Lecture 3. Fitting Distributions to data - choice of a model.

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Random variables and cdf.

Random variable is a numerical outcome X, say, of an experiment. To describe its properties one needs to find probability distribution $F_X(x)$. Three approaches will be discussed:

I Use only the observed values of X (data) to model the variability of X, i.e. normalized histogram, empirical cdf, see Lecture 2.

II Try to find the proper cdf by means of reasoning. For example a number of heads in 10 flips of a fair coin is Bin(10,1/2).

III Assume that F_X belongs to a class of distributions $b + a\,Y$, for example Y standard normal. Then choose values of parameters a, b that best "fits" data.

Case II - Example:

Let roll a fair die. Sample space $\mathcal{S} = \{1, \ldots, 6\}$ and let random variable K be the number shown. All results are equally probable hence $p_k = \mathrm{P}(K = k) = 1/6$.

In 1882, R. Wolf rolled a die $n = 20\,000$ times and recorded the number of eyes shown

Number of eyes k	1	2	3	4	5	6
Frequency n_k	3407	3631	3176	2916	3448	3422

Was his die fair?

The χ^2 test, proposed by Karl Pearson' (1857-1936), can be used to investigate this issue.

Pearson' χ^2 test:

Hypothesis H_0: We claim that

$$\mathrm{P}(\text{“Experiment results in outcome } k\text{”}) = p_k, \quad k = 1, \ldots, r.$$

In our example $r = 6$, $p_k = 1/6$.

Significance level α: Select the probability (risk) of rejecting a true hypothesis. Constant α is often chosen to be 0.05 or 0.01. Rejecting H_0 with a lower α indicates stronger evidence against H_0.

Data: In n experiments one observed n_k times outcome k.

Test: Estimate p_k by $p_k^* = n_k/n$. Large distances $p_k - p_k^*$ make hypothesis H_0 questionable. Pearson proposed to use the following statistics to measure the distance:

$$Q = \sum_{k=1}^{r} \frac{(n_k - np_k)^2}{np_k} \left(= n \sum_{k=1}^{r} \frac{(p_k^* - p_k)^2}{p_k}. \right) \tag{1}$$

Details of the χ^2 test

How large Q should be to reject the hypothesis? Reject H_0 if $Q > \chi^2_\alpha(f)$, where $f = r - 1$. Further, in order to use the test, as a rule of thumb one should check that $np_k > 5$ for all k.

Example 1 For Wolf's data Q is

$$Q = 1.6280 + 26.5816 + 7.4261 + 52.2501 + 3.9445 + 2.3585 = 94.2$$

Since $f = r - 1 = 5$ and the quantile $\chi^2_{0.05}(f) = 11.1$, we have $Q > \chi^2_{0.05}(5)$ which leads to **rejection of the hypothesis of a fair dice.**[1]

Example 2 Are children birth months uniformly distributed? Data, Matlab code:.

[1] Not rejecting the hypothesis does not mean that there is strong evidence that H_0 is true. It is recommendable to use the terminology "reject hypothesis H_0" or "not reject hypothesis H_0" but not to say "accept H_0".

Case III - parametric approach to find F_X.

Parametric estimation procedure of F_X contains three main steps:
choice of a model; **finding the parameters**; **analysis of error**:

- Choose a model, i.e. select one of the standard distributions $F(x)$ (normal, exponential, Binomial, Poisson ...). Next postulate that

$$F_X(x) = F\left(\frac{x-b}{a}\right).$$

- Find estimates (a^*, b^*) such that $F_n(x) \approx F\big((x-b^*)/a^*\big)$ ($F_X(x) \approx F_n(x)$), here first **method of moments** to estimates parameters will be presented. Then more advanced and often more accurate **maximum likelihood** method will be presented on the next lecture.

Moments of a rv. - Law of Large Numbers (LLN)

- Let $X_1, \ldots, X_k$ be a sequence of iid variables all having the distribution $F_X(x)$. Let $\mathrm{E}[X]$ be a constant, called the **expected value** of X,

$$\mathrm{E}[X] = \int_{-\infty}^{+\infty} x f_X(x)\,\mathrm{d}x, \text{ or } \mathrm{E}[K] = \sum_k k\, p_k$$

- If the expected value of X exists and is finite then, as k increases (we are averaging more and more variables), the average

$$\frac{1}{k}(X_1 + X_2 + \cdots + X_k) \approx \mathrm{E}[X]$$

with equality when k approaches infinity.

