

# Half-time Review of STA2001 (I)

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# Outline

1. Basic Concepts of Probability Theory
2. Univariate Random Variable
3. Typical Univariate Random Distributions

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1. Basic Concepts of Probability Theory
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# What is probability theory?

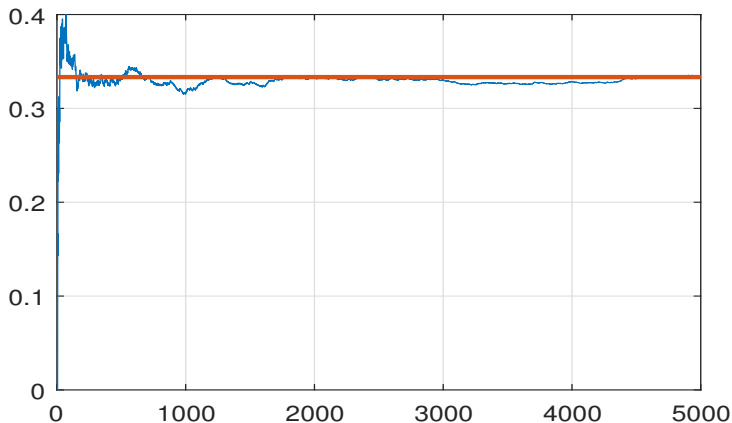
Probability theory is the branch of mathematics concerned with probability, the analysis of random phenomena - wikipedia

1. Random experiment
2. Sample space
3. Event
4. **Event  $A$  has happened**

# A first definition of probability

The limit of relative frequency:

$$P(A) = \lim_{n \rightarrow \infty} \frac{\mathcal{N}(A)}{n}$$



## A more formal definition of probability

Probability function is a function that assigns  $P(A)$  to an event  $A$ ,  $A \subseteq S$  such that the following three conditions are satisfied

1.  $P(A) \geq 0$
2.  $P(S) = 1$
3.  $A_1, A_2, \dots$  mutually exclusive ~~and exhaustive~~

$$P(A_1 \cup A_2 \cup \dots) = P(A_1) + P(A_2) + \dots$$

## Properties for probability function

- ▶  $P(A) = 1 - P(A')$
- ▶  $P(\emptyset) = 0$
- ▶  $P(A) \leq 1$
- ▶  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

# How to calculate probability of an event

For random experiments that satisfy

Assumption 1:  $S$  contains  $m$  possible outcomes

$$e_k, \quad k = 1, 2, \dots, m, \quad i.e., \quad S = \{e_1, e_2, \dots, e_m\}.$$

Assumption 2: The  $m$  outcomes are “equally likely”

$$P(\{e_k\}) = \frac{1}{m}, \quad k = 1, \dots, m.$$

$$P(A) = \frac{\mathcal{N}(A)}{\mathcal{N}(S)},$$

where  $\mathcal{N}(X)$  is the number of outcomes in  $X \subseteq S$ .





# Conditional Probability

Conditional probability of an event  $A$ , given that event  $B$  has occurred, is defined by

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

provided that  $P(B) > 0$ .

- ▶ The sample space shrinks to  $B$ .
- ▶ Conditional probability is a probability function.
- ▶  $P(A \cap B) = P(A)P(B|A)$ .

# Independent Events

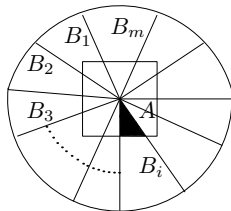
Events  $A$  and  $B$  are independent if

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

The occurrence of one of them does **NOT** change the probability of the occurrence of the other.

