

# Statistik Zusammenfassung

## Random experiment

→ process where the possible outcomes can be identified ahead of time

## Sample space

set  $\Omega$  of all possible outcomes of an experiment

↳ (Menge)

## Type of sets

### Countable set

$\Omega$  is countable if a bijection exists

↳ a one-to-one function exists →  $f: \Omega \rightarrow \mathbb{N}$

⇒ otherwise → uncountable

### Finite set

set is empty or has a finite number of elements

⇒ otherwise → infinite

## Event

collection of possible outcomes of an experiment that

is a subset of  $\Omega$  (including  $\Omega$  itself)

$$A \subseteq \Omega$$

## Set Theory

empty set:  $\emptyset$

$A \subseteq B \rightarrow A$  is part of  $B$

$A \cup B \rightarrow A$  or  $B$  (Vereinigung)

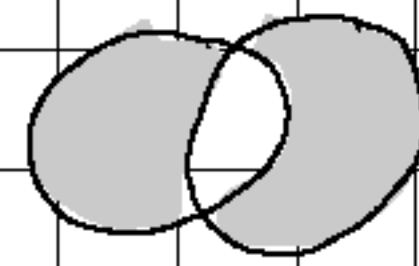
$A \cap B \rightarrow A$  and  $B$  (Gemeinsames)

$A \setminus B \rightarrow A$  without  $B = A - B$

$A^c = A' \rightarrow$  complement

$A \Delta B \rightarrow$  symmetric difference

$\hookrightarrow (A \setminus B) \cup (B \setminus A)$



## Singelton

subset  $\{\omega\}$  contains a single outcome  $\omega$  of  $\Omega$

## Null set

$\emptyset$  is part of every set (impossible event),  $\emptyset \subseteq \Omega$

## Universal set

$\Omega$  or  $\Omega$  (sure event),  $\Omega \subseteq \Omega$

## Power set

all subsets of a set

↳  $P(A)$  = all possible subsets of  $A$

$$\text{↳ } A = \{x, y\} \quad P(A) = \{\emptyset, \{x\}, \{y\}, \{x, y\}\}$$

$$|P(A)| = 2^n$$

↳ number of Elements of  $P(A) = 2^n$  ~ number of Elements in  $A$

## Properties of set Operations (Theorem)

for any  $A, B, C \subset \Omega$ :

commutativity:

$$A \cup B = B \cup A$$

$$A \cap B = B \cap A$$

associativity:

$$A \cup (B \cap C) = (A \cup B) \cap C$$

$$A \cap (B \cup C) = (A \cap B) \cup C$$

distributive law:

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$$

De Morgan's law:

$$(A \cup B)^c = A^c \cap B^c$$

$$(A \cap B)^c = A^c \cup B^c$$

## Partition

If  $A_1, A_2, \dots$  are pairwise disjoint and  $\bigcup_i A_i = \Omega$   
then the collection  $A_1, A_2, \dots$  forms a partition of  $\Omega$   
 $\Rightarrow$  collection of unique subsets where their union  
is the sample space

## disjoint

$\hookrightarrow$  mutually exclusive  $\rightarrow A \cap B = \emptyset$  (nothing in common)

pairwise disjoint  $\rightarrow A_i \cap A_j = \emptyset$  for all  $i \neq j$

## Field

A field is a set  $K$  (Körper) with two special elements  
 $0, 1 \in K$  and two maps  $+$  and  $\cdot \Rightarrow (K, +, \cdot)$

$$\underbrace{K}_{\substack{+ \\ \cdot}} \underbrace{K}_{\substack{+ \\ \cdot}} = K$$

$\Rightarrow$  satisfy 8 axioms

(elements written as  $\alpha, \beta, \dots$ )

$\hookrightarrow$  addition:  $\alpha + \beta = \beta + \alpha$

$$(\alpha + \beta) + \gamma = \alpha + (\beta + \gamma)$$

$$\alpha + 0 = 0 + \alpha = \alpha$$

$$\forall \alpha \in K \quad \exists -\alpha \in K \rightarrow \alpha + (-\alpha) = 0$$

multiplication:  $\alpha\beta = \beta\alpha$

$$(\alpha\beta)\gamma = \alpha(\beta\gamma)$$

$$\alpha \cdot 1 = 1 \cdot \alpha = \alpha$$

$$\forall \alpha \in K \rightarrow \exists \alpha^{-1} \in K \rightarrow \alpha \cdot \alpha^{-1} = 1$$

$$\Rightarrow (\alpha + \beta) \cdot \gamma = \alpha\gamma + \beta\gamma$$

## Boolean algebra of sets

collection  $\mathcal{G}$  of subsets of  $\Omega$  with following conditions

1. if  $A, B \in \mathcal{G} \Rightarrow A \cup B \in \mathcal{G}$  and  $A \cap B \in \mathcal{G}$   
↳ closed under countable  $\cup$  (unions) and  $\cap$  (intersections)
2. if  $A \in \mathcal{G} \Rightarrow A^c \in \mathcal{G}$   
↳ closed under complement
3.  $\emptyset \in \mathcal{G}$  (same as  $\Omega \in \mathcal{G}$  under 2.)

