# Analysis Methods for Cross-Sectional Data: Probability and Statistics

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- 1. Alice has 2 kids, her first child is a girl. Find the probability that the second child is also a girl.
- 2. Alice has 2 kids, one of them is a girl. Find the probability that both of them are girls.
- 3. Monty Hall Problem: Suppose you're on a game show, and you're given the choice of three doors: Behind one door is a car; behind the others, goats. You pick a door, say No. 1, and the host, who knows what's behind the doors, opens another door, say No. 3, which has a goat. He then says to you, "Do you want to pick door No. 2?" Is it to your advantage to switch your choice?

#### **Answers**:

1. A = { First child is a girl } B = { Second child is a girl }  $A \cap B$  = {Both kids are girls}

$$P(B|A) = P(A \cap B)/P(A) = P(A)P(B)/P(A) = P(B) = \frac{1}{2}$$

2.  $C = \{ \text{ One of the kids is a girl } \}$ 

$$P(A \cap B | C) = P(A \cap P \cap C)/P(C) = P(A \cap B)/P(C) = \frac{\frac{1}{4}}{\frac{3}{4}} = \frac{1}{3}$$



#### **Answers**

3. A = {Car is behind door 1},  
B = {Car is behind door 2},  
C = {Car is behind door 3},  
D = {Host shows door 3 after you pick door 1}  

$$P(A) = \frac{1}{3}, \quad P(B) = \frac{1}{3}, \quad P(C) = \frac{1}{3}, \quad P(D) = \frac{1}{2}$$

$$P(D|C) = 0, \quad P(D|A) = \frac{1}{2}, \quad P(D|B) = 1$$

$$P(A|D) = \frac{P(D|A)P(A)}{P(D)} = \frac{1}{3}$$

$$P(B|D) = \frac{P(D|B)P(B)}{P(D)} = \frac{2}{3}$$

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

### Independent events:

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

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

#### Likelihood:

 $P(target|input) \propto P(input|target)P(target)$ 

P(target|input) - Posterior probability

P(input|target) - Likelihood

P(target) - Prior probability

#### Definition

**Probability space** is a triple  $(\Omega, \mathcal{F}, P)$  consisting of:

- ightharpoonup Sample space  $\Omega$  of all possible outcomes of the experiment
- $ightharpoonup \sigma$ -algebra of events  $\mathcal{F}$
- ▶ A probability measure *P* that assigns probability to events

#### Definition

 $\sigma$ -algebra is a collection of sets of outcomes in  $\Omega$  such that:

- 1.  $S \in \mathcal{F} \implies S^c \in \mathcal{F}$
- 2.  $\Omega \in \mathcal{F}$  (an event of all possible outcomes)
- 3.  $S_1, S_2, \ldots \in \mathcal{F} \implies \bigcup S_i \in \mathcal{F}$

Experiment: Flip a coin once.

$$\Omega =$$

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Experiment: Flip a coin once.

 $\Omega = \{\text{heads, tails}\}\$ 

 $\mathcal{F} = \{ \text{heads, tails, heads or tails, neither heads nor tails} \}$ 

#### **Definition**

Probability measure is a function on  ${\mathcal F}$  such that

- 1. P(S) >= 0 for any  $S \in \mathcal{F}$
- 2.  $P(\Omega) = 1$
- 3.  $P(\bigcup_{i=1}^{n} S_i) = \sum_{i=1}^{n} S_i$ ,  $\lim_{n \to \infty} P(\bigcup_{i=1}^{n} S_i) = \sum_{i=1}^{\infty} S_i$

### Random variables

#### Definition

A random variable X is a measurable function from the space of possible outcomes  $\Omega$  to  $\mathbb{R}$ .

**Example:** Throwing two dice, X is the obtained score. There are multiple outcomes that yield a score.

Events {outcomes  $w \in \Omega : X(w) \in I$ } for all intervals  $I \subset \mathbb{R}$  form a  $\sigma$ -algebra.