- Linearity property $\mathrm{E}[a + b\,X + c\,Y] = a + b\mathrm{E}[X] + c\mathrm{E}[Y]$.

Example 3

Other moments

- Let X_i be iid all having the distribution $F_X(x)$. Let us also introduce constants called the **moments** of X, defined by

$$\mathsf{E}[X^n] = \int_{-\infty}^{+\infty} x^n \, f_X(x) \, \mathrm{d}x \quad \text{or} \quad \mathsf{E}[K^n] = \sum_k k^n \, p_k.$$

- If $\mathsf{E}[X^n]$ exists and is finite then, as k increases, the average

$$\frac{1}{k}(X_1^n + X_2^n + \cdots + X_k^n) \approx \mathsf{E}[X^n].$$

- The same is valid for other functions of r.v.

Variance, Coefficient of variation

- The **variance** V[X] and **coefficient of variation** R[X]

$$\mathrm{V}[X] = \mathrm{E}[X^2] - \mathrm{E}[X]^2, \qquad \mathrm{R}[X] = \frac{\sqrt{\mathrm{V}[X]}}{\mathrm{E}[X]}.$$

- IF X, Y are independent then

  $\mathrm{V}[a + b\,X + c\,Y] = b^2\mathrm{V}[X] + c^2\mathrm{V}[Y].$ *Example 4*

- Note that $\mathrm{V}[X] \geq 0$. If $\mathrm{V}[X] = 0$ then X is a constant.

Example: Expectations and variances.

Example 5 Expected yearly wind energy production, on blackboard.

Distribution		Expectation	Variance
Beta distribution, $\mathrm{Beta}(a,b)$	$f(x)=\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}x^{a-1}(1-x)^{b-1},\ 0<x<1$	$\frac{a}{a+b}$	$\frac{ab}{(a+b)^2(a+b+1)}$
Binomial distribution, $\mathrm{Bin}(n,p)$	$p_k=\binom{n}{k}p^k(1-p)^{n-k},\ k=0,1,\dots,n$	np	$np(1-p)$
First success distribution	$p_k=p(1-p)^{k-1},\quad k=1,2,3,\dots$	$\frac{1}{p}$	$\frac{1-p}{p^2}$
Geometric distribution	$p_k=p(1-p)^k,\quad k=0,1,2,\dots$	$\frac{1-p}{p}$	$\frac{1-p}{p^2}$
Poisson distribution, $\mathrm{Po}(m)$	$p_k=\mathrm{e}^{-m}\frac{m^k}{k!},\quad k=0,1,2,\dots$	m	m
Exponential distribution, $\mathrm{Exp}(a)$	$F(x)=1-\mathrm{e}^{-x/a},\quad x\ge 0$	a	a^2
Gamma distribution, $\mathrm{Gamma}(a,b)$	$f(x)=\frac{b^a}{\Gamma(a)}x^{a-1}\mathrm{e}^{-bx},\quad x\ge 0$	a/b	a/b^2
Gumbel distribution	$F(x)=\mathrm{e}^{-\mathrm{e}^{-(x-b)/a}},\quad x\in\mathbb{R}$	$b+\gamma a$	$a^2\pi^2/6$
Normal distribution, $\mathrm{N}(m,\sigma^2)$	$f(x)=\frac{1}{\sigma\sqrt{2\pi}}\mathrm{e}^{-(x-m)^2/2\sigma^2},\quad x\in\mathbb{R}$ $F(x)=\Phi((x-m)/\sigma),\quad x\in\mathbb{R}$	m	σ^2
Log-normal distribution, $\ln X\in\mathrm{N}(m,\sigma^2)$	$F(x)=\Phi(\frac{\ln x-m}{\sigma}),\quad x>0$	$\mathrm{e}^{m+\sigma^2/2}$	$\mathrm{e}^{2m+2\sigma^2}-\mathrm{e}^{2m+\sigma^2}$
Uniform distribution, $\mathrm{U}(a,b)$	$f(x)=1/(b-a),\quad a\le x\le b$	$\frac{a+b}{2}$	$\frac{(a-b)^2}{12}$
Weibull distribution	$F(x)=1-\mathrm{e}^{-\left(\frac{x-b}{a}\right)^c},\quad x\ge b$	$b+a\Gamma(1+1/c)$	$a^2\left[\Gamma(1+\frac{2}{c})-\Gamma^2(1+\frac{1}{c})\right]$

