

# Introduction to Machine Learning

## NPFL 054

<http://ufal.mff.cuni.cz/course/npfl054>

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# Lecture 6 – Statistical tests I

- Lady tasting tea
- Fair die
- Classifier accuracy
- Testing the normal population mean
- $t$ -tests

# Example 1 – historical

**Lady tasting tea** – a famous example introduced by R. Fisher (1935)

The example is based on a real story. Fisher met a lady (Muriel Bristol) who claimed to be able to tell whether the tea or the milk was added first to a cup.

**First we need to design an experiment to test her ability.**

**Then we need to meaningfully evaluate the result of the experiment.**

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## Lady tasting tea – Experiment 1

The Lady is provided with 2 randomly ordered cups of tea – 1 prepared by first adding milk, the other prepared by first adding the tea. She should select the one prepared by first adding milk.

**Result:** The Lady selected the cup prepared by first adding milk.

**What can we conclude from this experiment?**

## Lady tasting tea – Experiment 2

We repeat the Experiment 1 four times.

The Lady is provided with 4 pairs of 2 randomly ordered cups of tea – in each pair one cup is prepared by first adding milk, the other prepared by first adding the tea. From each pair she should select the one prepared by first adding milk.

**Result:** The Lady selected the 4 cups prepared by first adding milk.

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**Result:** The Lady selected the 4 cups prepared by first adding milk.

**What can we conclude from this experiment?**

**Obviously, the Experiment 2 is more convincing than the Experiment 1.**

### Lady tasting tea – Experiment 3 (Fisher's)

In fact, Fisher proposed to give her eight cups, four of each variety, in random order.

The Lady is provided with 8 randomly ordered cups of tea – 4 prepared by first adding milk, 4 prepared by first adding the tea. She should select the 4 cups prepared by first adding milk.

**Result:** The Lady selected the 4 cups prepared by first adding milk.

**What can we conclude from this experiment?**

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The Lady is provided with 8 randomly ordered cups of tea – 4 prepared by first adding milk, 4 prepared by first adding the tea. She should select the 4 cups prepared by first adding milk.

**Result:** The Lady selected the 4 cups prepared by first adding milk.

**What can we conclude from this experiment?**

**Both Experiment 2 and Experiment 3 indicate that the results are probably not random. Which one is more convincing?**



# Fisher's experiment – random selection

Compute the probability of getting the observed result **if** the selection is random?

```
# the eight cups -- four T and four F
> cups = c(T,T,T,T,F,F,F,F)

# one million random experiments
> N = 10^6; s = numeric(N)
> for(i in 1:N) s[i] = sum(sample(cups, 4, rep=F))
> table(s)
s
      0      1      2      3      4
14433 228323 514215 228763 14266

# the probability of getting 4 T at random is
> mean(s == 4)
[1] 0.014266
```

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```

Or, since the statistic has hypergeometric distribution, you can simply do

```
> dhyper(4,4,4,4)
[1] 0.01428571
```

# Lady tasting tea

## – interpretation and analysis of the experiments

How to interpret the three experiments in the framework of “statistical hypothesis testing” originally coined by R. Fisher?

- The **null hypothesis**  $H_0$  is that the Lady has no such ability to recognize cups prepared by first adding milk.
  - null hypothesis means that she (hypothetically) does random selection
- The **test statistic** is a simple count of the number of successes in selecting the correct cups.
- The probability of getting the observed result (= the statistic value) at random is
  - 50 % in the Experiment 1
  - 6.25 % in the Experiment 2
  - 1.43 % in the Experiment 3

# Rejecting the null hypothesis based on p-value

**Assuming that the null hypothesis is true**, the probability of getting the observed result in Experiment 3 is only 1.43%, which *could be considered as* a good reason to **reject the null hypothesis**.

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In statistical tests, p-value is the probability of obtaining a test statistic result at least as extreme as the one that was actually observed, assuming that the null hypothesis is true.

