Data Processing

Aprendizagem Aplicada à Segurança

Mestrado em Cibersegurança
DETI-UA

universidade de aveiro

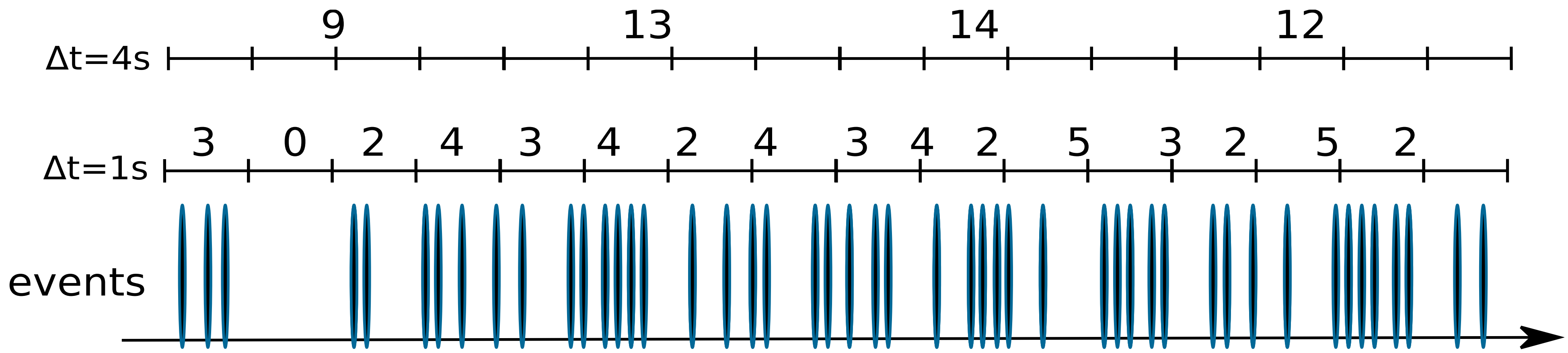
deti.ua.pt

Qualitative Data

- Most monitored data is qualitative.
  - An event (with description) at a specific time (with a time-stamp).
    - 00:01:23.4566 – IP Packet [from A to B with 64 bytes]
    - 21:04:23.4566 – Error [id 404]
    - ...
- Must be converted to quantitative data.
- Some is pre-processed and it is already presented as quantitative.
  - Packets sent: 5467.
  - Bytes seen in the last 10 minutes: 18471947.
  - May require some additional processing.
    - Packets sent at 1s: 300pkts, Packets sent at 2s: 350pkts → Packets sent between 1s-2s: 350-300=50pkts.

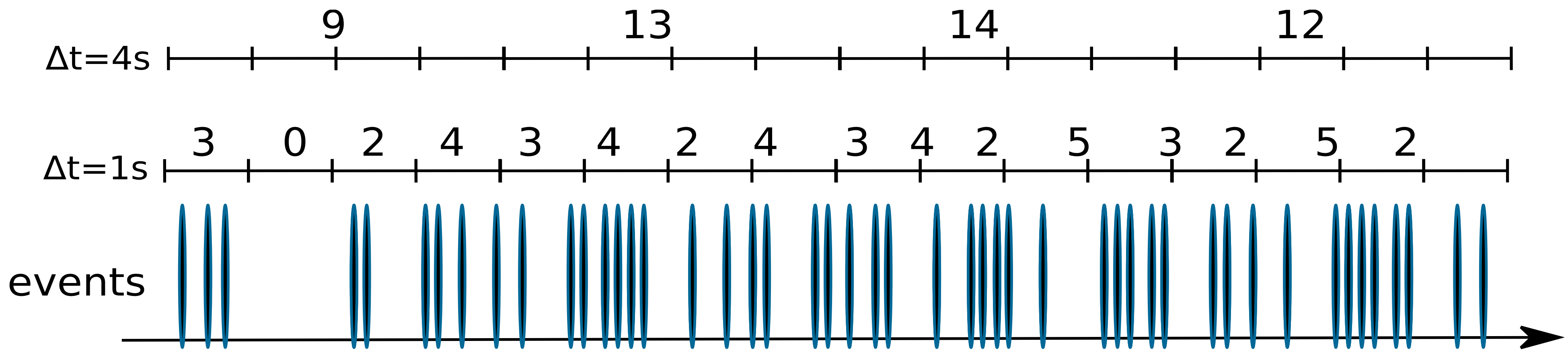
Qualitative → Quantitative Data (1)

- Events must be defined, identified and grouped:
  - All packets from IP 10.0.0.1,
  - All 400 errors accessing site X, etc...
- Sampling/Counting Interval
  - Time window in each the number of a specific event is counted, associated with a time index, and stored.
  - Minimum timescale.
- Events are counted in each sampling interval Δt.



Qualitative → Quantitative Data (2)

- Results in discrete time sequences for event:
  - For Δt=1: X_k={3,0,2,4,3,4,2,4,3,4,2,5,3,2,5,2}
    - X_0=3, X_1=0, …, X_{12}=2
  - For Δt=4: Y_k={9,13,14,12}
- Time sequences may be multi-dimensional:
  - Time sequences of n-tuples.
  - e.g., Number of packets, upload e download.
  - Z_k={(3,9),(0,45),...(67,90)}