Method of moments to fit cdf to data:

- When a cdf $F_X(x)$ is specified then one can computed the expected value, variance, coefficient of variation and other moments $\mathrm{E}[X^k]$.
- If cdf $F_X(x) = F\left(\frac{x-b}{a}\right)$, i.e. depends on two parameters a, b then also moments are function of the parameters.

$$\mathrm{E}[X^k] = m_k(a, b)$$

- LLN tells us that having independent observations $x_1, \dots, x_n$ of X the average values

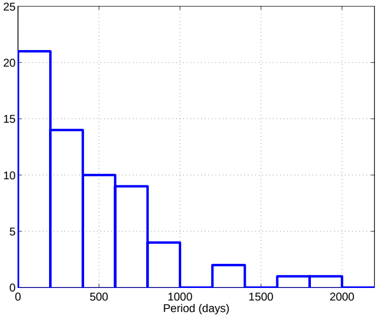
$$\bar{m}_k = \frac{1}{n}\sum_{i=1}^{n} x_i^k \to \mathrm{E}[X^k], \qquad \text{as } n \to \infty.$$

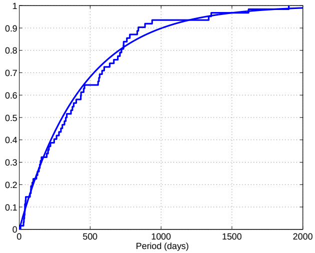
- **Methods of moments** recommends to estimate the parameters a, b by a^*, b^* that solve the equation system

$$m_k(a^*, b^*) = \bar{m}_k, \quad k = 1, 2.$$

Periods in days between serious earthquakes:

Example 6 By experience we choose exponential family $F_X(x) = 1 - e^{-x/a}$. Since $a = \mathrm{E}[X]$ we choose $a^* = \bar{\mathbf{x}} = 437.2$ days.





Left figure - histogram of 62 observed times between earthquakes. Right figure - comparison of the fitted exponential cdf to the earthquake data compared with ecdf - we can see that the two distributions are very close.

Is $a = a^*$, i.e. is error $e = a - a^* = a - 437.2 = 0$?

Example 7 **Poisson cdf** The following data set gives the number of killed drivers of motorcycles in Sweden 1990-1999:

$$39 \quad 30 \quad 28 \quad 38 \quad 27 \quad 29 \quad 38 \quad 33 \quad 33 \quad 36.$$

Assume that the number of killed drivers per year is modeled as a random variable $K \in \mathrm{Po}(m)$ and that numbers of killed drivers during consecutive years, are independent and identically distributed.

From the table we read that $\mathrm{E}[K] = m$ hence methods of moments recommends to estimate parameter m by the average number $m^* = \bar{k}$, viz. $m^* = (39 + \ldots + 36)/10 = 33.1$.

Is $m = m^*$, i.e. is error $e = m - m^* = m - 33.1 = 0$?

Gaussian model

Example 8 Since $\mathrm{V}[X] = \mathrm{E}[X^2] - \mathrm{E}[X]^2$ **LLN** gives the following estimate of the variance

$$s_n^2 = \frac{1}{n}\sum_{i=1}^{n} x_i^2 - \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right)^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \to \mathrm{V}[X], \quad \text{as } n \text{ tends to infinity.}$$

We proposed to model weight of newborn baby X by normal (Gaussian) cdf $N(m, \sigma^2)$. Since $\mathrm{E}[X] = m$ and $\mathrm{V}[X] = \sigma^2$ hence the method of moments recommends to estimate m, σ^2 by $m^* = \bar{x}$, $(\sigma^2)^* = s_n^2$. For the data $m^* = 3400$ g, $(\sigma^2)^* = 570^2$, g^2.