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## P-value

In statistical tests, p-value is the probability of obtaining a test statistic result at least as extreme as the one that was actually observed, assuming that the null hypothesis is true.

**The null hypothesis is rejected if the p-value is small enough**

So, we need to set a threshold for the p-value.

# Test significance level $\alpha$ and confidence level $1 - \alpha$

**Could we make wrong decision when rejecting the null hypothesis?**

- Yes, in the example above there is 1.43 % chance of getting the result even if the Lady selected randomly!
- Such an error is called error of the first kind or “Type I Error”.

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## The null hypothesis should be only rejected when an error is very unlikely

- Therefore we choose a **significance level**  $\alpha$  as a threshold for p-value
  - $\alpha$  is the test's probability of incorrectly rejecting the null hypothesis
- Then the null hypothesis will be only rejected when  $p\text{-value} < \alpha$
- Usually,  $\alpha = 5\%$  or  $1\%$  or  $0.5\%$  or something like that
- The corresponding value  $1 - \alpha$  is called **confidence level**
  - which is the probability of not doing the error of the first kind



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**Remember:** The significance level  $\alpha$  is a property of the test itself, while p-value is derived from the observed data!

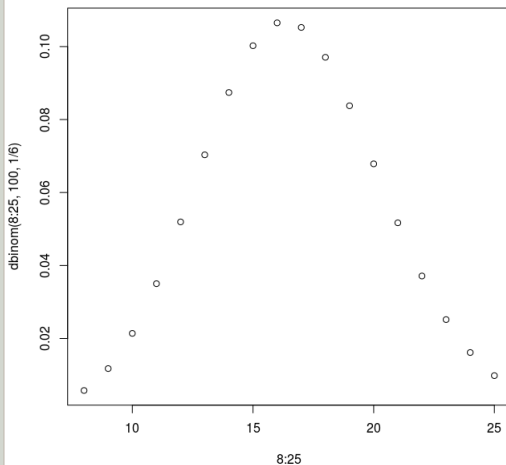
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## Example 3 – Classifier accuracy

### Example

Test sample size = 100; there are 73 correctly classified instances.

– **Is it possible that classifier accuracy is 76 %?**

## Example 4 – men's height mean

Assume that the population of men's height is normally distributed with the known variance  $\sigma^2 = 100$  and an unknown mean  $\mu$ . In other words, the men's height will be represented by a continuous random variable  $X$  so that

$$X \sim N(\mu = ?, \sigma^2 = 100).$$

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We have a sample of  $n = 10$  men's heights:

```
> observation  
[1] 174.7 178.0 195.9 181.0 181.6 197.5 184.9 167.6 173.4 175.8
```

**Are we able to reliably estimate the mean of the population?**

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```

**Are we able to reliably estimate the mean of the population?**

The best estimate is given by the **sample mean**:

```
> mean(observation)  
[1] 181.04
```

**Why do you believe that this estimate is the best one?**

**How confident are you about the estimated mean?**



# Men's height mean – test statistic distribution

The sample average  $\bar{x} = \frac{1}{n} \sum x_i$  will be used as a **test statistic**.

- What is the distribution of the average represented by the random variable  $\bar{X}$  when we randomly sample the population?

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## Theorem

*If  $X_1, \dots, X_n$  are independent and have the same distribution  $N(\mu, \sigma^2)$ , then*

$$\bar{X} = \sum_{i=1}^n X_i \quad \text{has the distribution} \quad N\left(\mu, \frac{\sigma^2}{n}\right).$$

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When we formulate a hypothesis about the population mean, we will know the hypothetical distribution of the statistic. Hence, we will be able to compute the probability of the observed statistic.

# Men's height mean – first hypothesis

Let us consider the following null hypothesis about the population mean  
 $H_0 : \mu = 190$ .

Under that assumption the distribution of the sample average is  
 $\bar{X} \sim N(\mu = 190, \sigma^2 = 10)$ .

Then, what is the probability that  $\bar{X} \leq 181.04$ ?