- ▶  $A$  and  $B$  are independent, if and only if any pair of the following events are independent
  - (a)  $A$  and  $B'$
  - (b)  $A'$  and  $B$
  - (c)  $A'$  and  $B'$
- ▶  $A, B, C$  are independent if
  1. pairwise independent
  2.  $P(A \cap B \cap C) = P(A)P(B)P(C)$

# Bayes' Theorem



Assume

1.  $S = B_1 \cup B_2 \cup \cdots \cup B_m, \quad B_i \cap B_j = \Phi$
2.  $P(B_i) > 0$

Then

$$P(A) = \sum_{k=1}^m P(A \cap B_i) = \sum_{k=1}^m P(B_i)P(A|B_i)$$

$$P(B_i|A) = \frac{P(B_i)P(A|B_i)}{P(A)}, \text{ provided } P(A) > 0$$

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# Random variable

## Definition[Random Variable]

Given a random experiment with sample space  $S$ , a function  $X : S \rightarrow \bar{S} \subseteq R$  that assign one real number  $X(s) = x$  to each  $s \in S$  is called Random Variable (RV).

Note: repeat a random experiment  $\Leftrightarrow$  generate a number from  $\bar{S}$

Depending on the property of  $\bar{S}$

1. Discrete RV, if  $\bar{S}$  is finite or countably infinite.
2. Continuous RV, if  $\bar{S}$  is union of intervals.

# Discrete RV Vs. Continuous RV

RV  $X$  is a function  $X : S \rightarrow \bar{S} \subseteq R$

Discrete RV:

pmf  $f(x) : \bar{S} \rightarrow (0, 1]$

1.  $f(x) > 0$

2.  $\sum_{x \in \bar{S}} f(x) = 1$

3.  $P(X \in A) = \sum_{x \in A} f(x)$

Continuous RV:

pdf  $f(x) : \bar{S} \rightarrow (0, \infty)$

1.  $f(x) > 0$

2.  $\int_{\bar{S}} f(x) dx = 1$

3.  $P(X \in A) = \int_A f(x) dx$

Very often, we extend the definition domain of  $f(x)$  from  $\bar{S}$  to  $R$  by letting  $f(x) = 0$  for  $x \notin \bar{S}$ .

# Discrete RV Vs. Continuous RV

RV  $X$  is a function  $X : S \rightarrow \bar{S} \subseteq R$

Discrete RV:

pmf  $f(x) : R \rightarrow [0, 1]$

1.  $f(x) \geq 0$

2.  $\sum_{x \in \bar{S}} f(x) = 1$

3.  $P(X \in A) = \sum_{x \in A} f(x)$

Continuous RV:

pdf  $f(x) : R \rightarrow [0, \infty)$

1.  $f(x) \geq 0$

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

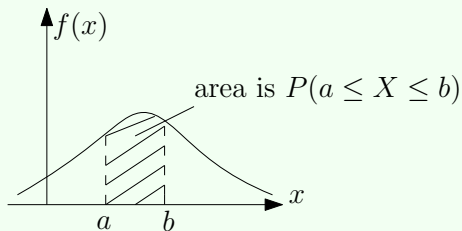
3.  $P(X \in A) = \int_A f(x) dx$

with  $f(x) = 0$  for  $x \notin \bar{S}$ ;  $\bar{S}$  is called the support set of  $f(x)$ .

# Interpretation of pdf

## Interpretation

$$P(a \leq X \leq b) = \int_a^b f(x) dx$$





# Cdf and its properties

## Definition

cdf  $F(x) : \mathcal{R} \rightarrow [0, 1]$

$$F(x) = P(X \leq x), \quad \text{nondecreasing function!}$$

1. relation between the probability function and the cdf

$$P(a \leq X \leq b) = F(b) - F(a)$$

2. for continuous RV,

$$f(x) = F'(x)$$

for those values of  $x$  at which  $F(x)$  is differentiable.