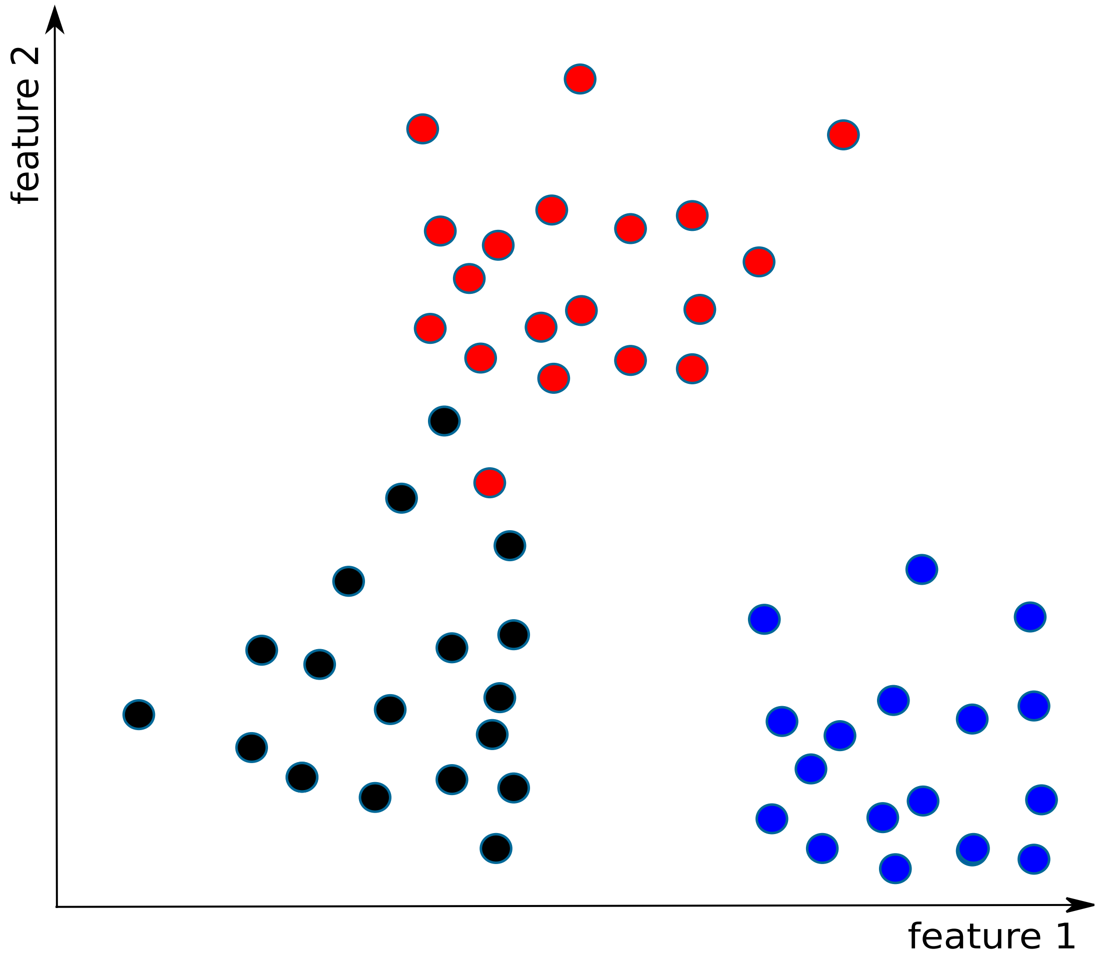


Time Windows and Entity Profile

- Sampling/Counting Window.
  - Provides time series of multiple metrics.
  - e.g., number of packets received by a terminal each second.
- Observation Window.
  - Features/Characteristics extraction Window.
  - Uses multiple Sampling/Counting Windows,
    - Statistics of respective time series.
  - Provides a n-tuple characterizing an entity behavior at a specif time.
  - e.g., 2-tuple with mean and variance of the number of packets received by a terminal in 30 seconds (30 counting 1s windows).
- Entity Profile
  - Pattern from multiple Observation Windows.
  - Provides a model to classify entities and detect anomalies.
  - May include time dynamics over time.

N-Dimensional Features Space

- A features' n-tuple defines a point in a N-Dimensional space that describes an entity behavior at a specific time.
- Allows to detect and define repetitive events and evolution over time.
- Allows to classify and discriminate behaviors.
- Allows to detect anomalies.



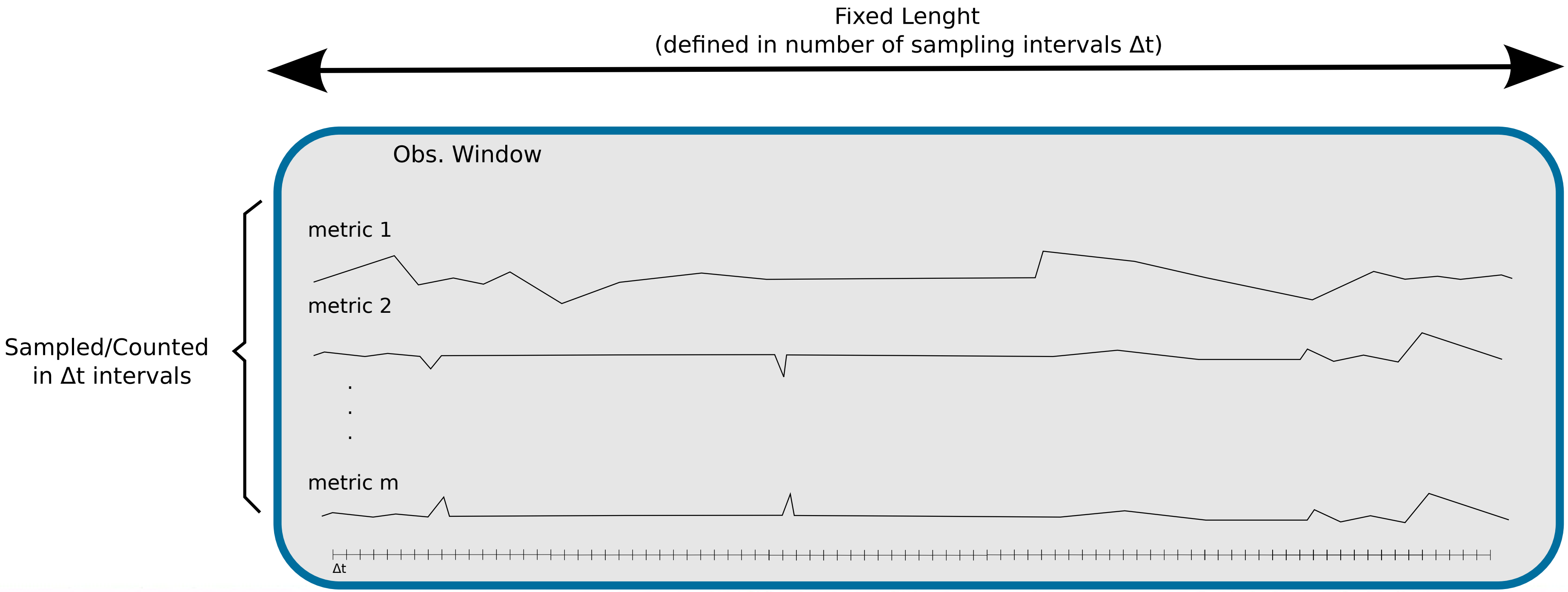
Data Formats

- The ideal data format is a n-tuple per time interval.
  - n metrics measured over time (n per observation).

    $(x1,x2,x3,x4,..,xn)_k$
  - Bi-dimensional data structure (time x metrics).
  - Optimal storing digital format:
    - Binary storage (array/matrix).
    - Sparse matrices could be advantageous.
    - Usage of fixed formats with integer indexes.
      - Avoid complex data structures with complex indexing of data, e.g.: python dictionaries.
    - Text formats are acceptable only in test scenarios.
    - Non-relational databases could also be an option.

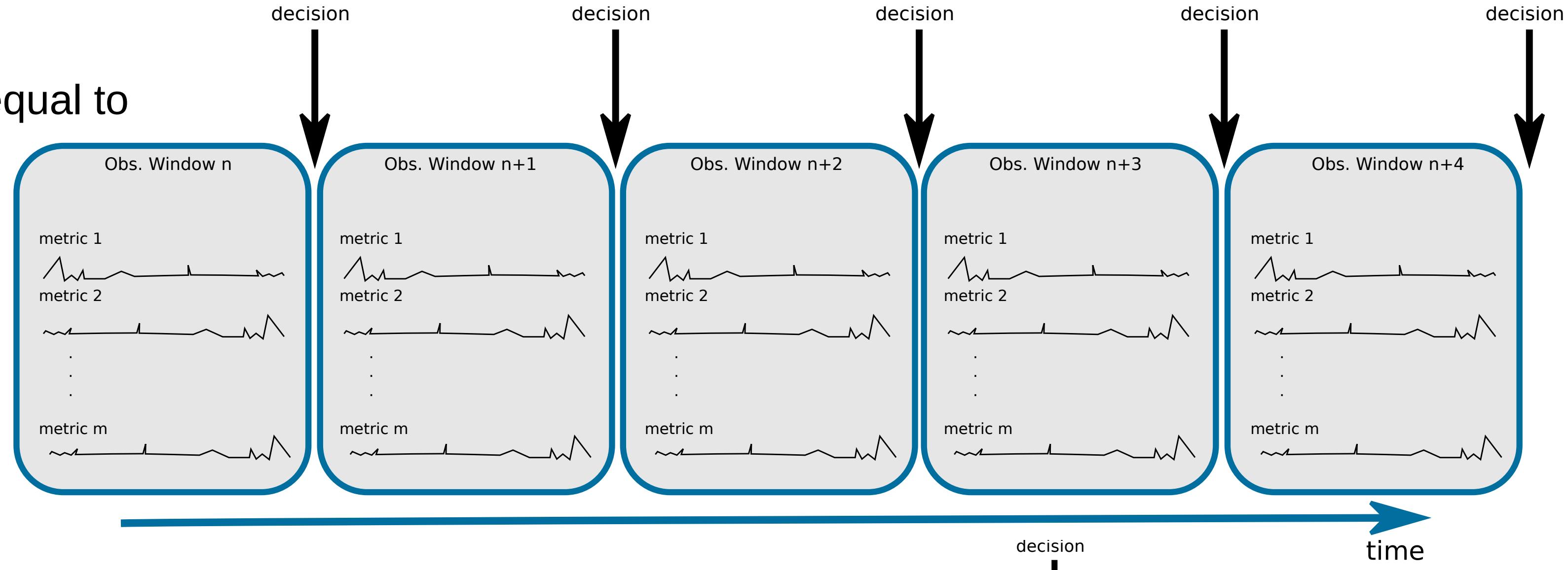
Observation Window (1)