## $\sigma$ -algebra

→ subset of algebra of sets where it only has to be closed under countable unions

1. if  $A_1, A_2, \dots, A_n \in \mathcal{F} \Rightarrow \bigcup_{i \in \mathbb{N}} A_i \in \mathcal{F}$   
↳ closed under countable unions
2. if  $A \in \mathcal{F} \Rightarrow A^c \in \mathcal{F}$   
↳ closed under complement
3.  $\emptyset \in \mathcal{F}$  (same as  $\Omega \in \mathcal{F}$  under 2.)

⇒ **smallest  $\sigma$ -algebra**  $\mathcal{F} = \{\emptyset, \Omega\}$  → **trivial algebra**

⇒ easiest way to construct with countable  $\Omega$

↳  $\mathcal{F} = P(\Omega) \Rightarrow$  with  $2^n$  elements

## Borel $\sigma$ -algebra

→ a  $\sigma$ -algebra with open sets

→ Borel  $\sigma$ -algebra of  $\mathbb{R}$   $]-\infty, a]$ ,  $a \in \mathbb{Q}$

## Probability measure (Kolmogorov Axioms)

$P$  on  $(\Omega, \mathcal{F})$  function  $P: \mathcal{F} \rightarrow [0, 1]$

1.  $P(A) \geq 0$  for any  $A \in \mathcal{F}$  (any outcome has a possibility)

2. if  $A_1, A_2, \dots \in \mathcal{F}$  are pairwise disjoint, then  $P(\bigcup_{i \in \mathbb{N}} A_i) = \sum_{i \in \mathbb{N}} P(A_i)$

↳ all outcome possibilities sum to 1 → one of the outcomes will always happen

3.  $P(\Omega) = 1$  |  $P(\emptyset) = 0$

↳ one of the possible outcomes will always happen

## Probability space

→ triple of  $(\Omega, \mathcal{F}, P)$

sample space    all outcomes    possibility of all outcomes

## Uniform Probability

↳ all outcomes are equally likely

## Probability of an Event

$$P(A) = \frac{|A|}{|\Omega|} \Rightarrow \frac{\text{nr of Events}}{\text{nr of possible Events}}$$

## counting rules

	order	no order
replacement	$n^k$	$\binom{n+k-1}{k}$
no replacement	$\frac{n!}{(n-k)!}$	$\binom{n}{k} = \frac{n!}{(n-k)! \cdot k!}$

$\binom{n}{k} \rightarrow$  combination  $\Rightarrow nCr$  auf TR

$\frac{n!}{(n-k)!} \rightarrow$  permutation  $\Rightarrow nPr$  auf TR

$n =$  Elements

$r = k =$  samples/  
unique  
values

## counting rules for groups

total objects  $n$  with  $n_i$  number of objects in each

$\Rightarrow$  number of orderings:

$$\frac{n!}{n_1! \cdot n_2! \cdot \dots \cdot n_k!}$$

## conditional Probability

$(A|B) \rightarrow$  Probability of  $A$  if  $P(B) > 0$

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

## Bayes Rule

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

$$\hookrightarrow P(A) = \sum_{i \in I} P(A|A_i) P(A_i)$$

$$\hookrightarrow P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j \in I} P(B|A_j)P(A_j)}$$

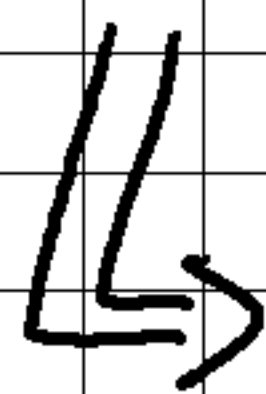


# Independence of Events

Events  $A, B$  are statistically independent if

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

generally: if the intersection of possibilities of events is the same as the product



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

$$\hookrightarrow P(A|B) = P(A)$$

$$P(B|A) = P(B)$$

## mutually independent

→ independence of a collection

⇒ collection  $\{A_i \in I\}$  is mutually independent if

$$P(A_i \cap A_j) = P(A_i) P(A_j) \text{ for all } i, j \in J, i \neq j$$

## conditionally independent

$C$  is an Event with  $P(C) > 0$

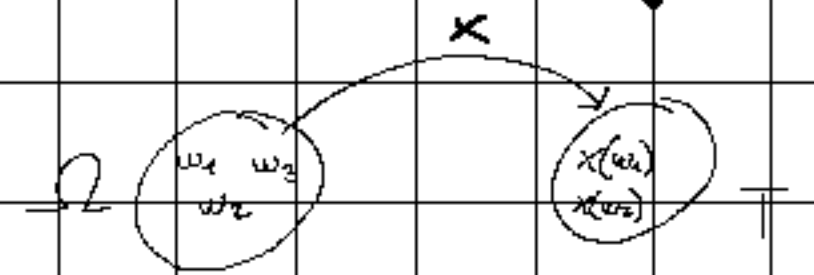
$$P(A \cap B | C) = P(A|C) P(B|C)$$

## Random Variable

$X$  can be all the possible values of an experiment

$$X: \Omega \rightarrow T$$

(function that projects the sample space to a measurable space)



