Introduction to statistics

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Recent history at the Observatory



- Request of "something on statistics" from PhD students, because of an impression of lack of knowledge
 - Daniel Schaerer
 - Amaury Triaud, Richard Anderson
 - Maria Suveges, Damien Segransan, Stéphane Paltani, Laurent Eyer
- Cafés statistiques in 2005-2006: <u>http://obswww.unige.ch/~eyer/CAFSTAT/</u>

Plan	 Statistical tests EYER, SUVEGES Chi2 statistics, maximum likelyhood SEGRANSAN
	3) Monte Carlo, Markov chain PALTANI
 ~8 sessions 	4) Robust, non-parametric statistics PALTANI, +SEGRANSAN, +EYER
 Wednesday 15h - 17h 	5) Non-Gaussian statistics SUVEGES6) Time series analysis EYER
• 3 first lectures:	7) Bayesian statistics EYER?, SEGRANSAN?8) Biases ??

- General Introduction, definitions, hypothesis testing, today
- Chi2 statistics, maximum likelihood, wednesday 6 October 2010
- Monte Carlo Markov chain, Wednesday 10 November 2010

Some statistical resources for this introduction

- Probabilités, analyse des données et statistique Gilbert Saporta
- Introduction à la statistique, Stephan Morgenthaler
- Advanced theory of statistics Maurice Kendall & Allan Stuart
- Statistics in theory and practice, Robert Lupton
- Introductory statistics with R, Peter Dalgaard
- wikipedia (it seems quite good, but always to take with care)



Random Variables

- Discrete:
 - Spectral type (G2V, KIII)
 - Galaxy type, galaxy zoo

Description Class Button Elliptical galaxy 1 $\mathbf{2}$ Clockwise/Z-wise spiral galaxy ര Anti-clockwise/S-wise spiral galaxy 3 4Spiral galaxy other (e.g. edge on, unsure) Star or Don't Know (e.g. artefact) $\mathbf{5}$ 6 Merger

- Continuous:
 - magnitude, flux, colour, radial velocity, parallax/distance, temperature, elemental abundances, magnetic field, age, etc...

Distribution

• Definition: density is a function f(x) such that:

$$\Pr(a < X < b) = \int_{a}^{b} f(x)dx \qquad \Pr(X = k) = p(k)$$

- Distribution of one variable: univariate f(x)
- Distribution of several variables: multivariate $f(x,y,\ldots)$
- Marginalization: $u(x) = \int_{-\infty}^{\infty} f(x, y) dy$
- \bullet If and only if: $\ f(x,y) = u(x)v(y)$ the variables are independent
- Cumulative Distribution Function CDF:

$$F(x) = \int_{-\infty}^{x} f(x') dx' \qquad \qquad \text{Digression on} \\ \text{``LateXiT''}$$

Example: Gaussian / Normal distribution



Poisson distribution

Discrete probability distribution (no density)

$$X \sim \mathrm{Poisson}(\lambda)$$
 Number on Number of Numbe

Number of photons on a detector Number of people in a shop



For large λ

 $\mathcal{N}(\lambda,\lambda)$

Moments of a distribution

• Information of location, the mean

$$E(X) = \mu = \int_{-\infty}^{\infty} x f(x) dx$$

• Information of dispersion, the variance

$$\operatorname{Var}(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

• Moment of order n about the mean:

$$\mu_n = \int_{-\infty}^{\infty} (x - \mu)^n f(x) dx$$

Normal: μ Poisson: λ

standard deviation

$$\sigma = \sqrt{\operatorname{Var}(X)}$$

Normal: σ^2 Poisson: λ

3d and 4th moments of a distribution

Skewness, asymmetry



• Kurtosis



$$\mu_4/\sigma^4 = \int_{-\infty}^{\infty} (x - \mu)^4 f(x) dx/\sigma^4$$
$$\mu_4/\sigma^4 - 3$$
Normal: 0
Poisson: 1/ λ

Example of different values of kurtosis: "boxiness" -- tail heaviness



Covariance and correlation

• Covariance

$$Cov(X,Y) = \int \int (x - \mu_x)(y - \mu_y)f(x,y)dxdy$$

• Correlation

$$Corr(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y}$$

Examples of correlation



from wikipedia

Quantiles

• x_p : p-quantiles of f(x)

$$p = \int_{-\infty}^{x_p} f(x) dx$$

• Measure of location: Median

$$1/2 = \int_{-\infty}^{x_{1/2}} f(x)dx$$



from www.aiacces.net

• Measure of dispersion: Inter-quantile range

$$IQR = x_{3/4} - x_{1/4}$$

Data, samples

• Usually we have observations, e.g. additive process

$$y_i = f(t_i) + \epsilon_i \qquad \qquad i = 1, \dots, n$$

- We want a characterisation of the deterministic and random parts
- Suppose something about the random variable, often normality: $\,\,\mathcal{N}(0,\sigma^2)$

Estimators

- Assumption of models
- Estimate the parameters of a distribution, moments

- Exercise 1: Sample mean:
$$\hat{\mu} = \bar{X} = rac{1}{n}\sum_{i=1}^n X_i$$
 $E(\bar{X}) = \mu$

- Exercise 2: Sample variance (bias):

$$\hat{\sigma^2} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \qquad E(\hat{\sigma^2}) = \frac{n}{n-1} \sigma^2$$

redefine
$$\hat{\sigma^2} = S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

- Sample quantiles are estimators of quantiles
 - Exercise 3: what is the sample median of {1, 2, 3, 109812308}?