- An observation is constructed based on multiple sampling/counting metrics.
- Sampling/counting metrics should quantify activity events:
  - Start/End of activity.
    - Traffic Flows, Calls, Service usage, etc…
  - Amount of activity.
    - Traffic per sampling interval, activity duration, actions per sampling interval, etc…
  - Activity targets
    - IP addresses contacted, UCP/TCP ports used, services user IDs, points of access, etc…

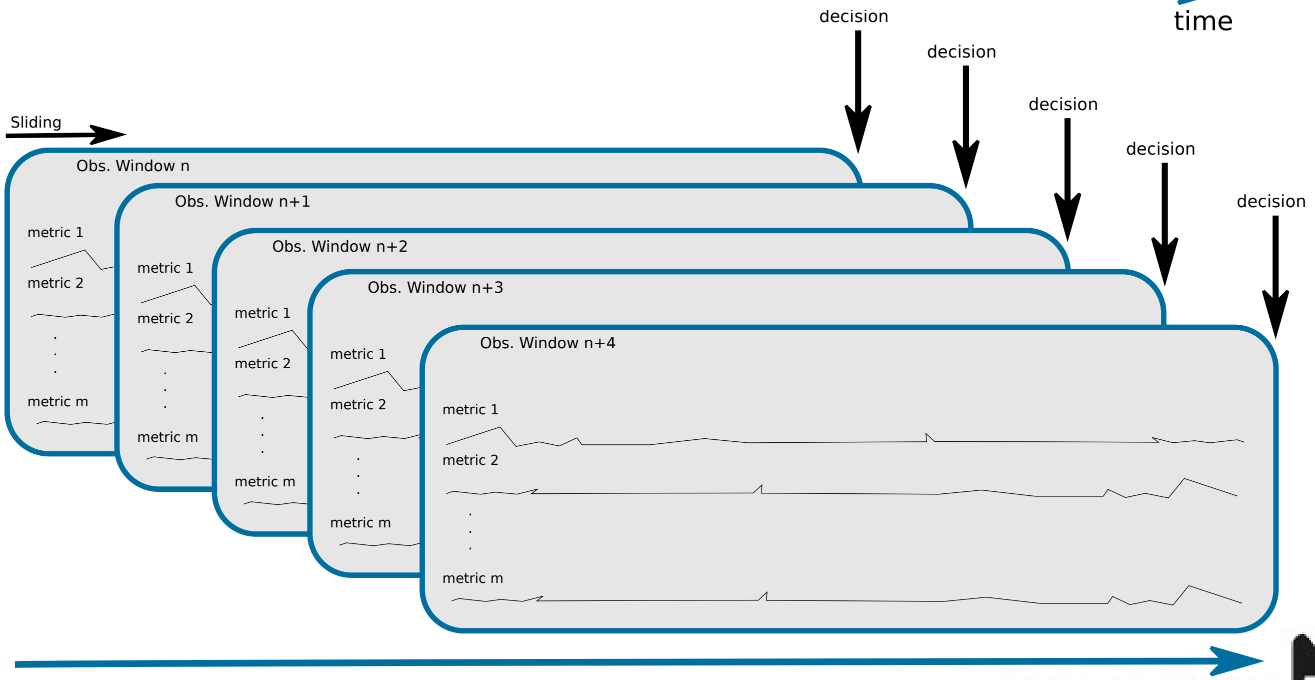


Observation Window (2)

- Sequential
  - Decision interval is equal to window size.

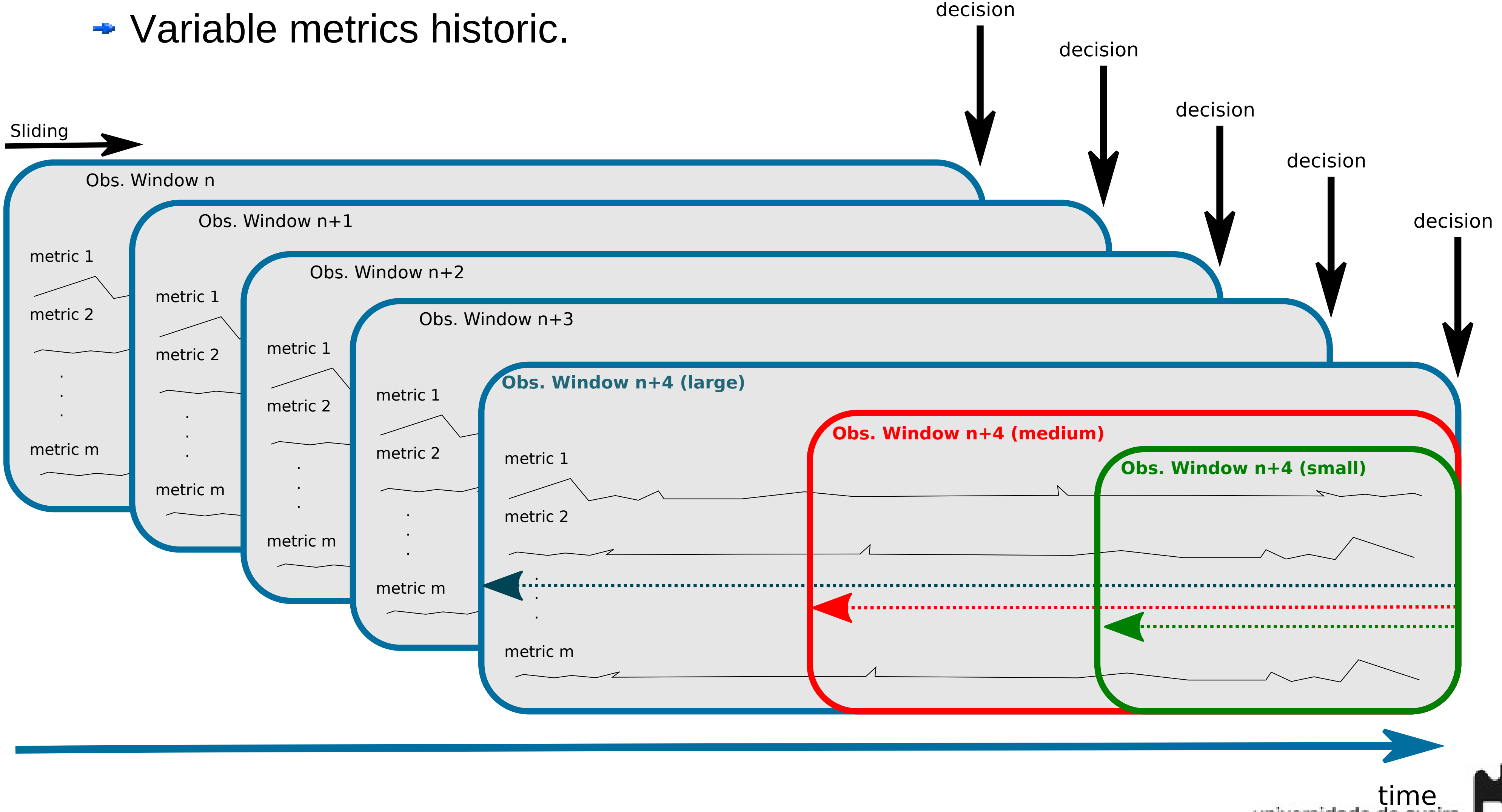


- Sliding
  - Allows for longer periods of observation, while maintaining a short period of decision.