# Mathematical Expectation

## Definition[Mathematical Expectation]

Let  $X$  be a RV with range  $\bar{S}$  and  $f(x)$  be its pmf or pdf. The mathematical expectation of  $g(X)$ , if exists, is denoted by

$$E[g(X)] = \begin{cases} \sum_{x \in \bar{S}} g(x)f(x), & \text{discrete RV} \\ \int_{x \in \bar{S}} g(x)f(x)dx, & \text{continuous RV} \end{cases}$$

## Property[Mathematical Expectation]

Mathematical expectation is a linear operator, i.e.,

$$E[c_1g_1(X) + c_2g_2(X)] = c_1E[g_1(X)] + c_2E[g_2(X)]$$

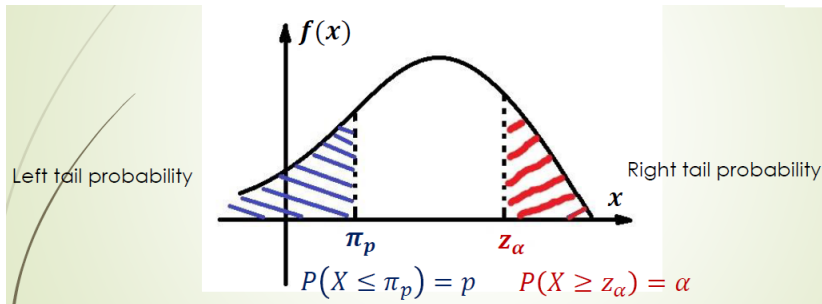
# Special mathematical expectation

## Definition[Special mathematical expectation]

$$E[g(X)] = \begin{cases} \sum_{x \in \bar{S}} g(x)f(x), & \text{discrete RV} \\ \int_{x \in \bar{S}} g(x)f(x)dx, & \text{continuous RV} \end{cases}$$

$$g(X) = \begin{cases} X \rightarrow \text{Mean} \\ (X - EX)^2 \rightarrow \text{Variance, } \text{Var}(X) = EX^2 - (EX)^2 \\ X^r \rightarrow \text{Moment} \\ e^{tX}, \text{ for } |t| < h, \rightarrow \text{Mgf: } M^{(r)}(0) = EX^r \end{cases}$$

## (100p)th percentile, the upper $100\alpha$ percent point



### Definition [(100p)th percentile]

The number  $\pi_p$  such that  $P(X \leq \pi_p) = p$ .  $\pi_{0.5}$ ,  $\pi_{0.25}$  and  $\pi_{0.75}$  are called the median (the second quantile), the first and third quantiles, respectively.

### Definition [the upper $(100\alpha)$ percent point]

The number  $z_\alpha$  such that  $P(X \geq z_\alpha) = \alpha$ .

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# Table of distributions

	pmf/pdf	mgf	mean	variance
Binomial ( $n = 1$ , Bernoulli)	$\binom{n}{x} p^x (1-p)^{n-x}$ $x = 0, 1, 2, \dots, n$	$[(1-p) + pe^t]^n$ $-\infty < t < \infty$	$np$	$np(1-p)$
Negative Binomial	$\binom{x-1}{r-1} p^r (1-p)^{x-r}$ $x = r, r+1, r+2, \dots$	$\frac{(pe^t)^r}{[1 - (1-p)e^t]^r}$ $(1-p)e^t < 1$	$\frac{r}{p}$	$\frac{r(1-p)}{p^2}$
Poisson	$\frac{\lambda^x e^{-\lambda}}{x!}, x = 0, 1, 2, \dots$	$e^{\lambda(e^t - 1)}$	$\lambda$	$\lambda$
Gamma ( $\alpha = 1$ , Exponential) ( $\theta = 2, \alpha = r/2, \chi^2$ )	$\frac{1}{\Gamma(\alpha)\theta^\alpha} x^{\alpha-1} e^{-\frac{x}{\theta}}$ $0 \leq x < \infty$	$\frac{1}{(1 - \theta t)^\alpha}$ $t < \frac{1}{\theta}$	$\alpha\theta$	$\alpha\theta^2$
Normal ( $\mu = 0, \sigma^2 = 1$ , standard normal)	$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)$ $-\infty < x < \infty$	$\exp(\mu t + \frac{1}{2}\sigma^2 t^2)$ $-\infty < t < \infty$	$\mu$	$\sigma^2$

# Descriptions of distributions

	Random Phenomena
Binomial ( $n = 1$ , Bernoulli)	The total number of successes in $n$ Bernoulli trials (the order does not matter)
Negative Binomial	For a given natural number $r$ , the number of Bernoulli trials on which the $r$ th success is observed
Poisson	The number of occurrences that a particular event happens in a given time interval or for a given physical object that can be described by APP
Gamma ( $\alpha = 1$ , Exponential) ( $\theta = 2, \alpha = r/2, \chi^2$ )	The waiting time until the $\alpha$ th occurrences of a particular event for an APP
Normal ( $\mu = 0, \sigma^2 = 1$ , standard normal)	When a large number of outcomes are observed, the outcomes have a "bell-shaped" relative frequency distribution.

