



# Recap

## Random variables

### Discrete random variable

- Sample space is finite or countable many elements
- The probability function  $f(x)$  is often tabulated
- Calculation of probabilities

$$P( a < X < b ) = \sum_{a < t < b} f(t)$$

### Continuous random variable

- Sample space has infinitely many elements
- The density function  $f(x)$  is a continuous function
- Calculation of probabilities

$$P( a < X < b ) = \int_a^b f(t) dt$$



# Variance Definition

## Definition:

Let  $X$  be a random variable with probability / density function  $f(x)$  and expected value  $\mu$ . **The variance of  $X$**  is then given

$$\sigma^2 = \text{Var}(X) = E[(X - \mu)^2] = \sum_x (x - \mu)^2 f(x)$$

if  $X$  is **discrete**, and

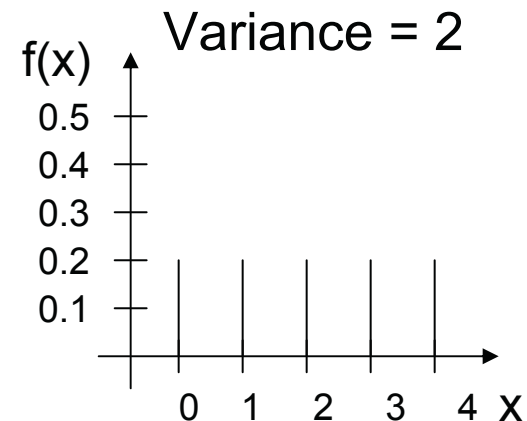
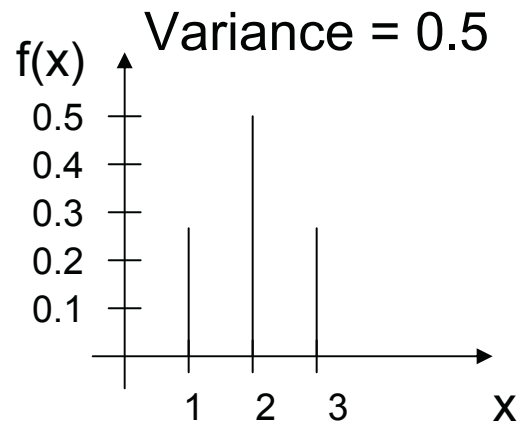
$$\sigma^2 = \text{Var}(X) = E[(X - \mu)^2] = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

if  $X$  is **continuous**.

The standard deviation is the positive root of the variance:  $\sigma = \sqrt{\text{Var}(X)}$

# Variance Interpretation

The variance expresses, how dispersed the density / probability function is around the mean.



Rewrite of the variance:

$$\sigma^2 = \text{Var}(X) = E[X^2] - \mu^2$$



# Variance

## Linear combinations

### Theorem: **Linear combination**

Let  $X$  be a random variable, and let  $a$  and  $b$  be constants. For the random variable  $aX + b$  the variance is

$$\text{Var}(aX + b) = a^2 \text{Var}(X)$$

### Examples:

$$\text{Var}(X + 7) = \text{Var}(X)$$

$$\text{Var}(-X) = \text{Var}(X)$$

$$\text{Var}(2X) = 4 \text{Var}(X)$$



# Covariance Definition

## Definition:

Let  $X$  and  $Y$  be two random variables with joint probability / density function  $f(x, y)$ . **The covariance** between  $X$  and  $Y$  is

$$\sigma_{XY} = \text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] = \sum_x \sum_y (x - \mu_X)(y - \mu_Y) f(x, y)$$

if  $X$  and  $Y$  are **discrete**, and

$$\sigma_{XY} = \text{Cov}(X, Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f(x, y) dx dy$$

if  $X$  and  $Y$  are **continuous**.

# Covariance Interpretation

Covariance between  $X$  and  $Y$  expresses how  $X$  and  $Y$  influence each other.

Examples: Covariance between

- $X$  = sale of bicycle and  $Y$  = bicycle pumps is **positive**.
- $X$  = Trips booked to Spain and  $Y$  = outdoor temperature is **negative**.
- $X$  = # eyes on red dice and  $Y$  = # eyes on the green dice is **zero**.





# Covariance Properties

## Theorem:

The **covariance** between two random variables  $X$  and  $Y$  with means  $\mu_X$  and  $\mu_Y$ , respectively, is

$$\sigma_{XY} = \text{Cov}(X, Y) = E[XY] - \mu_X \mu_Y$$

Notice!

$$\text{Cov}(X, X) = \text{Var}(X)$$

If  $X$  and  $Y$  are **independent** random variables, then

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

Notice!  $\text{Cov}(X, Y) = 0$  **does not** imply independence!