A discrete random variable is defined over a discrete space of outcomes  $X:\Omega\to\mathbb{D}_X$ . The **probability mass function** is then defined by:

$$p_X(x) = P(X = x) = P(\{w \in \Omega \mid X(w) = x\})$$

$$\sum_{x \in \mathbb{D}_X} p_X(x) = 1$$

**Example:** Let X be the random variable representing the score in the experiment of throwing two dice once. Then,

$$p_X(4) = P(X = 4)$$
  
=  $P(\{\text{dice } 1 = 2, \text{ dice } 2 = 2\} \text{ or } (1)$   
 $\{\text{dice } 1 = 3, \text{ dice } 2 = 1\}$   
 $\{\text{dice } 1 = 1, \text{ dice } 2 = 3\}) = 3\frac{1}{36} = \frac{1}{9}$ 

If X and Y are random variables on the same probability space, then the **joint probability mass function** is defined as:

$$p_{X,Y}(x,y) = P(\{w \in \Omega \mid X(w) = x \text{ and } Y(w) = y\})$$

and verifies the properties:

$$\sum_{x\in\mathbb{D}}p_{X,Y}(x,y)=p_Y(y),\quad \sum_{y\in\mathbb{D}}p_{X,Y}(x,y)=p_X(x)$$

Independent random variables:

$$p_{X,Y}(x,y) = p_X(x)p_Y(y)$$

Conditional probability mass function:

$$p_{X|Y}(x|y) = P(X = x|Y = y) = \frac{p_{X,Y}(x,y)}{p_X(x)}$$

#### Definition

**Expected value** of a function  $f : \mathbb{R} \to \mathbb{R}$  is defined by:

$$\mathbb{E}[f(X)] = \sum_{x \in \mathbb{D}_X} f(x) p_X(x)$$

$$\mathbb{E}[X] = \sum_{x \in \mathbb{D}_X} x \ p_X(x)$$

**Exercise 1:** Show that expectation is linear:

$$\mathbb{E}\left[\alpha X + \beta Y\right] = \alpha[X] + \beta[Y]$$

**Exercise 2:** Show that for independent random variables X, Y:

$$\mathbb{E}\left[XY\right] = \mathbb{E}\left[X\right]\mathbb{E}\left[Y\right]$$

**Solution 1:** Consider a tuple of random variables (X, Y) and a function  $f: x, y \mapsto \alpha x + \beta y$ . By definition:

$$\mathbb{E}\left[\alpha X + \beta Y\right] = \sum_{x \in \mathbb{D}_X} \sum_{y \in \mathbb{D}_Y} (\alpha x + \beta y) p_{X,Y}(x,y)$$

$$= \alpha \sum_{x \in \mathbb{D}_X} x \sum_{y \in \mathbb{D}_Y} p_{X,Y}(x,y) + \beta \sum_{y \in \mathbb{D}_Y} y \sum_{x \in \mathbb{D}_X} p_{X,Y}(x,y)$$

$$= \alpha \sum_{x \in \mathbb{D}_X} x p_X(x) + \beta \sum_{y \in \mathbb{D}_Y} y p_Y(y)$$

$$= \alpha \mathbb{E}[X] + \beta \mathbb{E}[Y]$$

**Solution 2:** Since X and Y are independent,  $p_{X,Y}(x,y) = p_X(x)p_Y(y)$ . Then,  $\mathbb{E}[X,Y] = \sum_{x \in \mathbb{D}_X} \sum_{y \in \mathbb{D}_Y} xyp_X(x)p_Y(y)$  $= \sum_{x \in \mathbb{D}_X} xp_X(x) \sum_{y \in \mathbb{D}_Y} yp_X(y) = \mathbb{E}[X]\mathbb{E}[Y]$ 

#### Definition

**Variance** of a random variable X is defined as:

$$var(X) = \mathbb{E}\left[(X - \mathbb{E}[X])^2\right] = \mathbb{E}\left[X^2\right] - (\mathbb{E}\left[X\right])^2$$

**Covariance** of two random variables *X* and *Y* is defined as:

$$cov(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$

**Exercise 3:** Show that for two independent random variables X and Y

$$var(X + Y) = var(X) + var(Y)$$

**Solution 3:** Since X and Y are independent,  $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$ , then

$$var(X + Y) = \mathbb{E}\left[ (X + Y)^{2} \right] - (\mathbb{E}\left[ X + Y \right])^{2}$$

$$= \mathbb{E}[(X^{2} + 2XY + Y^{2})] - (\mathbb{E}[X] + \mathbb{E}[Y])^{2}$$

$$= \mathbb{E}[X^{2}] + 2\mathbb{E}[X]\mathbb{E}[Y] + \mathbb{E}[Y^{2}]$$

$$- (E[X])^{2} - (E[X])^{2} - 2\mathbb{E}[X]\mathbb{E}[Y]$$

$$= var(X) + var(Y)$$

**Example 1:** The probability to win 10 dollars in the lottery is 0.001. What is my expected gain if I play only once?

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$$\mathbb{E}[gain(X)] = 10 * P(win) + 0 * P(loose)$$
$$= 10 \times 0.001 = 0.01 \text{ dollars}$$

**Bernoulli distribution** with parameter  $p \in [0, 1]$ :

$$P(X = 1) = p$$
,  $P(X = 0) = 1-p$ ,  $\mathbb{E}[X] =$ 

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**Example 2:** If play the lottery more than once my chances to win are better. How probabal is it that I will need to buy at least 100 tickets before I win? What is the expected number of tickets I need to buy before I win?

