

NMAI059 Probability and statistics 1

Class 10

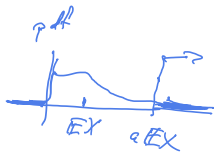
Robert Šámal

Inequalities we know from the last time (and one more)

- ▶ Markov:

rand. var.

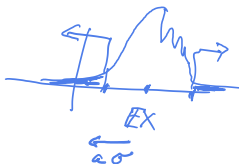
$$X \geq 0 \Rightarrow P(X \geq a\mathbb{E}(X)) \leq \frac{1}{a}$$



- ▶ Chebyshev

any r.v. with $\mathbb{E}(X)$ & $\text{var}(X)$

$$P(|X - \mathbb{E}(X)| \geq a\sigma_X) \leq \frac{1}{a^2}$$



- ▶ Chernoff ($\sigma_X = \sqrt{n}$)

$$X = \sum_{i=1}^n X_i, X_i = \pm 1 \Rightarrow P(|X - \mathbb{E}(X)| > a\sigma_X) \leq \underline{\underline{2e^{-a^2/2}}}$$

*ind. ...
i.i.d. r.v.*

Overview

Limit theorems – approximation

Statistics – an introduction

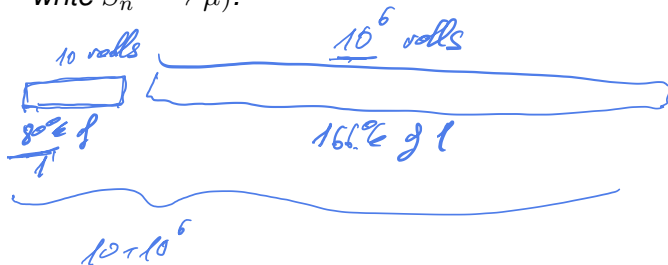
Strong law of large numbers

Theorem

Let X_1, \dots, X_n be i.i.d. with expectation μ and variance σ^2 . Let $S_n = (X_1 + \dots + X_n)/n$ be the sample mean. Then we have

$$\lim_{n \rightarrow \infty} S_n = \mu \quad \text{almost surely (i.e. with probability 1).}$$

We say that sequence S_n converges to μ almost surely, and write $S_n \xrightarrow{\text{a.s.}} \mu$.



Monte Carlo integration

How to compute $\int_{x \in A} g(x) dx$?

In particular

$$g(x) = \begin{cases} 1 & \text{for } x \in S \\ 0 & \text{otherwise} \end{cases}$$

... area of a circle

$$\frac{\pi}{4}$$

area circle



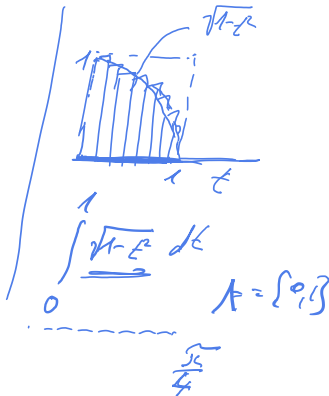
$$A = [-1, 1]^2$$

$\omega_1, \omega_2, \dots$

$\omega =$ sequence of random points in A

$$X_n(\omega) = g(\omega_n) \quad \mathbb{E} X_n = \frac{\int_{x \in A} g(x)}{\text{area of } A} = \underline{\underline{\mu}}$$

Law of Large Numbers $\rightarrow \underline{\underline{S_n}} \rightarrow \underline{\underline{\mu}}$ a.s.



Weak law of large numbers for Σ - error bound

Theorem

Let X_1, \dots, X_n be i.i.d. with expectation μ and variance σ^2 . Let $S_n = (X_1 + \dots + X_n)/n$ be the sample mean. Then for every $\varepsilon > 0$ we have

$$\lim_{n \rightarrow \infty} P(|S_n - \mu| > \varepsilon) = 0.$$

$$E S_n = \mu$$

Chebyshev

We say that sequence S_n converges to μ in probability and write $S_n \xrightarrow{P} \mu$.