## Types of random variables

### Discrete random variable

if  $X$  can only take a finite number or a countable infinite number of different values

### Continuous random variables

if  $X$  can take uncountable number of different values

→ uncountable many values in  $T'$

(ex: water in a glass → unlimited possibilities)

# Cumulative Distribution Function (CDF)

function that calculate the probability that the random variable will take a value less than or equal to a certain value

⇒ The CDF is the sum of all probabilities up to the given point

$$F: \mathbb{R} \rightarrow [0, 1]$$

$$F(x) = \mathbb{P}(X \leq x) = \mathbb{P}(\{\omega \mid X(\omega) \leq x\}) \quad \text{for all } x \in \mathbb{R}$$

$$(\text{Intervals: } \mathbb{P}([a, b]) = F(b) - F(a) \Rightarrow \mathbb{P}(X \leq b) - \mathbb{P}(X \leq a))$$

## Properties of CDF

- We can compute  $\mathbb{P}$  if we know  $F$

$F$  is a CDF of a unique Probability if the following properties hold:

1. **Right continuity**:  $\lim_{\Delta x \rightarrow 0} F(x + \Delta x) = F(x)$  at every  $x$   
↳ as  $\Delta x$  gets smaller we approach  $F(x)$  more and more

2. **Nondecreasing**:  $F(a) \leq F(b)$  for any  $a < b$

↳ the probability gets higher, as "past events" get more likely

3. **Limits**:  $\lim_{x \rightarrow -\infty} F(x) = 0$  and  $\lim_{x \rightarrow +\infty} F(x) = 1$

↳ 0 → event can't happen | 1 → event will happen

## Example CDF

The absolute difference between two rolled dice

$$X = |i - j| \quad i, j \in \{1, 2, \dots, 6\}$$

$\Rightarrow X$  can be 0-5

$\hookrightarrow$  calculate possibilities of the outcomes of  $X$

$$X = 0 \rightarrow 6 \text{ pairs} \rightarrow \frac{6}{36} = \frac{1}{6}$$

$$X = 1 \rightarrow 10 \text{ pairs} \rightarrow \frac{10}{36} = \frac{5}{18}$$

$$X = 2 \rightarrow 8 \text{ pairs} \rightarrow \frac{8}{36} = \frac{2}{9}$$

$$X = 3 \rightarrow 6 \text{ pairs} \rightarrow \frac{6}{36} = \frac{1}{6}$$

$$X = 4 \rightarrow 4 \text{ pairs} \rightarrow \frac{4}{36} = \frac{1}{9}$$

$$X = 5 \rightarrow 2 \text{ pairs} \rightarrow \frac{2}{36} = \frac{1}{18}$$

$$\Rightarrow F(x) = \begin{cases} 0 & x < 0 \\ 0 + \frac{1}{6} = \frac{1}{6} & 0 < x < 1 \\ 0 + \frac{1}{6} + \frac{5}{18} = \frac{4}{9} & 1 < x < 2 \\ 0 + \frac{1}{6} + \frac{5}{18} + \frac{2}{9} = \frac{5}{6} & 2 < x < 3 \\ 0 + \frac{1}{6} + \frac{5}{18} + \frac{2}{9} + \frac{1}{6} = \frac{5}{6} & 3 < x < 4 \\ 0 + \frac{1}{6} + \frac{5}{18} + \frac{2}{9} + \frac{1}{6} + \frac{1}{9} = \frac{17}{18} & 4 < x < 5 \\ 0 + \frac{1}{6} + \frac{5}{18} + \frac{2}{9} + \frac{1}{6} + \frac{1}{9} + \frac{1}{18} = 1 & x \geq 5 \end{cases}$$

## Probability Mass function (PMF)

for a discrete random variable

if there exists a non-negative function

$$f: \mathbb{R} \rightarrow [0, 1] \quad \text{any } x \in \mathbb{R}$$

$$F(x) = P(X \leq x) = \sum_{x_i \leq x} P(X = x_i) = \sum_{x_i \leq x} f(x_i)$$

$\Rightarrow$  PMF gives us a list of the possibilities of all possible outcomes

$$f(x) = P(X = x)$$

$\Rightarrow p_i = P(X = x_i)$  only positive at  $x = x_i$   
belonging to  $T'$  of  $X$

$$f(x) = P(X = x) = \begin{cases} p_i, & x = x_i \in T' \\ 0, & \text{else.} \end{cases}$$

