in one game?

$$N = 4, p = 0.3$$

$$f(4;4,0.3) = \frac{4!}{4!0!} \cdot 0.3^4 \cdot 0.7^0 = 0.0081$$

$$E[n] = 4 \cdot 0.3 = 1.2$$

$$V[n] = 4 \cdot 0.3 \cdot 0.7 = 0.84$$

Expect 1.2 ± 0.84 hits for a 0.300 hitter

Poisson Distribution

- Consider when

$$N \rightarrow \infty$$

$$p \rightarrow 0$$

$$E[n] = Np \rightarrow \nu$$

The Poisson pdf is

$$f(n; \nu) = \frac{\nu^n}{n!} e^{-\nu}$$

and one finds

$$E[n] = \nu$$

$$V[n] = \sigma^2 = \nu$$

Poisson Distribution

$$f(n; N, p) = \frac{N!}{n!(N-n)!} p^n (1-p)^{N-n}$$

$$\frac{N!}{(N-n)!} \approx N^n \text{ for } N \text{ large}$$

$$(1-p)^{N-n} = 1 - p(N-n) + \frac{p^2(N-n)(N-n-1)}{2!} + \dots$$

$$(1-p)^{N-n} \approx 1 - Np + \frac{N^2 p^2}{2!} + \dots = e^{-Np} = e^{-v}$$

$$f(n; N, p) \rightarrow \frac{N^n}{n!} p^n e^{-v} = \frac{v^n e^{-v}}{n!} \text{ for large } N \text{ and small } p$$

Poisson Distribution

- Examples
 - Number of customers/hour arriving at a store
 - Cosmic rays observed in a time interval t
 - Number of entries in a histogram bin when data is accumulated over a fixed time interval
 - Infant mortality
 - QC/failure rate predictions

Gaussian Distribution

- Gaussian distribution
 - Important because of the central limit theorem
 - For n independent variables x_1, x_2, \dots, x_N that are distributed according to any pdf, then the sum $y = \sum x_i$ will have a pdf that approaches a Gaussian for large N
 - Examples are almost any measurement error (energy resolution, position resolution, ...)

$$E[y] = \sum_i \mu_i$$

$$V[y] = \sum_i \sigma_i$$

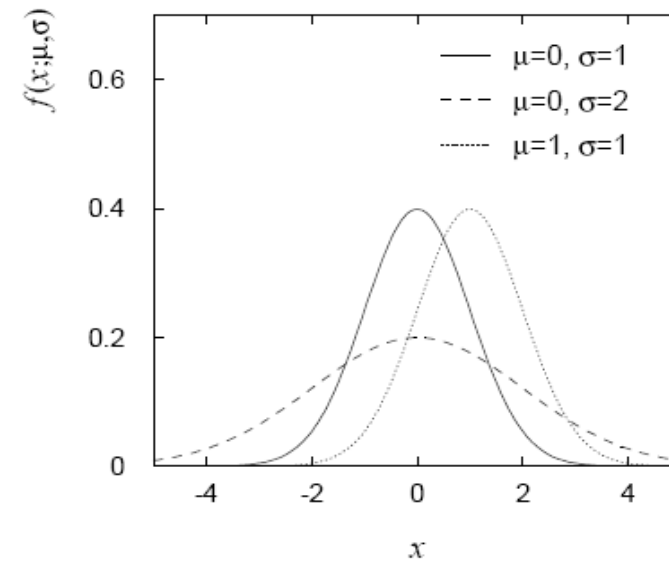
Gaussian Distribution

- The familiar Gaussian pdf is

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

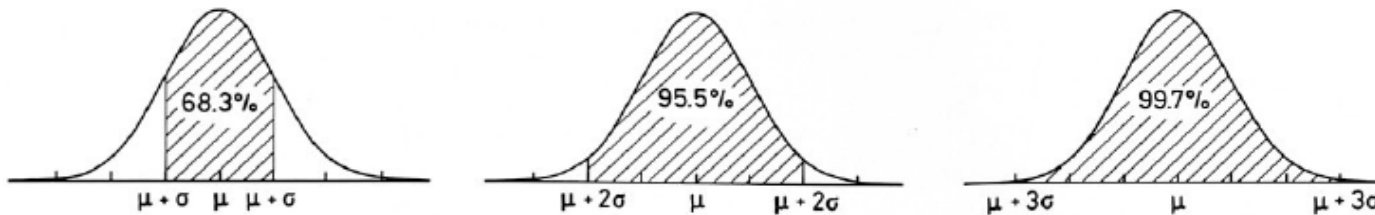
$$E[x] = \mu$$

$$V[x] = \sigma^2$$



Gaussian Distribution

- Some useful properties of the Gaussian distribution are
 - $P(x \text{ in range } \mu \pm \sigma) = 0.683$
 - $P(x \text{ in range } \mu \pm 2\sigma) = 0.9555$
 - $P(x \text{ in range } \mu \pm 3\sigma) = 0.9973$
 - $P(x \text{ outside range } \mu \pm 3\sigma) = 0.0027$
 - $P(x \text{ outside range } \mu \pm 5\sigma) = 5.7 \times 10^{-7}$