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$$p(\text{loose 100 times before win}) = (0.999)^{99} * 0.001 \sim 0.0009$$

**Geometric distribution** with parameter *p*:

$$P(x = k) = (1 - p)^{k-1}p, \quad k = 1, 2, \dots$$
  
 $\mathbb{E}[X] = \frac{1}{p}, \quad var(X) = \frac{1 - p}{p^2}$ 

In order to calculate the expectation and the variance, we calculate infinite sums:

$$\mathbb{E}[X] = \sum_{k=0}^{\infty} kp(1-p)^{k-1} = -p\frac{d}{dp}\sum_{k=0}^{\infty} (1-p)^k$$
$$= -p\frac{d}{dp}\left(\frac{1}{p}\right) = \frac{p}{p^2} = \frac{1}{p}$$

$$var(X) = \sum_{k=0}^{\infty} k^2 p (1-p)^{k-1} - \frac{1}{p} = \frac{1-p}{p^2}$$

Trick: represent the series as derivatives of well-known series

**Example 3:** I would like to win at least 20 dollars. How many tickets do I need to buy?

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$$\mathbb{E}[gain(\texttt{k tickets})] = k*\mathbb{E}[gain(1 \text{ ticket})] = k*0.01 = 20 \implies k = 2000$$

What is the probability that I win at least twice with 2000 tickets? What is the probability that I win exactly twice?

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What is the probability that I win at least twice with 2000 tickets? What is the probability that I win exactly twice?

$$P(\text{win at least twice}) = 1 - p(\text{never win}) - p(\text{win once})$$
$$= 1 - (0.999)^{2000} - 1000 \times (0.999)^{1999} \times 0.001 = 0.5943$$

$$p(\text{win exactly twice}) = {2000 \choose 2} \times 0.001^2 \times 0.999^{1998} = 0.2708$$

**Binomial distribution:** with parameter p:

$$P(X = k|n) = \binom{n}{k} p^k (1-p)^{n-k}, \quad k = 0, \dots, n$$
$$\mathbb{E}[X] = np, \ var(X) = np(1-p)$$



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### Hypergeometric distribution with parameters

N = 1000-population size, n = 200-number of draws without replacement, K = 10-number of successes in the population, k = 2-number of observed successes:

$$P(X = k) = \frac{\binom{K}{k} \binom{N-K}{n-k}}{\binom{N}{n}}$$

$$\mathbb{E}[X] = np$$
,  $var(X) = \frac{np(1-p)(N-n)}{N-1}$ ,  $p = \frac{K}{N}$ 

**Exercise:** Confirm the result using scipy.stats.hypergeom.



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Assume day = n time intervals only one lottery ticket can be won in one time interval  $p(\text{winner in one time interval}) = \frac{\lambda}{n}, \ n \to \infty$ 

$$P(k \text{ winners during the day}) = \lim_{n \to \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} = \frac{\lambda^k e^{-\lambda}}{k!}$$

$$P(k \text{ winners in t days}) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

**Poisson distribution** with parameter  $\lambda$ :

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \quad k = 0, 1, 2, \dots$$
  
 $\mathbb{E}[X] = \lambda, \quad var(X) = \lambda^2 + \lambda$ 

# Summary Discrete Random Variables

- One trial with binary outcome: success, failure ⇒ Bernoulli distribution
- 2. Number of trials till success  $\implies$  **Geometric distribution**
- 3. Number of successes in n trials  $\implies$  **Binomial distribution**
- Given the number of successes in the population, find number of successes in a sample (drawn without replacement) ⇒
   Hypergeometric distribution
- Number of successes in a time period, given the average number of successes per time period ⇒ Poisson distribution

### Continuous random variables

**Probability density function:** Probability that value of the random variable X belongs to the interval  $\Delta x$  ( $|\Delta x| \to 0$ ) can be approximated by  $p(x)\Delta x$ .