Proof

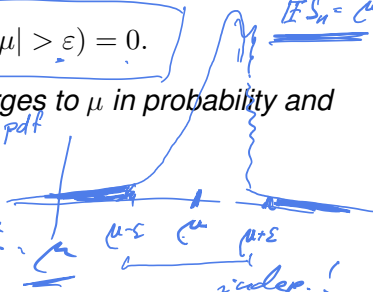
$$E(S_n) = E\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{E X_1 + \dots + E X_n}{n} = \frac{n \mu}{n} = \mu$$

$$\text{var}(S_n) = \text{var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{1}{n^2} \text{var}(X_1 + \dots + X_n) = \frac{1}{n^2} (\text{var}(X_1) + \dots + \text{var}(X_n))$$

$$P(|S_n - \mu| > a \sigma_{S_n}) \leq \frac{1}{a^2} = \frac{\sigma^2}{\varepsilon^2 \cdot n} \xrightarrow{n \rightarrow \infty} 0$$

$\varepsilon \Rightarrow a = \frac{\sigma}{\varepsilon} \sqrt{n}$

$$\sigma_{S_n} = \frac{\sigma}{\sqrt{n}}$$

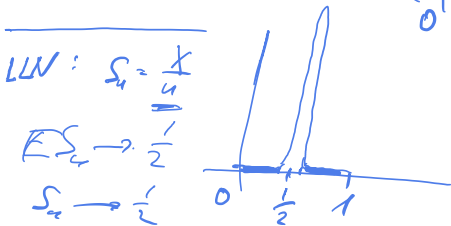
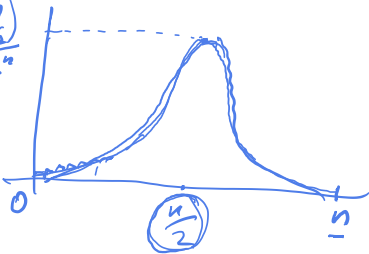


Law of Large numbers \rightarrow Central Limit Theorem

$$X_1, \dots, X_n \sim \text{Bern}\left(\frac{1}{2}\right)$$

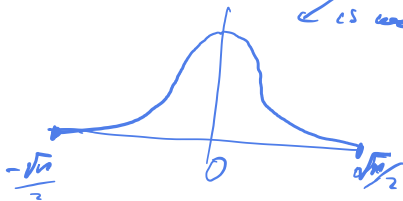
$$\underline{X = X_1 + \dots + X_n \sim \text{Bin}\left(n, \frac{1}{2}\right)}$$

$$\frac{1}{\sigma} = \frac{\binom{n}{k/2}}{2^n}$$



this shape
 \leftarrow is well-understood

$$U_n = \frac{X - \frac{n}{2}}{\sqrt{n}}$$



Central Limit Theorem

$$E Y_n = \frac{E(X_1 + \dots + X_n) - n\mu}{\sqrt{n}\sigma} = 0$$

Theorem

$$\text{var}(Y_n) = \frac{\text{var}(X_1 + \dots + X_n)}{n\sigma^2} = 1$$

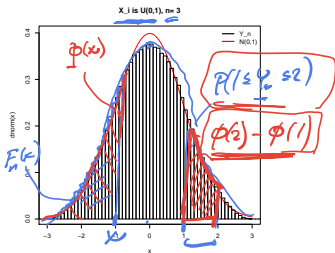
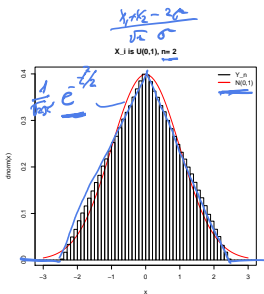
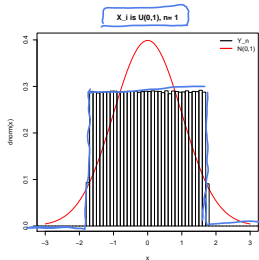
Let X_1, \dots, X_n be i.i.d. with expectation μ and variance σ^2 . Put $Y_n := ((X_1 + \dots + X_n) - n\mu) / (\sqrt{n} \cdot \sigma)$.

