

CV 510₁

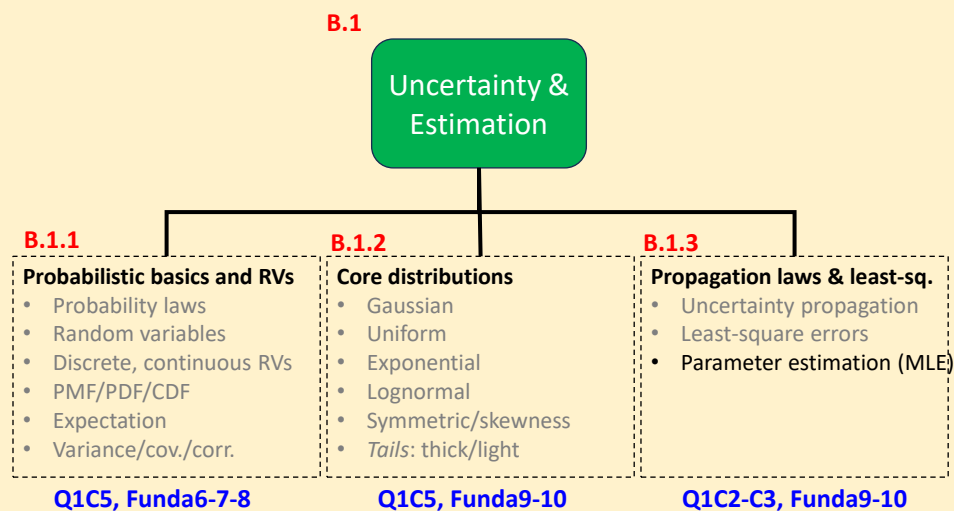
Modeling, Uncertainty, and Data for Engineers

(July – Nov 2025)

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Module Overview



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Flow (so far and week ahead)

- So far:
 - Probability axioms, rules, PMF/PDF/CDF
 - Variance, covariance, [correlation](#)
 - [Distributions](#): uniform, Gaussian, exponential, Gumbel, lognormal
 - Standard normal; reading [z-table](#)
 - [Uncertainty propagation](#): linear, nonlinear function (FO and SO approximation)
 - Fitting a distribution [Linear regression](#) (estimation): [least-square method](#)
- This week:
 - [Estimation](#): Method of moments ([MoM](#)), Maximum likelihood estimation ([MLE](#))
 - [Inference](#): Confidence interval ([CI](#))
 - [Inference](#): Hypothesis testing ([HT](#))
 - [Goodness of fit](#) ([GoF](#)): χ^2 , KS
- Check-in with textbook
 - MLE: Q1C3.6 and Q1C5.4.2
 - CI: Q1C3.5
 - HT: Q1C3.9
 - GoF: Q1C5.4

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Parameter estimation: method of moments

- Obtain the moments (e.g., mean, variance) from two sources:

- [Observations](#):

$$E[X] = \mu_X = \int_{-\infty}^{+\infty} x f_X(x) dx$$

$$\text{Var}[X] = \sigma_X^2 = E[(X - \mu_X)^2] = E[X^2] - \mu_X^2$$

- [Parameters](#):

[Depends on the distribution type](#)

- [Equate them to solve for the parameters](#)

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Distributions and parameters

Dist.	PDF	CDF	Mean & Variance
Normal/ Gaussian	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$	$F(x) = \Phi(x)$ Use z-table	$E[X] = \mu$ $\text{Var}[X] = \sigma^2$
Uniform	$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } x \in [a, b] \\ 0 & \text{otherwise} \end{cases}$	$F(x) = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a}{b-a} & \text{for } x \in [a, b] \\ 1 & \text{otherwise} \end{cases}$	$E[X] = \frac{1}{2}(a+b)$ $\text{Var}[X] = \frac{1}{12}(b-a)^2$
Exponential	$f(x) = \lambda \exp(-\lambda x)$	$F(x) = 1 - \exp(-\lambda x)$	$E[X] = \frac{1}{\lambda}$ $\text{Var}[X] = \frac{1}{\lambda^2}$
Gumbel	$f(x) = \frac{1}{\beta} \exp[-z + \exp(-z)]$, where $z = \frac{x-\alpha}{\beta}$	$F(x) = \exp[-\exp(-z)]$	$E[X] = \alpha + \beta\gamma$ $\text{Var}[X] = \frac{\pi^2}{6}\beta^2$ $\gamma = 0.577$
Lognormal	$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right]$	$F(x) = \Phi\left(\frac{\ln x - \mu}{\sigma}\right)$ Use z-table	$E[X] = \exp\left(\mu + \frac{\sigma^2}{2}\right)$ $\text{Var}[X] = [\exp(\sigma^2) - 1] \exp(2\mu + \sigma^2)$

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Example

- Assume that Earthquakes in Rome expressed as MCS index follow Gumbel type-I distribution. Earthquake intensity and number of earthquakes between 1000 CE – 1980 CE are:

MSC intensity, x_i	2	3	4	5	6	7	$\sum x = \sum x_i f_i$	$\sum x^2 = \sum x_i^2 f_i$	$\sum f_i$
Number, f_i	113	132	56	22	4	2	994	3328	329

Find the parameters of the distribution.