$$P(X \in (a,b]) = \int_a^b p(x)dx, \quad \int_{-\infty}^{\infty} p(x)dx = 1$$

**Cumulative distribution function:** 

$$F(x) = P(X \le x) = \int_{-\infty}^{x} p(x)dx$$

**Expected value** of a function  $f : \mathbb{R} \to \mathbb{R}$  of random variable X:

$$\mathbb{E}[f(X)] = \int_{-\infty}^{\infty} f(x)p(x)dx, \quad \mathbb{E}[X] = \int_{-\infty}^{\infty} xp(x)dx$$

### Continuous random variables

**Joint CDF** of random variables *X* and *Y*:

$$F(x,y) = P(X \le x, Y \le y) = \int_{-\infty}^{x} \int_{-\infty}^{y} p_{X,Y}(x,y) dx dy$$
$$\int_{-\infty}^{\infty} p_{X,Y}(x,y) dy = p_{X}(x), \quad \int_{-\infty}^{\infty} p_{X,Y}(x,y) dx = p_{Y}(y)$$

#### Conditional Distributions:

$$p_{Y|X}(y|x) = \frac{p_{X,Y}(x,y)}{p_X(x)}$$

If X and Y are independent random variables,

$$p_{Y|X}(y|x) = p_Y(y) \iff p_{X,Y}(x,y) = p_X(x)p_Y(y)$$

**Example 1:** The bus leaves the bus-stop every 15 minutes. What is the probability that you will wait less than 5 minutes for the next bus? How much time are you going to wait in average?

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The probability to wait less than x minutes increases at a constant speed when x increases.

$$P(X \le x) = cx$$
,  $\int_0^{15} c dx = 1 \implies c = \frac{1}{15}$ ,  $P(X \le 5) = \frac{1}{3}$ 

Uniform distribution over the interval (a, b):

$$p(x) = \begin{cases} \frac{1}{b-a}, & \text{if } a \le x \le b \\ 0, & \text{otherwise} \end{cases}$$

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$$\mathbb{E}[X] = \frac{1}{2}(a+b), \quad var(X) = \frac{1}{12}(b-a)^2$$



**Example 2:** You observe that the number of hits on your web-site follows a Poisson distribution at the rate 2 per day. What is the probability that you will have to wait less than 5 days until the next hit.

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$$P(X > t) = P(0 \text{ hits in t days}) = \frac{(\lambda t)^0 e^{-\lambda t}}{0!} = e^{-\lambda t}$$

$$P(X \le 5) = 1 - P(x > 5) = 1 - e^{-5\lambda} = 1 - e^{-10}$$

**Exponential distribution** with parameter  $\lambda$ :

$$P(X \le x) = 1 - e^{-\lambda x}, \quad p(x) = \lambda e^{-\lambda x}$$
 
$$\mathbb{E}[X] = \frac{1}{\lambda}, \quad var(X) = \frac{2}{-\lambda^2}$$

Normal (Gaussian) distribution with mean  $\mu$  and standard deviation  $\sigma$ :

$$p(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, \quad P(X \le x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt$$

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#### **Theorem**

**Central Limit Theorem**: Let  $X_1, X_2, ...$  be a sequence of i.i.d. random variables with  $\mathbb{E}[X_i] = \mu$  and  $var(X_i) = \sigma^2 < \infty$ , then

$$\frac{\frac{1}{n}\sum_{i=1}^{n}X_{n}-\mu}{\frac{\sigma}{\sqrt{n}}}\xrightarrow[n\to\infty]{}\mathcal{N}(0,1)$$
 in distribution

# Summary Continuous Random Variables

- If Probability of a random variable to belong to an interval grows linearly when the interval grows => uniform distribution
- 2. Given the average number of successes per time unit, time until success => **Exponential distribution**
- 3. Random variable representing an average value in a sample => **Normal distribution**

#### Sample mean and variance

What do we do if we have observations (data) but do not know the distribution followed by the data?