## Difference CDF PMF

$\rightarrow$  The CDF gives us the cumulative probabilities up to a point while the PMF gives us the probability of each specific outcome

## Uniform distribution

→ every outcome has the same probability

$$\stackrel{\text{PMF}}{\Rightarrow} f(x; N) = P(X=x | N) = \begin{cases} \frac{1}{N}, & x=1, 2, \dots, N \\ 0, & \text{else} \end{cases}$$

## Hypergeometric distribution

→ calculate the probabilities when picking elements from a set without replacing them

$$\text{PMF: } f(x; N, M, n) = P(X=x | N, M, n) = \frac{\binom{M}{x} \binom{N-M}{n-x}}{\binom{N}{n}}$$

## Example Hypergeometric distribution

balls with two different colors in a bag. calculate the probability of a certain outcome when taking a number of balls at once

$$|\Omega| = \binom{N}{n}_{\text{all}}, \quad \binom{M}{x}_{\text{red}}, \quad \binom{N-M}{n-x}_{\text{blue}}$$

⇒ 10 balls, 6 red, 4 blue

pick 3; what is the probability of drawing 2 red?

$$\Rightarrow \left. \begin{array}{l} N=10 \\ M=6 \end{array} \right\} \left. \begin{array}{l} n=3 \\ x=2 \end{array} \right\} P(X=2) = \frac{\binom{6}{2} \binom{10-6}{3-2}}{\binom{10}{3}}$$

$$= 0.5 = \underline{\underline{50\%}}$$

## Bernoulli distribution

→ simple distribution with only two possible outcomes  
Success and failure

$$f(x; p) = \begin{cases} 1-p, & x=0 \\ p, & x=1 \\ 0, & \text{else} \end{cases}$$

↑  
probability  
of success

## Binomial distribution

→ repetition of an experiment with only two possible outcomes

**PMF:**  $f(x, p, n) = \binom{n}{x} \cdot p^x \cdot (1-p)^{n-x}$   $x = 0, 1, 2, \dots, n$

$x$  = number of success  
 $p$  = Probability of success  
 $n$  = number of trials

## Poisson distribution

→ probability of a certain number of events happening in a fixed interval of time or space

**PMF:**  $f(x; \lambda) = \begin{cases} \frac{\lambda^x}{x!} \cdot e^{-\lambda}, & \text{for } x = 0, 1, 2, \dots \\ 0, & \text{else} \end{cases}$

$x$  = number of events we want to find the probability for  
 $\lambda$  = Average Rate of event happening

## Continuous random variable - CDF & PDF

### Probability Density Function (PDF)

→ calculate probabilities of a continuous random variable using integrals

$$f(x) = \frac{d}{dx} F(x)$$

### Cumulative Distribution Function (CDF)

→ function to show the probability, that the random variable will take a value less or equal to a certain value.

⇒ can be expressed using the PDF  $f$

$$F(x) = \int_{-\infty}^x f(t) dt$$

⇒ with  $A = ]a, b]$

$$\mathbb{P}(X \in A) = \mathbb{P}(a < X \leq b) = F(b) - F(a)$$

$$= \int_a^b f(x) dx = \int_A f(x) dx$$



# Properties of PDF

1.  $f(x) \geq 0$ , for all  $x \in \mathbb{R}$

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

$\Rightarrow$  any non negative finitely integrable function can be a PDF

$\nabla$  A PDF is not able to calculate the probability of a single point as it has no area

$$\Rightarrow P\left(X = \frac{1}{3}\right) = \int_{\frac{1}{3}}^{\frac{1}{3}} f(x) dx \stackrel{!}{=} 0$$

## Uniform Distribution

→ every value in a certain range has the same chance of being picked (ex. random selection)

$$\text{PDF: } f(x; a, b) = \begin{cases} \frac{1}{b-a} & , \text{ if } x \in [a, b] \\ 0 & , \text{ else} \end{cases}$$

## Exponential Distribution

→ calculate the time or distance until some specific event happens. (ex. time for a part to break)

$$\text{PDF: } f(x; \lambda) = \begin{cases} \lambda \cdot e^{-\lambda x} & , \text{ if } x \geq 0 \\ 0 & , \text{ else} \end{cases}$$

→  $\lambda$  = rate how often an event is expected to happen

⇒ can be "memoryless", if the time passed has no effect on the probability of an event happening

↳ ex: the chance of a bus arriving doesn't change with the amount of time you have been waiting.

## Gamma Distribution

→ calculate the time until a multitude of events happen. (ex. how long does it take a call center to receive its 5th call on an average rate of 1 per 10 min?)