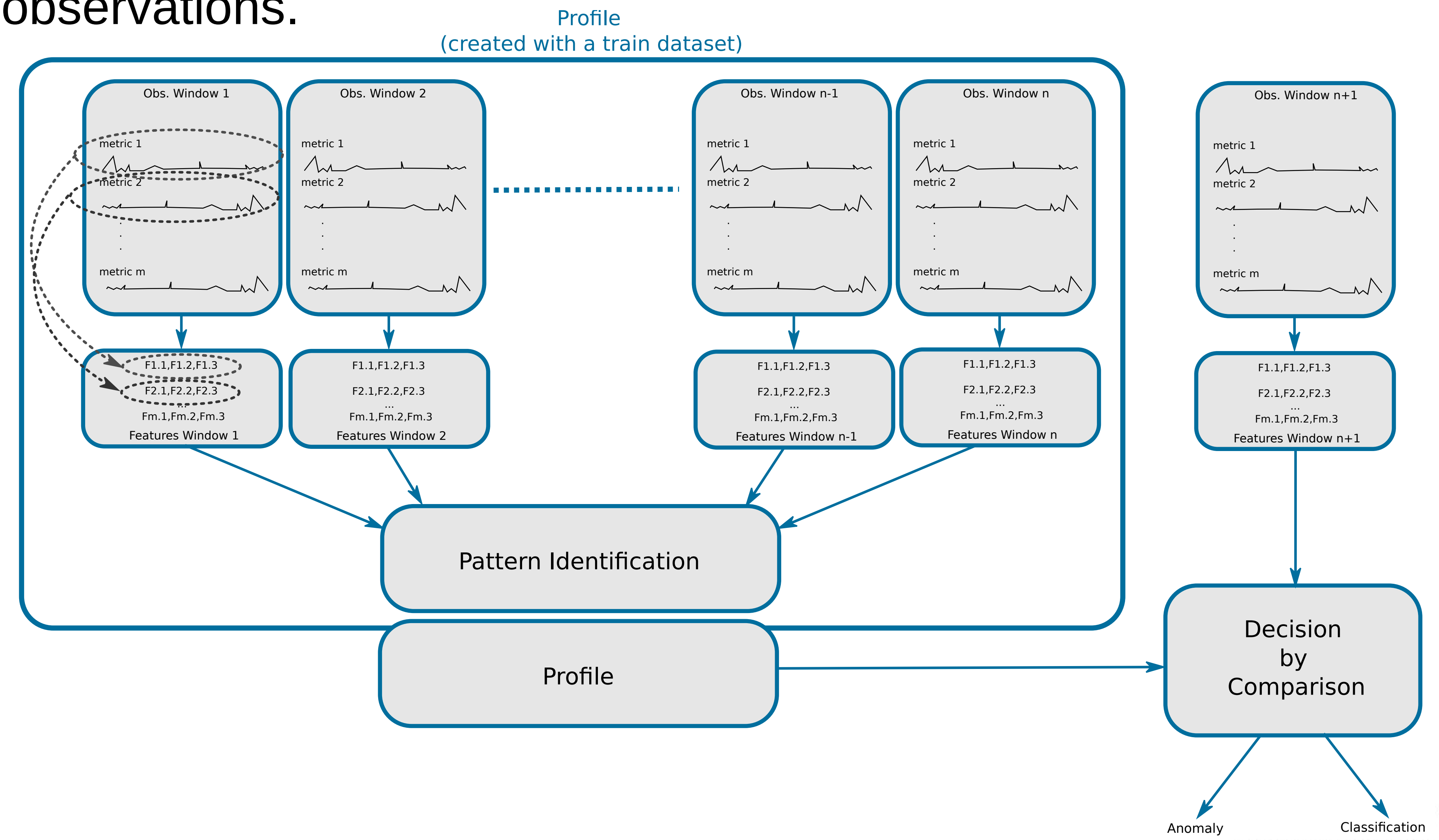
Multiple Observation Windows

- At each decision time point.
  - Construct observation widows with different lengths.
    - Variable metrics historic.



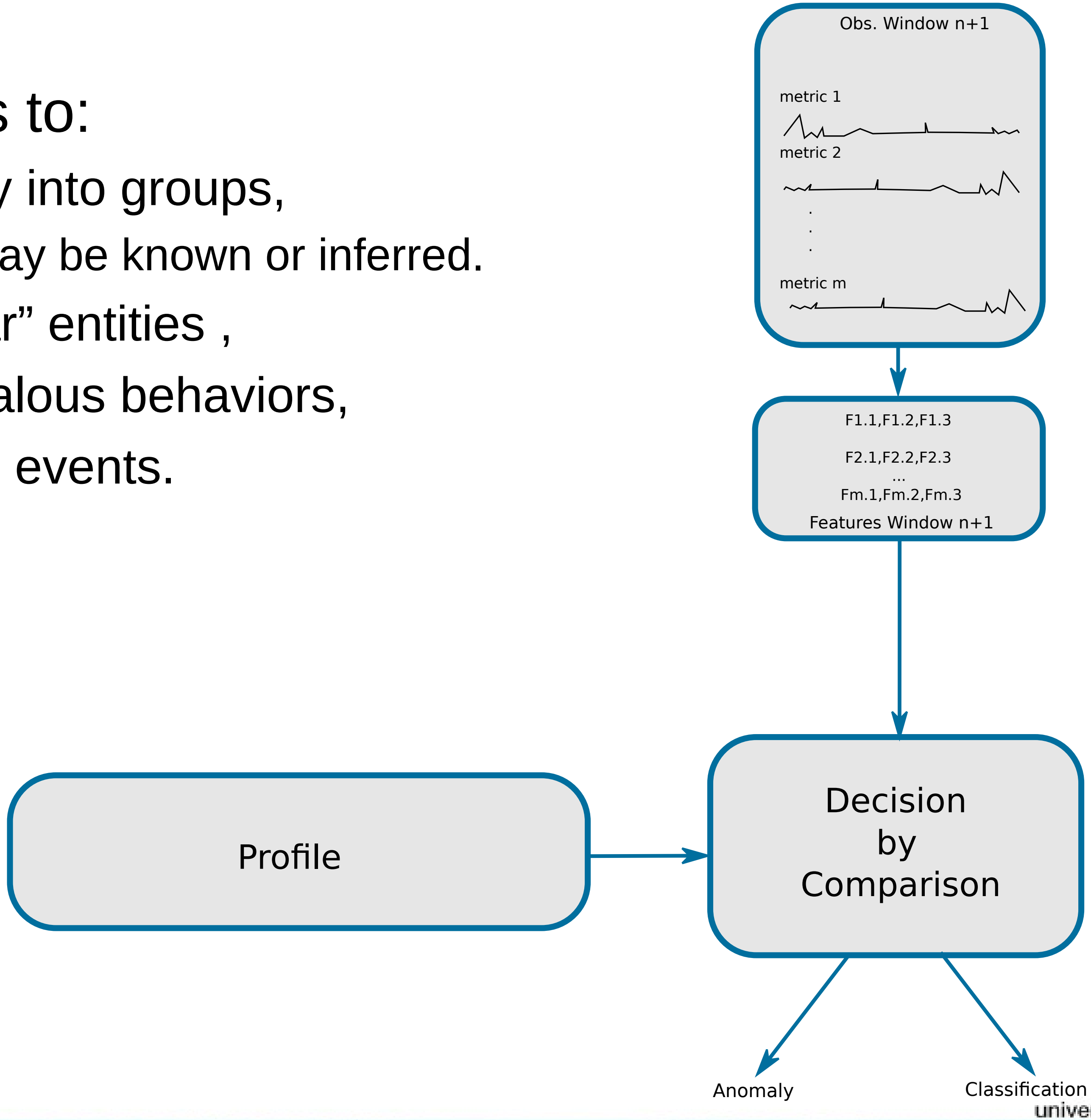
Entity Profiling

- Characterization of the observation windows after multiple observations.



Profile Comparison

- A profile allows to:
  - Classify entity into groups,
    - Groups may be known or inferred.
  - Group “similar” entities ,
  - Detect anomalous behaviors,
  - Predict future events.



Observation Features

- Time-independent descriptive statistics.
  - Mean, variance, quantiles, etc...
- Time-dependent descriptive statistics.
  - Time-relations between metrics over time
    - E.g., length of silences [number of sampling slots with metric equal to zero], length of activity [number of sampling slots with metric greater than zero], etc…
  - (Pseudo-)Periodicity components.
    - Time dependent.
      - Time multi-fractality (repetition of “similar events” in multiple time-scale).
    - Auto-correlation, FFT, CWT, DWT, and other spectral/frequency analysis.
- (Parameters of) Probabilistic functions/models.
  - Base function/model may be time independent or time dependent.