Law of large numbers: Let  $X_1, X_2, \ldots$ , be a sequence of i.i.d. random variables with the expected value  $\mu$  and variance  $\sigma^2$ . Then, the sample mean and the sample variance defined as

$$\mu_n = \frac{\sum_{k=1}^n x_k}{n}, \quad \sigma_n^2 = \frac{\sum_{k=1}^n (x_k - \mu_n)^2}{n}$$

converge in probability to the mean and the variance:

$$\mu_n \xrightarrow[n \to \infty]{} \mu, \quad \sigma_n^2 \xrightarrow[n \to \infty]{} \sigma^2$$

# Sample mean and variance

$$\mathbb{E}[\sigma_n^2] = \frac{1}{n} \sum_{k=1}^n \mathbb{E}\left[\left(x_k - \frac{1}{n} \sum_{i=1}^n x_i\right)^2\right]$$

$$= \frac{1}{n} \sum_{k=1}^n \mathbb{E}\left[\left((x_k - \mu) - \frac{1}{n} \sum_{i=1}^n (x_i - \mu)\right)^2\right]$$

$$= \frac{1}{n} \sum_{k=1}^n \left(\mathbb{E}\left[(x_k - \mu)^2\right] - \frac{2}{n} \sum_{i=1}^n \mathbb{E}\left[(x_k - \mu)(x_i - \mu)\right] + \frac{1}{n^2} \sum_{i=1}^n \mathbb{E}\left[(x_i - \mu)^2\right]\right) = \frac{n-1}{n} \sigma^2$$

#### Unbiased sample variance:

$$\tilde{\sigma}_n^2 = \sum_{k=1}^n \frac{(x_k - \mu_n)^2}{n-1}, \quad \mathbb{E}\left[\tilde{\sigma}_n^2\right] = \sigma^2$$

# Fitting a probability distribution to data

- 1. Choose the familty of probability distributions
- 2. Find the parameters of the distribution that maximize the likelihood of obtaining the data

$$P(x_1, \ldots, x_n | parameters) \rightarrow max$$

#### Maximum Likelihood Estimates

**Example:**  $x_1, \ldots, x_n$  - realizations of a **Bernoulli** random variable. Estimate the parameter p - probability of success.

$$P(x_1, \dots, x_n | p) = \prod_{k=1}^n P(x_k | p) = \prod_{k=1}^n p^{x_k} (1 - p)^{1 - x_k}$$

$$f(p) = \log P(x_1, \dots, x_n | p) = \sum_{k=0}^n (x_k \log p + (1 - x_k) \log(1 - p))$$

$$\frac{df}{dp} = \sum_{k=0}^n \left( \frac{x_k}{p} - \frac{1 - x_k}{1 - p} \right) = 0 \quad \iff p_{ML} = \frac{1}{n} \sum_{k=1}^n x_k$$

$$\frac{d^2 f}{dp^2} < 0$$

**Conclusion:** f is a convex function and attains its maximum when the probaility of success is approximated by the ratio of the successes in the sample data (sample mean).



#### Maximum Likelihood Estimates

#### Poisson, Exponential distribution:

$$\lambda_{ML} = \frac{1}{n} \sum_{k=1}^{n} x_k$$

#### Normal distribution:

$$\mu_{ML} = \frac{1}{n} \sum_{k=1}^{n} x_k, \quad \sigma_{ML}^2 = \frac{1}{n} \sum_{k=1}^{n} (x_k - \mu_{ML})^2$$

**Usecase**: You have an online shop and you pay facebook to show your add. You suspect that more people navigate to your web-site in the second part of the day. You make observations during 20 days and in 14 cases your conjecture confirmed.

Would you ask facebook to make more impressions of your add in the second part of day?

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- Would you ask facebook to make more impressions of your add in the second part of day?
- ▶ What if your conjecture was true in 1400 out of 2000 observations?

Techniques for evaluating a pre-defined conjecture is called **hypothesis testing**.

 $H_0$  - **null hypothesis**: hypothesis that our conjecture is false  $H_1$  - **alternative hypothesis**: hypothesis under which our conjecture is true

**Type I error**: conjecture is false, but  $H_0$  is rejected **Type II error**: conjecture is true, but  $H_0$  is not rejected

What type of error the hypothesis testing aims to avoid?

#### Definition

**p-value** is the probability (likelihood) to observe results at least as extreme as those measured under the assumption that the null hypothesis  $H_0$  is true.

Wrong interpretation: probability that the null hypothesis is true.

The null-hypothesis  $H_0$  is rejected if the p-value is less than a given **significance level** and the measured data is called statistically significant.