PDF:

$$f(x; \alpha, \beta) = \begin{cases} \frac{1}{\Gamma(\alpha) \beta^\alpha} \cdot x^{\alpha-1} \cdot e^{-\frac{x}{\beta}}, & \text{if } 0 < x < \infty \\ 0, & \text{else} \end{cases}$$

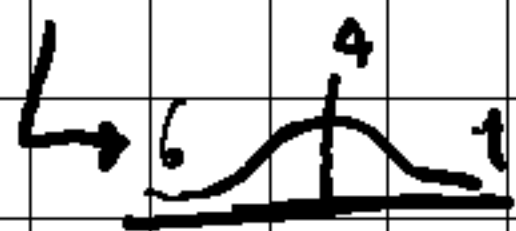
$\alpha$  = shape parameter → number of events we are waiting for (ex. 5 calls →  $\alpha = 5$ )

$\beta$  = scale parameter → average time between events (ex. call every 10 min →  $\beta = 10$ )

$\Gamma(\alpha)$  = Gamma function →  $\Gamma(\alpha) = \int_0^{\infty} t^{\alpha-1} e^{-t} dt$

## Normal Distribution

→ describes how a set of continuous data is spread out (ex. test scores of a class → how many were around average etc.)



PDF:  $f(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x-\mu}{2\sigma^2}}, -\infty < x < \infty$

$\mu$  = Mean → average center of the distribution

$\sigma$  = standard deviation → how spread out the data is (Standard Abweichung)  
↳ small → more clustered

# $\chi^2$ (Chi-Square) Distribution

→ Special case of gamma distribution

$$\text{PDF: } f(x) = \frac{1}{\Gamma\left(\frac{\Gamma}{2}\right) 2^{\frac{\Gamma}{2}}} x^{\frac{\Gamma}{2}-1} e^{-\frac{x}{2}}, \quad x > 0$$

$\Gamma$  = degrees of freedom → number of independent standard normal variables

↙ number of categories - 1!

# Integral Refresher

$$\int_a^b f(x) = F(x) \Big|_a^b = F(b) - F(a)$$

## Rules

$$\int_a^b f(x) \pm g(x) = \int_a^b f(x) \pm \int_a^b g(x)$$

$$\int_a^b c \cdot f(x) = c \cdot \int_a^b f(x)$$

## Integration by Parts

$$\int_a^b f(x) g'(x) dx = (f(x) g(x)) \Big|_a^b - \int_a^b f'(x) g(x)$$

## Substitution

Derivation (Ableitung)

$$\int_a^b \sin(x^2) x dx \Rightarrow u = x^2 \Rightarrow \frac{du}{dx} = 2x$$
$$\Rightarrow x dx = \frac{1}{2} du$$

$$= \int_a^b \sin(u) \frac{1}{2} du \Rightarrow \text{solve normal, then re-substitute}$$

## Integrations

Antiderivation  
Stammfunktion

$f(x)$	$F(x)$	$f(x)$	$F(x)$
$x^n$	$\frac{1}{n+1} x^{n+1}$	$x^{-1}$	$\ln x $
$a x^n$	$a \frac{1}{n+1} x^{n+1}$	$e^x$	$e^x$
$a + x^n$	$ax + \frac{1}{n+1} x^{n+1}$	$e^{-x}$	$-1 \cdot e^{-x}$
		$a^x$	$\frac{a^x}{\ln(a)}$

## Expected Value

↳ basically the mean

↳ repeat the experiment  $\infty$  times

↳ average of  $X$  is the expected value

discrete random variable:

$$E[X] = \sum_{x \in X} x \cdot P(x) \quad \sim \text{PMF}$$

Same goes for functions

$$E[g(X)] = \sum_{x \in X} g(x) \cdot P(x)$$

continuous random variable:

$$E[X] = \int_{x \in X} x \cdot f(x) dx \quad \text{PDF}$$

$$E[g(X)] = \int_{x \in X} g(x) \cdot f(x) dx$$

## Variance

↳ how far from the mean are the values spread?

general:

$$\text{Var}[X] = E[X^2] - E[X]^2$$

discrete random variable:

$$\text{Var}[X] = \sum_{x \in X} (x - E[X])^2 \cdot P(x)$$

continuous random variable:

$$\text{Var}[X] = \int_{x \in X} (x - E[X])^2 \cdot f(x) dx$$

## Multiple random variables

↳ multiple aspects of the outcome of an experiment that we want to look at

ex: 2 dice  $\rightarrow X = \text{sum}$   $Y = |\text{difference}|$

↳ we get a discrete random vector  $(X, Y)$

## Joint PMF

↳ PMF of discrete random vector

$$f_{X,Y}(x,y) = f(x,y) = \mathbb{P}(X=x, Y=y)$$

$$\mathbb{P}((X,Y) \in A) = \sum_{(x,y) \in A} f(x,y)$$

$A \subset \mathbb{R}^2$

## Joint Expected value (PMF)

$$\mathbb{E}[g(X,Y)] = \sum_{(x,y) \in \mathbb{R}^2} g(x,y) \cdot \mathbb{P}(X=x, Y=y)$$