Descriptive Statistics (1)

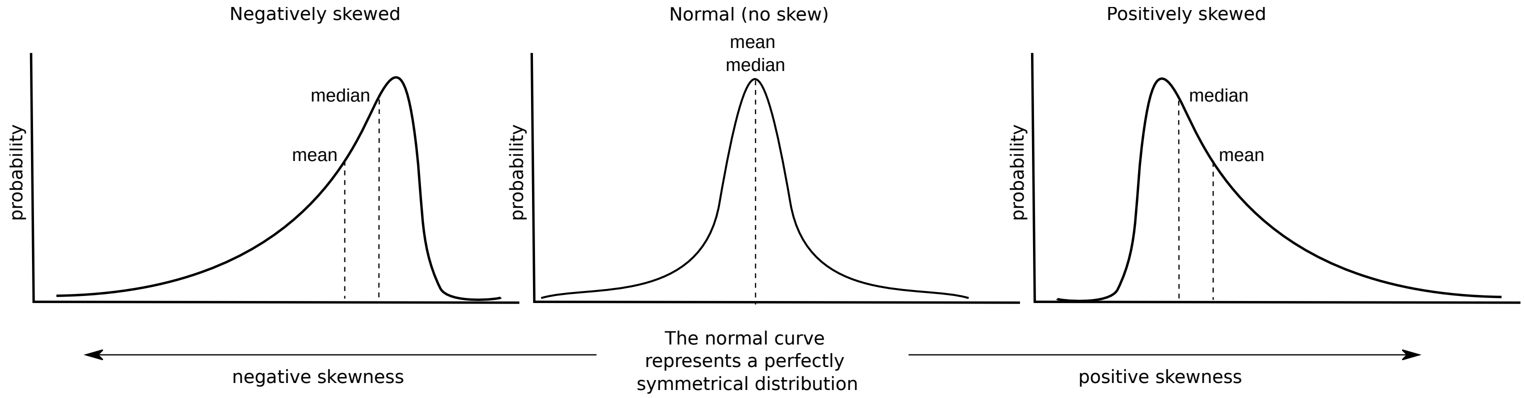
- For a (equally) sampled-continuous time process:

$$X = \{x'_t = x_k, T_0 + k\Delta t \leq t < T_0 + (k+1)\Delta t, k = 1, 2, \ldots, N\}$$

- **Mean**: $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
- **Median**: $m_d = F^{-1}(0.5)$
- **Variance**: $Var(X) = \sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2$
- **nth Central Moment**: $m_n = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^n$
- **Quantiles/Percentiles** $Y = \{y_j\}_{1\leq j\leq N} = \mathrm{sorted}(\{x_k\}_{1\leq k\leq N})$
  - 64th percentile (64%)=0.64 quantile $\pi_p = \min(y_{j\geq pN})$
  - Quartiles: 25%, 50%, and 75%

Descriptive Statistics (2)

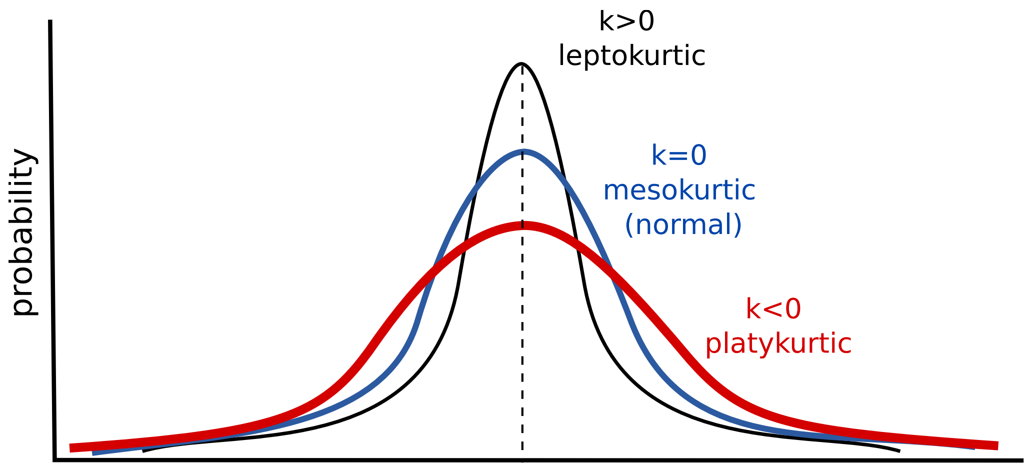
- **Skewness**:
  - Measure of the asymmetry of the probability distribution about its mean.



$$b_1 = \frac{m_3}{\sigma^3} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^3}{\left[\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu)^2\right]^{3/2}}$$

- **Excess Kurtosis**:
  - Measure of the "tailedness" of the probability distribution.
    - “-3” constant is used to normalize kurtosis to zero for a normal distribution.

$$k = \frac{m_4}{\sigma^4} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^4}{\left[\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu)^2\right]^{2}} - 3$$



Descriptive Statistics (3)

- Covariance
  - Metric that quantifies how much two random variables have simultaneous variations:

$$\mathrm{Cov}_{X,Y}=\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu_X)(y_i-\mu_Y)$$

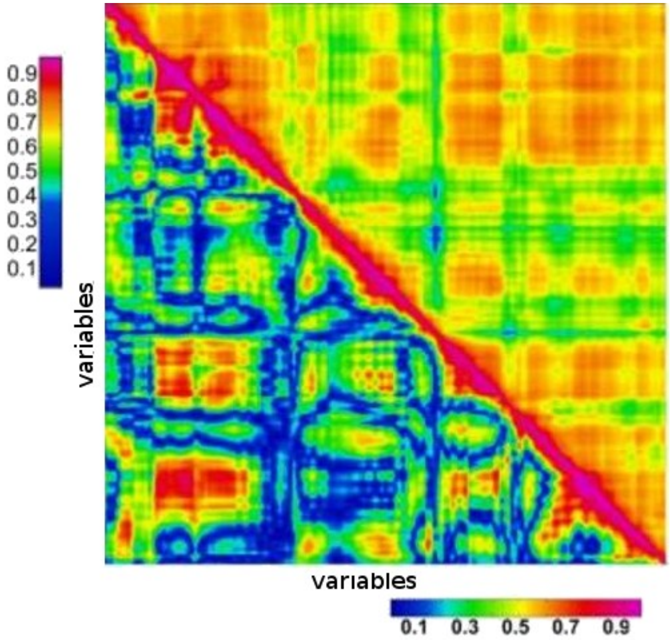
- Correlation coefficient
  - Normalized covariance, varies between -1 and 1:

$$\rho_{X,Y}=\frac{\mathrm{Cov}_{X,Y}}{\sigma_X\sigma_Y} \qquad \sigma_X=\sqrt{\mathrm{Var}(X)}$$

- Correlation matrix
  - Defined by a (MxM) matrix, to quantify the correlation between M variables X_i:

$$C=\{c_{i,j}\},i,j=1,\ldots,M$$

$$c_{i,j}=\rho_{X_i,X_j}$$

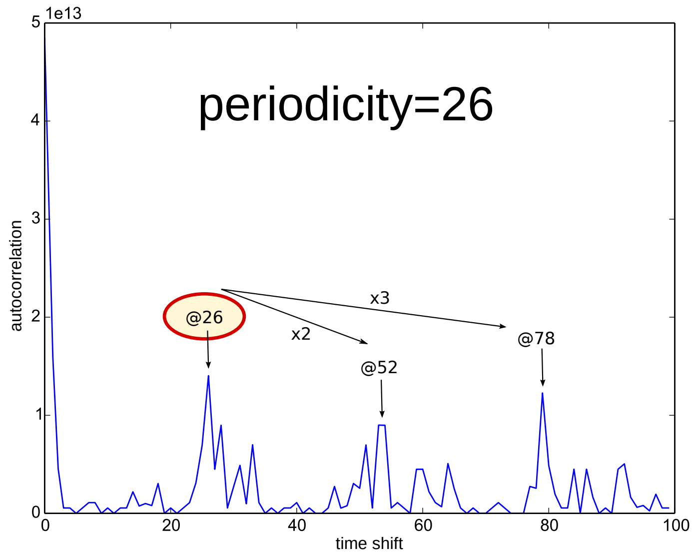


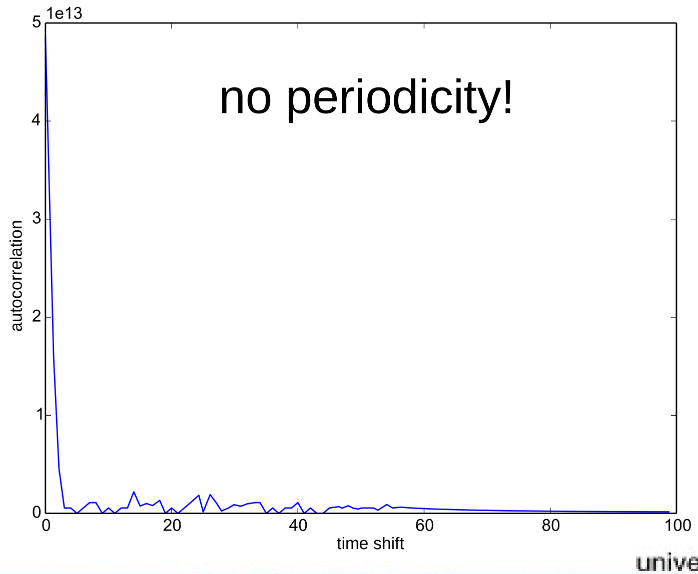
Periodicity Analysis (1)
Autocorrelation

- Autocorrelation
  - Correlation between the process and a shifted version (in time, by k samples) of the same process:

$$r_k = \frac{\sum_{i=1}^{N-k}(x_i - \mu_X)(x_{i+k} - \mu_X)}{\sum_{i=1}^{N}(x_i - \mu_X)^2}$$

- Autocorrelation local maximums (peaks), reveal periodicity.
  - Differences between positions (k) of local maximums give periodicity.



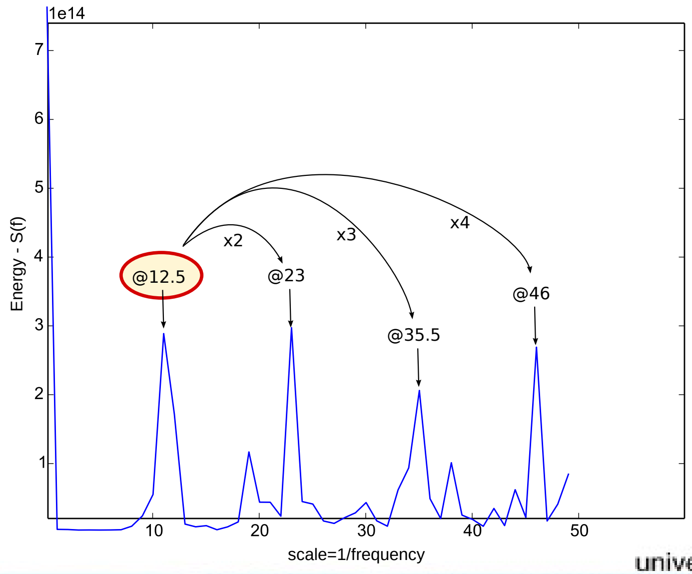


Periodicity Analysis (2)
Periodograms

- Periodogram
  - Frequency analysis → Spectral density estimation: Energy per frequency.
  - Given by the modulus squared of the discrete Fourier transform.
    - For a signal x_i sampled every Δt:

$$S(f) = \frac{\Delta t}{N} \left| \sum_{n=1}^{N} x_n e^{-j2\pi n f} \right|^2, -\frac{1}{2\Delta t} < t \leq \frac{1}{2\Delta t}$$

  - The inverse of the frequencies with higher energy give the different periods (of periodicity).



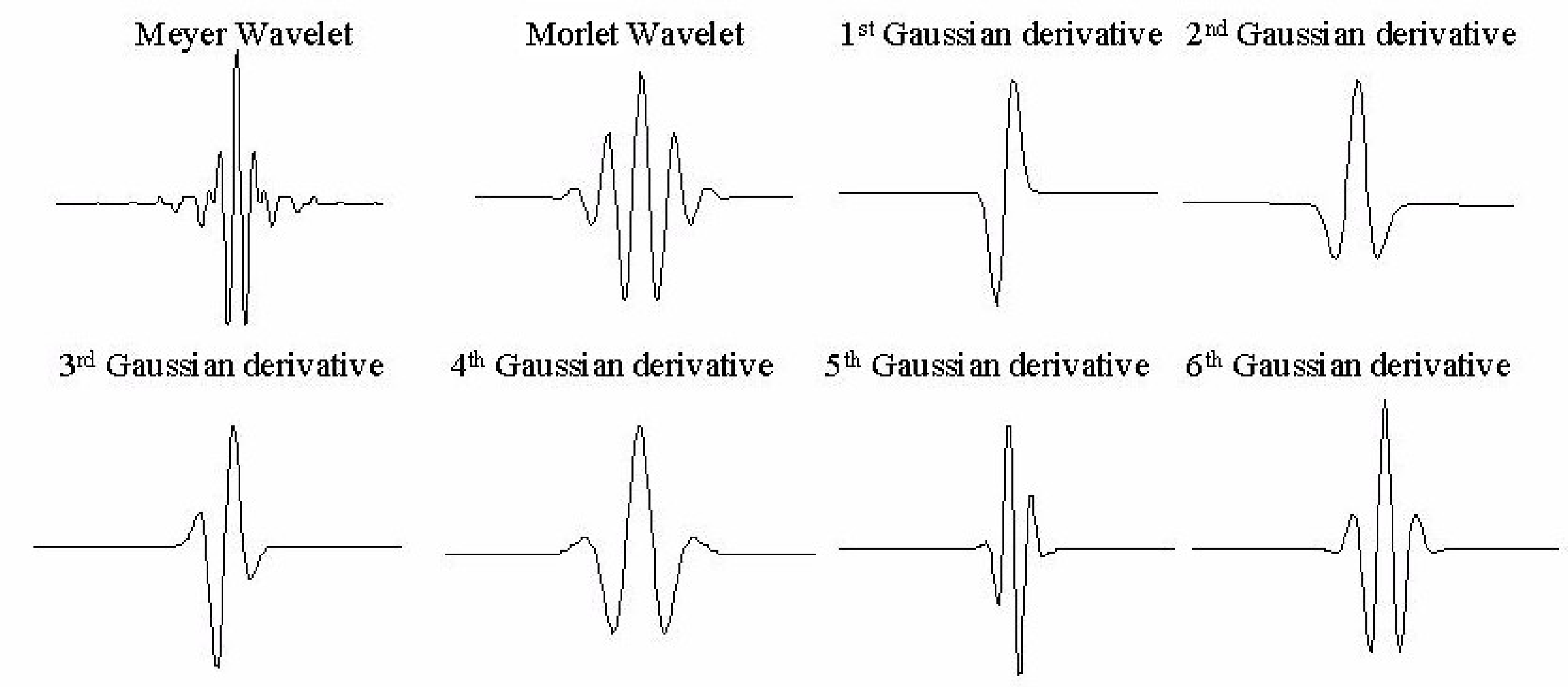
Periodicity Analysis (3)
Scalograms

- Scalogram
  - Joint Frequency/Time analysis → Wavelet Analysis
    - Energy per frequency/time.

$$\Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{+\infty}^{-\infty} x(t)\psi^*(\frac{t-\tau}{s})dt$$

