

ADA02 - 9am Tue 13 Sep 2022

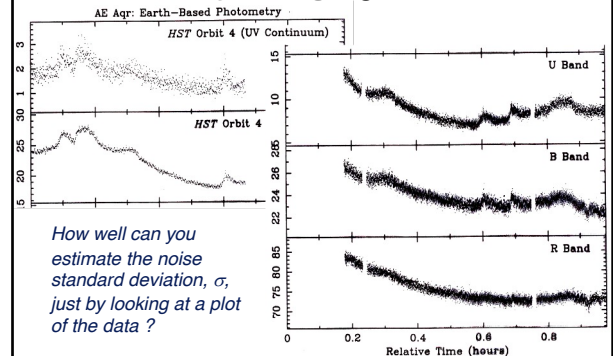
Eyeballing sigma (5-sigma rule)

Joint Probability Distributions
Independence vs Correlation

Algebra of Random Variables:
Linear Transformations
Covariance Matrix
Correlation Coefficient / Matrix

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Eyeballing Sigma



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Eyeballing Sigma

1. If lots of data points:
The 5-sigma rule:

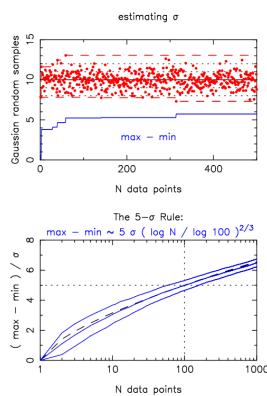
Estimate "by eye" the range (max-min) of the data (~100 data points).

That range (max-min) is about 5-sigma

Usually good to 20% by eye.

2. If only a few data points:

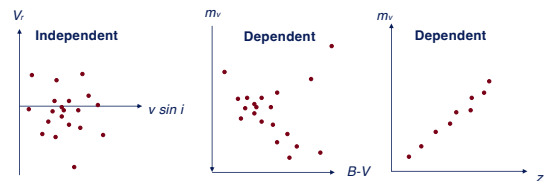
~2/3 of the data points should be inside +/- 1 sigma



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Multivariate Distributions

- Suppose we measure 2 (or more) different properties
 - e.g. rotational and radial velocities of stars in a cluster
 - colours and magnitudes of stars in a cluster
 - redshifts and peak apparent magnitudes of distant supernovae



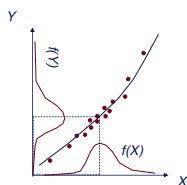
- Does knowing the value of one random variable X inform you about the other?

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Joint Probability Distribution $f(X, Y)$

- X and Y are two random variables.
- Their **joint probability distribution** is $f(X, Y)$
- Normalisation: $\iint f(X, Y) dX dY = 1$

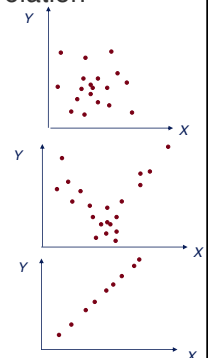
- Projection gives $f(X), f(Y)$: $f(Y) = \int f(X, Y) dX$
 $f(X) = \int f(X, Y) dY$



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Independence vs Correlation

- **Independent variables:**
 - knowing X does not inform about Y
 - Definition:
 $f(X, Y) = f(X) f(Y)$
- **Partially correlated:**
 - knowing X tells you something about Y
- **Perfect correlation:**
 - X determines Y



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The Algebra of Random Variables

Ordinary numbers are "sharp".

$$1 + 1 = 2$$

Random variables are "fuzzy" numbers.

$(\mu \pm \sigma)$ is a shorthand notation giving the mean μ and standard deviation σ of a random variable.

$$(1 \pm 1) + (1 \pm 2) = (? \pm ?)$$

How do the mean and variance change when we add or subtract or multiply fuzzy numbers?

How do the higher moments change?

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Linear Transformations: Scaling

Constants: $\langle a \rangle = ?$ $\text{Var}(a) = ?$

Scaling a random variable, X , by a constant, a :

- Mean:

$$\langle aX \rangle = a\langle X \rangle$$

$$\begin{aligned} \langle aX \rangle &= \int aX f(X) dX \\ &= a \int X f(X) dX = a\langle X \rangle \end{aligned}$$

- Variance:

$$\begin{aligned} \text{Var}(aX) &= a^2 \text{Var}(X) \\ \sigma(aX) &= |a| \sigma(X) \end{aligned}$$

$$\begin{aligned} \text{Var}(aX) &= \langle [aX - \langle aX \rangle]^2 \rangle \\ &= \langle [aX - a\langle X \rangle]^2 \rangle \\ &= \langle a^2 [X - \langle X \rangle]^2 \rangle \\ &= a^2 \text{Var}(X) \end{aligned}$$

"Stretch the paper" by a factor a .
Location μ and width σ then increase by factor a .