⇒ The sum of all possibilities has to be 1

⇒ for any  $(x,y)$ ,  $f(x,y) \geq 0$

$$\sum_{(x,y) \in \mathbb{R}^2} f(x,y) = \mathbb{P}((X,Y) \in \mathbb{R}^2) = 1$$

## Joint PDF

↳ pdf of continuous random vectors

$$P((X, Y) \in A) = \int_A \int f(x, y) dx dy$$

$\underbrace{\quad}_{AC \mathbb{R}^2}$        $\underbrace{\quad}_{\text{integrated over all } (x, y) \in A}$

## Joint Expected value (PDF)

$$E[g(X, Y)] = \int_{x \in X} \int_{y \in Y} g(x, y) f(x, y) dx dy$$



## Marginal Distribution (PMF)

↳ we look at only one of the discrete random variables

$$f_X(x) = \sum_{y \in Y} f_{X,Y}(x,y) \quad \& \quad f_Y(y) = \sum_{x \in X} f_{X,Y}(x,y)$$

ex: 2 dice  $\rightarrow X = \text{sum}$      $Y = |\text{difference}|$

↳ To get the probability of one of them being a certain number, we have to sum the probability of the other that gives us the desired value

$$\text{↳ } y = 0 \quad \Rightarrow \quad f_Y(0) = \sum_{x \in X} f_{X,Y}(x,y)$$

Sum of all probabilities over the other variable

## Marginal Distribution PDF

↳ only one of the continuous random variables

$$f_X(x) = \int_{y \in Y} f(x,y) \, dy$$

$$f_Y(y) = \int_{x \in X} f(x,y) \, dx$$

## Conditional PMF / PDF

↳ probability of one value if the other is fixed

$$f(y|x) = P(Y=y | X=x) = \frac{f(x,y)}{f_X(x)}$$

↳ probability of  $y$ , if  $x$  is set

$$= \frac{\text{probability of both happening}}{\text{probability of only } x \text{ happening}}$$

## Expected value

PMF:

$$E[g(y)|x] = \sum_{y \in Y} g(y) f(y|x)$$

PDF:

$$E[g(y)|x] = \int_{y \in Y} g(y) f(y|x) dy$$

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

## Covariance

↳ relationship between two random variables

↳ how much do they vary together?

$$\text{Cov}(X, Y) = E[(X - E[X]) \cdot (Y - E[Y])]$$

↳ if  $\text{Cov}(X, Y) > 0$  →  $X$  &  $Y$  move in the same direction

$\text{Cov}(X, Y) < 0$  →  $X$  &  $Y$  move in opposite direction

$\text{Cov}(X, Y) = 0$  → no linear relationship between  $X$  &  $Y$

## Rules:

-  $E[X, Y] = E[X] \cdot E[Y] + \text{Cov}(X, Y)$

-  $X, Y = \text{independent} \Rightarrow \text{Cov}(X, Y) = 0$

-  $\text{Cov}(X, Y) = \text{Cov}(Y, X)$

-  $\text{Cov}(aX + b, cY + d) = a \cdot c \cdot \text{Cov}(X, Y)$

## Correlation

↳ strength and direction of linear relationships

$$\rho_{X,Y} = \frac{\text{Cov}(X,Y)}{\sigma_X \cdot \sigma_Y} \quad \left\{ \begin{array}{l} \sigma_X \\ \sigma_Y \end{array} \right\} = \text{Standard deviation}$$

↳ if  $\rho_{X,Y} > 0 \rightarrow X, Y$  are positively correlated

if  $\rho_{X,Y} < 0 \rightarrow X, Y$  are negatively correlated

if  $\rho_{X,Y} = 0 \rightarrow X, Y$  are uncorrelated

↳  $\rho(X,Y)$  is between  $-1$  and  $1$

# Central Limit Theorem

↳ distribution of sample means approximates a normal distribution

⇒ Sample means are the means of a sequence of random variables  $(X_1, \dots, X_n)$

Sum of samples =  $S_n = X_1 + X_2 + \dots + X_n$

Sample mean =  $\bar{X}_n = \frac{S_n}{n}$

$$Z_n = \frac{S_n - nE[X_i]}{\sqrt{\text{Var}[X_i]} \cdot \sqrt{n}} = \frac{\bar{X}_n - E[X_i]}{\frac{\sqrt{\text{Var}[X_i]}}{\sqrt{n}}}$$

⇒ It tells us that the average sample means will be normally distributed if the sample size is large enough, no matter the distribution of the original data.

ex: Quality control of a product

↳ take 40 lightbulbs of each production batch and calculate the average life span  $\bar{X}$

↳ with enough  $\bar{X}$ s, the distribution of them will approximate a normal distribution.