- Observations:

$$E[X] = \mu_X = 994/329 = 3.02$$

$$\text{Var}[X] = E[X^2] - \mu_X^2 = 10.12 - 3.02^2 \approx 0.99$$

$$E[X^2] = 3328/329 \approx 10.12$$

- Parameters for Gumbel type-I:

$$E[X] = \alpha + \beta\gamma$$

$$\text{Var}[X] = \frac{\pi^2}{6}\beta^2$$

- Equate them to solve for the parameters

$$\text{Solve to find, } \alpha \approx 2.57, \beta \approx 0.77$$

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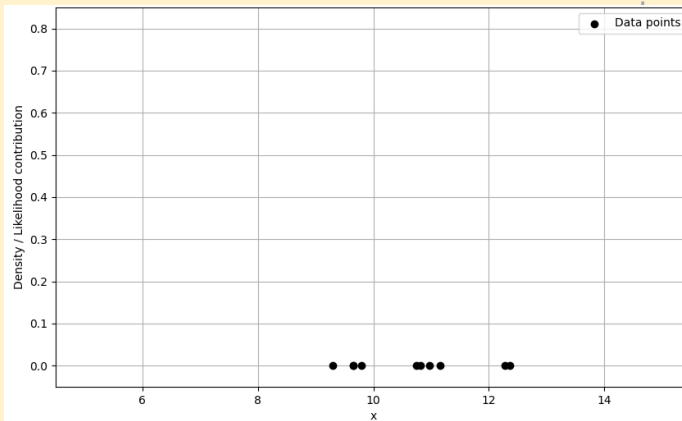
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Maximum likelihood estimation

Basic idea

Objective of MLE:

To determine the parameters of a model
such that
they maximize the likelihood of the observed data.



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Maximum likelihood estimation

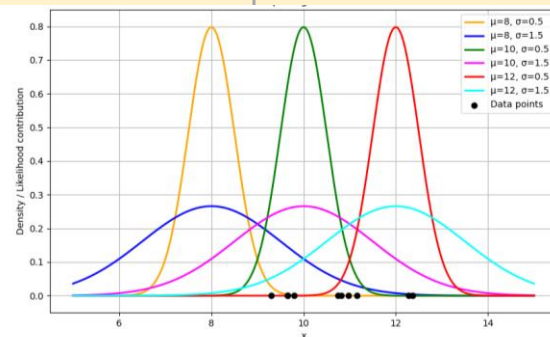
Find $\mathcal{L}(\mu, \sigma | x_i) = f(x_i | \mu, \sigma)$ for each data point, x_i .

Maximize the product of likelihood,

$$\mathcal{L}(\mu, \sigma | \mathbf{x}) = \prod_i^n f(x_i | \mu, \sigma)$$

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} \mathcal{L}(\mu, \sigma | \mathbf{x})$$

$$\hat{\mu}, \hat{\sigma} = \arg \max_{\mu, \sigma} \ln[\mathcal{L}(\mu, \sigma | \mathbf{x})]$$



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Maximum likelihood estimation

Find $\mathcal{L}(\mu, \sigma | x_i) = f(x_i | \mu, \sigma)$ for each dart, x_i .

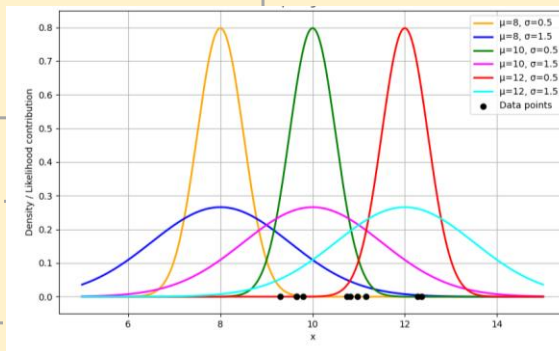
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Excel Demo!



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Questions, comments,
or concerns?

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