Significance level has to be decided on. (Popular choices 5%, 1%)

# Statistical Significance: Binomial Test

 $H_0 =$  number of conversions does not depend on the time of the day

$$X = \begin{cases} 1, & \text{if there more conversions in the second part of the day} \\ 0, & \text{otherwise} \end{cases}$$

Under 
$$H_0$$
:  $p(X = 1) = \frac{1}{2}$ 

 $t = \sum_{i=1}^{n} X_i$  - number of days with more conversions in the second part of the day

$$p(t >= k) =$$

# Statistical Significance: Binomial Test

 $H_0 =$  number of conversions does not depend on the time of the day

$$X = \begin{cases} 1, & \text{if there more conversions in the second part of the day} \\ 0, & \text{otherwise} \end{cases}$$

Under  $H_0$ :  $p(X = 1) = \frac{1}{2}$ 

 $t = \sum_{i=1}^{n} X_i$  - number of days with more conversions in the second part of the day

$$p(t>=k)=\frac{1}{2^n}\sum_{i=k}^n\binom{n}{k}$$

**Exercise**: calculate in python for n=20, k=14 (n=2000, k=1400) using function scipy.special.binom. Confirm the results with the function scipy.stats.binom\_test.



Now let's say that the online-shop considers to rearrange the landing page of its web-site. The metrics monitored by the shop are:

- Average time spent on the landing page per session
- ► Conversion rate = average proportion of sessions that end up with a transaction.

How are you going to evaluate if the changes in the landing page increase the income?

You split the traffic of the web-site randomly between two site versions in proportion 60%-40%:

Version	n sessions	avg(time)	stdtime	number of conversions
Α	6000	60s	40s	90
В	4000	62s	45s	80

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$$CR(A) = \frac{90}{6000} = 0.015, \quad CR(B) = \frac{80}{4000} = 0.02$$

Which web-site version is better in terms of time spent on the page and the conversion rate?



A/B versions == treatement/control groups

#### Use-cases for A/B testing:

- Product or service development
- Medicine (to test effects of a treatment)
- In economics (to undersand the behavior of economical actors)

#### **Important Aspects:**

- ▶ Randomization strategy: There should be no hidden factors that bias the the selection. Example: selling two versions of a product in two shops with different geo-locations. (A solution: increase the number of shops)
- ► Sample size should be sufficient to represent the population

 $\mathbf{H_0}$ : Time spent on the landing page does not depend on the page version.

 $\mathbf{H}_1$ : Time spent on the landing page depends on the page version.

- What distribution does the mean time spent on the web-site follow?
- What statistic should we consider?

# Statistical Significance: Normal test

$$\hat{t}_A = rac{1}{n_A} \sum_{i=1}^{n_A} t_i \sim \mathcal{N}(\mu_A, rac{\sigma_A}{\sqrt{n_A}}), \quad \hat{t}_B = rac{1}{n_B} \sum_{i=1}^{n_B} t_i \sim \mathcal{N}(\mu_B, rac{\sigma}{\sqrt{n_B}})$$
Under  $H_0$ :  $\hat{t}_A - \hat{t}_B \sim \mathcal{N}(0, \sqrt{rac{\sigma_A^2}{n_A} + rac{\sigma_B^2}{n_B}})$ 

$$Z = rac{\hat{t}_A - \hat{t}_B}{\sqrt{rac{\sigma_A^2}{A} + rac{\sigma_B^2}{B}}} \sim \mathcal{N}(0, 1)$$

**Exercise:** Find the corresponding p-value using scipy.stats.norm. Plot the function scipy.stats.norm.cdf.

# Statistical Significance: T-test

When the number of observations is very large, normal distribution is not a good approximation for the Z statistic. In this case, we use the Student's T-distribution:

$$T = rac{\hat{t}_A - \hat{t}_B}{\sigma_{pooled}\sqrt{rac{1}{n_A} + rac{1}{n_B}}} \sim \mathcal{T}(0, n_A + n_B - 1)$$

$$\sigma_{pooled} = \frac{(n_A - 1)\sigma_A^2 + (n_B - 1)\sigma_B^2}{n_A + n_B - 2}$$

follows the Student's t-distribution with  $n_A + n_B - 1$  degrees of freedom.