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The answer is 0.23 %.

```
> pnorm(181.04, 190, sqrt(10))  
[1] 0.00230278  
>
```

Similarly, the probability that  $\bar{X} \geq 198.96$  is also 0.23 %.

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## Conclusion

Assuming that the null hypothesis is true, the probability of obtaining the test statistic  $\bar{x}$  as extreme or more extreme as the one that was actually observed is only 0.46 % (= the p-value). Hence, with the significance level  $\alpha = 5\%$  we will reject the hypothesis.

# Men's height mean – second hypothesis

Let us consider the following null hypothesis about the population mean  $H_0 : \mu = 180$ .

Under that assumption the distribution of the sample average is  $\bar{X} \sim N(\mu = 180, \sigma^2 = 10)$ .

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Then, what is the probability that  $\bar{X} \geq 181.04$ ?

The answer is 37.1 %.

```
> 1 - pnorm(181.04, 180, sqrt(10))  
[1] 0.3711244  
>
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## Conclusion

We will not reject the hypothesis. Assuming that the null hypothesis is true, the probability of obtaining the test statistic  $\bar{x}$  as extreme or more extreme as the one that was actually observed is 74.2 %. If we rejected the hypothesis, we would take the 74.2 % risk of doing the error of the first kind.

# Men's height mean – confidence interval

Obviously, hypothesized values of  $\mu$  that are relatively close to the observed  $\bar{x}$  *would not be rejected*. On the other hand, values that are too far from the observed  $\bar{x}$  *would be rejected*.

**What is the interval of all possibly hypothesized values of  $\mu$  that would NOT be rejected?**

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- to determine this interval you need to know/choose the significance level  $\alpha$
- this interval is called **confidence interval** for the population mean with the confidence level  $1 - \alpha$

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## Exercise – confidence interval for the mean of normal population

Given the confidence level 99 %, find the confidence interval for the men's height population mean based on the given observation. The given assumptions are:

- the men's height population variance  $\sigma^2 = 100$
- the observed sample mean  $\bar{x} = 181.04$
- the observed sample size  $n = 10$

# Statistical tests – first little summary

## Statistical tests are used to test a hypothesis about a population

Always we observe only a sample (often only a small one) of the population. Then we should make a decision according to this observation. Having the observed data we compute a test statistic.

The value of the test statistic can be

- in contradiction with the hypothesis  
→ then we **reject** the hypothesis
- NOT in contradiction with the hypothesis  
→ then we **do not reject** the hypothesis

## **Get familiar with the hypergeometric distribution**

- Compute analytically and exactly the probability distribution of the test statistic from the Example 1, Experiment 3
- Get familiar with the `dhyper()` function in R

**Compute the confidence interval for men's height population mean**  
= the exercise from page 16

# Confidence interval for the mean of normal population with known variance $\sigma^2$

## Example exercise

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**To generally derive how to compute the confidence interval we will use standardized normal distribution and its critical values.**



# Expected value and variance – basic properties

For any random variables  $X, Y$  and any  $a, b \in \mathbb{R}$  the following holds true:

- $E(a + bX) = a + bEX$
- $E(X + Y) = EX + EY$