# Variance/Covariance

## Linear combinations

### Theorem: **Linear combination**

Let  $X$  and  $Y$  be random variables, and let  $a$  and  $b$  be constants.

For the random variables  $aX + bY$  the variance is

$$\text{Var}(aX + bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y)$$

In particular:  $\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y] + 2\text{Cov}(X, Y)$

If  $X$  and  $Y$  are **independent**, the variance is

$$\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y]$$





# Correlation Definition

## Definition:

Let  $X$  and  $Y$  be two random variables with covariance  $\text{Cov}(X, Y)$  and standard deviations  $\sigma_X$  and  $\sigma_Y$ , respectively.

The correlation coefficient of  $X$  and  $Y$  is

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

It holds that

$$-1 \leq \rho_{XY} \leq 1$$

If  $X$  and  $Y$  are independent, then  $\rho_{XY} = 0$



# Mean, variance, covariance

## Collection of rules

### Sums and multiplications of constants:

$$E(aX) = a E(X) \quad \text{Var}(aX) = a^2 \text{Var}(X) \quad \text{Cov}(aX, bY) = ab \text{Cov}(X, Y)$$

$$E(aX+b) = aE(X)+b \quad \text{Var}(aX+b) = a^2 \text{Var}(X)$$

### Sum:

$$E(X+Y) = E(X) + E(Y)$$

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

X and Y are **independent**:  $E(XY) = E(X) E(Y)$

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$



# Discrete distributions

Four important **discrete** distributions:

1. The **Uniform** distribution (discrete)
2. The **Binomial** distribution
3. The **Hyper-geometric** distribution
4. The **Poisson** distribution



# Uniform distribution

## Definition

Experiment with **k equally likely** outcomes.

### Definition:

Let  $X: S \rightarrow R$  be a discrete random variable. If

$$P(X_1 = x_1) = P(X_2 = x_2) = \cdots = P(X_k = x_k) = \frac{1}{k}$$

then the distribution of  $X$  is the (discrete) **uniform distribution**.

**Probability function:**

$$f(x; k) = \frac{1}{k} \text{ for } x = x_1, x_2, \dots, x_k$$

**(Cumulative) distribution function:**

$$F(x; k) = \frac{i}{k} \text{ for } x = x_1, x_2, \dots, x_k$$

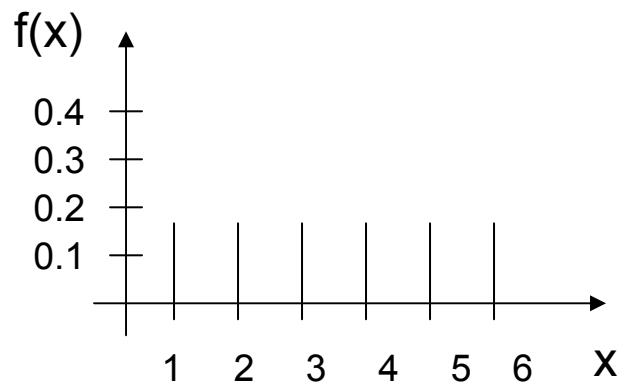
(We assume  $x_i < x_{i+1}$ )

# Uniform distribution

## Example

**Example:** Rolling a dice

X: # eyes



**Probability function:**

**Distribution function:**

**Mean value:**

$$E(X) = \frac{1+2+3+4+5+6}{6} = 3.5$$

**variance:**

$$\begin{aligned} \text{Var}(X) &= \frac{(1-3.5)^2 + \dots + (6-3.5)^2}{6} \\ &= \frac{35}{12} \end{aligned}$$

$$f(x; k) = \frac{1}{6} \text{ for } x = 1, 2, \dots, 6$$

$$F(x; 6) = \frac{x}{6} \text{ for } x = 1, 2, \dots, 6$$



# Uniform distribution

## Mean & variance

### Theorem:

Let  $X$  be a uniformly distributed with outcomes  $x_1, x_2, \dots, x_k$

Then we have

- **mean value** of  $X$ :  $E(X) = \mu = \frac{\sum_{i=1}^k x_i}{k}$
- **variance** of  $X$ :  $\text{Var}(X) = \frac{\sum_{i=1}^k (x_i - \mu)^2}{k}$



# Binomial distribution

## Bernoulli process

Repeating an experiment with **two possible outcomes**.

### Bernoulli process:

1. The experiment consists in repeating the same trail  $n$  times.
2. Each trail has two possible outcomes: “**success**” or “**failure**”, also known as **Bernoulli trial**.
3.  $P(\text{“success”}) = p$  is the same for all trails.
4. The trails are independent.



# Binomial distribution

## Bernoulli process

### **Definition:**

Let the random variable  $X$  be the number of “successes” in the  $n$  Bernoulli trials.