Are $m = m^*$ and $\sigma^2 = s_n^2$, i.e. are errors $e_1 = m - m^* = m - 33.1 = 0$, $e_2 = \sigma^2 - (\sigma^2)^* = \sigma^2 - 570^2 = 0$?

Weibull model

For environmental variables often Weibull cdf fits well data. Suppose that

$$F_X(x) = 1 - \exp\left(-\left(\frac{x}{a}\right)^c\right),$$

a is scale parameter, c shape parameter. Using the table we have that

$$\mathsf{E}[X] = a\Gamma(1+1/c), \qquad \mathsf{R}[X] = \frac{\sqrt{\Gamma(1+2/c) - \Gamma(1+1/c)^2}}{\Gamma(1+1/c)}.$$

Method of moments: estimate the coefficient of variation by $\sqrt{s_n^2}/\bar{x}$, solve numerically the second equation for c^*, see Table 4 on page 256, then $a^* = \bar{x}/\Gamma(1+1/c^*)$.

Example 9 Fitting Weibull cdf to bearing lifetimes

Example 10 Fitting Weibull cdf to wind speeds measurements

Estimation error:

In for the exponential, Poisson and Gaussian models the unknown parameter θ were $\mathrm{E}[X]$ and has been estimated by $\theta^* = \bar{\mathbf{x}}$. The estimation error $e = \theta - \theta^*$ is unknown (θ is not known). We want to describe the possible values of e by finding the distribution of the estimation error $\mathcal{E} = \theta - \theta^*$!

Let $X_1, X_2, \ldots, X_n$ be a sequence of n iid random variables each having finite values of expectation $m = \mathrm{E}[X_1]$ and variance $\mathrm{V}[X_1] = \sigma^2 > 0$. The **central limit theorem** (CLT) states that as the sample size n increases, the distribution of the sample average $\bar{\mathbf{X}}$ of these random variables approaches the normal distribution with a mean m and variance σ^2/n irrespective of the shape of the original distribution. [2]

[2] "The first version of CLT was postulated by the French-born mathematician Abraham de Moivre who, in a remarkable article published in 1733, used the normal distribution to approximate the distribution of the number of heads resulting from many tosses of a fair coin."

Computation of $m_{\mathcal{E}},\ \sigma^2_{\mathcal{E}}$.

Using **Central Limit Theorem** we can approximate cdf $F_{\mathcal{E}}(e)$ by normal distribution $N(m_{\mathcal{E}}, \sigma^2_{\mathcal{E}})$, where $m_{\mathcal{E}} = \mathsf{E}[\mathcal{E}]$, $\sigma^2_{\mathcal{E}} = \mathsf{V}[\mathcal{E}]$.

It is easy to demonstrate (see blackboard) that for the studied cases $\mathsf{E}[\Theta^*] = \theta$ and hence $m_{\mathcal{E}} = \mathsf{E}[\mathcal{E}] = 0.$ Estimators having $m_{\mathcal{E}} = 0$ are called **unbiased**.

Similarly one can show that $\sigma^2_{\mathcal{E}} = \mathsf{V}[\mathcal{E}] = \mathsf{V}(X)/n$ (see blackboard). Using the table we have that:

- $\sigma^2_{\mathcal{E}} = m/n$ if X is Poisson Po(m)
- $\sigma^2_{\mathcal{E}} = a^2/n$ if X is Exp(a)
- $\sigma^2_{\mathcal{E}} = \sigma^2/n$ if X is $N(m, \sigma^2)$[3]

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[3]Problem, variance $\sigma^2_{\mathcal{E}}$ depends on unknown parameters! Since $\theta^* \to \theta$ as $n \to \infty$ one is estimating $\sigma^2_{\mathcal{E}}$ by replacing θ by θ^* and denote the approximation by $(\sigma^2_{\mathcal{E}})^*$.

In this lecture we met following concepts:

- χ^2-test.
- Method of moments to fit(cdf) to data.
- Examples of data described using exponential, Poisson, Gaussian (normal) and Weibull cdf.
- Central Limit Theorem, giving normal distribution of estimation errors.

Examples in this lecture "click"