- if  $X$  and  $Y$  are independent, then  $E(XY) = EXEY$

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If a random variable  $X$  has finite variance, then the following holds true:

- $\text{var } X = EX^2 - (EX)^2$
- $\text{var}(a + bX) = b^2 \text{var } X$
- $\sqrt{\text{var}(a + bX)} = |b| \sqrt{\text{var } X}$

# Standardized random variable

## Definition

If a random variable  $X$  has non-zero finite variance, then  $Z = \frac{X - EX}{\sqrt{\text{var } X}}$  is called *standardized* random variable.

**Note:** If  $Z$  is standardized, then  $EZ = 0$  and  $\text{var } Z = 1$ .

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## Standardized normal distribution – notation

If  $X \sim N(\mu, \sigma^2)$  then standardized variable  $Z = \frac{X - EX}{\sqrt{\text{var } X}} = \frac{X - \mu}{\sigma}$  has the distribution  $N(0, 1)$ . Usual notation for standardized normal distribution is

- $\varphi$  for the density,
- $\Phi$  for the distribution function,
- $\Phi^{-1}$  for the quantile function.

# Quantiles and critical values

## Definition

Quantile function of a random variable  $X$  is defined as

$$F_X^{-1}(\alpha) = \inf\{x : F(x) \geq \alpha\},$$

where  $F_X$  is the distribution function of  $X$  and  $\alpha \in (0, 1)$ .

Value  $F^{-1}(\alpha)$  is called  $\alpha$ -quantile.

**Note:** 0.5-quantile  $F^{-1}(0.5)$  is called *median*.

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## Definition

Critical value of the standard normal distribution is defined as  $z(\alpha) = \Phi^{-1}(1 - \alpha)$ .

**Note:** If  $Z \sim N(0, 1)$ , then

- $\Pr\{Z > z(\alpha)\} = \alpha$
- $\Pr\{|Z| > z(\alpha/2)\} = \alpha$

# Computing confidence interval

## Example exercise

Given the confidence level 99 %, find the confidence interval for the men's height population mean based on the given observation. The given assumptions are:

- the men's height population variance  $\sigma^2 = 100$
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## Idea of the solution

The confidence interval is a symmetric interval around the observed sample mean  $\bar{x}$ . Hence, we are looking for the confidence interval radius  $r$  so that the null hypothesis  $H_0 : \mu = \mu_0$  is rejected if and only if  $|\bar{x} - \mu_0| > r$ .

Then the confidence interval will be given by  $(\bar{x} - r, \bar{x} + r)$ .

Assuming that  $H_0 : \mu = \mu_0$  is valid, we have  $\bar{X} - \mu_0 \sim N(0, \sigma^2/n)$ .

Since the significance level  $\alpha$ , which is the probability of incorrectly rejecting the null hypothesis, is given, we should choose the confidence interval radius  $r$  so that

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$$\Pr\{|\bar{X} - \mu_0| > r\} = \alpha,$$

and after standardization

$$\Pr\left\{\left|\frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}\right| > \frac{r}{\sigma/\sqrt{n}}\right\} = \alpha,$$

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which means that  $\frac{r}{\sigma/\sqrt{n}} = z(\alpha/2)$ , and thus  $r = \frac{\sigma}{\sqrt{n}} z(\alpha/2)$ .

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**Therefore the confidence interval for the population mean  $\mu$  is**

$$\left(\bar{x} - \frac{\sigma}{\sqrt{n}} z(\alpha/2), \bar{x} + \frac{\sigma}{\sqrt{n}} z(\alpha/2)\right),$$

and  $\Pr\left\{\bar{X} - \frac{\sigma}{\sqrt{n}} z(\alpha/2) < \mu < \bar{X} + \frac{\sigma}{\sqrt{n}} z(\alpha/2)\right\} = 1 - \alpha$ .

## Example 5 – testing the classifier accuracy mean

You have two models, **A** and **B**, and for each of them 10 results – accuracies obtained from 10-fold cross-validation experiment.

```
> A.acc  
[1] 0.853 0.859 0.863 0.871 0.832 0.848 0.863 0.860 0.850 0.849  
> mean(A.acc)  
[1] 0.8548  
  