# Univariate normal distribution

## Definition

A continuous RV  $X$  is said to be normal or Gaussian if it has a pdf of the form.

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

where  $\mu$  and  $\sigma^2$  are two parameters characterizing the normal distribution. Briefly,  $X \sim N(\mu, \sigma^2)$

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \frac{(x - \mu)^2}{\sigma^2}\right) dx = 1$$



# Univariate normal distribution

1. Mgf:

$$M(t) = \exp \left( \mu t + \frac{1}{2} \sigma^2 t^2 \right), \quad t \in R$$

2.  $Y$  is said to be a standard normal distribution if

$$Y \sim N(0, 1) \Leftrightarrow f(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$$

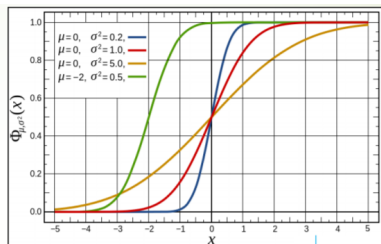
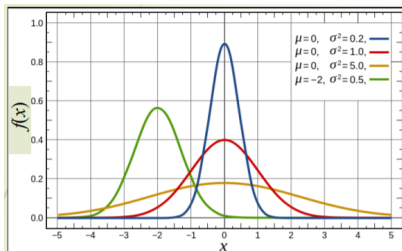
3. for  $Y \sim N(0, 1)$ ,  $P(a \leq Y \leq b) = \Phi(b) - \Phi(a)$

4. if  $X \sim N(\mu, \sigma^2)$ ,  $(X - \mu)/\sigma \sim N(0, 1)$  and

$$\begin{aligned} P(a \leq X \leq b) &= P\left(\frac{a - \mu}{\sigma} \leq \frac{X - \mu}{\sigma} \leq \frac{b - \mu}{\sigma}\right) \\ &= \Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right) \end{aligned}$$

5. if  $Y \sim N(0, 1)$ ,  $Y^2 \sim \chi^2(1)$

# Univariate normal distribution



$$P(Z \leq z) = \Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-w^2/2} dw$$

$$\Phi(-z) = 1 - \Phi(z)$$

$z$	0.00	0.01	0.02	0.03	0.04	0.05	0.06
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026

# The end

- ▶ Arrnagement of the midterm exam
- ▶ **Any questions?**

# Motivations for the double integral

To prove

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \frac{(s-\mu)^2}{\sigma^2}\right) ds = 1$$

we need to handle double integrals!

# Proof of $\int_{-\infty}^{\infty} f(s)ds = 1$

Let

$$I = \int_{-\infty}^{\infty} f(s)ds = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{1}{2} \frac{(s-\mu)^2}{\sigma^2}\right) ds \stackrel{?}{=} 1$$

Take a coordinate change  $x = \frac{s-\mu}{\sigma}$

$$I = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \stackrel{?}{=} 1.$$

Since  $I > 0$ , then if  $I^2 = 1$ , then  $I = 1$ .