The distribution of  $X$  is called the **binomial distribution**.

**Notation:**  $X \sim B(n, p)$






# Binomial distribution

## Probability & distribution function

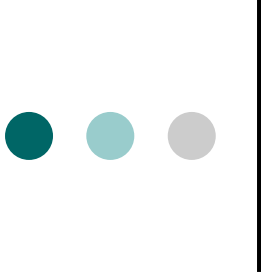
### Theorem:

If  $X \sim B(n, p)$ , then  $X$  has **probability function**

$$b(x; n, p) = P(X = x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}, \quad x = 0, 1, 2, \dots, n$$


and **distribution function**

$$B(x; n, p) = P(X \leq x) = \sum_{t=0}^x b(t; n, p), \quad x = 0, 1, 2, \dots, n \quad (\text{See Table A.1})$$



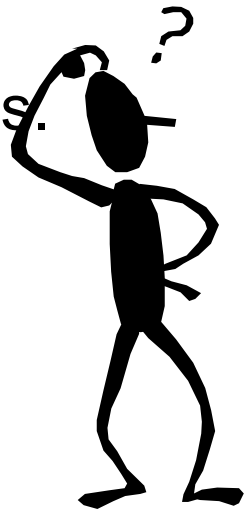
# Binomial distribution Problem

**BILKA** has the option to reject a shipment of batteries if they do not fulfil BILKA's "accept policy":

- A sample of 20 batteries is taken: If one or more batteries are defective, the entire shipment is rejected.
- Assume the shipment contains 10% defective batteries.

1. What is the probability that the entire shipment is rejected?

2. What is the probability that at most 3 are defective?





# Binomial distribution

## Mean & variance

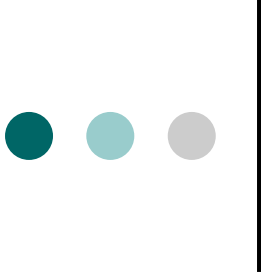
### Theorem:

If  $X \sim \text{bn}(n, p)$ , then

- **mean** of  $X$ :  $E(X) = np$
- **variance** of  $X$ :  $\text{Var}(X) = np(1-p)$

### Example continued:

What is the expected number of defective batteries?



# Hyper-geometric distribution

## Hyper-geometric experiment

### Hyper-geometric experiment:

1.  $n$  elements chosen from  $N$  elements **without** replacement.
2.  $k$  of these  $N$  elements are "**successes**" and  $N-k$  are "**failures**"

Notice!! Unlike the binomial distribution the selection is done **without** replacement and the experiments are **not independent**.

Often used in **quality control**.



# Hyper-geometric distribution

## Definition

### Definition:

Let the random variable  $X$  be the number of “successes” in a hyper-geometric experiment, where  $n$  elements are chosen from  $N$  elements, of which  $k$  are “successes” and  $N-k$  are “failures”.

The distribution of  $X$  is called the hyper-geometric distribution.

**Notation:**  $X \sim \text{hg}(N, n, k)$



# Hyper-geometric distribution

## Probability & distribution function

### Theorem:

If  $X \sim \text{hg}(N, n, k)$ , then  $X$  has **probability function**

$$h(x; N, n, k) = P(X = x) = \frac{\binom{k}{x} \binom{N-k}{n-x}}{\binom{N}{n}}, \quad x = 0, 1, 2, \dots, n$$

and **distribution function**

$$H(x; N, n, k) = P(X \leq x) = \sum_{t=0}^x h(t; N, n, k), \quad x = 0, 1, 2, \dots, n$$



# Hyper-geometric distribution Problem

**Føtex** receives a shipment of 40 batteries. The shipment is unacceptable if 3 or more batteries are defective.

Sample plan: take 5 batteries. If at least one battery is defective the entire shipment is rejected.

What is the probability of exactly one defective battery, if the shipment contains 3 defective batteries ?

Is this a good sample plan ?





# Hyper-geometric distribution

## Mean & variance

### Theorem:

If  $X \sim \text{hg}(N, n, k)$ , then

- **mean** of  $X$ :

$$E(X) = \frac{n k}{N}$$

- **variance** of  $X$ :

$$\text{Var}(X) = \frac{N-n}{N-1} n \frac{k}{N} \left(1 - \frac{k}{N}\right)$$





# Poisson distribution

## Poisson process

Experiment where events are observed during a time interval.

### Poisson process:

1. # events in the interval  $[a,b]$  is independent of  
# events in the interval  $[c,d]$ , where  $a < b < c < d$  } **No memory**
2. Probability of 1 event in a short time interval  $[a, a + \varepsilon]$  is proportional to  $\varepsilon$ .
3. The probability of more than 1 event in the short time interval is close to 0.