> B.acc  
[1] 0.851 0.848 0.862 0.871 0.835 0.836 0.860 0.859 0.841 0.843  
> mean(B.acc)  
[1] 0.8506
```

The average accuracy of **A** is 85.48 %, while the average accuracy of **B** is only 85.06 %.

**Is the model A *\*really\** better than the model B?**

**What if you do NOT know the variance?**

## What if you do NOT know the variance?

When we get  $k$  different results from the cross-validation experiment, we can assume that the values are (approximately) normally distributed. Then we use t-test.



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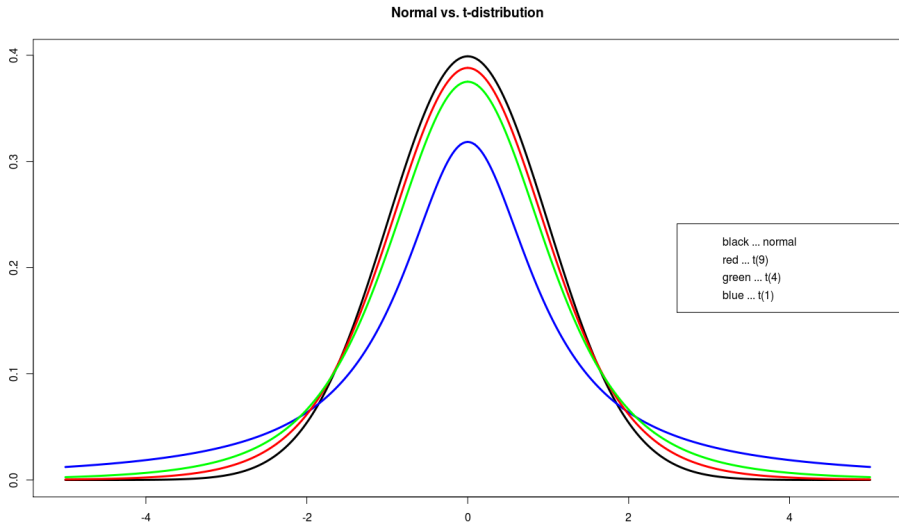
### Theorem

*If  $x_1, \dots, x_n$  is a random sample of size  $n$  selected from a normally distributed population, then*

$$T = \frac{\bar{X} - \mu}{S} \sqrt{n} \sim t_{n-1},$$

*where  $n$  is the sample size,  $\bar{X}$  is the sample mean,  $S$  is the sample standard deviation,  $\mu$  is the population mean,  $T$  is called  $t$ -statistic, and  $t_{n-1}$  is  $t$ -distribution with  $n - 1$  degrees of freedom.*

# Normal vs. t-distribution



# t-test – practically

First, compute **t-value**  $T = \frac{\bar{X} - \mu}{S} \sqrt{n}$ .

Then compare the t-value with the critical value  $t_k(\alpha)$ .

## Definition

Critical value  $t_k(\alpha)$  of the t-distribution  $t_k$  is defined by the equation  $\Pr\{|T| \geq t_k(\alpha)\} = \alpha$ , where  $\alpha$  is the test significance level.

Therefore  $\Pr\{-t_{n-1}(\alpha) < \frac{\bar{X} - \mu}{S} \sqrt{n} < t_{n-1}(\alpha)\} = 1 - \alpha$

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**Note:** Critical value corresponds to a given significance level and determines the boundary between those samples resulting in a test statistic that leads to rejecting the null hypothesis and those that lead to a decision not to reject the null hypothesis. If the calculated value from the statistical test is greater than the critical value, then the null hypothesis is rejected in favour of the alternative hypothesis, and vice versa.

# Confidence interval for the mean $\mu$ using t-test

- If  $\bar{x}$  is the sample mean of a sample of the size  $n$  randomly chosen from a normally distributed population and  $\alpha$  is a significance level, then **confidence interval** for the population mean  $\mu$  is

$$\left( \bar{x} - \frac{S}{\sqrt{n}} t_{n-1}(\alpha), \bar{x} + \frac{S}{\sqrt{n}} t_{n-1}(\alpha) \right).$$

- The probability that the (true) population mean  $\mu$  lies inside the confidence interval is equal to  $1 - \alpha$ , which is called **confidence level**.

$$\Pr \left\{ \bar{X} - \frac{S}{\sqrt{n}} t_{n-1}(\alpha) < \mu < \bar{X} + \frac{S}{\sqrt{n}} t_{n-1}(\alpha) \right\} = 1 - \alpha$$