- $P(x \text{ in range } \mu \pm 0.6745\sigma) = 0.5$

Multivariate Normal Distribution

Let

$$f(x_1, x_2) = \frac{1}{(2\pi)\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2}Q(x_1, x_2)}$$

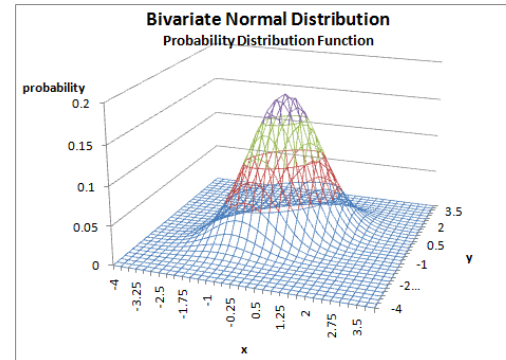
where

$$Q(x_1, x_2) = \frac{\left\{ \left(\frac{x_1 - \mu_1}{\sigma_1} \right)^2 - 2\rho \left(\frac{x_1 - \mu_1}{\sigma_1} \right) \left(\frac{x_2 - \mu_2}{\sigma_2} \right) + \left(\frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right\}}{1 - \rho^2}$$

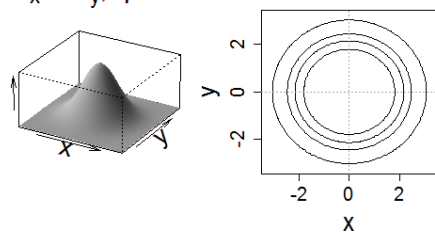
This distribution is called the **bivariate Normal distribution**.

The parameters are $\mu_1, \mu_2, \sigma_1, \sigma_2$ and ρ .

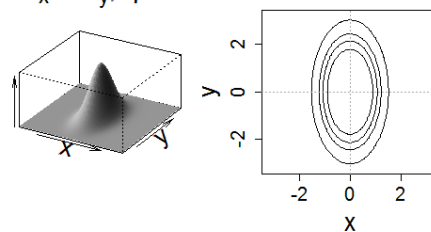
$$\begin{aligned} f_{\mathbf{X}}(x_1, \dots, x_k) &= \frac{\exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)}{\sqrt{(2\pi)^k |\boldsymbol{\Sigma}|}} \\ &= \frac{\exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)}{\sqrt{|2\pi \boldsymbol{\Sigma}|}}, \end{aligned}$$



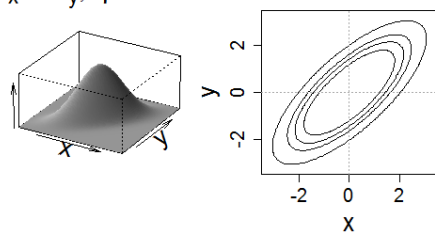
$$\sigma_x = \sigma_y, \rho = 0$$



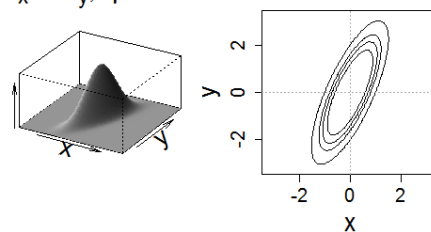
$$2\sigma_x = \sigma_y, \rho = 0$$



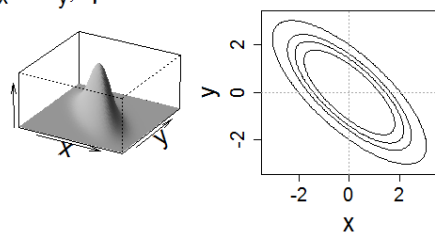
$$\sigma_x = \sigma_y, \rho = 0.75$$



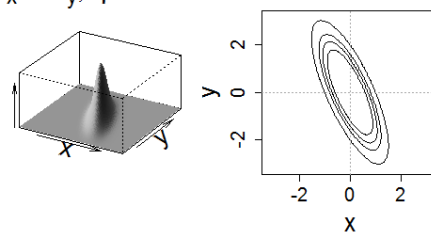
$$2\sigma_x = \sigma_y, \rho = 0.75$$



$$\sigma_x = \sigma_y, \rho = -0.75$$



$$2\sigma_x = \sigma_y, \rho = -0.75$$



For more on probability and statistics, download the following slides.

<http://users.encs.concordia.ca/~doedel/courses/comp-233/slides.pdf>