# Poisson distribution

## Definition

### Definition:

Let the random variable  $X$  be the number of events in a time interval of length  $t$  from a Poisson process, which has on average  $\lambda$  events pr. unit time.

The distribution of  $X$  is called the **Poisson distribution** with **parameter**  $\mu = \lambda t$ .

**Notation:**  $X \sim \text{Pois}(\mu)$  , where  $\mu = \lambda t$



# Poisson distribution

## Probability & distribution function

### Theorem:

If  $X \sim \text{Pois}(\mu)$ , then  $X$  has **probability function**

$$p(x; \mu) = P(X = x) = \frac{e^{-\mu} \mu^x}{x!}, \quad x = 0, 1, 2, \dots$$

and **distribution function**

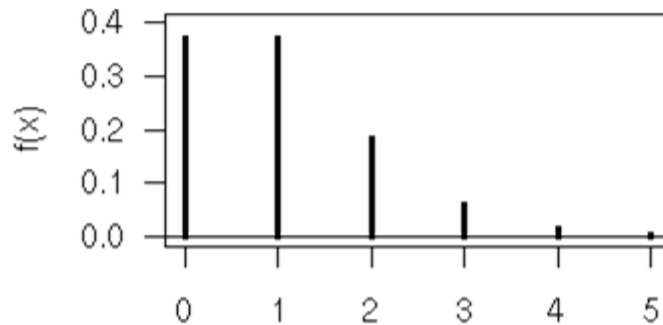
$$P(x; \mu) = P(X \leq x) = \sum_{t=0}^x p(t; \mu), \quad x = 0, 1, 2, \dots \quad (\text{see Table A2})$$

# Poisson distribution

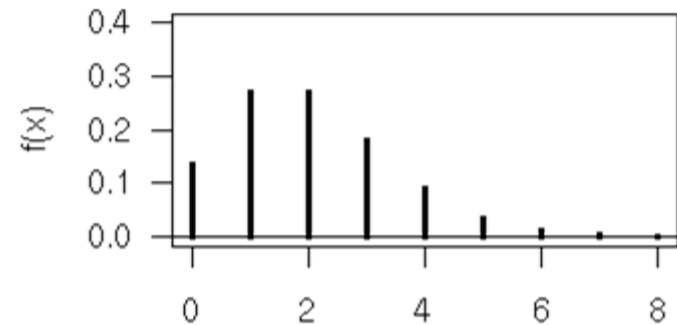
## Examples

Some examples of  $X \sim \text{Pois}(\mu)$  :

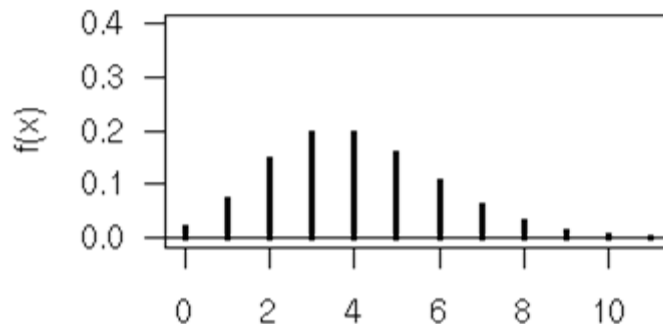
$X \sim \text{Pois}(1)$



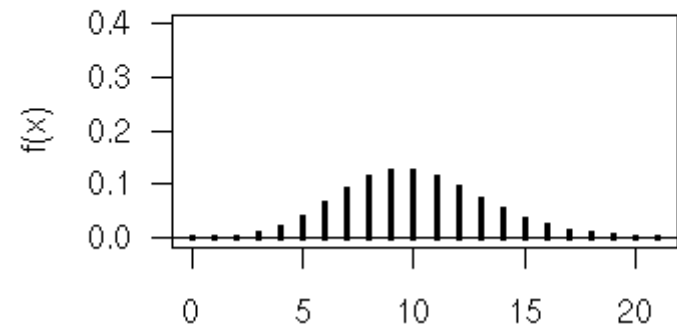
$X \sim \text{Pois}(2)$



$X \sim \text{Pois}(4)$



$X \sim \text{Pois}(10)$





# Poisson distribution

## Mean & variance

### Theorem:

If  $X \sim \text{Pois}(\mu)$ , then

- **mean** of  $X$ :  $E(X) = \mu$
- **variance** of  $X$ :  $\text{Var}(X) = \mu$



# Poisson distribution Problem

**Netto** have done some research: On weekdays before noon an average of 3 customers pr. minute enter a given shop.

1. What is the probability that exactly 2 customers enter during the time interval 11.38 - 11.39 ?
2. What is the probability that at least 2 customers enter in the same time interval ?
3. What is the probability that at least 10 customers enter the shop in the time interval 10.05 - 10.10 ?