# Descriptive Statistics

↳ ways to summarize data

## Scale of random variables

↳ choosing representative data to scale down the data set

## 3 basic scales

- **nominal scale** → categorize data without any quantitative value or order

ex: car brands (BMW, VW, Toyota ...)

- **ordinal scale** → introduce also an order to the categories

ex: car performance (luxury, sports ...)

↳ they can be ordered

- **ratio scale** → ordinal scale + zero point to be able to measure the distance between the objects

ex: Car horsepower

↳ car 1 is 20 km/h faster than car 2

## Summarize data using numerical techniques

Arithmetic mean (average) ( $\rightarrow$  ratio scale)

$$\Rightarrow \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

Median ( $\rightarrow$  ordinal & ratio scale)

$$\Rightarrow x_{\text{med}} = \begin{cases} x_{\frac{n+1}{2}} & \text{if } n \text{ is odd} \\ \frac{1}{2} (x_{\frac{n}{2}} + x_{\frac{n}{2}+1}) & \text{if } n \text{ is even} \end{cases}$$

$\Rightarrow$  the middle value of all the values

Mode ( $\rightarrow$  nominal, ordinal, ratio scale)

$$\Rightarrow x_{\mu} = x_i \quad \Rightarrow \text{most frequent value}$$

## Empirical Quantiles

$\hookrightarrow$  divide data into equal-sized, ordered segments

$$k = \lfloor \alpha n \rfloor + 1 \quad \Rightarrow \alpha = \text{percentile} \quad \left( \text{ex } \alpha = 75 \quad n = 100 \right. \\ \left. \lfloor \alpha n \rfloor + 1 = 76 \right)$$

$$\alpha\text{-quantile} = \begin{cases} x_k & \text{if } \alpha n = \text{integer} \\ \frac{1}{2} (x_k + x_{k-1}) & \text{if } \alpha n = \text{no integer} \end{cases}$$

## Range

↳ biggest - smallest value

$$\text{range} = x_{\max} - x_{\min}$$

## Mean - quartile

↳ range as dispersion measure

$$\text{MQA} = \frac{(Q_3 - Q_2) + (Q_2 - Q_1)}{2} = \frac{\text{IQA}}{2}$$

⇒ average Quartile size

## Variance

↳ spread of the data from the average

$$s_x^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

## Standard deviation

↳ amount of variation from the average (actual value)