Wavelet functions

$\psi^*(t)$



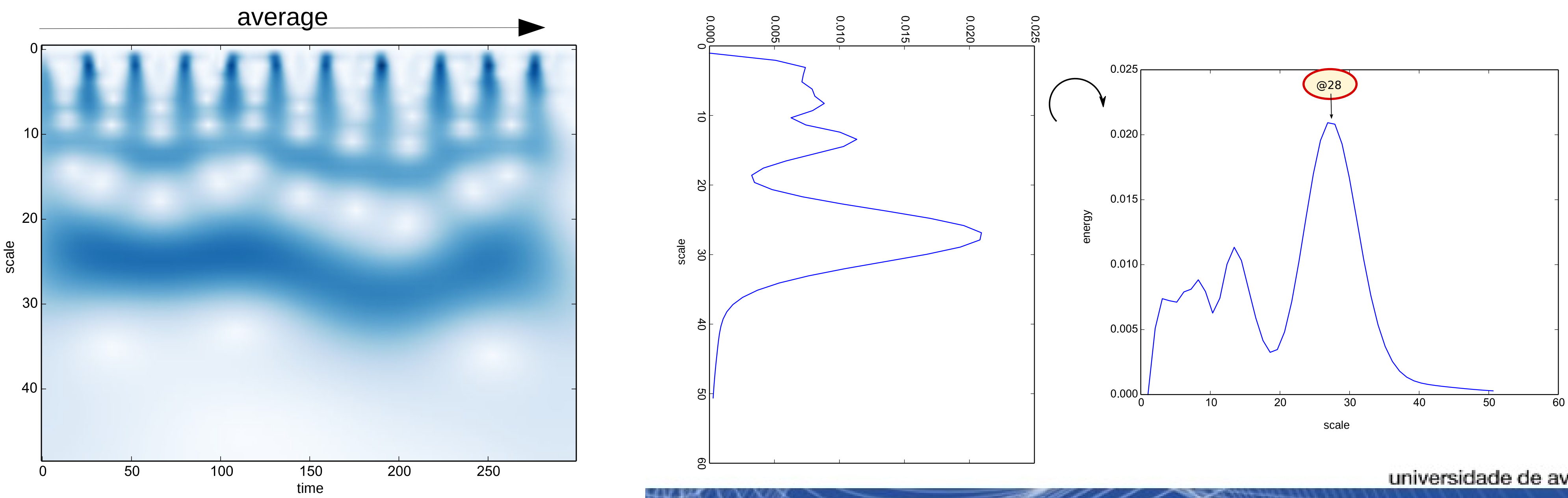
Periodicity Analysis (4)
Scalograms

- Given by the normalized modulus squared of the Wavelet transform.

$$\hat{E}_x(\tau, s) = \frac{\left|\Psi_x^{\psi}(\tau, s)\right|^2}{\sum_{\tau' \in \mathbf{T}} \sum_{s' \in \mathbf{S}} \left|\Psi_x^{\psi}(\tau', s')\right|^2}$$

  - Averaged over time.

$$\bar{e}_x(s) = \frac{1}{|\mathbf{T}|} \sum_{\tau \in \mathbf{T}} \hat{E}_x(\tau, s), \forall s \in \mathbf{S}$$



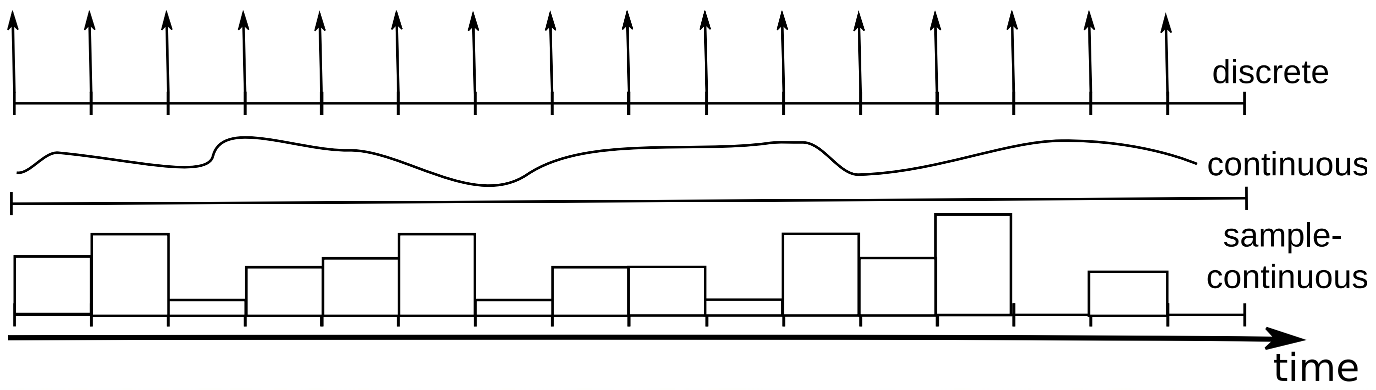
Stochastic Process

- A collection of variables indexed by a time variable, representing the evolution of some system over time.

$$X = \{x_t = a, t \in T\}$$

  - Discrete variables: $a \in A, A = \{\alpha_1, \alpha_2, \ldots, \alpha_S\}$
  - Continuous variables: $a \in \mathbb{R}$
  - Discrete time: $T = \{T_0 + k\Delta t, k \in \mathbb{N}_0\}$
  - Continuous time: $T = \mathbb{R}_0$
  - A continuous time process never exists in practice, what exists is a Sample-Continuous time process:

$$x_t = x'_{T_k}, t \in \mathbb{R}, T_k \leq t < T_{k+1}$$



Multivariate Stochastic Processes

- Variables belong to a multidimensional space of dimension N.

$$X = \{x_t = \vec{a}, t \in T\}$$

  - Discrete variables:

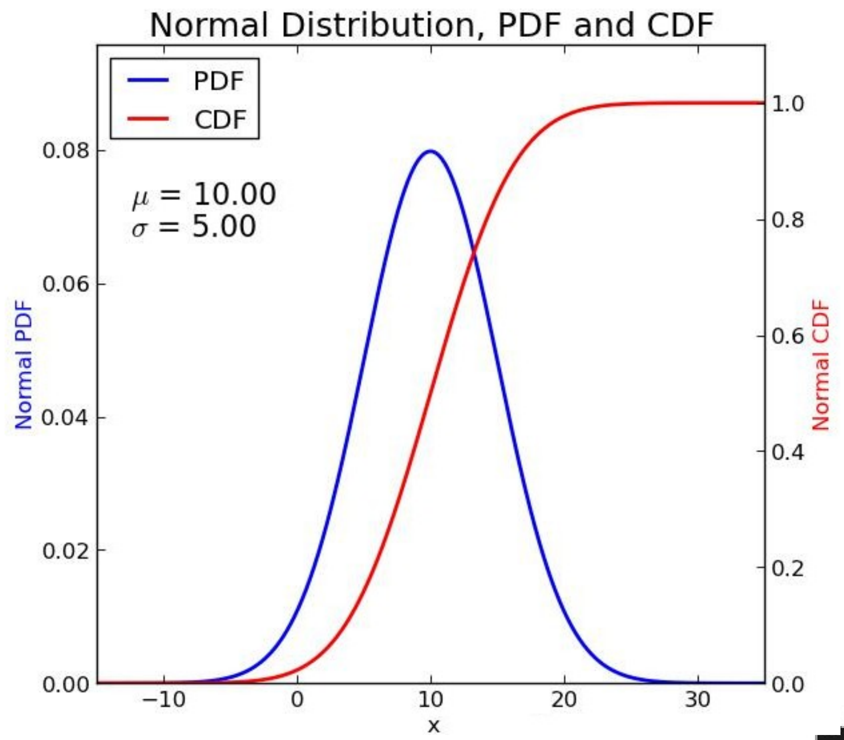
$$\vec{a} \in A, A = \{\vec{\alpha}_1, \vec{\alpha}_2, \ldots, \vec{\alpha}_S\}, \vec{\alpha}_i \in \mathbb{R}^N$$

  - Continuous variables:

$$\vec{a} \in \mathbb{R}^N$$

Probability Functions (1)

- Discrete
  - Probability Mass Function (PMF)
  - $\mathrm{pmf}_X(a) = Pr[X = a], a \in A, A = \{\alpha_1, \alpha_2, \ldots, \alpha_N\}$
  - $\sum_{\forall a \in A} \mathrm{pmf}_X(a) = 1$
- Continuous
  - Probability Density Function (PDF)
  - $f_X(a) = Pr[X = a], a \in \mathbb{R}$
  - $$\int_{-\infty}^{+\infty} f_X(x)dx = 1$$
  - Cumulative Density Function (CDF)
  - $$F_X(a) = Pr[X \leq a] = \int_{-\infty}^{a} f_X(x)dx$$