**Exercise:** Find the corresponding p-value using scipy.stats.t.



Let's say you distribute n objects in r boxes with the probability to arrive in the box  $B_j$  equal to  $p_j$ . And let  $\nu_j$  be a random variable that describes the number of objects in the box  $B_j$ . Than,

$$\mathbb{E}(
u_j) = np_j, \quad var(
u_j) = np_j(1-p_j), \quad rac{
u_j - np_j}{\sqrt{npj(1-p_j)}} 
ightarrow \mathcal{N}(0,1)$$

#### Pearson's Theorem:

$$\sum_{j=1}^r \frac{(\nu_j - np_j)^2}{np_j} \to \chi_{r-1}^2$$

convergence in distribution to  $\chi^2_{r-1}$  with r-1 degrees of freedom.

$$\sum \frac{(\text{observed - expected})^2}{\text{expected}}$$



If now you randomly distribute n objects of k colors and r boxes, let  $\nu_{ij}$  be the number of objects of color i in the box  $B_j$ . Let probability to arrive in the box  $B_j$  is equal to  $p_j$  and the probability to pick an object of color i is equal to  $q_i$ . Then,

#### Pearson's Theorem:

$$\sum_{i=1}^{k} \sum_{j=1}^{r} \frac{(\nu_{ij} - np_{j}q_{i})^{2}}{np_{j}q_{i}} \to \chi^{2}_{(r-1)\times(k-1)}$$

convergence in distribution to  $\chi^2_{(r-1)\times(k-1)}$  with  $(r-1)\times(k-1)$  degrees of freedom.

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"Boxes" - versions A and B of the web-site, with probabilities:

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$$p_A = 0.6, \quad p_B = 0.4$$

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"Colors" - conversion, no-conversion, with probabilities (under  $H_0$ ):

$$q_c = \frac{80 + 90}{6000 + 4000} = 0.017, \quad q_{nc} = 1 - q_c = 0.983, \quad n = 1000$$

$$\nu_{11} = 90, \quad \nu_{12} = 6000 - 90 = 5910$$

$$\nu_{21} = 80, \quad \nu_{22} = 4000 - 80 = 3920$$

$$s = \frac{(90 - 0.6 \times 0.017 \times 10000)^{2}}{0.6 \times 0.017 \times 10000} + \frac{(80 - 0.4 \times 0.017 \times 10000)^{2}}{0.4 \times 0.017 \times 10000}$$
$$= \frac{(5910 - 0.6 \times 0.983 \times 10000)^{2}}{0.6 \times 0.983 \times 10000} + \frac{(3920 - 0.4 \times 0.983 \times 10000)^{2}}{0.4 \times 0.983 \times 10000}$$

**Exercise**: Calculate p-value of s using scipy.stats.chi2.cdf with df=1

# Statistical Significance: Fisher's Test

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Total	7	29	36

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From a population of size N=36 with K=7 conversions we draw a sample of size n=20. What is the distribution of the number of conversion in that sample?

$$x \sim \text{Hypergeometric}(N=36, K=7, n=20), P(x=2)=?$$

What is the probability to observe values following the same distribution and as extreme as described x = 2?



#### Statistical Significance: Fishers test

**Fisher's exact test:** sum of probabilities of over all the tables that yield the observed marginal counts and values of x as extreme as above:

Version	n conversions	n sessions - n conversions	total
Α	X	*	20
В	*	*	*
Total	7	29	36

Answer: 
$$P\begin{pmatrix} x=0 & 8 \\ 7 & 21 \end{pmatrix} + P\begin{pmatrix} x=1 & 10 \\ 6 & 19 \end{pmatrix} + P\begin{pmatrix} x=2 & 5 \\ 18 & 11 \end{pmatrix}$$

**Exercise:** use scipy.stats.fisher\_exact to calculate the corresponding p-value

**Limitations:** Exact answer to a wrong question?

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**Limitations:** Exact answer to a wrong question? (*The total number of successes in the population is assumed to be fixed...*)



**Usecase**: Suppose that an accounting firm does a study to determine the time needed to complete one person's tax forms. It randomly surveys 100 people. The sample mean is 23.6 hours. There is a known standard deviation of 7.0 hours. Construct a 95% confidence interval for the population mean time to complete the tax forms.

#### Definition

Let's say we have a parameter  $\theta$  of the population (average number of time to complete a tax form). And we have a procedure that produces an estimate  $\hat{\theta}$  of this parameter on a sample from the population (sample mean).

Since we sample in a randomized way  $\implies \hat{ heta}$  is a random variable

$$P(-\alpha_1 \le \hat{\theta} - \theta \le \alpha_2) = 0.95 \implies P(\hat{\theta} - \alpha_2 \le \theta \le \hat{\theta} - \alpha_1) = 0.95$$

**Confidence Interval:**  $(\hat{\theta} - \alpha_2, \ \hat{\theta} - \alpha_1)$ 

Numbers  $\alpha_1, \alpha_2$  are chosen in such a way that the confidence interval is symmetric.