Then $Y_n \xrightarrow{d} N(0, 1)$. This means, that if F_n is the cdf of Y_n , then

$$\lim_{n \rightarrow \infty} F_n(x) = \Phi(x) \quad \text{for every } x \in \mathbb{R}.$$

We say that the sequence Y_n converges to $N(0, 1)$ in distribution.

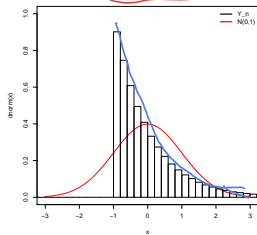
pdf



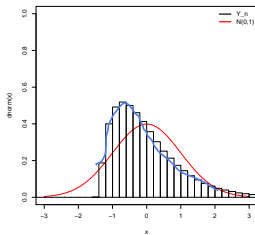
CLT another illustration

Gamma distr.

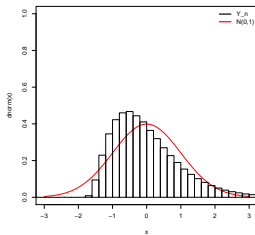
X_j is $\text{Exp}(1)$, $n=1$



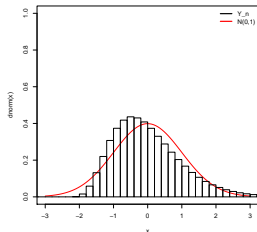
X_j is $\text{Exp}(1)$, $n=2$



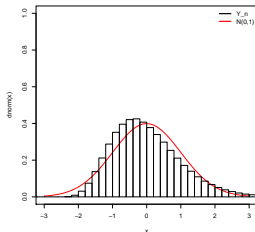
X_j is $\text{Exp}(1)$, $n=3$



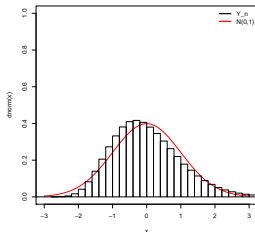
X_j is $\text{Exp}(1)$, $n=5$



X_j is $\text{Exp}(1)$, $n=7$



X_j is $\text{Exp}(1)$, $n=10$



Bonus: Moment generating function

Definition

For a random variable X we let

$$M_X(t) = \mathbb{E}(e^{tX}).$$

Function $M_X(t)$ is called the moment generating function.

- ▶ $M_X(t) = \sum_{n=0}^{\infty} \mathbb{E}(X^n) \frac{t^n}{n!}$.
- ▶ $M_{Bern(p)}(t) = p \cdot e^t + (1 - p)$.
- ▶ $M_{X+Y}(t) = M_X(t)M_Y(t)$, jsou-li X, Y n.n.v.
- ▶ $M_{Bin(n,p)} = (pe^t + 1 - p)^n$
- ▶ $M_{N(0,1)} = e^{t^2/2}$
- ▶ $M_{Exp(\lambda)} = \frac{1}{1-t/\lambda}$
- ▶ If $M_X(t) = M_Y(t)$ on $(-a, a)$ for some $a > 0$, then $X = Y$ a.s.

Overview

Limit theorems – approximation

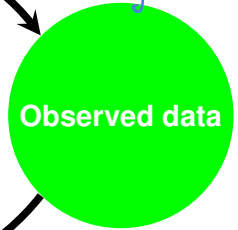
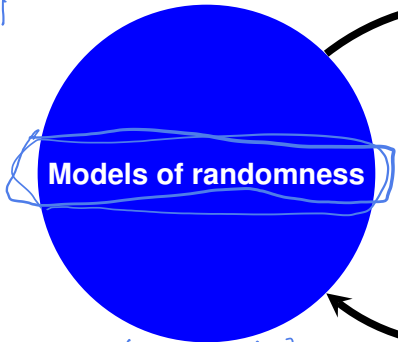
Statistics – an introduction

Lecture overview

prob. spaces
r.v.'s
prob. distrib. pdf's ...

Probability

how likely it is that ...
what is the mean
typ. long-term
f ...