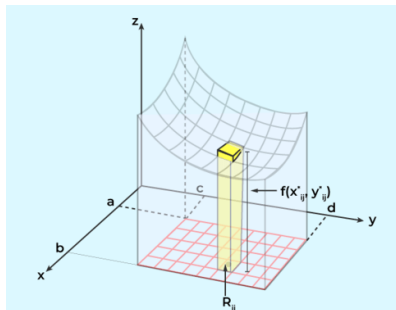
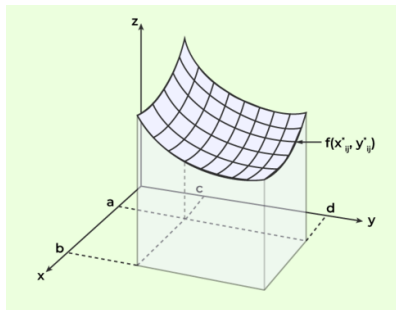
$$I^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx \int_{-\infty}^{\infty} e^{-\frac{y^2}{2}} dy = \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{x^2+y^2}{2}} dx dy$$

# Geometric interpretation of double integral

For  $f(x, y) \geq 0$

$$\text{Volume} = \iint_A f(x, y) dx dy$$

The double integral calculates the volume under the surface  $f(x, y)$  over the definition domain of  $f(x, y)$  or any region of interest  $A$ .



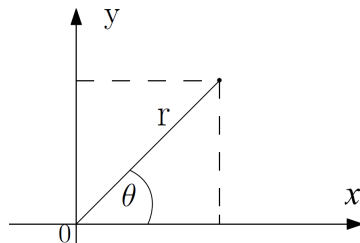
# Geometric interpretation of double integral in polar coordinate system

Take a coordinate change

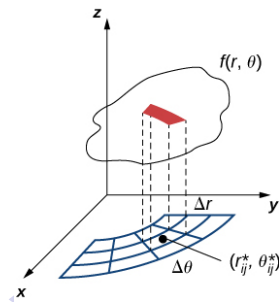
$$x = r \cos \theta$$

$$y = r \sin \theta$$

(polar coordinate)



The double integral calculates the volume under the surface  $f(x, y)$  over the definition domain of  $f(x, y)$  or any region of interest.



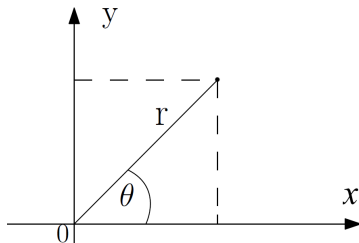
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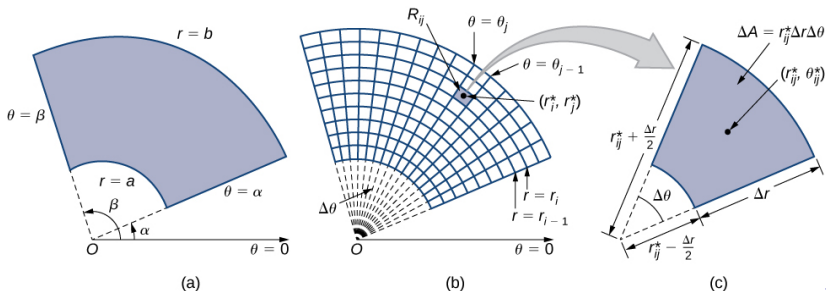
$$x = r \cos \theta$$

$$y = r \sin \theta$$

(polar coordinate)



The problem lies in to how to calculate the area of small trapezoid.





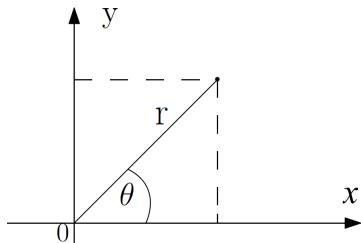
# Proof of $\int_{-\infty}^{\infty} f(s)ds = 1$

Take a coordinate change

$$x = r \cos \theta$$

$$y = r \sin \theta$$

(polar coordinate)



$$\begin{aligned} I^2 &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} e^{-\frac{r^2}{2}} r dr d\theta = \frac{1}{2\pi} \int_0^{2\pi} d\theta \int_0^{\infty} e^{-\frac{r^2}{2}} d\frac{r^2}{2} \\ &= \frac{1}{2\pi} \cdot 2\pi \cdot (-1) \cdot e^{-\frac{r^2}{2}} \Big|_0^{\infty} = 1 \end{aligned}$$