#### **Definition**

**Quantiles:** A number  $\alpha$  such that  $P(X \le \alpha) = p$  is called p-quantile of X.

we find 
$$\alpha_1, \alpha_2$$
 s.t.  $P(\alpha_1 \le \hat{\theta} - \theta \le \alpha_2) = 0.95$ 

$$\implies \alpha_1$$
 - 0.025 quantile,  $\alpha_2$  - 0.975 quantile

of the random variable  $\hat{\theta} - \theta$ 

**Important:** Estimate  $\hat{\theta}$  is a random variable  $\implies$  confidence interval is a pair of random variables!

**Correct interpretation:** There is a 95% probability that the confidence interval calculated for some future value of the estimate  $\hat{\theta}$  will contain the true value of the population parameter.

Wrong interpretation: Let's say we obtained an estimate  $\hat{\theta}=7$  of the population parameter and calculated the corresponding confidence interval  $(7-\alpha_2,7-\alpha_1)$ . We CANNOT say that there is 95% probability that the true parameter lies in this confidence interval!

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**Difference in statementes:** We can talk about  $P(X \le 5)$  for a random variable X. But if we have an outcome X = 7 of X we cannot talk about the probability that  $7 \le 5$ !

Let  $\bar{X} = \sum_{i=1}^{100} X_i$  be the sample mean time. By CLT,

$$Z = rac{ar{X} - \mu}{\sigma / \sqrt{n}} \sim \mathcal{N}(0, 1)$$

Find a value z s.t.

$$P(-z \le Z \le z) = 0.95 \implies z = q_{0.975} = 1.96$$

Then,

$$0.95 = P\left(-1.96 \le \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \le 1.96\right)$$
$$= P\left(\bar{X} - 1.96 \frac{\sigma}{\sqrt{n}} \le \mu \le \bar{X} + 1.96 \frac{\sigma}{\sqrt{n}}\right)$$

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$$= P\left(\bar{X} - 1.96 \frac{\sigma}{\sqrt{n}} \le \mu \le \bar{X} + 1.96 \frac{\sigma}{\sqrt{n}}\right)$$

For  $\bar{X}=23.6$ , the interval is equal to (22.23, 24.97) (scipy.stats.norm.interval).

#### Confidence Interval for unknown distributions

**Bootstrap confidence interval** Let's say you have a sample of the random variable  $X: x_1, \ldots, x_n$  and you can estimate a statistic  $\hat{\theta}$  of the parameter  $\theta$  from this sample (example  $\hat{\theta} = \frac{1}{n} \sum_{i=1}^{n} x_i$ )

From your sample  $x_1, \ldots, x_n$  generate m bootstrap samples of size n (draw with replacement):  $(x_{11}^*, \ldots, x_{1n}^*), \ldots, (x_{m1}^*, \ldots, x_{mn}^*)$ 

Calculate m statics 
$$\hat{\theta}_1^*, \dots, \hat{\theta}_m^*$$
 from  $(x_{11}^*, \dots, x_{1n}^*), \dots, (x_{m1}^*, \dots, x_{mn}^*)$  the same way you calculated  $\hat{\theta}$  from  $x_1, \dots, x_n$ 

# Bootstrap Confidence Interval

- $lackbox{ } heta_i^*$  approximates  $\hat{ heta}$  in the same way as  $\hat{ heta}$  approximates heta
- ▶ Even if  $\hat{\theta}$  is far from  $\theta$ , the difference  $\delta_i^* = \hat{\theta}_i^* \hat{\theta}$  is close to the difference  $\delta = \hat{\theta} \theta$
- $\blacktriangleright$  Estimate from the data the 0.025 and 0.975 quatiles  $q^*_{0.025}$  and  $q^*_{0.975}$  of  $\delta^*$
- The approximation of the confidence interval is then given by  $(\hat{\theta}-q_{0.025}^*,\hat{\theta}-q_{0.975}^*)$



## Bootstrap Confidence Interval

To estimate the quatile  $q_{0.025}$  of  $\delta^*$ :

- ightharpoonup calculate  $\delta_1^*,\ldots,\delta_m^*$
- order these values from smallest to highest
- ► calculate the index k = round(m \* 0.025)
- $ightharpoonup q_{0.025} = \delta_k^*$

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