Central limit theorem

The distribution of the mean of a sufficiently large number of random variables can be approximated by a Gaussian distribution!

$$X_i, i = 1, \dots, n$$
 iid with $E(X_i) = \mu Var(X_i) = \sigma^2$

iid= Independent identically distributed

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

One reason why the Gaussian distribution is so important

Distribution derived from Normal distribution 1) Chi square distribution

If
$$X_i \stackrel{\text{iid}}{\sim} \mathcal{N}(0, 1)$$

 $iid= \text{Independent identically distributed}$
mean: k
variance: 2 k
skewness: $\sqrt{(8/k)}$
kurtosis: 12/k
 $X_i \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma)$
 $\sum_{i=1}^{k} (X_i - \bar{X})^2 / \sigma^2 \sim \chi_{k-1}^2$
When k is large χ_k^2
approximates a $\mathcal{N}(k, 2k)$
 $\sum_{i=1}^{k} (X_i - \bar{X})^2 / \sigma^2 \sim \chi_{k-1}^2$
 $\sum_{i=1}^{k} (X_i - \bar{X})^2 / \sigma^2 \sim \chi_{k-1}^2$

from wikipedia

Distribution derived from Normal distribution 2) Student distribution

$$\begin{split} & \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim \mathcal{N}(0, 1) \\ & \frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t_{n-1} \\ & f(x) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi}\Gamma(n/2)} \left(1 + \frac{x^2}{n}\right)^{-(n+1)/2} \\ & \text{Note} \\ & t_{\infty} = \mathcal{N}(0, 1) \end{split}$$

Estimators of Variance of different statistics

from Kendall & Stuart

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Statistic	Variance multiplied by n	Notes
Mean, m'_1	$\mu_2 \ (= \ \sigma^2)$	True for any population with finite second moment μ_2 .
Sample variance, m_2	$\mu_4 - \mu_2^2$	For normal parent, $= 2\sigma^4$.
Sample s.d., s	$(\mu_4 - \mu_2^2)/(4\mu_2)$	For normal parent, $= \sigma^2/2$.
Third moment, ma	$\mu_6 - \mu_3^2 - 6\mu_4 \mu_2 + 9\mu_2^3$	For normal parent, $= 6\sigma^6$.
Fourth moment, m_1	$\mu_{e} - \mu_{4}^{2} - 8\mu_{e} \mu_{2} + 16\mu_{e}\mu_{3}^{2}$	For normal parent, = $96\sigma^8$.
$\sqrt{b_1} = m_3/m_2^{3/2}$	6	For normal parent only. See 12.18 and Exercise 12.9.
$b_2 = m_4/m_2^2 $	24	For normal parent only. See Exercise 12.10.
Coefficient of variation, V .	See Example 10.5	For normal parent, $= V^2/2$ approx.
Pearson mode (cf. 6.3) .	See Yasukawa (1926) for for- mulae and tables	Distribution skew for moderate n .
Mean deviation	See 10.13	For normal parent, = $\sigma^2(1-2/\pi)$.
Gini's mean difference	See 10.14	For normal parent, = $(0.8068)^2 \sigma^2$.
Median	$1/(4y_0^2)$ when y_0 is ordinate at median	For normal parent and small samples see Hojo (1931) and K. Pearson (1931).
		For large normal samples equals $(1.2533)^2 \sigma^2$.
Quartile	$3/(16y^2)$ where y is the ordin- ate at the quartile	For normal parent, = $(1.3626)^2 \sigma^2$.
	0 10 10	See also Hojo (1931).
Deciles	See 10.10	For normal parent, (deciles 4, 6) = $(1.2680)^2 \sigma^2$; (deciles 3, 7) = $(1.3180)^2 \sigma^2$; (deciles 2, 8) = $(1.4288)^2 \sigma^2$;
	1 (2/16-2 1 2/16-3	$(uccnes 1, 9) = (1.7094)^{*} \sigma^{*}$.
Semi-interquartile range	$\frac{1}{2}\left(\frac{3}{10y_1} + \frac{3}{10y_2}\right)$	$-(0.7867)^2 \sigma^2$
	$-1/\delta y_1 y_2 \delta^2$, where y_1, y_2	= (0.7307)- 8

See Example 10.6

Correlation coefficient r

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For bivariate normal parent,

Graphical representation QQ Plots



End of the Introduction