Statistics

Q: is it a fair die?
Poi ($\lambda = 50$)

dice: 1, 5, 2, 5, 3, 5, 5, ...
of heads: 51, 62, 32, ...

1st illustration – number of left-handed people

#L : 0 0% | 14%
#R : 4 100% |

estimate was correct!
4-8%

small sample



estimates about
a larger population

caveats:

unrepresentative sample
misleading questions

2nd illustration – running time of a program

- ▶ $X_1, \dots, X_n \sim F$ i.i.d., F is their CDF
- ▶ **Definition:** Empirical CDF is defined by

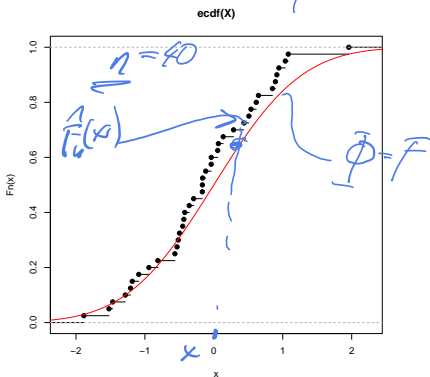
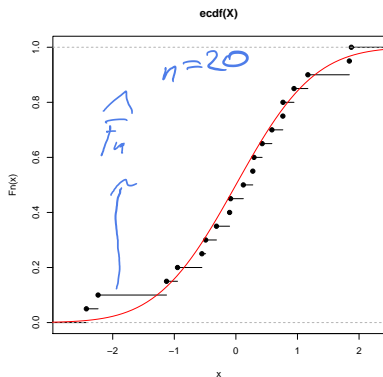
a random variable

$$\hat{F}_n(x) = \frac{\sum_{i=1}^n I(X_i \leq x)}{n},$$

where $I(X_i \leq x) = 1$ if $X_i \leq x$ and 0 otherwise.

$N(0,1)$

$F = \Phi$



Empirical CDF – properties

Theorem

For a fixed x

- ▶ $\mathbb{E}(\hat{F}_n(x)) = F(x)$
 - ▶ $\text{var}(\hat{F}_n(x)) = \frac{F(x)(1-F(x))}{n}$
 - ▶ $\hat{F}_n(x)$ converges to $F(x)$ in probability, $\hat{F}_n(x) \xrightarrow{P} F(x)$.
- $P(|\hat{F}_n(x) - F(x)| > \varepsilon) \rightarrow 0$

~~Dokaz.~~ Proof

Weak law of large numbers.

Note that $n\hat{F}_n(x) \sim \text{Bin}(n, F(x))$

$$\hat{F}_n(x) = S_n = \frac{Y_1 + \dots + Y_n}{n}$$

$$\mathbb{E}S_n = \mathbb{E}Y_1 = F(x)$$
$$\text{var}(S_n) = \frac{F(x)(1-F(x))}{n}$$

S_n $\mu = F(x)$

$$\mathbb{E} \underbrace{I(X_i \leq x)}_{Y_i} = P(X_i \leq x) = F(x)$$

$$Y_i \sim \text{Bernoulli}(F(x))$$
$$\text{var}(Y_i) = F(x)(1-F(x))$$

Empirical CDF – Dvoretzky-Kiefer-Wolfowitz (DKW)

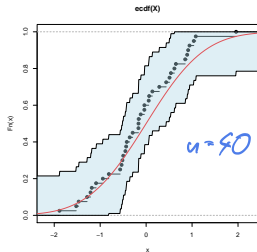
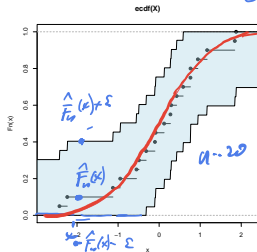
Theorem

Let $X_1, \dots, X_n \sim F$ be i.i.d., let \hat{F}_n be their empirical CDF. Let $\mathbb{E}(X_i)$ be finite. Choose $\alpha \in (0, 1)$ and let $\varepsilon = \sqrt{\frac{1}{2n} \log \frac{2}{\alpha}}$. The we have

$$P(\hat{F}_n(x) - \varepsilon \leq F(x) \leq \hat{F}_n(x) + \varepsilon) \geq 1 - \alpha.$$