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Linear Transformations: Addition

- Adding two random variables X and Y :

$$\begin{aligned} \langle X+Y \rangle &= \iint (X+Y) f(X,Y) dX dY \\ &= \iint X f(X,Y) dX dY + \iint Y f(X,Y) dX dY \\ &= \int X \left[\int f(X,Y) dY \right] dX + \int Y \left[\int f(X,Y) dX \right] dY \\ &= \int X f(X) dX + \int Y f(Y) dY \\ &= \langle X \rangle + \langle Y \rangle \end{aligned}$$

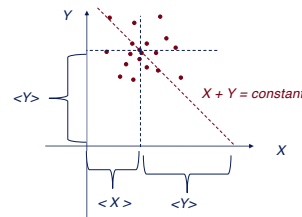
- True for **any** joint PDF!

$$\langle X+Y \rangle = \langle X \rangle + \langle Y \rangle$$

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Why it works...

- Centre of mass is a well-defined position.



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Variance and Co-variance

- Variance of $X+Y$ depends on how X and Y co-vary:

$$\begin{aligned} \text{Var}(X+Y) &= \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X,Y) \\ \text{Cov}(X,Y) &= \langle (X - \langle X \rangle)(Y - \langle Y \rangle) \rangle \end{aligned}$$

$$\begin{aligned} \text{Var}(X+Y) &= \langle [X+Y - \langle X+Y \rangle]^2 \rangle \\ &= \langle [X+Y - \langle X \rangle - \langle Y \rangle]^2 \rangle \\ &= \langle [(X - \langle X \rangle) + (Y - \langle Y \rangle)]^2 \rangle \\ &= \langle (X - \langle X \rangle)^2 + (Y - \langle Y \rangle)^2 + 2(X - \langle X \rangle)(Y - \langle Y \rangle) \rangle \\ &= \langle (X - \langle X \rangle)^2 \rangle + \langle (Y - \langle Y \rangle)^2 \rangle + 2\langle (X - \langle X \rangle)(Y - \langle Y \rangle) \rangle \\ &= \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X,Y) \end{aligned}$$

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Co-variance vs Independence

- Cov > 0



- Cov = ?

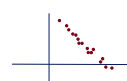
Independent?



- Cov < 0

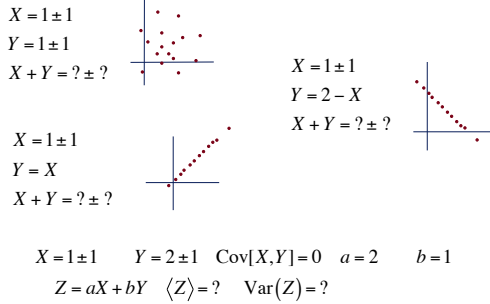


- Cov = ?



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Practice !



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Linear Transformations

• Scale and add any number of random variables:

$$\left\langle \sum_i a_i X_i \right\rangle = \sum_i a_i \langle X_i \rangle \quad \text{Var} \left[\sum_i a_i X_i \right] = \sum_{i,j} a_i a_j \text{Cov}(X_i, X_j)$$

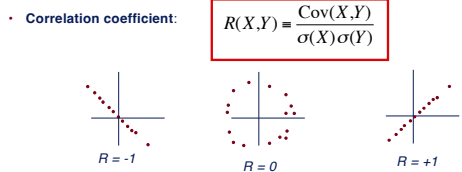
Or, in terms of the (symmetric) **Co-variance Matrix**:

$$\text{Var} \left[\sum_i a_i X_i \right] = \sum_{i,j} a_i C_{ij} a_j$$

$$\text{Var} \begin{bmatrix} (a_i \dots a_N) \begin{pmatrix} X_1 \\ \dots \\ X_N \end{pmatrix} \end{bmatrix} = \begin{pmatrix} a_i & \dots & a_N \end{pmatrix} \begin{pmatrix} C_{11} & \dots & C_{1N} \\ \dots & \dots & \dots \\ C_{N1} & \dots & C_{NN} \end{pmatrix} \begin{pmatrix} a_1 \\ \dots \\ a_N \end{pmatrix}$$

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Correlation Coefficient $R(X, Y)$



• Correlation matrix:

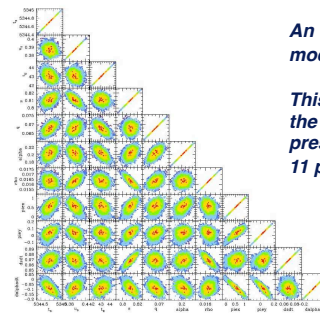
$$R_{ij} = \frac{\text{Cov}(X_i, X_j)}{\sigma(X_i)\sigma(X_j)} = \begin{bmatrix} 1 & \dots & \dots \\ \dots & 1 & \dots \\ \dots & \dots & 1 \end{bmatrix}$$

• Variance:

$$\text{Var} \left[\sum_i a_i X_i \right] = \sum_i \sum_j a_i a_j \sigma(X_i)\sigma(X_j) R_{ij}$$

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Example: Correlation Matrix



An 11-parameter model fitted to data.

This matrix shows the correlations present among the 11 parameters.

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Fini -- ADA 02

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