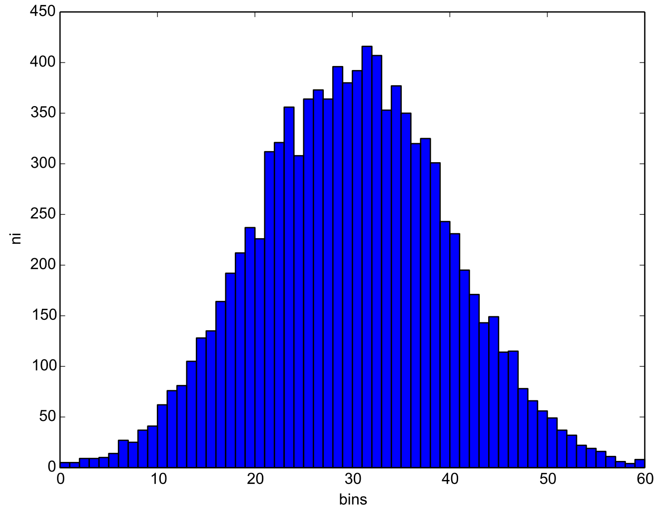
Probability Functions (2)

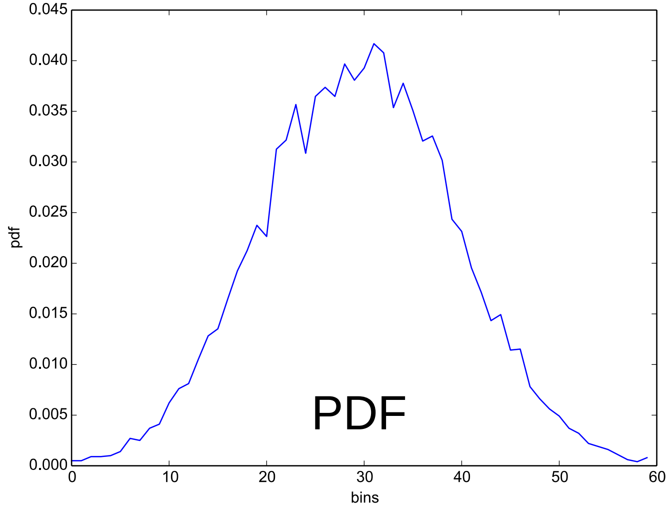
- Inference and interpretation
  - Histogram with bins $B = \{b_1, b_2, \ldots, b_{M+1}\}$

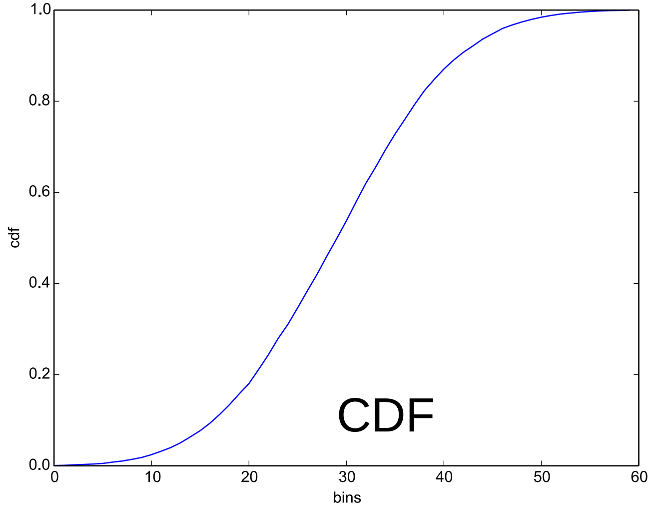
$$n_i = \text{count}(b_i \leq X < b_{i+1}), i = 1, 2, \ldots, M$$

$$f_X(a) = \frac{n_i}{N(b_{i+1} - b_i)}, \exists i, b_i \leq a < b_{i+1}$$

$$F_X(a) = \sum_{i=1}^{j} \frac{n_i}{N(b_{i+1} - b_i)}, \max_j : a < b_{j+1}$$

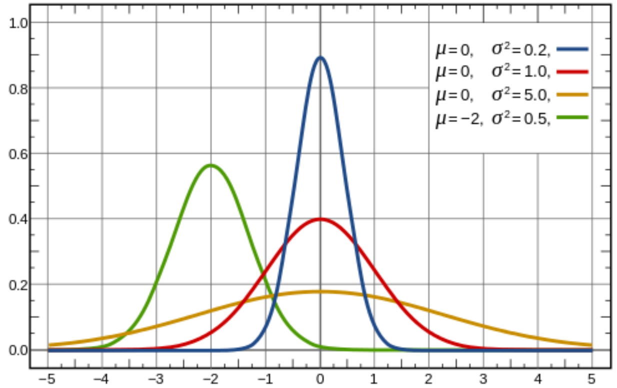


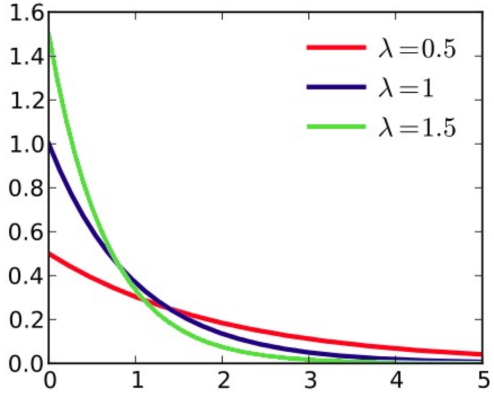




Statistical Univariate Distributions

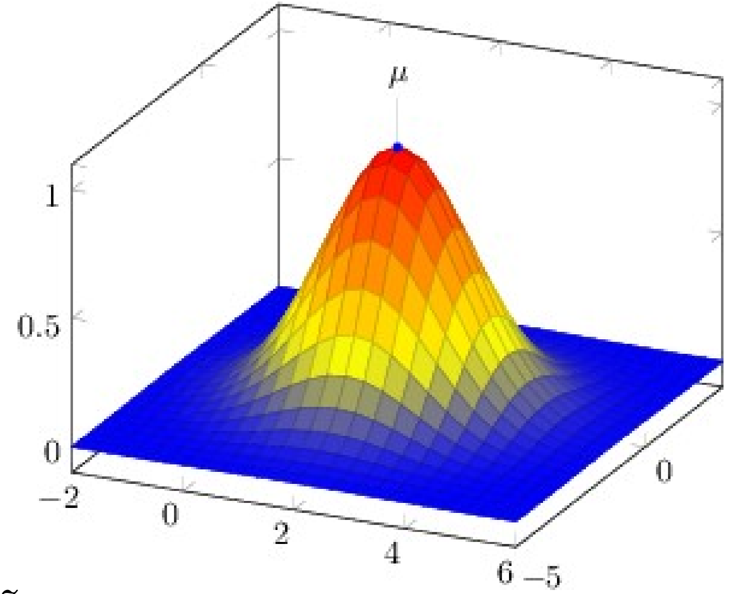
- Most commonly used distributions:
  - Discrete
    - Uniform: $\text{pmf}_X(a) = \begin{cases} \frac{1}{N}, a \in A \\ 0, a \notin A \end{cases}, A = \{\alpha_1, \alpha_2, \ldots, \alpha_N\}$
    - Poisson: $\text{pmf}_X(a) = \frac{\lambda^a e^{-\lambda}}{a!}, \lambda > 0$
  - Continuous
    - Uniform: $f_X(a) = \begin{cases} \frac{1}{a_{\max} - a_{\min}}, a \in [a_{\min}, a_{\max}] \\ 0, \text{otherwise} \end{cases}$
    - Normal/Gaussian: $f_X(a) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(a-\mu)^2}{2\sigma^2}}$
    - Exponential: $f_X(a) = \lambda e^{-\lambda a}$





Multivariate Distributions

- Joint probability of a multidimensional variable.
- Incorporates correlation (ρ) between dimensions.
- E.g., 2-Dimensions Gaussian:
  -



$$f_X((a_1,a_2)) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{z}{2(1-\rho^2)}}$$

$$z = \frac{(a_1-\mu_1)^2}{\sigma_1^2} - \frac{2(a_1-\mu_1)(a_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(a_2-\mu_2)^2}{\sigma_2^2}$$