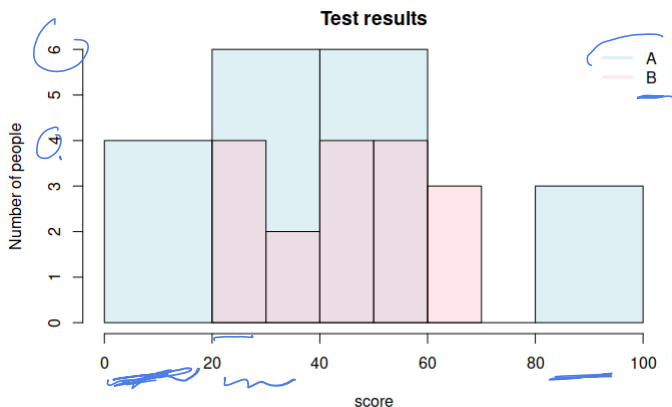
$\alpha = 0.05$

$\varepsilon = 5/15$



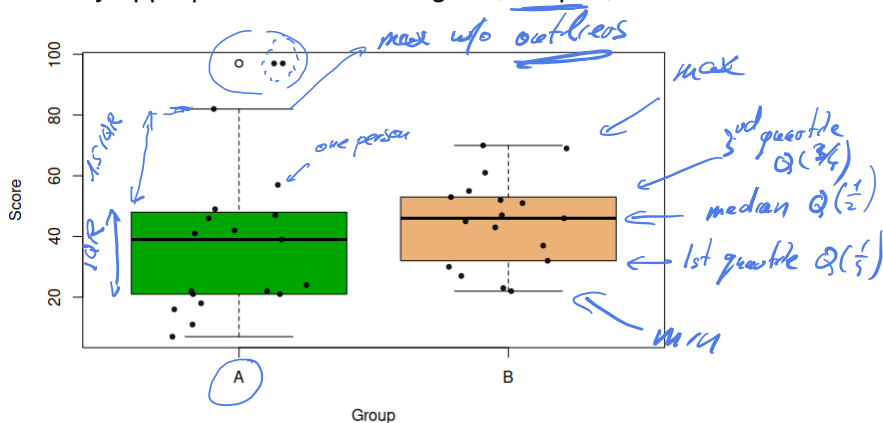
Intro – exploratory data analysis

- ▶ we collect data (and pay attention to systematic errors – independence, bias, ...)
- ▶ we make various tables
- ▶ any appropriate charts: histogram, boxplot, etc.



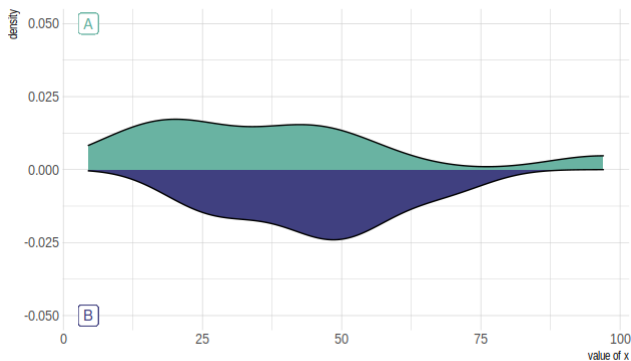
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Intro – exploratory data analysis

- ▶ we collect data (and pay attention to systematic errors – independence, bias, . . .)
- ▶ we make various tables
- ▶ any appropriate charts: histogram, boxplot, etc.



Goals of confirmatory data analysis

- ▶ point estimates
- ▶ interval estimates
- ▶ hypothesis testing
- ▶ (linear) regression

$\mu = 1.8 m$
 $\mu \in (1.5, 2)$
w 95% chance

Examples:

- ▶ We assume human height follows $N(\mu, \sigma^2)$. What are μ and σ ?
- ▶ Is our coin/dice fair?
- ▶ Is a medical treatment beneficial?
- ▶ Is new version of a program faster?
- ▶ How does running time depend on size of input?