$$s_x = + \sqrt{s_x^2}$$

## absolute dispersion

↳ how spread are the values

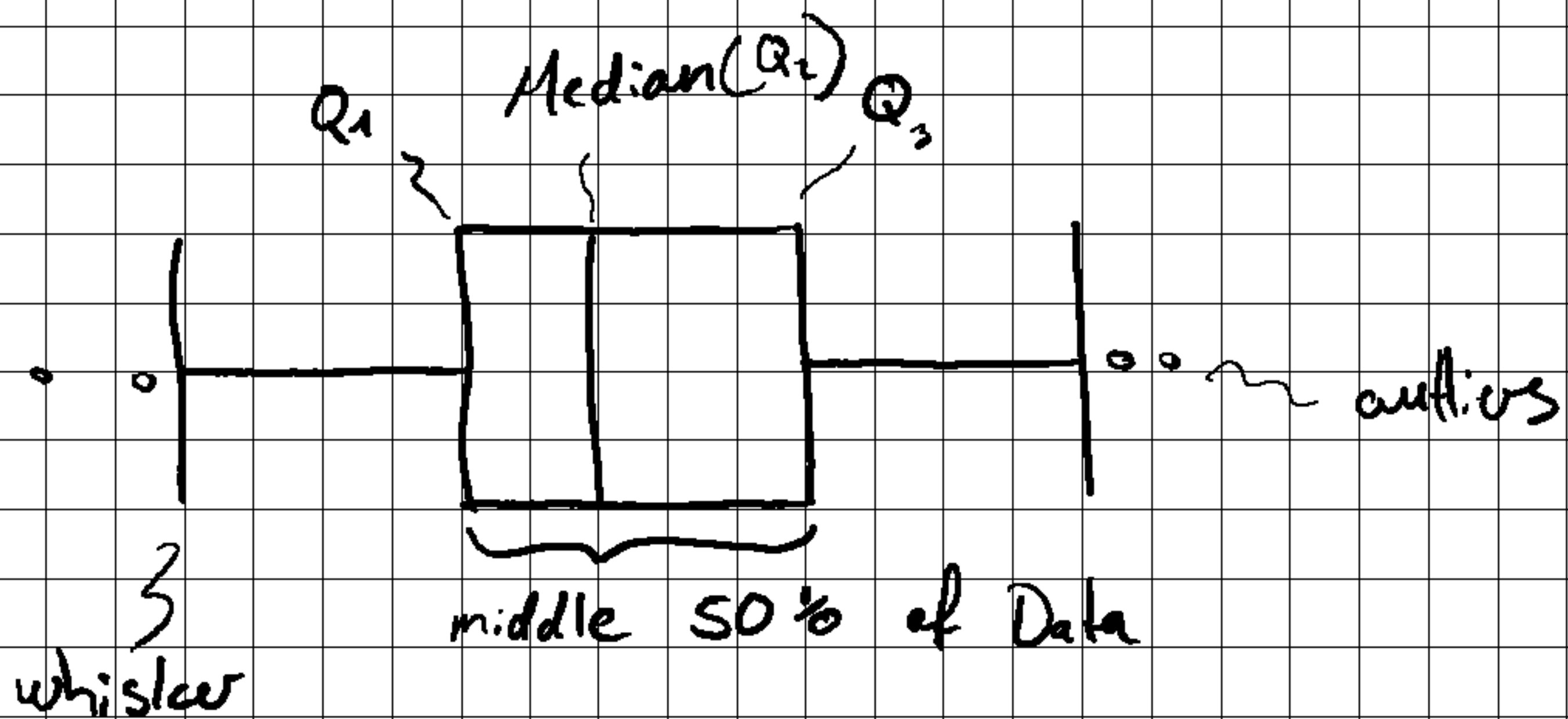
$$VK_x = \frac{s_x}{|\bar{x}|}$$



# Visualize Data

## Box Plot

↳ graph to show distribution & outliers of Data



↳  $Q_1 - 1.5 \cdot (IQR)$  } smallest value within this margin  
↳  $Q_3 - Q_1$  }

## Interpretation

- length of box and whisker indicate the spread
- if the median is centered, then the distribution is symmetrical
- outliers show possible errors in Data

## QQ-Plot

↳ Compare two distributions by plotting their quantiles against each other

⇒ Check how a distribution matches a theoretical distribution

## Draw

- calculate quantiles for both distributions
- plot corresponding quantiles

## Interpretation

- Depending on the spread you can see how closely one distribution follows the other

## Scatter Plot

↳ each value is a point on a line / plane

⇒ see groups and potential relations

⇒ - Single values are plotted on a line

- two dimensional values are plotted on a plane

↳ relation between two values

↳ e.g. exercise time & blood pressure

# Estimation of parameters

↳ estimate population parameter based on sample data

## two approaches

- point estimator → calculate single value
- confidence interval → interval in which the true value lies

## Point Estimator $\theta$

- **Sample mean** ( $\hat{\mu} = \bar{x}$ ) →  $\frac{\text{Sum of all values}}{\text{Number of values}} = \frac{1}{n} \sum_{i=1}^n x_i$

- **Sample variance** ( $\hat{\sigma}^2 = s^2$ ) → difference between each sample point and the mean

$$\Rightarrow \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n x_i^2 - \left( \frac{1}{n} \sum_{i=1}^n x_i \right)^2$$

## Bias

↳ the bias is the difference between the point estimator and the expected value

$$\text{Bias}(T) = E[T] - \theta$$

⇒ if the bias = 0, then is the estimator unbiased

⇒ if the bias becomes smaller with increasing sample size, and vanishes when  $\text{size} \rightarrow \infty$ , then we say that the estimator is asymptotically unbiased

$$\lim_{n \rightarrow \infty} E[T] = \theta$$

⇒ if the estimator  $\hat{\theta}$  converges to a certain value with an increasing sample size, we say  $\hat{\theta}$  is consistent

↳ estimator is consistent, when:

- it is unbiased / asymptotically unbiased

- variance  $\rightarrow 0$  when  $\text{size} \rightarrow \infty$

⇒ if the variance is smaller / equal to the unbiased estimator, then it is efficient

## Mean squared error (MSE)

↳ criteria to check if an estimator is good

$$\Rightarrow \text{MSE}(\theta) = E[(T - \theta)^2]$$

$$\text{MSE}(\theta) = \text{Var}(T) + \text{bias}^2$$

$\Rightarrow$  if  $\text{MSE}(\theta) = \text{Var}(T) \rightarrow$  then is  $\theta$  good

## Methods to get estimators

- Method of Moments → Sample mean & variance

- Least-Squares Method →

↳ find best fitting line through a set of data points by minimizing the sum of squares of the distances to the points.

- Maximum Likelihood Method

↳ the most plausible parameter

↳ find the values of the model parameters, that make the observed data most probable

## Confidence Intervals

↳ Interval that contains the true value of the estimator with a confidence  $X$